Julia Neidhardt
Wolfgang Wörndl *Editors*

Information and Communication Technologies in Tourism 2020

Proceedings of the International Conference in Surrey, United Kingdom, January 08–10, 2020

Springer

Information and Communication Technologies in Tourism 2020

Julia Neidhardt · Wolfgang Wörndl
Editors

Information and Communication Technologies in Tourism 2020

Proceedings of the International Conference in Surrey, United Kingdom, January 08–10, 2020

Springer

Editors
Julia Neidhardt
Institute of Information Systems Engineering
TU Wien
Vienna, Austria

Wolfgang Wörndl
Chair of Connected Mobility
TU Munich
Garching, Germany

ISBN 978-3-030-36736-7 ISBN 978-3-030-36737-4 (eBook)
https://doi.org/10.1007/978-3-030-36737-4

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

The 27th Annual International eTourism Conference ENTER2020 features new research, innovative systems, and industry case studies on the application of Information and Communication Technologies (ICT) in travel and tourism. Organized by the International Federation for IT and Travel and Tourism (IFITT), ENTER2020 takes place in Surrey, UK, from January 8 to 10, 2020. With the theme “Responsible eTourism,” the conference focuses on exploring ways, how technology can be used to ensure a positive impact of tourism on society, environment, and economy.

The research track of ENTER2020 received a total of 62 full paper submissions, covering a diverse variety of fields within the area of ICT and tourism. Each research paper submission went through a rigorous double-blind review process. As a result, 26 full research papers (42%) were accepted for presentation at the conference, one was withdrawn, so 25 papers are included in these proceedings.

While still maintaining a broad topic, the papers presented in this volume advance the current knowledge base of ICT and tourism in the following areas: social media, destination marketing, recommender systems and decision making, virtual and augmented reality, technology in tourism, and research related to hotels and activities. We hope these proceedings will serve as a valuable source of information on the state-of-the-art in ICT and tourism research.

We greatly appreciate the considerable time and effort put in by all members of the ENTER2020 Scientific Committee, who helped us to ensure that the content of the research papers is of high quality. We also would like to thank the panel of experts who helped with additional reviews in order to select candidates for the best paper award.

Furthermore, we are thankful to the ENTER2020 Overall Chairs Juho Pesonen and Anyu Liu, the IFITT President Iis Tussyadiah, other ENTER2020 organizers, the IFITT Board, and all members of IFITT for their support and for accommodating the many enquiries made while managing the research track.

Finally, we would also like to thank all authors for their willingness to disseminate their latest research at ENTER2020. This conference would not be possible without their efforts.

Julia Neidhardt
Wolfgang Wörndl

Organization

ENTER2020 Scientific Committee

Marina Abad	University of Deusto, Spain
Rami Al-Salman	trivago N.V., Germany
Alisha Ali	Sheffield Hallam University, UK
Aurkene Alzua-Sorzabal	University of Deusto, Spain
Norman Au	The Hong Kong Polytechnic University, Hong Kong
Rodolfo Baggio	Bocconi University, Italy
Catalin-Mihai Barbu	University of Duisburg-Essen, Germany
Pierre Benckendorff	The University of Queensland, Australia
Matthias Braunhofer	Free University of Bozen-Bolzano, Italy
Derek Bridge	University College Cork, Ireland
Claudia Brözel	University of Applied Sciences for Sustainable Development, Germany
Dimitrios Buhalis	Bournemouth University, UK
Jacques Bulchand-Gidumal	University of Las Palmas de Gran Canaria, Spain
Lorenzo Cantoni	USI–Università della Svizzera italiana, Switzerland
Federica Cena	University of Torino, Italy
Ludovik Coba	Free University of Bozen-Bolzano, Italy
Cynthia Corrêa	University of São Paulo, Brasil
Giacomo Del Chiappa	University of Sassari, Italy
Amra Delić	TU Wien, Austria
Linus W. Dietz	Technical University of Munich, Germany
Anneli Douglas	University of Pretoria, South Africa
Mehdi Elahi	Free University of Bozen-Bolzano, Italy
Marine-Roig Estela	University of Lleida, Spain
Alexander Felfernig	Graz University of Technology, Austria
Anna Fensel	University of Innsbruck, Austria
Gerhard Friedrich	AAU Klagenfurt, Austria

Matthias Fuchs	Mid Sweden University, Sweden
Christos Gatzidis	Bournemouth University, UK
Damianos Gavalas	University of the Aegean, Greece
Robert Goecke	Munich University of Applied Sciences, Germany
Maria Rosario González-Rodríguez	University of Seville, Spain
Ulrike Gretzel	University of Southern California, USA
Vincent Grèzes	University of Applied Sciences Western Switzerland, Switzerland
Szilvia Gyimothy	Aalborg University, Denmark
Noor Hazarina Hashim	Universiti Teknologi Malaysia, Malaysia
Jesus Herrero	Tecnalia, Spain
Daniel Herzog	Technical University of Munich, Germany
Wolfram Höpken	University of Applied Sciences Ravensburg-Weingarten, Germany
Alessandro Inversini	Ecole hôtelière de Lausanne, HES-SO/University of Applied Sciences Western Switzerland, Switzerland
Athina Ioannou	University of Surrey, UK
Dietmar Jannach	AAU Klagenfurt, Austria
Tomasz Janowski	Gdańsk University of Technology, Poland | Danube University Krems, Austria
Timothy Jung	Manchester Metropolitan University, UK
Myunghwa Kang	University of Nebraska–Lincoln, USA
Stefan Klein	University of Muenster, Germany
Peter Knees	Vienna University of Technology, Austria
Chulmo Koo	Kyung Hee University, Korea
Jan Krasnodebski	Expedia, Switzerland
Rob Law	The Hong Kong Polytechnic University, Hong Kong
Daniel Leung	The Hong Kong Polytechnic University, Hong Kong
Rosanna Leung	I-Shou University, Taiwan
Maria Lexhagen	Mid Sweden University, Sweden
Gang Li	Deakin University, Australia
Andreas Liebrich	Hochschule Luzern–Wirtschaft, Switzerland
Bernd Ludwig	University of Regensburg, Germany
Enric López	EUHT CETT–UB, Spain
David Massimo	Free University of Bozen-Bolzano, Italy
Christian Maurer	IMC University of Applied Sciences Krems, Austria
Luiz Mendes-Filho	Federal University of Rio Grande do Norte, Brasil
Elina (Eleni) Michopoulou	University of Derby, UK

Roberta Minazzi	University of Insubria, Italy
Valeria Minghetti	CISET–Ca' Foscari University, Italy
Jean-Claude Morand	CYBERSTRAT, France
Antonio Moreno	Universitat Rovira I Virgili, Spain
Jamie Murphy	University of Eastern Finland, Finland
Barbara Neuhofer	Salzburg University of Applied Sciences, Austria
Thuy Ngoc Nguyen	Free University of Bozen-Bolzano, Italy
Lyndon Nixon	MODUL University Vienna, Austria
Elena Not	Fondazione Bruno Kessler, Italy
Peter O'Connor	ESSEC Business School, France
Irem Önder	University of Massachusetts, USA
George Papadopoulos	University of Cyprus, Cyprus
Sangwon Park	The Hong Kong Polytechnic University, Hong Kong
Katja Pasanen	University of Eastern Finland, Finland
Juho Pesonen	University of Eastern Finland, Finland
Ilona Pezenka	FH Wien der WKW University of Applied Sciences for Management and Communication, Austria
Birgit Proell	Johannes Kepler University Linz, Austria
Mattia Rainoldi	Salzburg University of Applied Sciences, Austria
Francesco Ricci	Free University of Bozen-Bolzano, Italy
Jia Rong	Victoria University, Australia
Laurens Rook	Delft University of Technology, Netherlands
Roland Schegg	HES-SO Valais, Switzerland
Mete Sertkan	TU Wien, Austria
Marianna Sigala	University of South Australia, Australia
Brigitte Stangl	University of Surrey, UK
Jason Stienmetz	University of Surrey, UK
Marko Tkalcic	Free University of Bozen-Bolzano, Italy
Pasi Tuominen	Haaga-Helia University, Finland
Giampaolo Viglia	University of Portsmouth, UK
Vania Vigolo	University of Verona, Italy
Dan Wang	The Hong Kong Polytechnic University, Hong Kong
Christian Weismayer	MODUL University, Austria
Masahito Yamamoto	Hokkaido University, Japan
Kyung-Hyan Yoo	William Paterson University, USA
Markus Zanker	Free University of Bozen-Bolzano, Italy

Contents

Social Media

Adapting to an Emerging Social Media Landscape: The Rise of Informalization of Company Communication in Tourism

Corné Dijkmans[1(✉)], Peter Kerkhof[2], and Camiel Beukeboom[2]

[1] Breda University of Applied Sciences, Breda, The Netherlands
dijkmans.c@buas.nl
[2] Vrije Universiteit Amsterdam, Amsterdam, The Netherlands

Abstract. This study investigates the evolvement of informalization of company communication on social media over time, based on actual social media data from the tourism industry. The development in the use of emoticons and emoji by companies is examined, as an expression of informalization and humanization of online company communication. We selected 33 companies from the tourism industry in The Netherlands and investigated their Facebook and Twitter messages supplemented with the messages of consumers who interacted with these companies, for the period 2011–2016. Results show that the use of emoticons and emoji in online company communication increased significantly over the period covered in this study, demonstrating a higher level of informalization of company communication. Since this is a key factor for improving relational outcomes, this finding has scholarly as well as managerial relevance. We discuss the implications of the results for the presence of organizations on social media.

Keywords: Social media · Conversational human voice · Informalization of communication · Textual paralanguage · Emoticons · Emoji

1 Introduction

Through social media, the world wide web has developed into a social environment, where people can interact, share ideas and generate content [1]. Consumers can easily connect with other consumers but also with organizations, brands and companies. As a result, for companies, customer involvement and engagement through social media have become an important factor in their marketing approach [2]. Social media platforms, such as Facebook and Twitter, offer companies various ways to communicate and interact with customers, to provide online customer service and product assistance, and to obtain feedback [3]. Several studies indicate that social media use by companies is beneficial if utilized correctly (e.g., [4]).

In the early days of social media, however, it was by no means evident that company social media use would be successful. Consumers were reluctant to companies intervening in their activities on social media. In a 2011 study, Heller Baird and Parasnis [5] argue that most consumers (70%) mainly wanted to connect with friends and family on social media, while only 23% wanted to interact with companies and

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 3–14, 2020.
https://doi.org/10.1007/978-3-030-36737-4_1

brands. Fournier and Avery [6] argue that companies were viewed with suspicion on social media, and their presence was easily perceived as intrusive. Companies were seen as “uninvited crashers of the Web 2.0 party” [6] (p. 192).

At the same time, it became increasingly important to establish a successful social media presence to engage with online consumers [7]. Traditional one-way company communication strategies were losing trust in favor of more conversational communication approaches. As a result, for companies, to (re)gain this trust, interactivity in online communication started to play a more important role. Interactivity has been defined as “the degree to which two or more communication parties can act on each other, on the communication medium, and on the messages and the degree to which such influences are synchronized” [8] (p. 54). Company interactivity in online communication reinforces consumer trust, satisfaction, and commitment [9], and consumer trust declines if consumers’ expectations with regard to interactivity are not met [10].

To optimize consumers’ level of perceived interactivity of a company, cognitive as well as affective cues must be present in communication [11]. Since computer-mediated communication may – through its mainly text-based orientation – more easily facilitate the cognitive aspects of communication, it poses challenges for companies with respect to its affective aspects. That is, communication via social media platforms lacks the ability of conveying nonverbal cues (e.g., facial expressions, tone of voice, physical touch, gestures, appearance) that are important for a correct mutual understanding and to pursue interpersonal goals [12, 20]. The absence of nonverbal cues negatively influences the quality of communication and may result in misinterpretations, and in a decreased feeling of humanness, connectedness and intimacy [14]. To compensate for these shortcomings in social media, people have developed ways to give substance to these important affective (i.e., emotional and social) aspects of communication. This can be realized by fine-tuning text and using the correct tone of voice in social media messages, but also by the use of emoticons and emoji [15]. An emoticon is defined as “a group of keyboard characters (such as :-)) that typically represents a facial expression or suggests an attitude or emotion and that is used especially in computerized communications (such as e-mail)” [16]. Emoji are small pictograms of facial features, animals, and objects (e.g., ☀ or ☺). Emoticons and emoji intend to elucidate and fortify the meaning of messages between sender and receiver [12] and have become a popular means to improve the understanding of messages that was previously absent in online communication [17].

In conclusion, for companies to be successful on social media, properly dealing with the constraints of the medium (i.e., the difficulty to provide emotional and ‘humane’ cues as a result of its predominant text-based character) is of great importance. Remarkably, while social media have become increasingly important in company communication [18], there is a lack of research based on real-life data to describe and explain how companies have dealt with this challenge of computer-mediated communication with consumers as described above. This study tries to fill this gap by investigating actual real-life company social media data, and by examining how the use of emoticons and emoji has developed as an indication of the level of informalization and humanization of online company communication.

2 Theoretical Background

Once company-consumer connections on social media became more common, consumers started to use companies' social media channels to ask questions, vent their complaints, give compliments, and share their ideas. Consequently, delivering customer service became a new part of company social media activities: webcare – often provided by designated teams/employees – emerged as a service and brand communication tool. Webcare was defined by Van Noort and Willemsen [3] as "the act of engaging in online interactions with (complaining) consumers, by actively searching the web to address consumer feedback (e.g., questions, concerns and complaints)" (p. 133). Several studies have emphasized the importance of providing proper webcare for companies [3, 19, 20]. Since webcare takes place in public and has to deal with (dis) satisfied customers, closely watched by bystanders, within short response times, it sets high requirements for company communication (e.g., [4]). Several studies show that to be successful in delivering webcare, using a personal voice that is relationship oriented (i.e., being authentic, 'human'), conversational capabilities and prompt responsiveness are important factors [9, 21–24].

These requirements of online company presence relate to the concept of *conversational human voice* (CHV), defined by Kelleher [9] as "an engaging and natural style of organizational communication as perceived by an organization's publics based on interactions between individuals in the organization and individuals in publics." (p. 177). Through this style of communicating, companies try to mimic face-to-face communication and to informalize and 'humanize' the corporate voice [25]. Within computer-mediated settings, applying a CHV by companies has proven to have positive effects on relational outcomes, such as trust, stakeholder involvement, and corporate reputation [3, 14, 19, 21, 26, 27]. In conclusion, successful company presence on social media depends strongly on successful interactions, and previous research shows that CHV is a crucial factor in accomplishing these fruitful interactions.

Applying a CHV in computer-mediated communication can be put into practice through the use of human representatives (i.e., webcare employees), informal language use, use of personal pronouns and – since nonverbal cues are lacking in online communication – textual paralanguage, defined by Luangrath et al. [13] as "written manifestations of nonverbal audible, tactile, and visual elements that supplement or replace written language and that can be expressed through words, symbols, images, punctuation, demarcations, or any combination of these elements." (p. 98). Important forms of such textual paralanguage are emoticons and emoji, which can be used to convey meaning and emotion to online textual communication [13], and thus contribute substantially to perception of CHV. The word 'emoticon' is a contraction of 'emotion' and 'icon'. Originally, emoticons were merely composed of regular keyboard characters, but as of October 2010, graphical emoticons (i.e., emoji) have been introduced and added to Unicode, the computing industry standard for encoding, representation, and handling of text, expressed in most of the world's writing and input systems. An emoji is a small graphical symbol, ideogram, or icon used to express an idea or emotion, and is originating from the Japanese words for picture ('e') and letter/character ('moji'). Authorities on language use have acknowledged emoji; for instance, The Oxford

Dictionaries chose the 'face with tears of joy' emoji as Word of the Year in 2015 [28]. Since 2010, emoji are also included on default keyboards of mobile devices and have become very popular worldwide. For example, Instagram (an online mobile photo and video sharing platform) reported in March 2015 that nearly half of the texts on their platform contained emoji [29].

All these reports suggest that emoticons and emoji are now an undeniable part of the world's electronic communication vocabulary. They offer a range of sentiment and feelings that portray specific emotions through facial gestures, but also concepts and ideas, such as celebration, weather, vehicles and buildings, food and drink, animals and plants, and activities. Use of emoticons and emoji increases information richness, which plays an important role in facilitating social connectedness and identity expressiveness between users [30], and may thus drive intimacy, trust and commitment. Lo [15] found that the use of emoticons improved the level of understanding of messages in an online context, and emoticon us positively influenced the level and direction of emotion and attitude. The expression of emotions in online communications by the use of emoticons was found to be similar to the expression of emotions in face-to-face communication [31].

In sum, emoticons and emoji have proved to add value to computer-mediated interactions between individuals. However, to our knowledge, research to date has not yet investigated the use of emoticons and emoji by companies, and the developments therein. Given the relevance of non-verbal cues for successful online and interactive communication, and the lack of insights from actual practice in this field, in this study we will therefore investigate the development of emoticon and emoji use in real-life company communication. This results in our research question: how has the use of emoticons and emoji in social media communication of companies developed over time?

3 Methodology

For this study, we selected 33 large companies from the Dutch tourism Top 50 [32] with an active presence on Facebook as well as on Twitter. The remaining 17 companies from the Dutch tourism Top 50 had no active presence on social media (i.e., on Facebook and Twitter).

In order to answer our research question (i.e., how the use of emoticons and emoji in social media communication of companies has developed over time), we focused on the number and types of company social media messages over a six-year period, ranging from 2011 to 2016. In our study, we included all Facebook and Twitter messages of the selected Dutch tourism and travel companies. Facebook and Twitter are the two most commonly used online platforms for company-consumer communication and webcare; worldwide as well as in The Netherlands [33]. In 2017, Facebook is used by 94% of the companies using social media and Twitter by 68% [18]. In order to best capture interactivity and the two-way flow of information, we not only included the companies' messages, but also the messages of consumers that interacted with these companies. To investigate our research question, we content analyzed the companies'

Facebook and Twitter messages from 2011 to 2016 on the presence of emoticons and/or emoji.

Our data were collected by performing a data mining exercise with the use of Coosto, a Dutch online social media monitoring platform [34]. The infrastructure provided by Coosto monitors online channels in 150 languages and in 200 countries [35]. With regard to The Netherlands, Coosto covers over 3 billion public social media messages, posted since 2009. Around 2.5 million new messages are added to its database per day. Messages can be selected and exported from the database with a query language and a web interface.

The overall profile of the number of social media messages created in general showed that, as to be expected, from the end of 2010 onwards an increasing number of messages were generated in The Netherlands. Therefore, we used January 2011 as the starting point for our study, and December 2016 as the end date, covering six years in total.

3.1 Measures

Posts and Reactions. We determined whether social media messages are either *posts* or *reactions*. In Coosto, a message is categorized as a post if the message is not preceded by an earlier message in the same conversation. In conversations, a post is always the opening message (i.e., the first message in a 'message thread'). A reaction is a response to a post or to another reaction (i.e., the second and further messages in a 'message thread'). For both posts and reactions, we distinguish between company and consumer messages. Company messages consist of all posts and reactions sent by the selected 33 tourism companies during the time period under investigation in this study (2011–2016). Consumer messages consist of posts and reactions addressed at the company channels included in our study (i.e., for Twitter: message contained a reference – i.e., an @ mention – to one of the selected companies; for Facebook: message was posted on one of the selected companies' Facebook pages). References to the 33 companies in messages not posted on the selected companies' social media channels were not included in this study (i.e., messages mentioning the company name or brand on Facebook/Twitter other than on the channels of the selected companies).

Emoji and Emoticons. To investigate the development of emoticons/emoji in the social media messages, the full content of all messages of the tourism companies on their Twitter and Facebook accounts was downloaded with a time stamp ranging from 2011 to the end of 2016. Additionally, we also downloaded the full content of the consumer posts and reactions connecting to the Twitter account of the 33 companies. Content of the consumer posts/reactions on the Facebook channels of the selected tourism companies (over 1.7 million messages) was not included in the analyses, because all full content downloads had to be performed in small batches of 10,000 (as a result of constraints by the Coosto software), making the total message volume too large for download.

In total, the content of 772,884 messages was downloaded (i.e., for Twitter: company as well as consumer posts and reactions; for Facebook: only company posts and reactions). Since we were interested in changes of the occurrence of emoji and emoticons, duplicate messages were removed (based on the URL and the content of the message) in order to avoid counts based on the occurrence of emoji and emoticons in the same reposted or retweeted message. After deduplication, 201,890 messages were removed, resulting in a final dataset of 570,994 messages. Table 1 shows the number of messages for the different categories.

Table 1. Volume of messages used for content analysis (total N = 570,994). *(compiled by authors)*

	Facebook		Twitter	
	Posts	Reactions	Posts	Reactions
Tourism companies	37,111	71,759	63,372	99,290
Consumers	–	–	134,993	164,469

A list of 33 often used emoticons (e.g., :-), ;-)) was retrieved from the Github website [36] and used to scan the messages. Some infrequently occurring emoticons resulted in errors and were removed from the list (such as : c and :-*), resulting in a list of 22 emoticons. In order to code emoji, we retrieved an emoji dictionary from the Github website [37], containing 2,378 emoji and their UTF8 codes. From this script, we removed the part of the UTF8 code that referred to variations in skin tone of the 'people' emoji, thus reducing the list to 1,111 emoji. Using an R script, all 570,994 remaining company and consumer social media messages after deduplication were scanned on the occurrence of emoji and emoticons included on the final list, and categorized in 3 groups (i.e., messages containing emoticons, containing emoji, and messages without emoticons/emoji). Finally, we calculated the proportion of company messages with emoticons/emoji in the total number of messages.

4 Results

Scanning the 570,994 messages for emoji and emoticons resulted in 551 different emoji and 22 different emoticons. For each message, only unique occurrences of emoji and emoticons were counted, thus resulting in a score indicating the number of unique emoticons rather than the total number of emoji and emoticons. The 271,532 messages by tourism companies contained a total of 3,524 emoji and 41,277 emoticons; 0.9% of all messages contained one or more emoji, whereas 14.9% contained one or more emoticon. Table 2 gives a global summary of the emoji and emoticon proportions per year, showing a growth in emoticon and emoji use by companies in posts, and in particular in reactions.

Table 2. Proportion of tourism company messages containing emoticons and emoji. *(compiled by authors)*

	Facebook		Twitter	
	Company posts	Company reactions	Company posts	Company reactions
2011	2,2%	12,3%	3,0%	11,9%
2012	2,9%	10,1%	3,1%	13,4%
2013	4,6%	17,3%	2,3%	13,3%
2014	8,6%	28,5%	3,1%	14,7%
2015	10,5%	51,8%	3,5%	23,7%
2016	16,3%	47,9%	4,9%	26,7%
Total	*9,1%*	*41,7%*	*3,1%*	*19,6%*

The 299,462 consumer messages contained 19,350 emoji and 25,142 emoticons; 5.1% of all consumer messages contained one or more emoji, whereas 8.3% contained one or more emoticons.

Tables 3 and 4 (see below) show the most frequently used emoticons and emoji by tourism companies and consumers. Interestingly, all of the top 10 emoticons used by consumers are also used by companies (see Table 3 below). The top 4 emoticons, which comprise of 95.3% of all emoticons used by companies and 86.8% of those used by consumers, are all of the ‘smiling face’ type. Only 2.0% of the emoticons used by companies are negative/sad emoticons, versus 7.0% among consumers.

Table 3. Top 10 of emoticons used by tourism companies and consumers, as a percentage of the total number of messages containing emoticons. *(compiled by authors)*

Companies		Consumers	
Emoticon	% of total	Emoticon	% of total
:)	34.4%	:)	28.7%
:-)	27.5%	:-)	27.5%
;)	19.0%	;-)	17.3%
;-)	14.4%	;)	13.3%
:D	1.9%	:(	4.0%
:-(	1.1%	:D	3.3%
:(	0.9%	:-(	2.9%
:-D	0.4%	<3	1.0%
<3	0.3%	:-D	0.9%
=)	0.1%	=)	0.3%
Total	*99.2%*	*Total*	*97.0%*

The use of emoji is more varied (see Table 4 below), with the top 10 of emoji accounting for only half of all emoji used. Half of the top 10 emoji used by tourism companies are also in the top 10 of emoji used by consumers. All emoji that refer to human emotions are positive. Tourism companies more often use emoji that refer less directly to human emotions (e.g., a sun, an airplane, a palm tree).

Table 4. Top 10 of emoji used by tourism companies and consumers, as a percentage of the total number of messages containing emoji. *(compiled by authors)*

Companies			Consumers		
UTF8	emoji	%	UTF8	emoji	%
e2 98 80	☀	11.9%	f0 9f 91 8d	👍	9.6%
f0 9f 98 89	😉	8.7%	f0 9f 98 89	😉	9.3%
f0 9f 98 8a	😊	8.0%	f0 9f 98 8a	😊	7.1%
f0 9f 8c b4	🌴	4.1%	f0 9f 98 82	😂	5.2%
e2 9c 88	✈	3.5%	f0 9f 98 83	😃	4.0%
c2 ae	®	3.3%	f0 9f 98 84	😄	3.7%
f0 9f 98 84	😄	3.1%	e2 98 ba	☺	2.8%
f0 9f 8e 89	🎉	3.0%	f0 9f 98 81	😁	2.8%
f0 9f 91 8d	👍	2.3%	e2 98 80	☀	2.6%
f0 9f 98 8d	😍	2.2%	f0 9f 98 80	😀	2.5%
Total		*50.1%*	*Total*		*49.6%*

Subsequently, we investigated the trends in emoticon/emoji use by companies. To this end we performed Mann-Kendall (M-K) trend tests on the emoticon/emoji proportions on a per week basis for the 6 years included in this study. The M-K test is a commonly used nonparametric test for identifying a trend in series, resulting in the M-K statistic (S) per time series. The purpose of the M-K test is to statistically assess if there is a monotonic upward or downward trend in a variable over time. Except for company Twitter posts (S = 8833, Kendall's τ = .18, *n.s.*), this analysis indeed revealed significant increases (p < .001) in emoticon/emoji use in company communication for the years 2011–2016 (Twitter reactions: S = 22409, Kendall's τ = .46; Facebook posts: S = 30806, Kendall's τ = .63; Facebook reactions: S = 27710, Kendall's τ = .57).

5 Conclusion and Discussion

The advent of social media has presented major opportunities and challenges for traditional business communication strategies. Consumers can effortlessly share their thoughts about companies and services anywhere, anytime and to anyone. Companies want to participate in this online consumer communication [18], and have invested in online strategies and webcare teams to directly connect with consumers, for delivering customer service [38], protecting reputation [4], enhancing brand popularity [5], and improving company trust [39, 40].

However, little research has investigated trends in volume and type of company social media communication based on actual data, from a macro perspective. To fill this gap, in this study we provided empirical evidence of the increase of informalization and humanization of company communication as indicated by the use of emoticons and emoji. This is an important finding: since vital cues that normally regulate interactions and impressions between communicators are absent in online social interaction (e.g., someone's voice or facial expression, observable information about personal and physical characteristics) [26], companies are looking for ways to overcome this shortage, for instance by incorporating emoticons and emoji in their messages. The use of emoticons has proven to have a positive effect on enjoyment, personal interaction, and perceived information richness [41]. By using emoticons and emoji, we argue that companies contribute to their perceived level of conversational human voice (CHV), which has proven to be an important mechanism for effective company communication in social media [9, 29]. First, incorporating a more humanized voice makes consumers sense they are having a one-to-one conversation instead of a one-to-many conversation, which in turn contributes to a better relationship with customers [38, 42]. Second, by using a CHV, the company seems to focus on creating a dialogue rather than solely on commercial and profit-driven motives, which makes the company appear more authentic in its intentions [25]. Thirdly, companies can be perceived as more trustworthy when they use a more human tone of voice [43]. In sum, by adding informal cues such as emoticons to their online communication, company-consumer relations may be evaluated more easily as interpersonal relationships by consumers. This builds on the concept of *parasocial interaction* [44], stating that the impact of (online) communications depends on the degree to which the counterparty in a computer mediated communication environment is perceived as a real person [45].

Another finding was that the use of emoticons and emoji by companies and consumers shows remarkable similarities. The top 10 of used emoticons and half of the top 10 of emoji are identical among companies and consumers. Although the repertoire of emoticons/emoji is limited, this equality is nevertheless striking. This may be the result of *social synchrony* in online social media: "the tendency of a large group of people to perform similar actions in unison, in response to a contextual trigger" [46] (p. 151). Mimicry of the nonverbal cues and tone of voice of an online communication partner may contribute to the feeling of connectedness in online interactions, and thus may improve relational outcomes.

Several limitations of this study should be noted. First, social media monitoring tools such as Coosto only give access to public social media messages; therefore we were not able to include private messages between companies and consumers in this study. This may have affected the quantity or quality of messages and/or the use of emoticons. Second, we focused on Facebook and Twitter in this study. Although these two platforms are by far the largest for company-consumer interaction [18], additional perspectives of including other platforms may have been missed. Third, since this study is limited to the tourism industry and more specifically to The Netherlands, the findings may not be representative for all industries or countries. Fourth, although the use of emoticons and emoji are important clues for the level of informalization of company communication, other indicators (such as the use of informal and colloquial language, degree of openness to dialogue, promptness of feedback) may yield important additional perspectives. In order to more fully investigate the developments in these fields, future research may include a broader range of measures for humanization of communication. This may be part of a broader research avenue on the role of emotions in corporate communication. That is, emotions are abundant in online communication and key factors for its success [47], but their role and effects are – to our knowledge – not profoundly studied in a setting of online company-consumers interactions.

Despite these limitations, this study contributes to a better understanding of the development of informalization of online company communication over the last years. In this study we have shown that over recent years, companies have enhanced their sense of informality and humanness in online conversations. By learning step by step how to engage with consumers in an environment that was initially created for people-to-people interaction, tourism companies that appropriately utilize the power of social media and the connected consumer are well on their way to evolve from 'party crashers' to 'party hosts'.

References

1. Kaplan AM, Haenlein M (2010) Users of the world, unite! The challenges and opportunities of Social Media. Bus Horiz 53:59–68. https://doi.org/10.1016/j.bushor.2009.09.003
2. Harrigan P, Evers U, Miles M, Daly T (2017) Customer engagement with tourism social media brands. Tour Manag 59:597–609. https://doi.org/10.1016/j.tourman.2016.09.015
3. van Noort W (2012) Online damage control: the effects of proactive versus reactive webcare interventions in consumer-generated and brand-generated platforms. J Interact Mark 26:131–140. https://doi.org/10.1016/j.intmar.2011.07.001
4. Dijkmans C, Kerkhof P, Beukeboom CJ (2015) A stage to engage: social media use and corporate reputation. Tour Manag 47:58–67. https://doi.org/10.1016/j.tourman.2014.09.005
5. Heller Baird C, Parasnis G (2011) From social media to social customer relationship management. Strategy Leadersh 39:30–37. https://doi.org/10.1108/10878571111161507
6. Fournier S, Avery J (2011) The uninvited brand. Bus Horiz 54:193–207. https://doi.org/10.1016/j.bushor.2011.01.001
7. Rather RA, Hollebeek LD, Islam JU (2019) Tourism-based customer engagement: the construct, antecedents, and consequences. Serv Ind J 39:519–540. https://doi.org/10.1080/02642069.2019.1570154
8. Liu Y, Shrum LJ (2002) What is interactivity and is it always such a good thing? Implications of definition, person, and situation for the influence of interactivity on advertising effectiveness. J Advert 31:53–64. https://doi.org/10.1080/00913367.2002.10673685
9. Kelleher T (2009) Conversational voice, communicated commitment, and public relations outcomes in interactive online communication. J Commun 59:172–188. https://doi.org/10.1111/j.1460-2466.2008.01410.x
10. Bauer HH, Grether M, Leach M (2002) Building customer relations over the internet. Ind Mark Manag 31:155–163. https://doi.org/10.1016/S0019-8501(01)00186-9

11. Cui N, Wang T, Xu S (2010) The influence of social presence on consumers' perceptions of the interactivity of web sites. J Interact Advert 11:36–49. https://doi.org/10.1080/15252019.2010.10722176
12. Derks D, Bos AER, von Grumbkow J (2008) Emoticons and online message interpretation. Soc Sci Comput Rev 26:379–388. https://doi.org/10.1177/0894439307311611
13. Luangrath AW, Peck J, Barger VA (2017) Textual paralanguage and its implications for marketing communications
14. Janssen JH, Ijsselsteijn WA, Westerink JH (2014) How affective technologies can influence intimate interactions and improve social connectedness. Int J Hum-Comput Stud 72:33–43. https://doi.org/10.1016/j.ijhcs.2013.09.007
15. Lo S-K (2008) The nonverbal communication functions of emoticons in computer-mediated communication. Cyberpsychol Behav 11:595–597. https://doi.org/10.1089/cpb.2007.0132
16. Merriam-Webster (2019) Definition of 'Emoticon'. https://www.merriam-webster.com/dictionary/emoticon
17. Aldunate N, González-Ibáñez R (2017) An integrated review of emoticons in computer-mediated communication. Front Psychol 7:2061. https://doi.org/10.3389/fpsyg.2016.02061
18. Stelzner M (2017) Social media marketing industry report 2017. Social Media Examiner
19. Schamari J, Schaefers T (2015) Leaving the home turf: how brands can use webcare on consumer-generated platforms to increase positive consumer engagement. J Interact Mark 30:20–33. https://doi.org/10.1016/j.intmar.2014.12.001
20. Willemsen L, Neijens P, Bronner F (2013) Webcare as customer relationship and reputation management? Motives for negative electronic word of mouth and their effect on webcare receptiveness. In: Rosengren S, Dahlén M, Okazaki S (eds) Advances in Advertising Research. Springer, vol. IV, pp 55–69
21. Dijkmans C, Kerkhof P, Buyukcan-Tetik A, Beukeboom CJ (2015) Online conversation and corporate reputation: a two-wave longitudinal study on the effects of exposure to the social media activities of a highly interactive company. J Comput-Mediat Commun 20:632–648. https://doi.org/10.1111/jcc4.12132
22. Kent ML, Taylor M (1998) Building dialogic relationships through the world wide web. Public Relat Rev 24:321–334. https://doi.org/10.1016/S0363-8111(99)80143-X
23. Rybalko S, Seltzer T (2010) Dialogic communication in 140 characters or less: how fortune 500 companies engage stakeholders using Twitter. Public Relat Rev 36:336–341. https://doi.org/10.1016/j.pubrev.2010.08.004
24. Weinberg BD, Pehlivan E (2011) Social spending: managing the social media mix. Bus Horiz 54:275–282. https://doi.org/10.1016/j.bushor.2011.01.008
25. Kwon ES, Sung Y (2011) Follow me! Global marketers' Twitter use. J Interact Advert 12:4–16. https://doi.org/10.1080/15252019.2011.10722187
26. Beldad A, de Jong M, Steehouder M (2010) How shall I trust the faceless and the intangible? A literature review on the antecedents of online trust. Comput Hum Behav 26:857–869. https://doi.org/10.1016/j.chb.2010.03.013
27. Beukeboom CJ, Kerkhof P, de Vries M (2015) Does a virtual like cause actual liking? How following a brand's Facebook updates enhances brand evaluations and purchase intention. J Interact Mark 32:26–36. https://doi.org/10.1016/j.intmar.2015.09.003
28. Oxford Dictionaries (2015) Oxford dictionaries word of the year 2015 is…. In: OxfordWords Blog. https://blog.oxforddictionaries.com/2015/11/word-of-the-year-2015-emoji/
29. Dimson T (2015) Emojineering part 1: machine learning for emoji trends. In: Instagram Eng. https://engineering.instagram.com/emojineering-part-1-machine-learning-for-emoji-trends-machine-learning-for-emoji-trends-7f5f9cb979ad

30. Hsieh SH, Tseng TH (2017) Playfulness in mobile instant messaging: examining the influence of emoticons and text messaging on social interaction. Comput Hum Behav 69:405–414. https://doi.org/10.1016/j.chb.2016.12.052
31. Derks D, Bos AER, von Grumbkow J (2007) Emoticons and social interaction on the internet: the importance of social context. Comput Hum Behav 23:842–849. https://doi.org/10.1016/j.chb.2004.11.013
32. TravMagazine (2016) Travel Top 50
33. Chaffey D (2016) Global social media statistics summary 2016. In: Smart Insights. http://www.smartinsights.com/social-media-marketing/social-media-strategy/new-global-social-media-research/
34. Coosto (2017) About Coosto. In: Coosto. https://www.coosto.com/en/about-us
35. Coosto (2015) Coosto facilitates worldwide social media analysis. In: Coosto. https://www.coosto.com/en/press/coosto-facilitates-worldwide-social-media-analysis
36. Malhotra E (2017) EmoticonSentiment: evaluating the relative sentiment attached to each emoticon
37. Suárez Colmenares F (2017) Emoji dictionary. In: GitHub. https://raw.githubusercontent.com/felipesua/sampleTexts/master/emojis.csv
38. van Noort G, Willemsen L, Kerkhof P, Verhoeven J (2014) Webcare as an integrative tool for customer care, reputation management, and online marketing: a literature review. In: Integrated communications in the postmodern era. Palgrave Macmillan, pp 77–99
39. Laroche M, Habibi MR, Richard M-O, Sankaranarayanan R (2012) The effects of social media based brand communities on brand community markers, value creation practices, brand trust and brand loyalty. Comput Hum Behav 28:1755–1767. https://doi.org/10.1016/j.chb.2012.04.016
40. Turri AM, Smith KH, Kemp E (2013) Developing affective brand commitment through social media. J Electron Commer Res 14:201–214
41. Huang AH, Yen DC, Zhang X (2008) Exploring the potential effects of emoticons. Inf Manage 45:466–473
42. Locke C, Searls D, Weinberger D, Levine R (2001) The cluetrain manifesto: the end of business as usual. Basic Books
43. Kelleher T, Miller BM (2006) Organizational blogs and the human voice: relational strategies and relational outcomes. J Comput-Mediat Commun 11:395–414. https://doi.org/10.1111/j.1083-6101.2006.00019.x
44. Horton D, Wohl RR (1956) Mass communication and para-social interaction: observations on intimacy at a distance. Psychiatry 19:215–229
45. Labrecque LI (2014) Fostering consumer–brand relationships in social media environments: the role of parasocial interaction. J Interact Mark 28:134–148. https://doi.org/10.1016/j.intmar.2013.12.003
46. Choudhury MD, Sundaram H, John A, Seligmann DD (2009) Social synchrony: predicting mimicry of user actions in online social media. In: 2009 International conference on computational science and engineering. pp 151–158
47. Derks D, Fischer AH, Bos AER (2008) The role of emotion in computer-mediated communication: a review. Comput Hum Behav 24:766–785. https://doi.org/10.1016/j.chb.2007.04.004

The Dualistic Model of Passion for Online Travel Community Activities: The Role of Real-Me and Emotional Loneliness

Kwang-Ho Lee[1], Sangguk Kang[2(✉)], and Byeong Cheol Lee[3]

[1] Ball State University, Muncie, IN 47306, USA
klee2@bsu.edu
[2] Macau University of Science and Technology, Taipa, Macao, Special Administrative Region of China
ksangguk@must.edu.mo
[3] Kyonggi University, Seoul 03746, South Korea
2bclee@kyonggi.ac.kr

Abstract. This study applies the Dualistic Model of Passion (DMP) and tests the relationships between passion types (obsessive passion and harmonious passion), real-me, and behavioural loyalty (knowledge-sharing continuance intentions and community promotion) in online travel communities. Through online survey methods, the data collection procedure focused on U.S. consumers who were members of the online travel community. A total of 314 samples were applicable for testing structural relationships among observed constructs. A structural equation modelling analysis was conducted to test the proposed hypotheses. This study also provides a multi-group analysis to examine the moderating effect of emotional loneliness on the relationship between real-me and behavioural loyalty (knowledge-sharing continuance intentions and community promotion, respectively). The results provide support for all hypotheses except for the one about the moderating effect of emotional loneliness on the relationship between real-me and knowledge-sharing continuance intentions. The results offer new insights into the extended model and have valuable implications for operational practices in online travel communities.

Keywords: Dualistic Model of Passion (DMP) · Online Travel Community (OTC) · Real-me · Knowledge-sharing continuance intentions · Community promotion · Emotional loneliness

1 Introduction

Online travel communities (OTCs) are a key communication platform to change the way that online users can share travel-related experiences in a virtually passionate environment. Some critics posit that accessing OTCs is critical for community users to interact with each other by sharing authoritative knowledge and information [1]. A critical role of OTCs is known to persuade their members to be collaborative community members and actual travelers [2]. Given this recognition, the majority of research on promoting online communities has confirmed that psychological factors

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 15–26, 2020.
https://doi.org/10.1007/978-3-030-36737-4_2

(e.g., motivation and personality traits) might act as determinants of online community loyalty, consequently enabling members of OTCs to reveal their true-self aspects on the online activities [3]. In this regard, some studies have tested the assumption that individuals' passion for their online activities varies depending on the magnitude to which online platforms allow them to express their real identity [4], which in turn leads to positive behaviour consequences [5].

The Dualistic Model of Passion (DMP) has urged scholars to recognize the salience of passion types (obsessive passion and harmonious passion) which can be utilized as the prominent antecedent of real-me (true-self) and emotional loneliness in online community behaviour models [6]. For instance, previous studies pointed out the importance of passion that can be regarded as individuals' psychological states. Specifically, they underlined the distinctive effect of the two types of passion (i.e., harmonious and obsessive passions) for online activities on behavioural loyalty and subjective well-being [7]. Given this recognition, Amichai-Hamburger and colleagues proposed the necessity of understanding the role of real-me (i.e., psychological states) in online platforms [8].

To date, some studies have demonstrated the relationship between passion types (ob-sessive and harmonious passions) and real-me in a cognitive-behavioural model [7]. Understanding the role of individuals' psychological trait such as real-me makes it possible to expose new aspects of online users' behavioural contributions to OTCs, especially for more socially isolated users who are less emotionally connected in offline interactions and are more connected in online interactions [9, 10]. Despite these theoretical discussions, tourism researchers may neglect exploring salient psychological states of users accessing OTCs in a holistic model. For example, it appears that those with high obsessive passion or harmonious passion may be less or more likely to express fully the real self, which in turn determine their willingness to contribute to OTCs. Therefore, it is essential to learn how to optimally operate OTCs based on the types of users' passion (e.g., harmonious and obsessive passion) [7, 11, 12].

This study applies the DMP and examines the relationships between passion types, real-me, and behavioural loyalty (knowledge-sharing continuance intentions and community promotion) in OTCs. This study also provides a multi-group analysis to examine the moderating effect of emotional loneliness on the relationship between real-me and behavioural loyalty. The results offer new insights into an extended DMP model and have valuable implications for operational practices in OTCs.

2 Literature Review

2.1 Dualistic Model of Passion (DMP)

Passion, which is dualistically valenced, is defined as "a strong inclination toward an activity that people like, that they find important, and in which they invest time and energy" [12, p. 236]. Research on passion for online activities should be extended by assessing the DMP that encompasses the role of passion types in cognitive-behavioural models. Given the previous studies using the DMP in psychology and philosophy, exploring an extended DMP may allow researchers to understand the effects of passion types on not only determining individuals' cognitive feelings but also fostering the magnitude of individuals' attitudes and behaviours in online community activities. Similar with the traditional DMP research, passion for online activities is classified into two desirable traits in online settings: harmonious and obsessive [7]. First, harmonious passion is regarded as the degree to which an individual feels a sense of ability to succeed in aggregating online activities with other relevant activities in their life. Research into the DMP has revealed that harmonious passion should be a motivational trait which allows online users to engage in their activities with the experiences of internal pressures in online communities, which in turn leads to adaptive outcomes (e.g., behavioural loyalty) [13, 14]. Second, obsessive passion originates from a controlled internalization of the activity in one's identity, and it is defined as the degree to which an individual perceives difficulty in incorporating online activities with other activities in a certain context, which leads to positive intrapersonal outcomes (e.g., cognition and loyalty). In consumer research, obsessive passion might be regarded as a negative trait that is less adaptive in cognitive-behavioural models. On the other hand, obsessive passion is known as a facilitator of individual's psychological desire and behavioural loyalty in the context of online knowledge-sharing. Therefore, the theoretical function of obsessive passion has not been sufficiently proved to have either a positive or negative effect in a cognitive-behavioural model of OTCs. Taken together, the two types of passion should be utilized to predict cognitive mediators and behavioural consequences in OTCs [13, 14].

2.2 Behavioural Loyalty in Online Travel Communities

The current study focuses on two constructs of behavioural loyalty in OTCs: knowledge-sharing continuance intentions and community promotion. First, knowledge-sharing continuance intentions refer to "the subjective probability that an individual will continue sharing knowledge in the future" [15, p. 236], which can be utilized as an index for measuring the degree to which members of OTCs are likely to continue their contribution to a given OTC. Lee and Hyun confirmed the role of knowledge-sharing continuance intentions as a key consequence of online tourist community loyalty [5]. Second, community promotion reveals "the extent to which a member promotes an online community to introduce his or her peers or friends to the community and invite close acquaintances to join the community" [5, p. 7]. Community promotion can be employed as a proxy for estimating the probability to detect the number of actual OTC members who have been voluntary contributors to the OTC. Understanding the two consequences of behavioural loyalty may encourage OTC members to continue their involvement in their online communities, promoting and sustaining such OTCs.

2.3 Obsessive and Harmonious Passions

The majority of contemporary research on passion has been assessed under the umbrella of the DMP. Specifically, theoretical evidence on the relationship between obsessive and harmonious passions and psychological desire (e.g., real-me) has been demonstrated by some empirical studies in online consumer behaviours. Previous studies concluded that both harmonious passion and obsessive passion should be hypothesized to have positive effects on real-me. However, the influence of harmonious passion on outcomes might be stronger than that of obsessive passion [11, 12]. Importantly, Tosun and Lajunen verified that real-me mediates between psychological variables and behavioural consequences in online contexts, concluding that real-me on the Internet is strongly correlated with obsessive passion (r = 0.64) and harmonious passion (r = 0.61) [3]. Given the empirical findings, the following hypotheses are proposed:

Hypothesis 1: Harmonious passion has a positive effect on real-me in OTCs.
Hypothesis 2: Obsessive passion has a positive effect on real-me in OTCs.

2.4 Real-Me

The concept of real-me originates from the conceptual meaning of the real self, proposing that the discovery of the true self is an essential part of therapy, which indicates the degree of ability to express fully the real self in a social environment [16]. Yurchisin and colleagues addressed that individuals are more likely to create and re-create his or her strong identity (true self) in social media channels (e.g., Facebook) [17], which is associated with a theory of enjoyable alterations of players' self-perception underlying a need for using online spaces to alleviate their bad mood and feelings [18]. In this vein, previous studies pointed out the functional values of real-me, enabling people to (a) over-come loneliness [19] and (b) better express their real selves with online peers than with offline peers [9, 10]. Similarly, some studies also provoked that online users are likely to share a great deal of information and knowledge to receive attention from other online users [20], revealing that users' active tendencies to disclose travel-related information and knowledge can be observed in OTCs. To verify the relationships between real-me and behavioural loyalty (i.e., knowledge-sharing continuance intentions and community promotion) in OTCs, the following hypotheses are proposed.

Hypothesis 3: Real-me has a positive effect on knowledge-sharing continuance intentions in OTCs.
Hypothesis 4: Real-me has a positive effect on community promotion in OTCs.

2.5 Emotional Loneliness

Emotional loneliness is regarded as a moderator in cognitive-behavioural models, which refer to "the affective state of feeling isolated" [21, p. 798]. In general, emotional loneliness can be utilized as an index to foster cognitive processing and psychological adaptation [22]. Given the fact that understanding the role of emotional loneliness is of considerable importance in online settings, previous studies have demonstrated that those with a higher subjective feeling of emotional loneliness are likely to pursue online social interaction with others in diverse online contexts. For example, Caplan found that emotional loneliness is significantly correlated with a preference for online social interaction (r = .350) [23]. Seidman demonstrated that those with a higher sense of "true self" online are likely to post more personally emotional content on Facebook

[24]. More importantly, Lee and Hyun verified that loneliness (e.g., emotional loneliness) is linked to identification with the peer group and online tourist community behaviour in the context of OTCs [10]. Given the aforementioned discussions, the following hypothesis is proposed:

Hypothesis 5a: Emotional loneliness moderates the relationship between real-me and knowledge-sharing continuance intentions in OTCs.
Hypothesis 5b: Emotional loneliness moderates the relationship between real-me and community promotion in OTCs.

2.6 The Theoretical Framework

Given the above theoretical and empirical evidence of relationships between passion for OTC activities (obsessive and harmonious passions), real-me, knowledge-sharing continuance intentions, and community promotion, Fig. 1 shows the proposed theoretical framework.

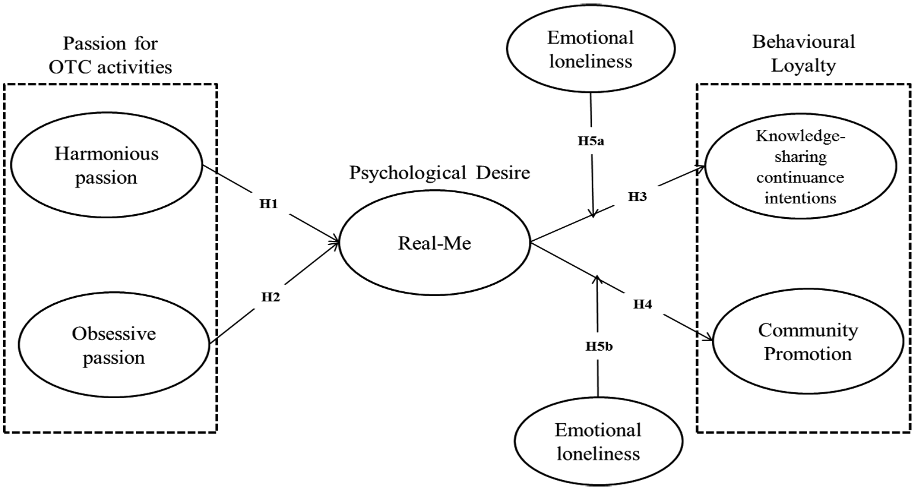


Fig. 1. The proposed theoretical framework (source: authors).

3 Research Methods

3.1 The Measurement Instrument

A self-reported questionnaire was developed based on a critical review of the literature in the domains of information sharing, communication, and online marketing. Before the actual survey, a pilot test was conducted to determine the validity of the instrument. The respondents were asked to evaluate the relevance of each item for members of OTCs. First, the respondents addressed thirteen items for obsessive and harmonious passions from Tosun and Lajunen [3] and, Seguin-Levesque and colleagues [7] to assess obsessive passion (e.g., I have a tough time controlling my need for OTC activities, I am emotionally dependent on my activities in OTCs, and the urge is so strong, I cannot help connecting to the members of OTCs.) and harmonious passion (e.g., OTCs allow me to live memorable experiences, OTCs reflect the qualities that I like about myself, and the new things that I discover on OTCs allow me to appreciate it even more).

Second, real-me for OTC activities was measured using three items refined from Tosun and Lajunen [3] and Amichai-Hamburger, Wainapel, and Fox [25] (e.g., “Do you think you reveal more about yourself to other members you know from OTCs than to real-life friends?”, “Are there things your OTC friends know about you that you cannot share with real-life friends?”, and “To what extent would your family and friends be surprised if they read your postings (e.g., sharing travel information/ experiences) on OTCs?”). Higher scores indicate higher levels of revealing oneself on the OTC.

Third, three items for each knowledge-sharing continuance intentions (e.g., “If I can, I would like to continue sharing knowledge with other members of the OTC in the future”, “It is likely that I will continue sharing knowledge with other members of the OTC in the future”, and “I expect to continue sharing knowledge with other members of the OTC in the future”) and community promotion (e.g., “I would like to recommend OTCs to nonmembers.”, “I would like to introduce online travel communities to nonmembers”, and “I will eagerly talk to non-members about benefits of OTCs”) were adapted from Lee and Hyun [5] and Fang and Chiu [15].

Finally, three items for emotional loneliness were adapted from previous studies proposing the role of emotional loneliness in OTCs [8] (e.g., “I often feel rejected”). All measurement items were assessed based on a seven-point Likert-type scale ranging from “strongly disagree” (1) to “strongly agree” (9). The instrument included items for demographic information such as gender, education level, age, and household income.

3.2 The Sample and Data Collection

The data collection procedure focused on U.S. consumers who were members of OTCs (OTC membership indicates that individuals have joined an OTC with personal user-names by agreeing to the OTC terms of use and guidelines). Data were collected over a period of one month in March 2017. A convenience sample of online travel community members was obtained using Amazon Mechanical Turk. To ensure the appropriateness of respondents, the following item was employed at the beginning of the online questionnaire: “Online travel communities (e.g., Tripadvisor.com, lonelyplanet.com, and virtual-tourist.com) represent travel review sites that offer a great opportunity for travel searchers to find out what other people think about potential travel products (e.g., destinations) and facilities (e.g., hotels, restaurants, and attractions).” [10, p. 43] In the online questionnaire, a screening question (“Are you a member of an online travel community site?”) was included to detect unqualified respondents, who have never been the members of any online travel communities (e.g., TripAdvisor.com, Travel-blog.org, and other travel blogs.). Those who answered “yes” (n = 369) were invited to continue the online survey, whereas those who chose “no” (n = 31) were told to stop. As a result, a total of 369 responses were obtained. Among these, 55 were eliminated because of incomplete responses (n = 39) and the outliers based on criterion of 3.29 SD above/below the mean (n = 16), resulting in a usable sample of 314 responses. A total of 314 samples are applicable for testing structural relationships among observed constructs that contain 22 variables based on the criteria that at least 10 cases per variable are required for testing structural equation modeling [26].

3.3 The Measurement Instrument

Several statistical techniques were employed to determine support for the proposed hypotheses. The following three statistical steps were followed to test the hypotheses. The first step tested H1 to H4, and here, structural equation modelling (SEM) was utilized based on the maximum likelihood estimation method. H5, which addressed whether the level of emotional loneliness would vary according to the interaction effect of real-me and emotional loneliness (high- vs. low- emotional loneliness groups), was investigated through a multi-group approach. The multi-group analysis method can be used to verify whether the same path model can be applied across different data sets. That is, if there is any significantly different causal path between two emotional loneliness groups (i.e., high- vs. low- emotional loneliness groups), then there is a stronger causal relationship between real-me and community promotion (or weaker) for a high- emotional loneliness group (or low- emotional loneliness group) than the counterpart.

4 Results

4.1 Respondent Characteristics

A majority of the respondents were Caucasian (N = 247, 77.9%). In terms of gender, about 52.1% and 42.5% of the respondents showed female (N = 165) and male (N = 152). A majority of the respondents were in their twenties and thirties (N = 236, 67.0%). About 86% of the respondents had a college degree or more. In addition, about 72% of the respondents indicated their household income to be \$25,001–\$50,000 (35.3%), \$50,001–\$75,000 (22.7%), and less than \$20,000 (14.8%), respectively.

4.2 Measurement Model Validation

A confirmatory factor analysis (CFA) using the maximum likelihood estimation method was conducted with 314 cases to specify the structure of observed indicators and latent constructs and test the multi-factor models. The results reveal a sufficient fit to the data: χ^2 = 650.960, df = 242, χ^2/df = 2.690, confirmatory fit index (CFI) = 0.92, Tucker-Lewis Index (TLI) = 0.93, the root mean square error of approximation (RMSEA) = 0.07. Additionally, Table 1 shows the composite reliability (CR) of constructs, which indicates the internal consistency of multiple indicators for each construct, ranged from 0.82 to 0.95, exceeding the recommended threshold of 0.7 [27]. The average variance extracted (AVE) for identifying the discriminant validity of major constructs was calculated for the measures. The AVE values ranged between 0.59 and

0.73, exceeding the recommended threshold of 0.5 [28]. In addition, the square root of the AVE for each construct exceeded the correlation between the construct and all other constructs, ranging from 0.775 to 0.854. These results show the satisfactory discriminant validity of all constructs (Table 1).

Table 1. Correlations of constructs (source: authors).

Constructs	1	2	3	4	5
1. Obsessive passion	(.837)				
2. Harmonious passion	.441**	(.768)			
3. Real-Me	.779**	.430**	(.854)		
4. Knowledge-sharing continuance intentions	.001	.348**	.281**	(.775)	
5. Community promotion	.086	.410**	.174**	.682**	(.775)
Mean	2.80	4.19	3.27	4.97	5.24
SD	1.47	1.38	1.65	1.17	1.09
AVE	0.70	0.59	0.73	0.60	0.60
CR	0.95	0.85	0.91	0.86	0.82

Note: [a] Value in parentheses indicate the square root of the AVE for each construct.

4.3 Hypothesis Testing

The full structural model was tested to demonstrate the relationships between obsessive and harmonious passions, real-me, knowledge-sharing continuance intentions, and community promotion. The model fit was assessed using multiple indices. Figure 2 shows the model's overall fit to the data based on various goodness-of-fit measures. Overall, the results show a reasonable fit [29]: $\chi^2 = 705.939$, df = 246, $\chi^2/df = 2.870$, CFI = 0.92, TLI = 0.93, RMSEA = 0.077. Specifically, the results provide support for all hypotheses. First, obsessive passion had a significant positive effect on real-me ($\beta = .724$, $t = 11.909$, and $p < .01$). Second, harmonious passion had a significant positive effect on real-me ($\beta = .117$, $t = 2.376$, and $p < .05$). Finally, real-me had significant positive effects on knowledge-sharing continuance intentions ($\beta = .163$, $t = 2.561$, $p < .01$) and community promotion ($\beta = .270$, $t = 4.104$, $p < .01$), respectively. In sum, the results provide support for H1, H2, H3, and H4. Figure 2 shows the results for the proposed model.

Hypotheses 5a and 5b reveals that emotional loneliness moderates the relationship between real-me and behavioural loyalty (knowledge-sharing continuance intentions and community promotion). To test the hypotheses, a cluster analysis approach was utilized to assign the respondents to two high- and low-emotional loneliness groups. The cluster solution results in 152 cases with high emotional loneliness (mean = 4.47) and 162 cases with low emotional loneliness (mean = 1.86). To demonstrate the moderating effect, a multiple-group analysis was tested using the subgroups (high vs. low). The result revealed that the estimated path coefficient from real-me to community promotion was higher in the high-emotional loneliness group ($\beta = .368$, $p < .01$) than in the low-emotional loneliness group ($\beta = .354$, $p < .01$). That is, the direct effect of

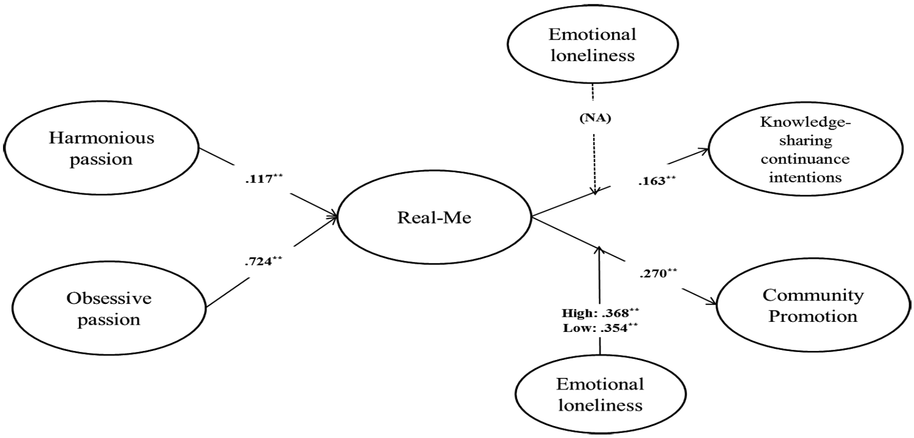


Fig. 2. Results of the proposed model (source: authors).

real-me on community promotion was more evident for users of online travel communities in the high-emotional loneliness group, indicating that H5b was supported.

5 Results

The study empirically tests the structural relationships between passion (obsessive and harmonious passions), real-me, knowledge-sharing continuance intentions, and community promotion and explores the moderating effect of emotional loneliness on the relationship between real-me and behavioural loyalty (knowledge-sharing continuance intentions and community promotion). The results showed that there were significant relationships between obsessive and harmonious passions, real-me, knowledge-sharing continuance intentions, and community promotion. In addition, emotional loneliness was a significant moderator of the relationship between real-me and community promotion.

From a theoretical perspective, this study sheds light on an extended DMP encompassing obsessive and harmonious passions, real-me, emotional loneliness, knowledge-sharing continuance intentions, and community promotion in OTCs. Social psychologists have pointed out that those with a higher sense of obsessive and harmonious passion are likely to express their true self in OTC settings, which in turn enhance their willingness to be loyal to the OTCs. Interestingly, the results showing the positive effect of obsessive passion (β = .724) and harmonious passion (β = .117) on real-me are in line with the findings of previous studies illustrating users of social networking sites (e.g., Facebook) are likely to be more obsessive than harmonious in online activities [12]. On the other hand, the result reveling the positive effect of obsessive passion on real-me is inconsistent with the findings of previous studies confirming that obsessive passion for social networking sites (e.g., Facebook) is negatively related to basic psychological needs (e.g., real-me). Furthermore, the findings of previous studies showed that the effect size of harmonious passion on cognitive and behavioural consequences is higher than that of obsessive passion [11, 12], which is inconsistent with the results of this study. This implies that those who are struggling to incorporate and organize online activities (e.g., combining authoritative data towards identifying useful information for collaborative knowledge-sharing) are more likely to discover the true self (one's identity) in OTCs. Finally, the moderating effects of emotional loneliness on the relationship both between real-me and knowledge-sharing continuance intentions and between real-me and community promotion were tested. According to the results, emotional loneliness moderated the relationship between real-me and community promotion. This might be consistent with the findings of Lee and Hyun [10], verifying that emotional trait (i.e., emotional expressivity) acts as a moderator of relationships between users' psychological satisfaction and behavioural loyalty in OTCs. This implies that those who perceive a higher sense of emotional loneliness are more likely to discover the true self (e.g., their values) and promote OTCs to nonmembers. Therefore, the concept of emotional loneliness should be considered to extend the DMP in OTC settings.

Despite the fact that the possibility that real-me could be prominent in the relationship between obsessive and harmonious passions and behavioural loyalty, no prior studies had demonstrated the dominant mediator that help members link from obsessive and harmonious passions to behavioural loyalty in OTCs. Consistent with the theoretical aspects of the DMP [10–12], it is necessary to examine whether real-me plays a critical role in converting members who perceive a sense of passion into those who are more likely to be engaged in OTC activities (e.g., they would spontaneously persuade non-members to be involved in their OTCs), which may vary depending on the level of emotional loneliness. Investigating the proposed integrated model may allow future researchers to facilitate lonely members' behavioural intentions to follow travel advice according to the online socialization activities that act as a buffer against loneliness from a perceived lack of offline social interactions in favor of sharing travel-related knowledge promoting their OTCs. Therefore, the empirical results offer original insights into the theoretically grounded platform for future researchers in light of new aspects of online users' cognitive patterns (willingness to express their true self) in the linkage between passion for OTC activities and behavioural loyalty.

When it comes to practical implications, this study advances substantial knowledge of interactive marketing and management practices (e.g., give recognition to those who show harmonious and obsessive passions for online activities in OTCs) in building a positive sense of real-me in OTCs, which can help OTC operators facilitate their knowledge-sharing continuance intentions and community promotion, thereby sustaining OTC operations.

Despite the significant implications from theoretical and practical perspectives, this study has some limitations. First, more generic and well-known constructs such as big five personality traits were not considered as generic constructs in the proposed model, which should be improved to predict real-me and behavioural loyalty in OTC settings. Second, the collected sample was mostly Caucasian which limits this study to generalize to other ethnic groups. Third, control variables such as socio-demographic characteristics (e.g., the average time spent on the OTC activities per day or week) were not included to predict behavioural loyalty in the proposed model, which should be improved for future research in OTC settings.

Acknowledgement. This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2019S1A5B8099551).

References

1. Lee H, Reid E, Kim W (2014) Understanding knowledge sharing in online travel communities: antecedents and the moderating effects of interaction modes. J Hospit Tour Res 38(2):222–242
2. Qu H, Lee H (2011) Travelers' social identification and membership behaviors in online travel community. Tour Manag 32(6):1262–1270
3. Tosun L, Lajunen T (2009) Why do young adults develop a passion for internet activities? The associations among personality, revealing "true self" on the internet, and passion for the internet. Cyber Psychol Behav 12(4):401–406
4. Bargh J, McKenna K, Firzsimons G (2002) Can you see the real me? Activation and expression of "true self" on the internet. J Soc Issues 58:33–48
5. Lee K, Hyun S (2018) The effects of tourists' knowledge-sharing motivation on online tourist community loyalty: the moderating role of ambient stimuli. Curr Issues Tour 21(13): 1521–1546
6. Vallerand RJ (2010) On passion for life activities: the dualistic model of passion. In: Zanna MP (ed) Advances in experimental social psychology. Academic Press, New York
7. Seguin-Levesque C, Libertea M, Pelletier L, Blanchard C, Vallerand R (2003) Harmonious and obsessive passion for the internet: their associations with the couple's relationship. J Appl Soc Psychol 33(1):197–221
8. Amichai-Hamburger Y, Fine A, Goldstein A (2004) The impact of Internet interactivity and need for closure on consumer preference. Comput Hum Behav 20(1):103–117
9. Correa T, Hinsley A, De Zuniga H (2010) Who interacts on the Web?: the intersection of users' personality and social media use. Comput Hum Behav 26(2):247–253
10. Lee K, Hyun S (2015) A model of behavioral intentions to follow online travel advice based on social and emotional loneliness scales in the context of online travel communities: the moderating role of emotional expressivity. Tour Manag 48:426–438
11. Mageau G, Vallerand R, Charest J, Salvy S, Lacaille N, Bouffard T, Koestner R (2009) On the development of harmonious and obsessive passion: the role of autonomy support, activity specialization, and identification with the activity. J Pers 77(3):601–646
12. Vallerand R, Blanchard C, Mageau GA, Koestner R, Ratelle C, Léonard M, Marsolais J (2003) Les passions de l'ame: on obsessive and harmonious passion. J Pers Soc Psychol 85 (4):756–767
13. Vallerand R, Salvy S, Mageau G, Elliot A, Denis P, Grouzet F, Blanchard C (2007) On the role of passion in performance. J Pers 75(3):505–534
14. Vallerand R (2015) The psychology of passion. Oxford University Press, New York
15. Fang Y, Chiu C (2010) In justice we trust: exploring knowledge-sharing continuance intentions in virtual communities of practice. Comput Hum Behav 26(2):235–246
16. Bargh J, McKenna K, Fitzsimons G (2002) Can you see the real me? Activation and expression of the "true self" on the internet. J Soc Issues 58(1):33–48
17. Yurchisin J, Watchravesringkan K, Mccabe D (2005) An exploration of identity re-creation in the context of internet dating. Soc Behav Pers: Int J 33(8):735–750
18. Klimmt C, Hefner D, Vorderer P (2009) The video game experience as "true" identification: a theory of enjoyable alterations of players' self-perception. Commun Theory 19(4):351–373

19. Coget J-F, Yamauchi Y, Suman M (2002) The internet, social networks and loneliness. IT Soc 1(1):180–201
20. Lim J, Nicholson J, Yang S, Kim H (2015) Online authenticity, popularity, and the "real me" in a microblogging environment. Comput Hum Behav 52:132–143
21. Ireland J, Power C (2004) Attachment, emotional loneliness, and bullying behaviour: a study of adult and young offenders. Aggressive Behav 30(4):298–312
22. Oldmeadow J, Quinn S, Kowert R (2013) Attachment style, social skills, and Facebook use amongst adults. Comput Hum Behav 29(3):1142–1149
23. Caplan S (2003) Preference for online social interaction: a theory of problematic internet use and psychosocial well-being. Commun Res 30(6):625–648
24. Seidman G (2014) Expressing the "true self" on Facebook. Comput Hum Behav 31:367–372
25. Amichai-Hamburger Y, Wainapel G, Fox S (2002) On the internet no one knows i'm an introvert": extroversion, neuroticism, and internet interaction. Cyberpsychol Behav 5 (2):125–128
26. Nunnally B (1967) Psychometric theory. McGraw-Hill, New York
27. Hair J, Black W, Babin B, Anderson R, Tatham R (2006) Multivariate data analysis, 6th edn. Prentice Hall, Upper Saddle River
28. Fornell C, Larcker D (1981) Structural equation models with unobservable variables and measurement error: algebra and statistics. J Mark Res 18(3):382–388
29. Anderson J, Gerbing D (1988) Structural equation modeling in practice: a review and recommended two-step approach. Psychol Bull 103(3):411–423

Classification and Visualization of Travel Blog Entries Based on Types of Tourism

Naoki Shibata[1(✉)], Hiroto Shinoda[1], Hidetsugu Nanba[2], Aya Ishino[3], and Toshiyuki Takezawa[1]

[1] Graduate School of Information Sciences, Hiroshima City University, Hiroshima, Japan
{shibata, shinoda, takezawa}@ls.info.hiroshima-cu.ac.jp

[2] Faculty of Science and Engineering, Chuo University, Tokyo, Japan
nanba@kc.chuo-u.ac.jp

[3] Faculty of Media Business, Hiroshima University of Economics, Hiroshima, Japan
ay-ishino@hue.ac.jp

Abstract. We propose a method for classifying travel blog entries into one or more tourism types among six predetermined types by using textual and image information in each entry. Together with this information, we use Wikipedia entries, which are automatically linked from each travel blog entry by entity-linking technology, because information beneficial for classifying blog entries is often mentioned in Wikipedia entries, and we combine this information by using a deep-learning-based method. We conducted an experiment with a neural network using three types of input data. Using the Sparse Composite Document Vector (SCDV) technique, we obtained precision, recall, and F-measure scores of 0.743, 0.217, and 0.336, respectively. We also conducted ensemble learning by using SCDV and support vector machines (SVM), and obtained precision, recall, and F-measure scores of 0.807, 0.179, and 0.293, respectively. Finally, we constructed a system that enables travelers to look for travel blog entries from a map in terms of tourism type.

Keywords: Types of tourism · Travel blog · Document classification · Wikification

1 Introduction

In recent years, tourism has expanded into various types. For example, tourism for the purpose of health recovery is called “health tourism”, and that for the purpose of experiencing sports is called “sports tourism”. If the types of tourism could be automatically classified for travel blog entries, it would enable people to determine what types are available at tourist spots around the world. It would also be possible to recommend tourist sites and travel plans on the basis of tourism types. In this study, we define six types of tourism and propose a method for classifying a large amount of travel blog entries into these types automatically by using machine learning that considers multiple input data.

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 27–37, 2020.
https://doi.org/10.1007/978-3-030-36737-4_3

At present, many people around the world use social networking services (SNSs). If a user has information to share, they will post it to SNSs. The tourism industry is no exception. We can help the development of the tourism industry by extracting useful information from such enormous data on SNSs. In particular, many travel blog entries have detailed information such as experiences and photos taken at a tourist site. In this study, we analyze travel blog entries.

The remainder of this paper is organized as follows. In Sect. 2, we discuss related work. Section 3 describes our method. To investigate the effectiveness of our method, we conducted experiments, whose results are reported in Sect. 4. Section 5 shows the behavior of a system we developed in terms of snapshots. We present our conclusion in Sect. 6.

2 Related Work

In this study, we use Wikification [1, 2] methods in addition to textual and image information. Wikification is the linking of text and Wikipedia entities. We classify travel blog entries automatically on the basis of tourism types by using this information. Furthermore, we map the classification results.

To enable the distributed representation of documents, Iyyer et al. [3] proposed a model called a "deep averaging network" (DAN) that converts words contained in a document into vectors and uses the average of them for classification. Furthermore, Mekala et al. [4] proposed the Sparse Composite Document Vector (SCDV) technique as an alternative method of generating document vectors. SCDV takes word vectors into consideration with Gaussian mixture modelling (GMM) and inverse document frequency (IDF) and uses the average of the generated word vectors as a document vector. A schematic diagram of SCDV is shown in Fig. 1. In this figure, classification is performed for each cluster (a–e) by using GMM, and a document vector is generated by averaging the result and the word vector in consideration of the IDF. In this study, we use this SCDV in the proposed method and a baseline method in an experiment on classifying travel blog entries on the basis of tourism types.

There have been a number of studies related to document classification regarding tourism [5, 6]. Takahashi et al. [5] used travel tweets from Twitter and proposed a method of classifying a traveler's behaviors, i.e., what the traveler is doing, into "sightseeing", "business", "eating", and "shopping". In addition to that, Fujii et al. proposed a method of classifying a traveler's behaviors, i.e. what the traveler is doing, into "buy", "eat", "experience", "stay", and "see" from travel blog entries written in English [6] and Japanese [7]. In their study, although there is some relevance to the classification focusing on types of tourism in our study, it is basically considered to be another viewpoint. Combining Fujii et al.'s classification with our proposed one based on tourism types could potentially enable more detailed searches, such as examining information related to "eat" content with "cultural tourism".

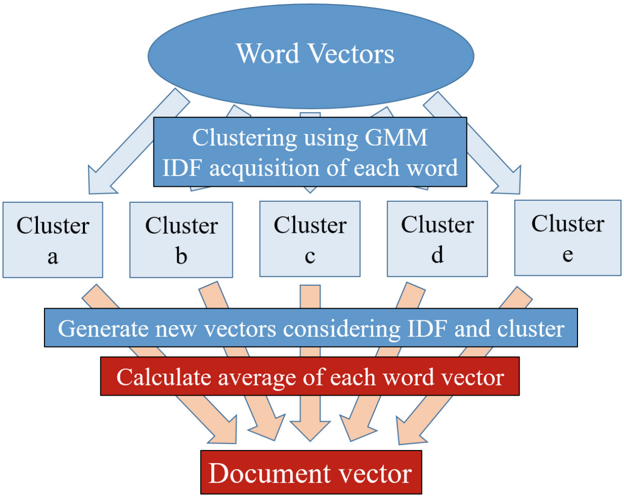


Fig. 1. Schematic of SCDV (Mekala et al. [4]) (compiled by author)

To enable travel information recommendations, Xiong et al. [8] constructed a personalized online hotel marketing recommendation system by extracting hotel characteristic factors and analyzing customers' browsing and purchasing behaviors. Also, Iinuma et al. [9] proposed a method for generating a summary of multiple travel blog entries that contain images and constructed a system. The system classifies the travel blog entries, which were collected by Nanbas' method (Nanba et al. [10]), by using Fujii et al.'s method.

3 Classification of Travel Blog Entries on the Basis of Tourism Types

3.1 Definition of Tourism Types

At present, there are many types of tourism, and most of them have no strict definitions. We selected and defined six tourism types on the basis of the ease of automatically clarifying them. Table 1 shows the different types, their definitions, and examples. We automatically classify travel blog entries written in English to clarify the tourism types of travelers on the basis of the six types.

Table 1. Definition and example of the types of tourism (own material)

Types of tourism	Definition	Examples
Infrastructure and hard tourism	Tourism for modern buildings and recreational facilities	Bridges, dams, theme parks, shopping malls, aquariums
Health tourism	Tourism aimed at health recovery, health maintenance, and health improvement	Religious pilgrimages, hot springs, hiking, trekking
Sports tourism	Tourism aimed at experiencing or watching sports	MLB, Soccer World Cup, Olympics
Green tourism	Tourism aimed at interacting with nature	Agricultural experience, fruit hunting, picnics
Heritage tourism	Tourism for historic buildings such as world heritage sites	World Heritage sites, national treasures, castles
Cultural tourism	Tourism for life, culture, ethnicity, and tradition of areas	Festivals, interchange with local people

3.2 Classification of Travel Blog Entries Based on Types of Tourism

In this study, we classify travel blog entries automatically on the basis of the types of tourism shown in Sect. 3.1. In this section, we explain the policy of automatic classification and the automatic classification of travel blog entries with machine learning.

3.2.1 Automatic Classification Policy

We analyze text, images, and Wikification results from travel blog entries and automatically classify them into tourism types by using the results of the analysis. Among them, textual information is the most important. For example, if a blog entry contained the phrase “I went to Mont Saint Michel, a UNESCO World Heritage Site”, this is considered to be an example of “heritage tourism” because the blog text contains the expression “UNESCO World Heritage Site”.

A disadvantage of text analysis is that misinterpreted context could produce inaccurate results. For example, if a blog entry contained the phrase “I wanted to ski but I could not do it”, although the word “ski” is present, the entry would not be related to “sports tourism”. However, if an image related to skiing is in the blog entry, it can be assumed that the author was skiing. In this study, we used the Google Cloud Vision API[1] for detecting objects in images. The API can classify images into thousands of categories, detect objects/faces, etc. We used words that obtained the object detection results in addition to textual information when classifying blog entries.

Classification requires external knowledge of what can be read from text or images. For example, if a blog entry contained the phrase “I saw Pyramid in Egypt. It was very big”, this blog entry is classified as “heritage tourism” because the Pyramid is a World Heritage Site. However, there is no information in the text. To judge this correctly as

[1] https://cloud.google.com/vision/?hl=en.

"heritage tourism", the inclusion of external knowledge such as information from Wikipedia is required. For this, we used the Google Cloud Natural Language API[2]. When text is sent to the cloud via the API, in addition to part-of-speech tagging, parsing, and lexical expression extraction, Wikification is also performed. By using the results of Wikification, we can obtain the information that the Pyramid is a World Heritage Site from the linked page of Wikipedia. Accordingly, in this study, we aim to achieve more accurate classification by using Wikification information as external knowledge in addition to the information from text and images.

3.2.2 Automatic Classification of Travel Blog Entries Using Machine Learning

In this study, we first prepare input data from the text, images, and Wikification results of a travel blog entry. Objects are detected in images, and words included in the linked Wikipedia abstract (the first paragraph) from the Wikification results are extracted. After that, we construct classifiers in consideration of each piece of input data. Since the classifiers are binary classifications, blog entries that do not fall into the six tourism types are classified as "other". A schematic of the classifier is shown in Fig. 2, where each piece of input data is processed, and the results are combined in a hidden layer.

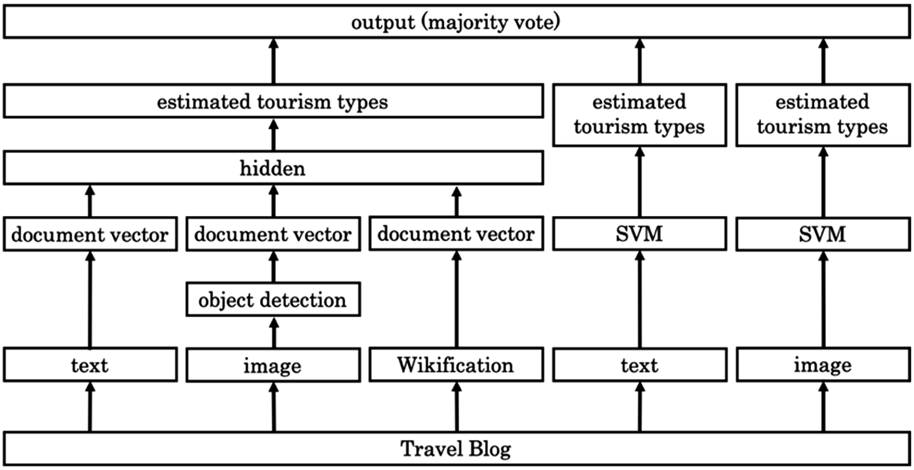


Fig. 2. Schematic of proposed classifier (authors' own figure)

This classifier integrates the analysis results of each piece of input data in the hidden layer. This is why the number of words included in each is significantly different. For example, in a travel blog, when the text includes 1,000 words, the object detection result includes 30 words, and the abstract of Wikipedia includes 100 words, so the number of words differs; thus, the influence of input data with a small number of

[2] https://cloud.google.com/natural-language/?hl=en.

words is reduced. For this reason, analysis results for each piece of input data are integrated in the hidden layer in this study.

4 Experiments

We conducted an experiment by using TravelBlog[3], one of the largest travel blog websites. It hosted over 700,000 blog entries in 2013. The aim of this experiment was to achieve a high precision accuracy as the number of blog entries is very high.

4.1 Experimental Conditions

Each blog entry was classified into one or more tourism types among six predetermined types manually and used as training data and test data for machine learning. A breakdown of the results classified manually is shown in Table 2. First, we originally defined nine tourism types, i.e. dark tourism, contents tourism, study tourism, and the six tourism types listed in Table 1. Second, we manually classified 2,017 randomly-selected travel blog entries. This data was created by a student, whose major is International Studies and is good at speaking English. Third, due to a lack of blog entries related to dark, contents, and study tourism (less than 30), we discarded those types because it was insufficient for machine learning. Finally, we obtained 2,017 travel blog entries and categorized them into the remaining tourism types as shown in Table 2. Also, it should be noted that 227 entries were classified with multiple types of tourism and 1,227 could not be classified at all.

Table 2. Breakdown of results classified manually (own material)

Types of tourism	Number
Infrastructure and hard tourism	168
Health tourism	125
Sports tourism	57
Green tourism	453
Heritage tourism	198
Cultural tourism	49
Targeted for classification	2,017

For the distributed expression of words, we used a pre-trained model provided by Google, the Word2Vec model of 300-dimension vectors[4]. This well-known model learned from the Google News dataset about 100 billion words, which is much larger than the TravelBlog corpus. The object detection function used the Google Cloud Vision API described in Sect. 3.2.1. We conducted classification by taking into account

[3] https://www.travelblog.org/.

[4] https://github.com/mmihaltz/word2vec-GoogleNews-vectors.

the results of Wikification, which, as stated above, is a method of obtaining a distributed expression from a Wikipedia abstract. Also, we experimented with ensemble voting methods with the same weights. For the ensemble (proposed) method, it used three classifiers: SCDV(txt+img+wiki) (proposed), SVM(txt), and SVM(img). For the ensemble (baseline) method, we used three classifiers: SCDV(txt), SVM(txt), and SVM (img). We applied the radial basis function (RBF) kernel to both SVM(txt) and SVM (img). We obtained the best epoch values using the optimization function "RMSpropGraves". For the activation function, we adopted ReLU in the hidden layer and softmax in the output layer.

The evaluation was performed by 5-fold cross validation to decrease problems like overfitting or selection bias, and precision, recall, and F-measure scores were used. The cross-validation process was repeated five times, with each of the five subsamples (the number of data samples are 403, 403, 403, 403, and 405) being used as the test data with the remaining four as training data. The five results can then be averaged to produce a single estimation. To calculate these, we used a micro average to take into account the bias in the number of data for each type of tourism. The precision and recall formulas are shown below.

$$\boldsymbol{precision} = \frac{\textbf{\textit{Travel blog entries classified correctly}}}{\textbf{\textit{Travel blog entries classified as tourism types}}}$$

$$\boldsymbol{recall} = \frac{\textbf{\textit{Travel blog entries classified correctly}}}{\textbf{\textit{Travel blog entries labelled manually as tourism types}}}$$

Generally, a trade-off between precision and recall is necessary. In our study, high precision is more important even if recall is low, and because more than 230,000 travel blog entries are available, this will resolve the low recall. In this experiment, we used the following three proposed methods (Table 3) and six baseline methods (Table 4). We conducted t-tests ($p < 0.01$), which confirmed that there were significant differences between SCDV(txt) and SCDV(txt+img) (proposed), and between SCDV(txt +img) and SCDV(txt+img+wiki).

Table 3. Proposed methods and features for use (own material)

	Text	Image	Wikification
Ensemble (proposed) • SCDV(txt+img+wiki) • SVM(txt) • SVM(img)	○	○	○
SCDV(txt+img+wiki)	○	○	○
SCDV(txt+img)	○	○	–

Table 4. Baseline methods and features for use (own material)

	Text	Image	Wikification
Ensemble (baseline) • SCDV(txt) • SVM(txt) • SVM(img)	○	○	–
SCDV(txt)	○	–	–
SVM(txt)	○	–	–
SCDV(img)	–	○	–
SVM(img)	–	○	–
SCDV(wiki)	–	–	○

4.2 Results and Discussion

Table 5 shows the experimental results of each baseline and the proposed methods described in Sect. 4.1. The highest precision of 0.807 was obtained with Ensemble (proposed). Also, the highest recall and F-measure scores of 0.272 and 0.385 were obtained with SVM(txt).

Table 5. Experimental results (micro average) (own material)

Method	Epoch	Precision	Recall	F-measure
Ensemble (proposed) • SCDV(txt+img+wiki) • SVM(txt) • SVM(img)	–	**0.807**	0.179	0.293
SCDV(txt+img+wiki) (proposed)	30	0.752	0.218	0.338
SCDV(txt+img) (proposed)	30	0.729	0.227	0.347
Ensemble (baseline) • SCDV(txt) • SVM(txt) • SVM(img)	–	0.747	0.216	0.335
SCDV(txt) (baseline)	20	0.639	0.169	0.268
SVM(txt) (baseline)	–	0.654	**0.272**	**0.385**
SCDV(img) (baseline)	10	0.725	0.140	0.235
SVM(img) (baseline)	–	0.788	0.170	0.279
SCDV(wiki) (baseline)	30	0.528	0.116	0.191

Compared with SVM(img), which had the highest precision among the baseline methods, Ensemble (proposed) produced better results for precision, recall, and F-measure, indicating that it is more effective. In terms of different input data, the proposed SCDV(txt+img) obtained a higher precision than the baseline SCDV(txt) and SCDV(img). Furthermore, the proposed SCDV(txt+img+wiki) obtained a higher

Table 6. The number of blog entries changed from ensemble (baseline) method to ensemble (proposed) method (own material)

	Green	Heritage
Correctly classified into “a tourism type”	25	9
Incorrectly classified into “a tourism type”	15	1
Correctly classified into “not a tourism type”	47	1
Incorrectly classified into “not a tourism type”	69	4
Total number of blog entries (as show in Table 2)	453	198

precision than the proposed SCDV(txt+img), and baseline SCDV(txt), SCDV(img), and SCDV(wiki).

Table 6 shows the number of blog entries changed from ensemble (baseline) method to ensemble (proposed) method. The reason only two types are shown in this table is that there was no difference between outputs of the two methods. Focusing on green tourism, the number of misclassifications decreased, while the number of correctly classified blog entries also decreased. It appears that textual information is more important than image and Wikipedia information when classifying travel blog entries as green tourism. On the other hand, the number of correctly classified blog entries increased in heritage tourism. In this case, image and Wikipedia information are useful, and they contribute to improve the recall value. Thus, increasing the number of inputs is valid when classifying travel blog entries.

5 System Behavior

In this section, we introduce our system's behavior in terms of the travel blog entries collected and classified by our proposed method. The system intuitively reveals the features of the tourism types for each tourist site. The procedure for visualization is as follows.

(1) Collect travel blog entries, and extract text and images from entries.
(2) Analyze images by using the Google Cloud Vision API, and estimate object detection and location information.
(3) Perform Wikification on text by using the Google Cloud Natural Language API.
(4) Collect Wikipedia entity information with the results obtained by Wikification and extract abstracts of linked Wikipedia articles.
(5) Classify on the basis of tourism types automatically using the obtained text, image analysis results, and abstracts of Wikipedia.
(6) Visualize data on a Google Earth map by using the location information obtained by the image analysis results. If multiple location information references can be extracted, the first one extracted is adopted.

We collected about 230,000 random travel blog entries from TravelBlog, and used 24,023 entries whose location information could be estimated for classification. The system is shown in Fig. 3. This figure illustrates Egypt and its surrounding. We used

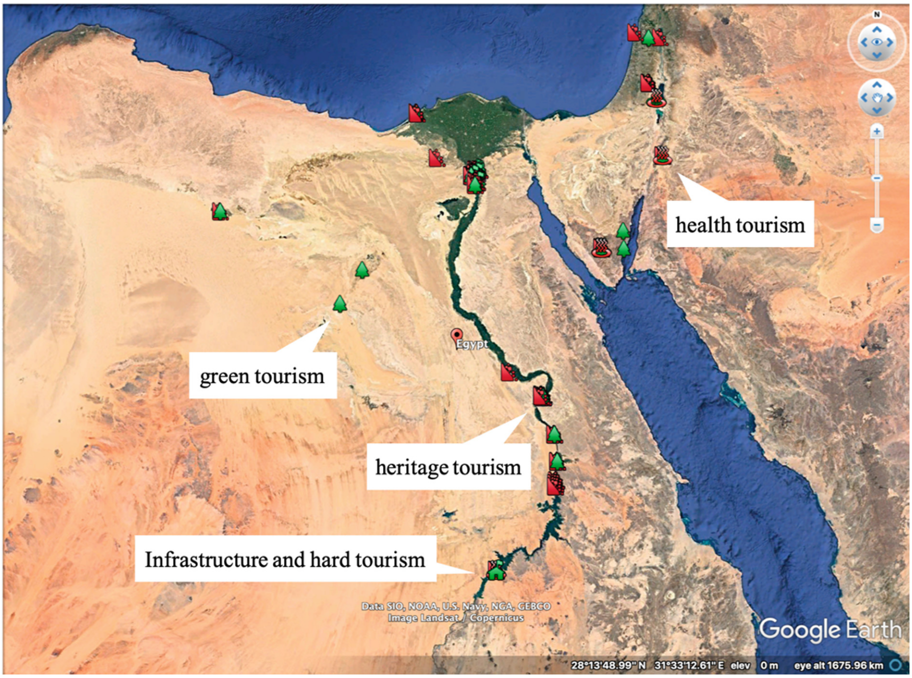


Fig. 3. Travel blog entries classified on the basis of tourism types (Egypt) (compiled by author)

icons to indicate type, such as a green house for "infrastructure and hard tourism", a hot spring for "health tourism", a bike for "sports tourism", a tree for "green tourism", the rocks for "heritage tourism", and a temple for "cultural tourism". If the user clicks an icon, the corresponding travel blog entry is shown on the map. From this figure, we can confirm many icons of the rocks, "heritage tourism" around the Nile River. In addition, the users of this system can find other tourism types information, such as "green tourism", "health tourism", and "infrastructure and hard tourism". Thus, this system enables to look up the information about tourism types that are useful for the users.

6 Conclusion

In this study, we proposed a method for automatically classifying travel blog entries into one or more tourism types among six predetermined types in consideration of text and images found in them and Wikipedia information. For images, we used the Google Cloud Vision API to detect objects and adopted the results as classification features. For Wikipedia information, we performed Wikification by using the Google Cloud Natural Language API, and we used the word sets included in the abstracts of linked Wikipedia articles as classification features. The experimental results show that a precision score of 0.807 was obtained for ensemble learning, which combined SCDV (txt+img+wiki), SVM(txt) and SVM(img).

For the visualization system, we classified 24,023 travel blog entries and visualized travel blob data on a map by using Google Earth. The proposed system enables analysts to investigate traveler behavior (Wenger et al. [11]) and marketing (Mack et al. [12]) via massive numbers of travel blog entries. However, currently, the system assumes travel blog entries written in English as input. Our future work is to expand to blog entries written in other languages.

References

1. Mihalcea R, Csomai A (2007) Wikify! Linking documents to encyclopedic knowledge. In: The ACM conference on information and knowledge management, pp 233–242
2. Yugo M, Sinsuke M (2016) Wikification for scriptio continua. In: The 10th edition of the language resources and evaluation conference, LREC, pp 1346–1351
3. Iyyer M, Manjunatha V, Boyd-Grader J, Daume III H (2015) Deep unordered composition rivals syntactic methods for text classification. In: The association for computational linguistics. ACL
4. Mekala D, Gupta V, Paranjape B, Karnick H (2017) SCDV: sparse composite document vectors using soft clustering over distributional representations. In: Conference on empirical methods in natural language processing, EMNLP, pp 659–669
5. Takahashi K, Kato D, Endo M, Araki T, Hirota M, Ishikawa H (2017) Analyzing travel behavior using multi-label classification from Twitter. In: The 9th international conference on management of digital ecosystems, MEDES 2017
6. Fujii K, Nanba H, Takezawa T, Ishino A, Okumura M, Kurata Y (2016) Travellers' behavior analysis based on automatically identified attributes from travel blog entries. In: Workshop of artificial intelligence for tourism, PRICAI
7. Fujii K, Nanba H, Takezawa T, Ishino A (2016) Enriching travel guidebooks with travel blog entries and archives of answered questions. In: International eTourism conference, ENTER 2016
8. Xiong Y, Geng L (2010) Personalized intelligent hotel recommendation system for online reservation–a perspective of product and user characteristics. In: Management and service science, MASS, pp 1–5
9. Iinuma S, Nanba H, Takezawa T (2019) Investigating the effectiveness of computer-produced summaries obtained from multiple travel blog entries. Inform Technol Tour 21 (1):83–103
10. Nanba H, Taguma H, Ozaki T, Kobayashi D, Ishino A, Takezawa T (2009) Automatic compilation of travel information from automatically identified travel blogs. In: The joint conference of the 47th annual meeting of the association for computational linguistics and the 4th international joint conference on natural language processing, short paper, pp 205–208
11. Wenger A (2008) Analysis of travel bloggers' characteristics and their communication about austria as a tourism destination. J Vacat Mark 14(2):169–176
12. Mack RW, Blose JE, Pan B (2008) Believe it or not: credibility of blogs in tourism. J Vacat Mark 14(2):133–144

Customer Value Framework and Recommendation Intention: The Moderating Role of Customer Characteristics in an Online Travel Community

Dandison C. Ukpabi[1], Heikki Karjaluoto[1], Sunday Olaleye[2](✉), and Emmanuel Mogaji[3]

[1] University of Jyväskylä, Jyväskylä, Finland
{dandison.c.ukpabi,heikki.karjaluoto}@jyu.fi
[2] University of Oulu, Oulu, Finland
sunday.olaleye@oulu.fi
[3] University of Greenwich, Greenwich, UK
e.o.mogaji@greenwich.ac.uk

Abstract. The aim of this study was to develop and test a model that examined the interactions among the customer value framework, recommendation intention and customer characteristics in an online travel community (OTC). Data were obtained using Amazon Mechanical Turk from 251 members of an OTC as a sample. The partial least squares method was used to analyse the data. We found that all the variables of the customer value framework, including functional value, hedonic value and social value, were positively related to recommendation intention. In addition, using multi-group analyses, the study found differences between how different customer segments perceive each of the value dimensions and their effect on recommendation intention. Theoretical and managerial implications are offered.

Keywords: Customer value framework · Recommendation intention · Customer characteristics · Online travel community

1 Introduction

Online travel communities (OTCs) provide consumers with a platform for sharing travel experiences [1]. Due to the value that consumers gain from such a platform, the OTC has become a motivator and a critical information source for travel decisions [2]. For instance, while those who join travel booking sites are motivated by the informational content (i.e. the quality of the reviews), including information on the brand or the destination's offering and attractiveness [3], community members on social networking and blogsites are motivated by social, hedonic and altruistic value [4, 5].

Consumer behaviour theorists argue that consumer needs and preferences underlie value perceptions [6]. Thus, the customer value framework has been conceptualised to clarify the understanding and enhance the measurement of customer value [7]. The

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 38–49, 2020.
https://doi.org/10.1007/978-3-030-36737-4_4

components of customer value vary across different contexts; however, most consumer behaviour literature typifies customer value into functional, social and hedonic value [6]. Several studies have linked customer value to either positive word of mouth or recommendation intention [8, 9]. In the OTC literature, a positive association exists between customer value and continuous participation [10]. Additionally, consumer characteristics have been found to play different roles in different consumption contexts. For instance, [11] found that males and females differ significantly regarding satisfaction, relationship maintenance, entertainment and disconfirmation of entertainment with Facebook. Understanding how customer value impacts recommendation intention in OTCs is critical because the sustainability of OTCs depends on new members who join the platform, of whom a significant number have often been motivated by the recommendations of existing users [12]. Accordingly, this study has two main objectives: examining the effect of the customer value framework on recommendation intention and understanding the role of the customer value framework on a participant's characteristics in relation to recommendation intention.

2 Literature Review

2.1 Consumer Value Framework

Consumer value is considered the overall assessment of the utility of a product based on perceptions of what is received and what is given [13]. [14, p. 46] defined customer value as an 'interactive, relativistic preference and experience'. [6] recognised the inconclusive effort towards properly describing what consumer value entails because it was not made clear whether customer value is a summative-based (benefits/fewer sacrifices) or a ratio-based (benefits divided by sacrifices) evaluation. They drew on integrated and extended previous conceptual foundations of customer value to develop the customer value framework, which identifies four major types of value that can be created by organisations—functional/instrumental, experiential/hedonic, symbolic/expressive and cost/sacrifice. A recent study sought to develop a better understanding of the framework. [15] posited that consumer value involves a trade-off process, where customers evaluate the benefits received (either utilitarian or hedonic) and the sacrifices given (either monetary or non-monetary) from using a product/service. This was further reiterated by [9], who defined consumer value as the process by which producers and consumers, as peer subjects, co-create value for themselves and each other; these authors also presented customer value creation as a three-dimensional construct that has functional, hedonic and social value.

Functional value is based on the assumption that individuals are rational problem solvers [9]. From the perspective of OTCs, functional value encompasses their members' need for information, which leads to financial savings and high-quality service. It also recognises the desired characteristics of the OTC, which makes it more encouraging to use [6]. Functional value is derivable if an OTC has the appropriate features, functions, attributes, appropriate performance levels (e.g. reliability) and appropriate outcomes and operational benefits [9]. By contrast, social value is considered an independent dimension in total customer value that enhances user status and selfesteem [16]. These value offers are derived as evidence of long-term engagement within the community; they represent a symbolic status that is used to emphasise unique traits [16]. Social value closely relates to the symbolic and expressive value of OTCs, which highlight the extent to which users attach or associate psychological meaning to their engagement in the community [6]. Previous research has only focused on online engagement for co-creating consumer value, but little is known about its influence on recommendation intention in an OTC. Finally, hedonic value has been conceptualised as the feelings and emotive aspects of community involvement [17]. It represents the extent to which an OTC creates appropriate experiences, feelings and emotions for its users [6]. [18] reported that enjoyable features are critical in influencing participation levels in OTCs.

2.2 The Dynamics of Customer Characteristics in OTCs

While customer segmentation has been performed mainly based on gender, it is essential to recognise that gender refers to psychological features that are related to biological nature and sociological variables [19]. Notably, these differ between males and females. Studies have shown that there are differences in how men and women think and behave based on their role in society. Research on gender differences has suggested that males and females possess different attitudes and preferences in using different information systems [20]. [21] recognised that these attributes can influence the behaviours and attitudes of each gender differently regarding consumption activities. [22] also found that female consumers are more likely to look for hedonic value because they are sensitive, intuitive, passionate, communal goal-oriented and linked with femininity. In addition, females are relationally oriented, and they like to maintain ties by connecting with friends and engaging in social activities [11]. Conversely, male consumers are more likely to look for functional value because they tend to be independent, rational and individually goal-oriented [22]. They are also more rational and focused on task-oriented activities [11].

Age has been used as a variable to ascertain how individuals evaluate value based on their experience with brands [19]. Several studies have shown that patterns of consumption differ significantly between age groups [21]. While young consumers often have a low-income status and are less experienced in product purchasing compared to older consumers, they exhibit quite different and distinctive online shopping patterns [21] and information searching processes. For instance, young people are more likely to engage in consumer-generated media when planning their vacations than are older people [23]. However, because older consumers have wider circles of friends, they are more likely to recommend OTCs when their information needs are met. Customers who perceive that they obtain greater value from using a service and thus are satisfied with it will continue to use it [15]. The time spent engaging with other users on an OTC is important for its survival [10], suggesting the need to make it more valuable for users. Individuals participate in social networks due to perceived value as hedonic value, utilitarian value and social value [24]. Likewise, stickiness—an integrated index for measuring individuals' duration of stay in online communities, frequency of visits and willingness to revisit [24]—has been considered an important behavioural outcome to explore in online communities [18]. It will help ensure a longer period of participation in community activities and interaction with other members in the community [25]. Given that OTCs are relationship-centric and inherently participatory [26], the adequate sharing of travel information and knowledge is a fundamental concern. A community cannot exist, let alone be vibrant and effective, without engagement [27]. Likewise, users' perception of hedonic and utilitarian value offers in OTCs is considered a component of customer satisfaction and a form of positive loyalty (frequency of visits to online virtual communities) [21]. The value offers that are inherent in OTCs should make individuals engage within the community and encourage them to continually use the brand. Thus, we propose the following (Fig. 1):

H1. The perceived functional value of OTCs is positively related to recommendation intention.
H2. The perceived hedonic value of OTCs is positively related to recommendation intention.
H3. The perceived social value of OTCs is positively related to recommendation intention.

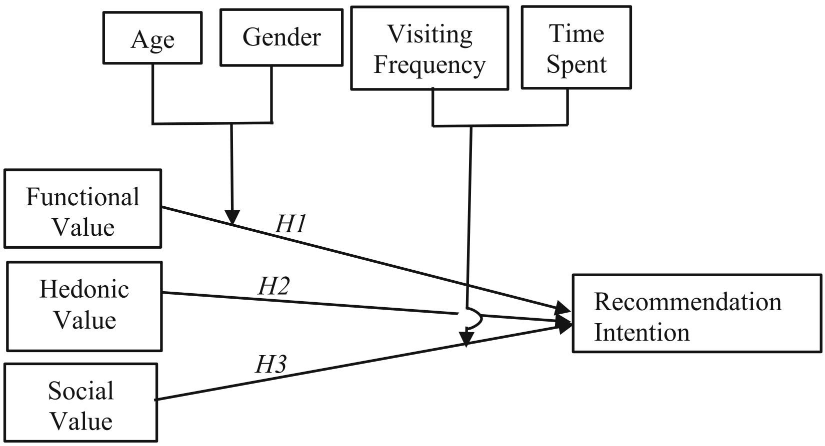


Fig. 1. Conceptual framework of our study (authors' own figure)

3 Research Methodology

The data for this study were collected online through the crowdsourcing of Amazon Mechanical Turk (MTurk). The study opted for MTurk due to its low cost and quick data collection ability. Further, its validity was scrutinised by [28], who explained its peculiar benefits for social science research. Of 253 responses, which were received in August 2018, only 2 cursory responses were deleted, and 251 valid responses were used for the data analysis. Among the respondents, 165 males (66%) and 86 females (34%) participated. See Table 2 for the profile of respondents including five of the most frequently occurring OTCs in the sample.

Table 1. Online travel community measurement indicators (compiled by authors)

Latent variables	Indicators
Functional Value (FV) **(0.71[a]; 0.88[b])**	FV1. The content (information) on this online travel community is helpful to me **(0.89[c])** ***FV2. The content (information) on this online travel community is useful to me** FV3. The content (information) on this online travel community is functional for me **(0.86[c])** FV4. The content (information) on this online travel community is practical for me **(0.79[c])**
Hedonic Value (HV) **(0.78[a]; 0.88[b])**	***HV1. I feel pleased and relaxed in this online travel community** HV2. I gain joy and happiness from this online travel community **(0.88[c])** HV3. I feel inspired in this online travel community **(0.88[c])**
Social Value (SV) **(0.82[a]; 0.93[b])**	SV1. I can make friends with people who share common interests with me in this online travel community **(0.90[c])** SV2. This online travel community helps strengthen my connections with other members (0.89[c]) SV3. I can expand my social network through participation in this online travel community (0.92[c])
Recommendation Intention (RI) **(0.72[a]; 0.89[b])**	RI1. I would recommend this online travel community to friends **(0.86[c])** ***RI2. I will participate in this online travel community more often than in others** RI3. I will say positive things about this online community to other people **(0.89[c])** RI4. I would encourage friends and relatives to do business with the brand of this online community **(0.79[c])**

*Removed indicators < 0.5
*Average Variance Extracted[a]; Composite Reliability[b]; Item Loadings[c]

Table 2. Online travel community respondent descriptive statistics (compiled by authors)

Descriptive	Classification	Frequency	Percentage
Gender	Male	165	66
	Female	86	34
Age	Young	122	49
	Old	129	51
Visiting frequency	Frequent	116	46
	Infrequent	135	54
Average time spent	Longer time	61	24
	Lesser time	190	76
Selected OTCs	TripAdvisor	73	
	Facebook	35	
	Yelp	33	
	Reddit	30	
	Advocate communities	29	

This study utilised existing validated measures and modified the wording of items to suit the context. The items for functional, social and hedonic value and recommendation intention were adapted from [9]. The study measured items on a seven-point Likert scale, with ‘strongly disagree (1)’ as the lowest and ‘strongly agree (7)’ as the highest. Table 1 shows the details of the measurement items.

4 Data Analysis

This study used SmartPLS version 3 with the Structural Equation Modelling (SEM) approach [29]. SmartPLS software is appropriate for both reflective and formative data analysis. Additionally, [30] contended that partial least squares structural equation modelling (PLS-SEM) and covariance-based structural equation modelling (CB-SEM) are complementary rather than competitive. Thus, PLS-SEM is recommended for either predicting or identifying key target constructs and/or drivers. Compared to covariance SEM, SmartPLS was preferable for this study because it simplified the issue of sample size [31, 32]. With SmartPLS software, the study was able to assess the measurement scales and examine the structural model [33]. Further, the study embarked on reliability and validity tests of the measurement model. The composite reliability (CR) as a reliability criterion, as shown in Table 1, was above the average of 0.70, as recommended by [34]. The CR and average variance extracted (AVE), as criteria for convergent validity, were of high quality. The CR values were all higher than 0.70, and the AVE for each latent variable was greater than the threshold of 0.50 [33]. Overall, the results revealed acceptable convergent validity of the measurements. Discriminant validity, as suggested by [34], should reflect that the square root of the AVE, diagonally, is greater than the correlation under the latent variables. In this study, the square root of the AVE for the latent variable was greater than the correlation values under the constructs. The results suggest discriminant validity of the study measurements.

4.1 Structural Model Analysis

This study used the bootstrapping technique with 5,000 samples to determine both the structural explanatory power and the structural model path significance [33, 35]. Specifically, the study tested the proposed model with five distinct samples: the full sample, gender subsample, age subsample, frequency visit subsample and average time visit subsample. The original model explained 62% of the variance in recommendation intentions. In Tables 4 and 5, males and females had equal R^2 (61%). The younger R^2

Table 3. Online travel community path coefficient analysis result (compiled by authors)

Hypotheses	Variable relationship	Beta	Std. Dev.	t-values	Decision
H1	FV -> RI	0.44	0.07	6.28***	Accepted
H2	HV -> RI	0.36	0.06	5.97***	Accepted
H3	SV -> RI	0.11	0.05	2.10*	Accepted

Notes. Significant levels *p < 0.05; ***p < 0.001

(68%) was higher than the older R^2 (56%). In addition, the high frequency R^2 (68%) was higher than the lesser frequency R^2 (54%). Higher users recorded the highest R^2 (82%), while lower users accounted for 56%. The functional value had the highest f^2 (0.28) and Q^2 (0.12). These results suggest that functional value has a moderate effect on recommendation intentions and moderate predictive relevance (Q^2) for the recommendation intention [36]. The hypotheses for the full model (H1–3) were significant at $p < 0.05$ and $p < 0.001$. The functional value ($\beta = 0.44$, $p < 0.001$), hedonic value ($\beta = 0.36$, $p < 0.001$) and social value ($\beta = 0.11$, $p < 0.05$) each had a direct significant relationship with recommendation intentions (Fig. 2 and Table 3).

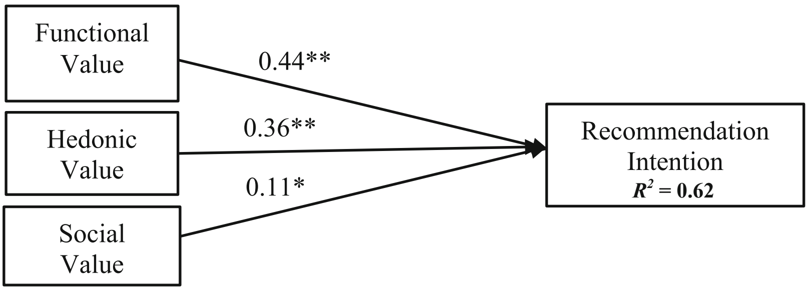


Fig. 2. Partial least square result of the full sample (authors' own figure)

This study conducted a multi-group analysis for gender, age, frequency of visit and duration of visit to determine how the perception of value by the different customer segments would influence their recommendation intention (Tables 4, 5, 6 and 7). The age bracket of 19–60 was divided into younger (19–29) and older (30–60) groups. The younger groups had 122 accounts (49%), while the older group had 129 accounts (51%). Visiting frequency was classified into high and less frequency. High frequency had 116 respondent accounts (46%), and less frequency had 135 accounts (54%). In addition, the average time spent was grouped into high and low users, with 61 response accounts for high users (24%), and 190 response accounts for low users (76%).

Table 4. Grouping for multi-group analysis (compiled by authors)

Grouping			
Group A		Group B	
Male	165 cases	Female	86 cases
High frequency	116 cases	Less frequency	135 cases
High users	61 cases	Low users	190 cases
Young	122 cases	Old	129 cases

The moderation result between the genders indicates that the influence of functional value on recommendation intention was stronger for the males than it was for the

Table 5. Online travel community model summary (compiled by authors)

Variable relationship	OS (n = 251)	f^2	q^2	Male (n = 165)	Female (n = 86)	Male vs female (t-value)	Young (n = 122)	Old (n = 129)	Young vs old (t-value)
Functional Value -> Recommendation Intention	0.44	0.28	0.12	0.46	0.42	6.966***	0.48	0.40	6.915***
Hedonic Value -> Recommendation Intention	0.36	0.14	0.06	0.34	0.39	6.321***	0.34	0.39	6.67***
Social Value -> Recommendation Intention	0.11	0.02	0.01	0.10	0.15	2.012*	0.12	0.10	2.14*
R2	0.62			**0.61**	**0.61**		**0.68**	**0.56**	

Notes: 0.02–0.15 weak, 0.15–0.35 moderate effect, > 0.35 strong effect
Significant levels *p < 0.05; ***p < 0.001
OS: original sample

Table 6. Online travel community model summary (continued) (compiled by authors)

Variable relationship	Fre. (n = 116)	LF (n = 135)	Fre vs LF (t-value)	HU (n = 61)	LU (n = 190)	HU vs LU (t-value)
Functional Value -> Recommendation Intention	0.43	0.45	6.63***	0.69	0.39	6.561***
Hedonic Value -> Recommendation Intention	0.42	0.30	6.444***	0.18	0.39	6.139***
Social Value -> Recommendation Intention	0.11	0.12	1.95	0.09	0.10	2.015*
R2	**0.68**	**0.54**		**0.82**	**0.56**	

Notes: 0.02–0.15 weak, 0.15–0.35 moderate effect, > 0.35 strong effect
Significant levels *p < 0.05; ***p < 0.001
Fr: frequent users; LF: low frequent users; HU: high users; LU: low users

Table 7. Online travel community multi-group analysis result (compiled by authors)

Variable relationship	A	B
FV*Male[a] vs Female[b] -> RI	5.35***	4.65***
FV*Older[a] vs Younger[b] -> RI	4.65***	7.37***
HV*Frequent visitors[a] vs Less Frequent Visitors[b] -> RI	5.34***	3.54***
HV*More Times[a] vs Fewer Times[b] -> RI	1.57	6.01***
SV* Frequent visitors[a] vs Less Frequent Visitors[b] -> RI	1.83	1.26
SV* More Times[a] vs Fewer Times[b] -> RI	0.68	1.70

Notes: Significant levels ***p < 0.001; FV: Functional Value; HV: Hedonic Value; SV: Social Value
RI: Recommendation Intention

females (male, $p < 0.001$; female, $p < 0.001$). However, in our tests for the age groups, we proposed that the influence of functional value on recommendation intention was stronger with the older than with the younger participants, which was not accepted, although it was significant (older, $p < 0.001$; younger, $p < 0.001$).

Similarly, we tested for how hedonic and social value influence frequency and duration of visits in relation to recommendation intention (Tables 4, 5 and 6). Our results indicate that the influences of hedonic value on recommendation intention are stronger for frequent visitors than they are for infrequent visitors (frequent visitors, $p < 0.001$; infrequent visitors, $p < 0.001$). By contrast, our assumption that the influences of hedonic value on recommendation intention are stronger with those who spend more time than those who spend less time on OTCs was not supported (more time, $p > 0.05$; less time, $p < 0.001$). Frequent visitors perceive more social value and show stronger recommendation intention than infrequent visitors (frequent visitors, $p > 0.05$; less frequent, $p > 0.05$), while participants who spent more time on an OTC did not perceive social value as strong enough to influence their recommendation intention (more times, $p > 0.05$; fewer times, $p > 0.05$).

5 Discussion

The objective of this study was to develop and test a model that examines the impact of the customer value framework on recommendation intention and how the perceived value influences different customer segments to recommend OTCs. Three main hypotheses were proposed and tested for the multi-group analyses. The three hypotheses were related to the structural model, while the multi-group analyses examined how different customer segments respond to the customer value framework and its effect on their recommendation intention. Thus, functional value, hedonic value and social value showed positive relationships with recommendation intention. Value is at the fabric of consumers' relationships with service providers and destinations; as such, services or places that are perceived to offer value will ultimately be recommended [12]. Additionally, functional value demonstrated the strongest relationship with recommendation intention compared to social and hedonic value. This finding also corroborates [4, p. 462], who contended that 'the stronger the functional motive, the greater were all the various aspects of participation—frequency of visits, duration of visits, exposure to others' eWOM and contribution to knowledge.' The study also found that, while males were impacted more by functional value to recommend the platform, the relationship between functional value and recommendation intention had less effect on older users than it did on younger users. Similarly, frequent visitors perceived that hedonic value demonstrated a greater effect on recommendation intention than did infrequent visitors. This finding also aligns with extant studies [15], which, in the context of mobile applications, have found that hedonic benefits affect recommendation intention. Finally, the link between social value and recommendation intention was positive for frequent visitors. As argued by [5], individuals with weak social ties will perceive more pleasure in online communities; thus, they will visit online communities more frequently than others.

5.1 Implications

Practically, this study contributes to the OTC literature by developing a model that tests the role of the customer value framework on recommendation intention. Firms spend large sums of money on advertising to recruit new customers annually, even though customer recommendation remains one of the most potent weapons for recruiting new customers [1, 15]. Accordingly, our study makes a novel contribution by explicating how the typologies of the customer value framework influence recommendation intention. Furthermore, the variables of customer characteristics introduce a new perspective to the OTC literature by highlighting how different customer segments perceive the customer value framework and its effect on recommendation intention. Extant studies [4, 11] have explained the interrelationships of these variables on general social media. To the best of our knowledge, the current study is the first to test different customer characteristics in the customer value framework regarding recommendation intention.

From a practical perspective, the core contribution of this study is that functional value has the strongest effect on recommendation intention. This implies that OTCs that promote information that facilitate members' travel decisions are likely to receive positive recommendation by members. Additionally, our conceptual framework offers managers and administrators of OTCs critical insights on how existing customers can valorize their platforms by recommending them to non-members. For company-owned OTCs, platform managers, such as hotel OTCs, should regularly post information on various services, particularly newly created ones, such as for cuisine, sporting activities, new luxury cars and fishing trips. OTCs can target specific customer segments. Our findings highlight that younger consumers are more susceptible to these services. Thus, focusing on this customer segment as well as peer influence, which is more dominant among young consumers, will help generate a large following on the platform. Similarly, independent OTCs should encourage the posting of vital information from different hospitality and tourism services to aid members in their travel decisions. To increase social and hedonic value, managers should regularly organise offline activities and embed entertainment and pleasure-fulfilling content on their platforms as well as primarily target frequent visitors.

5.2 Limitations and Future Research Direction

One of the limitations of our study is that certain scales were dropped from the measurements because they could not meet the threshold. This could have implications on our results. In addition, because our sample was obtained from members of MTurk, many of them were motivated to participate in the study due to pecuniary interests. It is likely that a neutral sample could have a different result. Despite these limitations, we believe that our study offers an interesting perspective to managers and extends the OTC literature by introducing the interrelationships between the customer value framework, recommendation intention and customer characteristics.

References

1. Ku EC (2011) Recommendations from a virtual community as a catalytic agent of travel decisions. Internet Res 21(3):282–303
2. Jung H, Lee G, Hur K, Kim TT (2018) Online travel information value and its influence on the continuance usage intention of social media. Serv Bus 12(1):85–120
3. Lee HA, Law R, Murphy J (2011) Helpful reviewers in TripAdvisor, an online travel community. J Travel Tour Mark 28(7):675–688
4. Ben-Shaul M, Reichel A (2018) Motives, modes of participation, and loyalty intentions of Facebook tourism brand page consumers. J Travel Res 57(4):453–471
5. Lee KH, Hyun SS (2018) The effects of tourists' knowledge-sharing motivation on online tourist community loyalty: the moderating role of ambient stimuli. Curr Issues Tour 21 (13):1521–1546
6. Smith JB, Colgate M (2007) Customer value creation: a practical framework. J Mark Theory Pract 15(1):7–23
7. Jung Choo H, Moon H, Kim H, Yoon N (2012) Luxury customer value. J Fash Mark Manag: Int J 16(1):81–101
8. Shi W, Tang L, Zhang X, Gao Y, Zhu Y (2016) How does word of mouth affect customer satisfaction? J Bus Ind Mark 31(3):393–403
9. Zhang M, Guo L, Hu M, Liu W (2017) Influence of customer engagement with company social networks on stickiness: mediating effect of customer value creation. Int J Inf Manage 37(3):229–240
10. Ukpabi D, Karjaluoto H, Olaleye S, Mogaji E (2019) Influence of offline activities and customer value creation on online travel community continuance usage intention. In: Information and Communication Technologies in Tourism 2019. Springer, Cham, pp 450–460
11. Chan TK, Cheung CM, Shi N, Lee MK (2015) Gender differences in satisfaction with Facebook users. Ind Manag Data Syst 115(1):182–206
12. Li L, Lee KY, Yang SB (2019) Exploring the effect of heuristic factors on the popularity of user-curated 'best places to visit' recommendations in an online travel community. Inf Process Manage 56(4):1391–1408
13. Zeithaml VA (1988) Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. J Mark 52(3):2–22
14. Holbrook MB (2005) Customer value and autoethnography: subjective personal introspection and the meanings of a photograph collection. J Bus Res 58(1):45–61
15. Xu C, Peak D, Prybutok V (2015) A customer value, satisfaction, and loyalty perspective of mobile application recommendations. Decis Support Syst 79:171–183
16. Rintamäki T, Kanto A, Kuusela H, Spence MT (2006) Decomposing the value of department store shopping into utilitarian, hedonic and social dimensions: evidence from Finland. Int J Retail Distrib Manag 34(1):6–24
17. Wang HY (2016) Predicting customers' intentions to check in on Facebook while patronizing hospitality firms. Serv Bus 10(1):201–222
18. Lee KH, Hyun SS (2015) A model of behavioral intentions to follow online travel advice based on social and emotional loneliness scales in the context of online travel communities: the moderating role of emotional expressivity. Tour Manag 48:426–438
19. Deshwal P (2016) Customer experience quality and demographic variables (age, gender, education level, and family income) in retail stores. Int J Retail Distrib Manag 44(9):940–955

20. Debrand CC, Johnson JJ (2008) Gender differences in email and instant messaging: a study of undergraduate business information systems students. J Comput Inform Syst 48(3):20–30
21. Kim C et al (2012) Factors influencing Internet shopping value and customer repurchase intention. Electron Commer Res Appl 11(4):374–387
22. Yang K, Lee H (2010) Gender differences in using mobile data services: utilitarian and hedonic value approaches. J Res Interact Mark 4(2):142–156
23. Mogaji E, Erkan I (2019) Insight into consumer experience on UK train transportation services. Travel Behav Soc 14:21–33
24. Yu J, Zo H, Kee Choi M, Ciganek A (2013) User acceptance of location-based social networking services: an extended perspective of perceived value. Online Inf Rev 37(5):711–730
25. Tsai HT, Huang HC, Chiu YL (2012) Brand community participation in Taiwan: examining the roles of individual group, and relationship-level antecedents. J Bus Res 65(5):676–684
26. Tsai WH, Men LR (2013) Motivations and antecedents of consumer engagement with brand pages on social networking sites. J Interact Advert 3(2):76–87
27. Lee H, Reid E, Kim WG (2014) Understanding knowledge sharing in online travel communities: antecedents and the moderating effects of interaction modes. J Hospit Tour Res 38(2):222–242
28. Berinsky AJ, Huber GA, Lenz GS (2012) Evaluating online labor markets for experimental research: Amazon. com's mechanical turk. Polit Anal 20(3):351–368
29. Ringle CM, Wende S, Becker J-M (2015) SmartPLS 3. SmartPLS, Bönningstedt. http://www.smartpls.com
30. Hair JF, Ringle CM, Sarstedt M (2011) PLS-SEM: indeed a silver bullet. J Mark Theory Pract 19(2):139–152
31. Chin WW, Newsted PR (1999) Structural equation modeling analysis with small samples using partial least squares. In: Hoyle RH (ed) Statistical strategies for small sample research. Sage, Thousand Oaks, pp 307–341
32. Dijkstra TK (2014) PLS'Janus face – response to professor rigdon's 'rethinking partial least squares modeling: in praise of simple methods'. Long Range Plan 47(3):146–153
33. Hair JF, Sarstedt M, Ringle CM, Gudergan SP (2018) Advanced issues in partial least squares structural equation modeling (PLS-SEM). Sage, Thousand Oaks
34. Fornell CD, Larcker F (1981) Evaluating structural equation models with unobservable variables and measurement errors. J Mark Res 18(1):39–50
35. Sarstedt M, Henseler J, Ringle CM (2011) Multi-group analysis in partial least squares (PLS) path modeling: alternative methods and empirical results. Adv Int Mark 22:195–218
36. Hair JF, Hult GTM, Sarstedt M, Ringle C (2014) A primer on partial least squares structural equation modeling (PLS-SEM). SAGE Publications, Thousand Oaks

Destinations

Which Photo Themes Evoke Higher Intention to Visit Switzerland?

Meng-Mei Chen(✉) and Andreina Irene Ramon Scovino

Ecole hôtelière de Lausanne, HES-SO University of Applied Sciences and Arts Western, Delémont, Switzerland
meng-mei.chen@ehl.ch

Abstract. Photos are means to communicate information. The ubiquity of smartphones and social media platforms allow nowadays the rapid exchange of images, and destination photos are no exception. Destination marketing experts need to understand these new sources of destination information to continue attracting tourists with success. Yet, destination image research incorporating pictorial content is scarce, and focused mainly on comparing content themes between destination marketing organizations (DMOs) and user generated content (UGS). However, the influence of different themes on intention to visit a destination is rarely addressed. This research aims to (1) identify those themes which are more effective in evoking intention to visit; and (2) expand the affective image understanding by incorporating different bipolar items than the ones traditionally used when studying destination image. This research used 36 photos from nine different themes to examine the relationship between cognitive image, affective image, and intention to visit Switzerland. From 278 responses, "Tradition", "Nature", and "F&B" were themes provoking higher levels of intention to visit. This research incorporated six affective image items, including stressful-relaxing, routine-adventure, ugly-breathtaking, uninspiring-inspiring, boring-exciting, and trapped-free; the results indicated that affective image was more influential than cognitive image on the variable intention to visit. This research contributes to academia by advocating the progress in image recognition which may free researchers from time consuming theme coding tasks, and move toward understanding the relationship between pictorial content and intention to visit. For practitioners, marketing campaign efforts should focus on themes identified above as they evoke higher intention to visit Switzerland.

Keywords: Photos · Affective image · Intention to visit

1 Introduction

An image is worth a thousand words. The ubiquity of smartphones and photo sharing apps empowers tourists to document and share their travel photos. Consequently, tourists actively participate in destination marketing, and become influential in potential travelers' decision making process. Destination Marketing Organizations (DMOs) responsible for creating and promoting destination image are competing with user generated content for the attention from potential tourists.

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 53–64, 2020.
https://doi.org/10.1007/978-3-030-36737-4_5

On the other hand, given the limited resources available for DMOs, the short attention span of the audiences, and the overwhelming information available to the audiences; DMOs must optimize their content to communicate a strong message [12]. As destination images are primarily visual, DMOs need to understand the relationship between pictorial content, and the intention to visit. In other words, DMOs need to know the right kind of pictorial content that evokes intention to visit.

Researchers have used pictorial content to understand DMO's marketing strategy [11], tourists' in-destination behaviors and their experiences [6, 23, 26]. Researchers also compared the similarities and differences of pictorial content between DMOs and user generated content by developed categories or themes, used them as a coding scheme, conducted content analysis and frequency counts of themes [10, 20, 22]. With the advance of image recognition technology and the metadata from photos, these time consuming processes could soon be done automatically by image recognition programs [13, 16].

On the other hand, only a limited number of research studied the relationship between pictorial content, emotions and feelings, and the intention to visit [7]. In these studies, emotions or feelings were considered affective image, and were measured with four bipolar questions including pleasant-unpleasant, relaxing-distressing, arousing-sleepy, and exciting-gloomy. Previous researchers found that affective image contributed to overall positive destination image and hence the intention to visit. Given the advance of image recognition technology, the themes or categories of photos could be easily identified. Yet, what needs to be done is to understand the relationship between affective image and intention to visit. Hence, the aim of this research is to expand the understanding of the relationship between pictorial content and intention to visit by investigating (1) if some themes could evoke stronger intention to visit; and (2) if different affective items, rather than the traditional four, could catch affective image and its influence on intention to visit.

2 Literature Review

Destination image and its relationship to intention to visit is a popular tourism research topic. Cognitive image and affective image contribute to the overall destination image, and the overall destination image influences intention to visit [2]. Cognitive image refers to all knowledge, perceptions, and beliefs that travelers have regarding a destination; while affective image refers to the feelings about the destination [2, 21]. However, most research instruments were written as descriptive texts. Destination images presented in descriptive texts may not be realistic, and may limit respondents in having a vivid mental image of the destination [20]. [10] found pictorial content is more effective in conveying affective attributes. Yet, researchers rarely investigated the impact of pictorial content on the intention to visit for potential tourists [20].

Most pictorial content related research, such as [20, 22], used content analysis aiming to identify objects and their frequencies, co-occurrence, clustering, and the relationship among objects [5]. Table 1 lists categories or themes used in three studies [7, 20, 22]. These studies focused mostly on the cognitive image, as they are considered knowledge or rational variables subject to limited bias. Some pictorial content research studies were limited by sample sizes, numbers of attributes, or both [7].

Table 1. Review of themes used in three recent studies (complied by authors)

Authors	Destination	Categories
Kim and Stepchenkova (2015)	Russia	Nature landscape; Activity; Transport/infrastructure; People; Place; Space; Architecture; Heritage; Season
Stepchenkova and Zhan (2013)	Peru	Nature & landscape; Art object; Festivals & Rituals; Food; Leisure activities; Transport/Infrastructure; Urban landscape; Other; People; Archaeological sites; Way of life; Traditional clothing; Architecture/building; Outdoor adventure; Tourism facilities; Wild life; Domesticated animals; Plants; Country landscape
Song and Kim (2016)	3 cities in Japan	Nature/Nature landscape; Art object/statue; Festival/Ritual; Food/Restaurant; Leisure activity/Facility; Transport/Infrastructure; Urban/Urban landscape; Other; Ordinary scene; Modern architecture; Religious building/object; Traditional art work/object; Traditional or historic building

Some researchers [5, 7, 9, 15] used photos to investigate the relationship between pictorial content and intention to visit. [9] found that iconic photos are more effective than generic photos to evoke potential tourists' intention to visit. [15] found that natural resource photos are frequently associated with "arousing" and "pleasant" feelings, while culture, history, and art are associated with "pleasant". [5] found that affective comments are similar regardless of destination, while the photo content to express them are localized. In other words, the pictorial content will differ by location, even though they evoke the same affective feelings.

Hence, it is important to identify the localized pictorial content. On the other hand, [7] found that photos taken by American and Korean tourists were evaluated in the same way by respondents across different cultures. Thus, when tourists with different cultural backgrounds take different photos, these photos will be "decoded in the same way on the receiving end of communication with respect to the latent destination feature" [7]. Based on this finding, [7] question if destinations have a true score with respect to some attributes. [14] conducted pre-photo and post-photo research, concluded that photos could influence respondents' destination image. These five research studies generally confirmed that pictorial content evoke affective feelings, nonetheless more research is needed to identify the relationship between the triggering pictorial content and the induced emotions.

[7] advocated to develop a list of latent attributes (cognitive and affective) suitable for visual research on destination image. [7] measured cognitive image with the following attributes: overcrowded-sparse, clean-dirty, developed-underdeveloped, safe-unsafe, modern-traditional, friendly-unfriendly, uniquely Russian-ordinary, and touristy-authentic; and affective image with pleasant-unpleasant, relaxing-distressing, arousing-sleepy, and exciting-gloomy attributes [7]. It is interesting to note that these four affective attributes were first used in [18], and became the standard items used by most researchers [7, 12]. On the other hand, some researchers used only two items to

measure affective image, such as pleasant-unpleasant, and exciting-boring by [3]; pleasant-unpleasant and sleepy-arousing by [1, 17]. [19] measured both cognitive and affective images, and their exploratory factor analysis found a factor of affective image consists of arousing, exciting and pleasant, while relaxing is in another factor in the category atmosphere along with peaceful place and place to rest. Yet, [8] argued that these dimensions used by previous researchers did not measure affective feelings but cognitive knowledge and evaluation.

The popularity of the four affective image items, the validity of using only two items, and arguments raised by [8] lead authors of this paper to question if further work can be done to expand our understanding of affective image. In particular, because these four items do not seem to be the only ones travelers could use to describe or evaluate their emotions associated with a destination, or a destination photo. Figure 1 was photo taken by the first author and Fig. 2 was downloaded from www.niesen.ch, the website of a famous Swiss cable company. These four affective image items (pleasant-unpleasant, relaxing-distressing, arousing-sleepy, and exciting-gloomy) probably could not capture all affective feelings. Could more items be added to better capture the affective feelings?

Fig. 1. Image of Switzerland category Nature (author's own photo)

Fig. 2. Image of Switzerland category Transportation (photo provided by www.niesen.ch)

In fact, the progress made in visual semantic analysis provides interesting insights for understanding the relationship between emotions and pictorial content. For example, [4] explained their methodology in predicting photo viewers' affective comments, and part of their study involved extracting adjectives from viewer comments. In [4], after eliminating adjectives with an absolute sentiment value of less than 0.125 and the frequency of less than 20, they had 400 adjectives. [5] used the same methodology as [4] and worked with UGC photos related to New York, and found the most observed adjectives were great, beautiful, light, and wonderful. Hence, could additional affective items, expressed in bipolar adjectives, be incorporated to advance our understanding of affective image?

Given the ubiquity of smartphones and photo sharing apps such as Instagram and Pinterest, photos are easily taken and shared. DMOs are responsible for the inducement of the intention to visit from potential tourists [9], and are competing with user generated content created by tourists [12, 20]; and must create and present advertising that maximizes the effectiveness of their limited marketing budget [9].

For the above reasons, we aim to investigate the process through which pictorial content influence potential travelers' intention to visit. The research questions are

(1) Do different photo themes evoke different levels of intention to visit Switzerland?
(2) What drives the intention to visit Switzerland? Cognitive image or affective image?

3 Method

3.1 Photo Themes and Selection

Based on the literature review of themes used by previous researchers and considering Switzerland as the destination, we selected nine themes of photos, including "Art", "F&B", "Historic", "Leisure", "Modern", "Natural", "Tourist", "Tradition", and "Transportation". For each theme, eight photos were downloaded from mainly myswtzerland.com and complemented with photos found from other websites relating to Switzerland. These photos and categories were validated by four Swiss citizens as typically Swiss photos. The researchers then selected four photos for each theme (36 photos).

3.2 Survey Instrument

Based on previous destination image research, a list of bipolar attributes were selected to explore cognitive and affective destination image: (a) cognitive image was measured through the attributes common-unique, unfriendly-friendly, unsafe-safe, traditional-modern, and unfamiliar-familiar; (b) affective image was measured with the attributes stressful-relaxing, routine-adventure, ugly-breathtaking, uninspiring-inspiring, boring-exciting, trapped-free [3, 7]. Specifically, affective items were chosen from a list of 150 bipolar adjectives previously mentioned in destination image studies, then narrowed down to six, taking into account: (a) their usage frequencies in previous destination image studies, (b) the relevance to tourism, (c) the relevance to photograph perception. The number of attributes was limited to avoid exhausting the participants with a long questionnaire. In addition, after showing a photo of Switzerland, the participants were asked to rate their overall positive impression of the destination and their intention to visit it. In summary, each photo was evaluated on five cognitive image items, six affective image items, one overall impression item, and one intention to visit item. All items used 7-point semantic differential scale.

The researchers created four surveys. Each survey included nine photos (one photo per theme), and finished with the demographic and previous travel experience questions. The order of the photos and the attributes to evaluate were randomized.

3.3 Data Collection

Given the length of the survey and the goal to reach diversified respondents, a convenient sample was used. The authors used their LinkedIn and Facebook connections to recruit respondents. The four surveys were distributed online in April 2018, and the data collection period lasted approximately three weeks. After the data collection, descriptive statistics, ANOVA, and the Tukey HDS tests were conducted using SPSS 24.

4 Results and Discussions

A total of 278 respondents completed the surveys. Most respondents were below 45 years old (84%), female (76%), and almost half of the respondents had been to Switzerland (46%). Table 2 presents the demographic profiles of the respondents.

Table 2. Demographic profile of survey respondents (complied by authors)

Age	25 or younger	96	35%
	26–35	114	41%
	36–45	22	8%
	46–55	18	6%
	56–65	23	8%
	Older than 65	5	2%
	Total	278	100%
Gender	Male	68	24%
	Female	210	76%
	Total	278	100%
Switzerland Travel	Yes	128	46%
	No	150	54%
	Total	278	100%

Two summated variables (average cognitive and average affective) were created by averaging the related individual cognitive and affective items. The Cronbach's alpha have been calculated to assess the reliability test for the cognitive image and the affective image, and the results were 0.868 and 0.933, respectively. Table 3 presents the means and standard deviations of summated cognitive and affective variables, and intention to visit for the nine photo themes. In terms of intention to visit, "Tradition" had the highest mean (5.97), followed by "Nature" (5.87), "F&B" (5.83), "Modern" (5.51), "Transportation" (5.17), "Tourist" (4.77), "Leisure" (4.63), "Historic" (4.59), and "Art" (3.34).

A one-way ANOVA test was conducted to compare the effect of photo themes on intention to visit. There was a significant effect of photo themes on intention to visit at the $p < 0.05$ level, $F (8, 2493) = 87.082$, $p = 0.000$. Furthermore, post hoc comparison

Table 3. Means and Standard deviations of summated cognitive and affective variables (complied by authors)

Theme	Var.	Mean (S.D)	Theme	Var.	Mean (S.D)
Art	C	4.17 (1.10)	Nat	C	4.85 (0.96)
Art	A	3.86 (1.26)	Nat	A	5.59 (1.09)
Art	I	3.34 (1.78)	Nat	I	5.87 (1.28)
F&B	C	4.56 (0.91)	Tou	C	4.52 (1.10)
F&B	A	5.56 (0.96)	Tou	A	4.31 (1.50)
F&B	I	5.83 (1.28)	Tou	I	4.77 (1.62)
His	C	4.46 (0.99)	Trad	C	4.76 (0.99)
His	A	4.22 (1.24)	Trad	A	5.57 (1.02)
His	I	4.59 (1.64)	Trad	I	5.97 (1.19)
Lei	C	4.28 (1.04)	Tran	C	4.52 (1.04)
Lei	A	4.29 (1.27)	Tran	A	4.65 (1.47)
Lei	I	4.63 (1.70)	Tran	I	5.17 (1.58)
Mod	C	4.73 (0.92)			
Mod	A	5.30 (1.18)			
Mod	I	5.51 (1.43)			

using the Tukey HSD test indicated that the mean scores for intention to visit were different among photo themes. Specifically, “Art” was significantly different from all other themes at $p = 0.000$ level. “F&B” was significantly different from “Historic”, “Leisure”, “Tourist”, and “Transportation” at $p = 0.000$ level. “Historic” was significantly different from “Modern”, “Nature”, “Tradition”, and “Transportation” at $p = 0.000$ level. “Leisure” was significantly different from “Modern”, “Nature”, “Tradition” at $p = 0.000$ level, and “Transportation” at $p = 0.05$ level. “Modern” was significantly different from “Tourist” and “Tradition” at $p = 0.000$ and $p = 0.005$ level, respectively. “Nature” was significantly different from “Tourist” and “Transportation” at $p = 0.000$ level. “Tourist” was significantly different from “Tradition” at $p = 0.000$ level. Finally, “Tradition” was significantly different from “Transportation” at $p = 0.000$ level.

The first research question was “Do different photo themes generate different levels of intention to visit Switzerland”? Based on the Tukey HSD test results, one can conclude that different photo themes evoke different intention to visit Switzerland. The second research question was “What drives the intention to visit Switzerland? Cognitive image or affective image”? To answer this question, liner regressions have been conducted with two independent variables (average cognitive and average affective) and dependent variable (intention to visit). The results are presented in Table 4. It is interesting to note that although the nine regression models were all significant at $p = 0.000$ level, the R^2 or the effect sizes, vary between 0.33 to 0.62, but only Average Affective was significant for all models. Hence, affective image is driving intention to visit Switzerland more than cognitive image.

Table 4. Linear regressions conducted with the variables average cognitive and average affective and intention to visit Switzerland (complied by authors)

Themes	R2	F	Intercept	Ave Cog	Ave affect
Art	0.33	68.06 ***	−0.14	0.24	0.64 ***
F&B	0.32	65.92 ***	1.46 ***	0.12	0.69 ***
Historic	0.55	168.14 ***	0.18	0.13	0.90 ***
Leisure	0.58	188.57 ***	−0.08	0.27 **	0.83 ***
Modern	0.50	137.66 ***	0.83 **	0.09	0.81 ***
Nature	0.52	149.22 ***	1.00 **	0.11	0.77 ***
Tourist	0.57	183.26 ***	0.96 **	0.14	0.74 ***
Tradition	0.46	115.96 ***	1.48 ***	0.12	0.70 ***
Transport	0.62	225.25 ***	1.07 ***	0.08	0.80 ***

*** Significant at $p = 0.000$
** Significant at $p \leq 0.05$

5 Discussion

5.1 The Photo Themes Evoke Higher Intention to Visit

This research investigated the relationship between photo themes and intention to visit Switzerland. The nine photo themes studied are “Art”, “F&B”, “Historic”, ”Leisure”, “Modern”, “Natural”, “Tourist”, “Tradition”, and “Transportation”. From the ANOVA and Tukey HSD test results show that, in terms of intention to visit, “Tradition”, “Nature”, and “F&B” evoke higher intention to visit, while “Art”, “Historic”, and “Leisure” have lower intention to visit. The various levels of intention to visit could help Switzerland’s DMOs to prioritize their marketing campaigns focusing more on “Tradition”, “Nature”, and “F&B”, and build stronger associations between these themes and Switzerland. Previous studies [10, 20] have identified and compared photos controlled by DMOs and shared by tourists, and focused more on seizing the commonalities and differences. Yet, research related to identifying the photos evoked stronger affective image or intention to visit are scarce. Hence, this research contributes to the understanding of the relationship between photos and intention to visit, as well as different themes that could evoke different levels of intention to visit.

Even though this research has identified some themes that evoke higher intention to visit than other themes, the photos best representing each theme have not been identified. [9] stated that iconic photos rather than generic photos should be used in destination marketing to evoke intention to visit. Hence, in addition to the generic themes identified above, tourism marketers may further concentrate on identifying and using icon photos within each theme.

5.2 Will Coding Photos into Themes or Categories Be Done by Technology?

Previous photo-related destination image research coded photos into themes manually. When coding is done manually, the number of photos studied were limited by the high costs of time and human resources. Given the advance of image recognition technology, will this part of research be replaced by technology [13, 16]? Figures 3 and 4 (author's own photos) demonstrate a simple example using Google Cloud AI & Machine Learning Tool (https://cloud.google.com/vision/). Google AI & Machine Learning Tool analyzed the photo and provided the geographic location and object labels and corresponding probabilities.

In addition, [25] shard their methodology to develop both image recognition and situation recognition. Landmark recognition is also a popular image recognition topic [24] and could certainly facilitate analyzing pictorial content. On the other hand, [13] already compared the image annotation services (GERTH and Watson) and identified the potential bias favoring categories the systems are trained for. With these developments, the research agenda could move from identifying and classifying photo themes to identifying photos evoking stronger affective image.

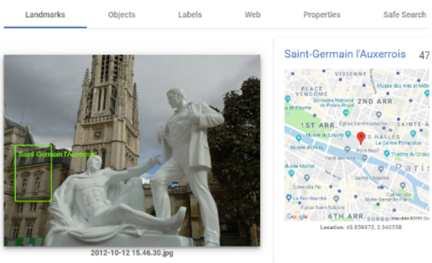


Fig. 3. Google Cloud AI & Machine Learning to Recognize and Tag Image (author's own photo)

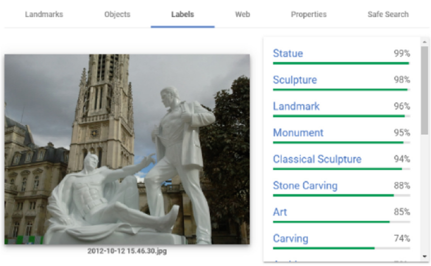


Fig. 4. Google Cloud AI & Machine Learning to Recognize and Tag Image (author's own photo)

5.3 Different Ways to Measure Affective Image?

To measure affective image, previous researchers generally used four bipolar items, pleasant-unpleasant, relaxing-distressing, arousing-sleepy, and exciting-gloomy. This research measured affective image with six bipolar items, including stressful-relaxing, routine-adventure, ugly-breathtaking, uninspiring-inspiring, boring-exciting, trapped-free. The reason for using different bipolar items was to explore alternatives to express affective feelings. [15] found natural resource photos are frequently associated with "arousing" and "pleasant" feelings, while culture, history, and art are associated with "pleasant". [4, 5] found popular photo viewers' comments were mostly adjectives, and provided examples such as "splendid" correlated with "beautiful scenic views" [4], and "great", "beautiful", "light", and "wonderful" are associated with New York photos [5].

In addition, the wheel of emotions developed by Plutchik identified eight emotions, including joy, sadness, fear, surprise, trust, disgust, ecstasy, and vigilance. It seems that the traditional four bipolar items (pleasant-unpleasant, relaxing-distressing, arousing-sleepy, and exciting-gloomy) could not catch all emotions. Previous researchers found cognitive image as more influential than affective image on the overall image formation, and intention to visit. Nevertheless, this research found that affective image is more influential than cognitive image in influencing intention to visit. Could different items used in this study to measure affective image better catch respondents' affective responses, and strengthen its validity? In the same vein, could other items be used to measure affective image? More research is needed to answer these questions.

6 Conclusions

This research used 36 photos from nine different themes to examine the relationship between cognitive image, affective image, and intention to visit Switzerland. "Tradition", "Nature", and "F&B" are themes provoking higher intention to visit. This research incorporated six affective image items, including stressful-relaxing, routine-adventure, ugly-breathtaking, uninspiring-inspiring, boring-exciting, and trapped-free; and found that affective image is more influential than cognitive image in intention to visit. This research contributes to understanding the relationship between pictorial content and intention to visit. Another contribution is incorporating different items to measure affective image, and found that affective image is more influential than cognitive image in intention to visit. This finding may encourage researchers to incorporate different sentiment items to measure affective image. For practitioners, this research identified the most popular themes, "Tradition", "Nature", and "F&B" as raising more intention to visit than other themes, and could direct practitioners to focus their marketing campaign efforts in these themes.

6.1 Limitations

Although this research has collected demographic and previous travel experience (the learning effect) data, the analysis has not been conducted. Furthermore, the affective items were more related to Switzerland, and may limit its generalizability. Lastly, the intention to visit should have been measured before the exposure to photos in order to detect the changes in perceptions.

6.2 Suggestions for Future Research

This research authors advocate researchers to switch the research focus from "confirming the relationship between cognitive image, affective image, overall image, and intention to visit" to "identifying the most effective photos for marketing campaigns". Specifically, which affective items should be used to better catch photo viewers' affective responses need to be further investigated. In addition, the relationship between these affective items and the intention to visit needs more research. Whether there is a set of affective items tourists used to express their affection to all destinations, or these affective items have to be localized also should be addressed. Definitely, whether these affect responses differ between cultures or travel experiences should also be further investigated.

References

1. Agapito D, Oom do Valle P, da Costa Mendes J (2013) The cognitive-affective-conative model of destination image: a confirmatory analysis. J Travel Tourism Mark 30(5):471–481
2. Baloglu S, McCleary KW (1999) A model of destination image formation. Ann Tourism Res 26(4):868–897
3. Beerli A, Martin JD (2004) Factors influencing destination image. Ann Tourism Res 31 (3):657–681
4. Chen YY, Chen T, Hsu WH, Liao HYM, Chang SF (2014) Predicting viewer affective comments based on image content in social media. In: Proceedings of international conference on multimedia retrieval. ACM, p 233
5. Deng N, Li XR (2018) Feeling a destination through the "right" photos: a machine learning model for DMOs' photo selection. Tourism Manag 65:267–278
6. Giglio S, Bertacchini F, Bilotta E, Pantano P (2019) Using social media to identify tourism attractiveness in six Italian cities. Tourism Manag 72:306–312
7. Kim H, Stepchenkova S (2015) Effect of tourist photographs on attitudes towards destination: manifest and latent content. Tourism Manag 49:29–41
8. Kock F, Josiassen A, Assaf AG (2016) Advancing destination image: the destination content model. Ann Tourism Res 61:28–44
9. Litvin SW, Mouri N (2009) A comparative study of the use of "iconic" versus "generic" advertising images for destination marketing. J Travel Res 48(2):152–161
10. Mak AH (2017) Online destination image: Comparing national tourism organisation's and tourists' perspectives. Tourism Manag 60:280–297
11. Mariani MM, Di Felice M, Mura M (2016) Facebook as a destination marketing tool: evidence from italian regional destination management organizations. Tourism Manag 54:321–343
12. Molinillo S, Liébana-Cabanillas F, Anaya-Sánchez R, Buhalis D (2018) DMO online platforms: image and intention to visit. Tourism Manag 65:116–130
13. Nixon, L. (2018). Assessing the usefulness of online image annotation services for destination image measurement. *e-Review of Tourism Research*
14. Nixon L, Popova A, Önder I (2017) How Instagram influences Visual Destination Image: a case study of Jordan and Costa Rica. In: ENTER2017 eTourism conference, Rome, Italy, January 2017
15. Pan S, Lee J, Tsai H (2014) Travel photos: motivations, image dimensions, and affective qualities of places. Tourism Manag 40:59–69
16. Picazo P, Moreno-Gil S (2019) Analysis of the projected image of tourism destinations on photographs: a literature review to prepare for the future. J Vacation Mark 25(1):3–24
17. Pike S, Ryan C (2004) Destination positioning analysis through a comparison of cognitive, affective, and conative perceptions. J Travel Res 42(4):333–342
18. Russell JA, Snodgrass J (1987) Emotion and the environment. Handb Environ Psychol 1 (1):245–281
19. San Martín H, Del Bosque IAR (2008) Exploring the cognitive–affective nature of destination image and the role of psychological factors in its formation. Tourism Manag 29 (2):263–277

20. Song SG, Kim DY (2016) A pictorial analysis of destination images on Pinterest: the case of Tokyo, Kyoto, and Osaka, Japan. J Travel Tourism Mark 33(5):687–701
21. Stepchenkova S, Mills JE (2010) Destination image: a meta-analysis of 2000–2007 research. J Hospitality Mark Manag 19(6):575–609
22. Stepchenkova S, Zhan F (2013) Visual destination images of Peru: comparative content analysis of DMO and user-generated photography. Tourism Manag 36:590–601
23. Vu HQ, Li G, Law R, Ye BH (2015) Exploring the travel behaviors of inbound tourists to Hong Kong using geotagged photos. Tourism Manag 46:222–232
24. Weyand T, Leibe B (2015) Visual landmark recognition from internet photo collections: a large-scale evaluation. Comput Vis Image Underst 135:1–15
25. Yatskar M, Zettlemoyer L, Farhadi A (2016) Situation recognition: visual semantic role labeling for image understanding. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 5534–5542
26. Yu CE, Sun R (2019) The role of Instagram in the UNESCO's creative city of gastronomy: a case study of Macau. Tourism Manag 75:257–268

Influencer Marketing for Tourism Destinations: Lessons from a Mature Destination

Francisco Femenia-Serra[1](✉) and Ulrike Gretzel[2]

[1] Tourism Research Institute, University of Alicante, Alicante, Spain
paco.femenia@ua.es
[2] Annenberg School for Communication and Journalism, University of Southern California, Los Angeles, USA
gretzel@usc.edu

Abstract. Influencer marketing has impacted all industries, including travel and tourism. Many Destination Management Organizations (DMOs) are leveraging the influence of online personalities for diverse purposes, including attracting visitors to their destinations. This paper sheds light on the use of social media influencers by DMOs, reveals the inner dynamics of influencer marketing for tourism destinations, and discusses the impacts of this practice. Relying on interviews with destination representatives, social media content analysis and data from internal reports, this research expands the scarce knowledge on influencer marketing in the travel and tourism domain hitherto, and provides valuable insights for destination managers.

Keywords: Influencer · Influencer marketing · Social media influencer · Destination marketing · Tourism marketing · Social media marketing

1 Introduction

Influencer marketing is a marketing practice that takes advantage of well-followed online users, who are able to influence consumers' attitudes and decision-making processes in favour of brands or ideas [1–3]. This burgeoning method was initially applied to fashion, beauty and style, but has permeated almost every economic activity, with travel and tourism being one of the sectors in which influencers have become especially prominent. In tourism, influential individuals can be used to attract more or different type of tourists to a given geographical area and to shape the perception of the destination, among other purposes [4]. However, while there is an increasing use of influencer marketing by tourism organizations and many social media influencers (SMIs) can be specifically classified as 'travel SMIs', there is a lack of research on influencer marketing in the travel and tourism domain [5]. In line with this, Xu and Pratt [6] call for a better understanding of SMI practices in destinations and the adoption of complementary perspectives to clearly depict the power influencers exert. There is a need to portray how decisions related to the selection and employment of influencers are made [2, 3]. Little is known about how DMOs proceed when selecting

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 65–78, 2020.
https://doi.org/10.1007/978-3-030-36737-4_6

these partners [7], and few studies have focused on factors affecting influencer marketing decisions or campaign design and performance [8, 9]. Moreover, as Glover [4] argues, apart from looking at persuasive effects, research also needs to focus on analysing the content of endorsers' campaigns. Considering this, the objective of the present paper is to better understand why and how tourism destinations apply influencer marketing. We aim to: *(i)* unveil destination marketers' views on influencer marketing; *(ii)* depict how DMOs manage influencer marketing campaigns; and, *(iii)* contrast practitioners' perspectives and objectives with the real content of campaigns as well as their actual impact. To fulfil these objectives, the paper focuses on the case of Benidorm (Spain), a well-known mature mass destination striving for innovative strategies to maintain its competitive position [10]. The findings shed light on the dynamics of influencer marketing and illustrate how destinations can properly leverage this flourishing marketing practice.

2 Literature Review

2.1 Influencer Marketing in Travel and Tourism

Social media influencers are 'vocational, sustained and highly branded social media stars' who 'exert influence over a large pool of potential customers' [11 pp. 71–72]. Generally, influencers possess attributes such as a high number of followers or a targeted, otherwise hard-to-reach 'audience', a privileged position in social media, and enjoy public recognition, which translates into influence on other people's decisions [1]. SMIs are a new type of online opinion leader and brand endorser [12] with a great power to influence their followers, which has made them the focus of influencer marketing strategy [3, 7, 13–15]. Hence, influencer marketing can be described as industry efforts that attempt 'to promote products or increase brand awareness through content spread by social media users who are considered to be influential' [2 p. 2]. From another perspective [3], influencer marketing is seen as an exchange between brands and well-followed content creators who endorse products or services by interweaving these promotions with their personal life narration.

As reported by Gretzel [5], influencer marketing in the travel and tourism domain has been mainly used by international hotel firms, while the use by destinations is increasing but still lagging behind. Influencer marketing is in this field a solid alternative to direct endorsement of destinations by DMOs, and has been proven to be more effective [4]. In the context of global competition, DMOs can use influencers to reach more people, as they normally do not have as many engaged followers [7], and to attract demographic segments that seem more influenceable via social media, such as women [16] and digital natives (i.e. millennials, Gen Z) [17]. Additionally, influencer marketing can enhance a destination's image [4], thus forming a critical part of destinations' branding strategy [5]. Effective management of social media by DMOs, including influencers, can also fight destination stereotypes [18], and despite being one of the potential instigators of overtourism in given locations, influencers can also be used to drive behavioral change and redirect tourism flows to less saturated areas [19]. Additionally, because of information overload, saturation of marketer-consumer direct relationships on social media and ad blockers, destinations need to adopt new strategies and adapt to social media affordances [5]. In this context, the right influencer strategy can deliver many benefits to DMOs. Initial findings show that practitioners seem to take into account several factors in their influencer selection, including fit between the brand and SMIs, number of followers, type of created content, reliability and communicative style [14]. Recently, emphasis has been placed on 'microinfluencers' as grassroots online celebrities who exert influence on a smaller scale but in a very effective way [5].

2.2 Destinations and Social Media Marketing

Social media have become the preferred marketing channel for tourism organizations and have been extensively adopted by tourists across their whole customer journey [20, 21]. The empowerment of tourists on social media has led to the production of 'user generated content' (UGC) on a massive scale, which has had deep implications for DMOs [22]. UGC is the most prominent form of electronic Word-of-Mouth (eWOM) [23] and has critically stifled DMOs' control over messages about their destinations [18]. Consumer-to-consumer communication is becoming ever more prevalent while traditional information sources (including DMOs and mass media) are declining in popularity [24]. Although destination image formation has always been dependent on a combination of organic and marketer-induced images [25], co-creation of destination images now happens on a much larger scale [22, 26]. According to Hays et al. [24] DMOs find it hard to adjust to this situation. They face difficulties in projecting the desired destination image in the overcrowded information space [27] and in managing the many forms and sources of UGC [24, 28]. Therefore, the marketing mandate of DMOs is increasingly difficult to implement. In this context, influencer marketing emerges as a viable option for DMOs to recapture tourists' attention, differentiate from the rest, and potentially take back part of the control over the online dissemination of destination-relevant information. Importantly, SMIs have proven to be more effective than traditional advertising practices [3, 14].

3 Methods

This paper employs a case study methodology, which allows to investigate influencer marketing as a "contemporary phenomenon, in depth and within its real-world context" [29 p. 16]. Benidorm was chosen for being a successful mass tourism destination based on an allegedly obsolete 'sun and sand' model which in fact has avoided decline over time and reversed the tourist area life cycle through a series of renewal and innovation initiatives, the latest example of which is the incorporation of cutting-edge marketing strategies as part of its global smart destination project [30].

Three different sources of data were employed to triangulate data and obtain a higher consistency in the results [31], including data from interviews, social media and an internal DMO report (see Fig. 1). First, face-to-face semi-structured interviews were conducted with five experts from the Benidorm DMO, including its general manager, chief data officer, digital marketing manager, project manager and external advisor. All interviews, with an average duration of over 1 h, were audio recorded and transcribed verbatim. Explicit permission from the participants was obtained to report their opinions. The transcripts were analyzed using Atlas.ti and following Braun and Clarke's [32] thematic analysis process: *(i)* familiarisation by listening, transcribing, reading and re-reading, *(ii)* coding excerpts with emerging, initial codes, *(iii)* re-coding, collating, and identifying themes, *(iv)* reviewing and refining themes, *(v)* defining and naming identified themes and *(vi)* producing the report. Second, this paper examines a specific influencer marketing campaign that emerged as a remarkable example during the interviews. 'The Other Benidorm' influencer marketing campaign is analyzed using two data sources: social media content (visual and textual data) and an internal report facilitated by the DMO. As a first step, pictures shared by the SMI on Instagram, Twitter and Facebook (total = 30) were manually gathered. Then, the main output of the campaign, a video (https://bit.ly/2Y4p3bd), was dissected by extracting its main features, examining its structure and summarising its content [33]. The clip was decomposed into shots, scenes and sequences using "Video Analysis 4All", an online service developed by the Greek Information Technologies Institute. Representative key frames (single pictures) [34] were selected and extracted from each scene, with a scene being defined as "a series of consecutive shots grouped together because they're shot in the same location or because they share some thematic content" [33 p. 43]. In total, 35 frames were selected from 11 scenes, representing a summary of a narrative unit that encapsulates a single spatiotemporal event and features the same characters. Following this, a set of categories was inductively developed considering the features of each of the 65 analyzed images (key frames plus pictures on social media) and the functional attributes of the destination [35]. Each image was taken as a single unit of content classifiable into up to four categories [36]. Moreover, textual data accompanying pictures (SMI's comments, captions, hashtags and mentions) and the audio from the video were scrutinised. For this task, the video was transcribed verbatim and analyzed together with the rest of the text using Atlas.ti. As shown in Fig. 1, different sources of data and analysis were employed in order to obtain a clearer understanding of the practitioners' views (*interviews*), of the actual development of influencer marketing campaign (*posts*) and its real impact (*report*).

Fig. 1. Research process. Source: Authors

4 Results

4.1 Practitioners' Perspective

In this section, the main themes from the interviews analysis are presented, including: influencer marketing 'design and objectives', 'development and implementation', 'impact', and 'volatility and future'.

Design and Objectives. As a first step, participants emphasise that the destination carries out an exhaustive research and monitoring of potential candidates to use for their influencer marketing campaigns. They follow each candidate for long periods of time and select them according to particular demand segments they target (e.g. millennials, families), specific products they aim to promote (e.g. MICE, gastronomy), the destination image they aspire to disseminate (Benidorm as LGTB+friendly/green/winter destination) or markets they expect to attract (France, Israel, Russia, etc.). If any inconsistency appears during the screening process of a candidate, the DMO consults with other destinations and brands that have worked with the influencer under study. One of the DMO representatives argued Benidorm "has to be there and invest in this" as a strategy to diversify its type of visitors, change the destination image, focus on niche segments and be recognised as the perfect choice for almost every tourist.

> "What we do is analyse which influencer is best for each product we aim to promote… it's a result of previous analysis and a long task of monitoring potential candidates" (Project manager)

Experts particularly highlight the need to use young influencers to attract this segment of tourists because of current predominance of seniors in Benidorm, particularly during low season. However, the objectives occasionally adapt to the changing circumstances of the market and *ad hoc* campaigns are planned on the go:

> "The airport of Alicante has launched two direct flights with Portugal. Following this, we decided to bring four or five Portuguese influencers to start attracting families and people under 40 from this market. Influencers give you the notoriety you need" (Chief data officer)

Long-term monitoring and thorough assessment of candidates are seen as key to avoiding poor results and fraud, including 'fake influencers'. The chief data officer of Visit Benidorm recalled a particular alleged influencer from Spain who made contact with the organization, offering them an audience of 15,000 followers. When required to provide statistics about her audience, it was discovered that more than 80% of followers where located in India, which according to the interviewee clearly indicated these were bots. Another relevant factor for the design of campaigns is that the specific objective and target market shape the type of content about the destination to be created and how it will be communicated by the influencer. Therefore, the objectives of influencer marketing in the case of Benidorm range from attracting tourists from certain markets, especially underdeveloped demand segments, to promote products and change perceptions of the destination (image). Influencer marketing is moreover perceived by the practitioners as an accessible and affordable practice that has higher credibility, reflects authentic opinions, elicits deeper engagement with potential visitors and adapts to current preferences of audiences, who value visuals over text:

> "It doesn't work anymore as a destination to tell the tourists: come visit us, our beach is great! What we have now is a society in which everyone has an opinion on social media and reviews everything […] so if you don't have someone else telling you how good this place is, we won't have any results" (Chief data officer)

> "These people create high-quality content because they produce great videos, have good cameras and spend hours editing the videos. But they also have thousands of followers and subscribers. This means people interested in that topic will get a notification and will see the video. That's an amazing power" (Digital marketing manager)

Development and Implementation. Narratives show how the DMO acknowledges that influencers have become much more professional, but also that DMOs are now much more precise regarding campaign specifications. The DMO establishes the number and types of posts to be shared, hashtags and keywords to be used, mentions to collaborators, and even part of the content to be shown. All these elements are formally included in a contract and organized along a timeline:

> "People think we pay 1.000€ for a kid to come and take a couple of pictures… but we watch them closely to ensure a good promotion. We're very demanding. We don't ask for a particular picture or forbid them to do anything, but we control them a lot. But people don't see that." (General manager)

In line with this control, Benidorm employs a tool provided by Brandmanic to monitor influencers during and after campaigns. This platform additionally applies algorithms to calculate the impact of each SMI in terms of equivalent monetary investment in traditional media. Obtaining these figures helps the DMO to justify expenses to the board members. Moreover, Visit Benidorm has designed and implemented together with a local startup a platform (*Visit Benidorm Analytics*) to monitor in real time the engagement influencers are rendering through each action on each platform. Metrics from different platforms are obtained in a visual, filtered way and are easy to interpret for managers, and therefore support a faster and more efficient decision making. This tool includes an alarm system and a time-based analysis that allows understanding how social media platform algorithms change and how to better leverage them. Another relevant factor for the development of influencer marketing campaigns is cost. Participants revealed that the DMO usually only remunerates the influencer's basic fee, but the rest of services are frequently covered by local partners. Agreements and collaboration with the regional and national tourism authorities can also reduce costs for the DMO, as the Ministry or regional tourism agency might co-fund transport or accommodation if they consider the campaign relevant for the image of the whole country or region. Visit Benidorm acts in any case as an intermediary between the local service providers, the authorities and the SMI, getting all required permits, organizing the route, accommodation and food provision, providing the SMI with full information about the destination and hiring professional services if needed (e.g. professional sports instructors, drivers, tour guides). Finally, when posting the content, the destination managers make sure they comply with the contract and that the posts meet expectations in terms of professionalism:

> "Each post has many hours of hard work behind… people think they're just having a free holiday, but for an ephemeral picture on Instagram, the influencer needs to edit the photo with professional software, create the perfect light and use the right filter, and then post it." (Digital marketing manager)

Impact. Another theme from the interviews is the impact of influencer marketing. According to interviewees, the influencer marketing strategy is rendering Visit Benidorm a high following on social media (verified account with more than 22K followers on Instagram and 50K on Facebook as of July 2019, ranking second in the region just after Valencia), and is granting the DMO a notable reputation among professionals in the sector. However, backlash from traditional press (mainly criticism towards expenses on influencers) has also been reported by two of the participants.

> "Benidorm has become a reference. There are many professionals working in the world of marketing talking about what Benidorm is doing, and how it's doing it." (External advisor)

Influencer marketing is perceived by practitioners as more effective and cost-effective compared to traditional media. Participants highlight the low cost of influencers taking into account their potential reach. They also underline how influencer marketing is nowadays the best alternative given the immense difficulty to gain visibility on social media. Each platform has its own advantages and disadvantages. For instance, the durability of a video on YouTube, virtually available forever compared to the ephemerality of an Instagram story, could be seen as a fundamental factor when assessing impact and deciding an investment. Another positive impact of SMIs is the benefit local providers who collaborate with the DMO get, as their visibility on social media rises rapidly. Additionally, interviewees argue that influencer marketing impact, thanks to the intermediaries and available technology, is easy to monitor, and also acknowledge the advantages of using their own single platform to control multiple results from different influencers acting across social media. This allows managers to better understand the impact of each campaign, save time and effort, and direct their future actions. Metrics are available for single specific actions, including number of views/likes/comments/shares (engagement of each post) and also for followers (country, age, gender). Metrics are therefore a basic feature of influencer marketing from the very selection of the influencer to results assessment, conferring this marketing practice an aura of *objectivity*. However, despite this data, the real impact of influencers on overall objectives is still hard to assess:

> "To calculate returns is very difficult, but it's not an expensive alternative. There's a strong collaboration between Visit Benidorm and private operators. Someone pays for the flights, another one offers a bed in a good hotel, another lowers his/her prices, another offers a tour around the destination or arranges the food…" (External advisor)

> "While it's true that the tool we use tells us how the impact of each campaign is, they can't tell you the % of the influencer's followers are going to come because of it. That doesn't exist." (Chief data officer)

Consequently, one of the main challenges identified by experts is to assess the real impact of influencer marketing in terms of arrivals of a given segment or image of the destination.

Volatility and Future. A recurring theme in the interviews were the constantly changing affordances of social media and the uncertainty about the future evolution of influencer marketing. The DMO general manager acknowledged that working with social media marketing nowadays necessarily requires understanding how platform algorithms work and how to best adapt to them. Innovations are continually implemented in social media (e.g. stories, lives, stickers), which makes tasks challenging for DMO employees. The quick obsolescence of social media marketing tactics is therefore a real burden for DMOs. Regarding the future of influencer marketing, experts highlight different lines of improvement and development. One participant reflects on the evolution of influencer marketing towards niche segments and micro-influencers, as the fees of big SMIs are unaffordable to many DMOs. Influencers with 1,000 to 3,000 followers might be key for destinations in the forthcoming years. Furthermore, another tendency forecasted by interviewees is a tighter regulation by authorities. Detailed disclosure of commercial partners in every single post and shared content will become a widespread practice. Almost all interviewees agreed about the existing hype around influencers and were worried about fake followers. One participant emphasised how detection of bot followers might get difficult in the future with the progress of these technologies (which may be capable of creating bots that could engage through comments in the future). Finally, the interviewed experts recommended collaborating not only with service providers but also with social media platforms in order to allow tourists to purchase services directly from the influencer videos they watch on YouTube, for instance.

4.2 Content of 'The Other Benidorm' Influencer Marketing Campaign

In line with their interest on attracting tourists from France, Visit Benidorm participated for many years in fairs and meetings with French tour operators. However, it was learnt that the local market perceived Benidorm as an unsustainable, overcrowded destination with a congested beach as its only attraction. Based on this problem, the DMO made a decision to engage in influencer marketing:

> "We started looking for French influencers, with young followers, probably more women than man, because we wanted to start working with this market from the bottom. Then we found this girl, who has many followers, a profile based on sustainable travel. She has pictures in the Maldives, in the middle of the African jungle working on conservation projects with Disney, with Greenpeace… I don't want to tell French people that Benidorm is sustainable, I want her to tell it from her point of view." (General manager)

The narratives of the DMO experts reveal the objective of this campaign was to promote Benidorm in the French market to attract a higher number of tourists from this country, particularly of a young age, and to change the destination image. Specific objectives included: Promoting Benidorm as a sustainable destination and as a diverse destination in terms of types of attractions, summarized by the slogan 'The Other Benidorm' [37]. Following these intentions, Visit Benidorm selected SMI Léa Camilleri, who has over 365 K followers on Instagram and 523K subscribers on YouTube, and who describes herself as an adventurous full-time traveller who advocates for sustainability, volunteers, and supports preservation initiatives on her trips. Léa was formally invited to visit Benidorm for a week in the summer of 2017.

The results from the social media content analysis (Table 1) reveal how the campaign content addressed the DMO objectives. The category frequencies for the 65 analyzed images show a high prevalence of images representing people (more than a third), mainly featuring the influencer and her team, followed by depictions of natural spaces and outdoor activities (both categories together build up almost 40% of content). This shows that the main focus of the campaign content is devoted to showing the destination in terms of nature-based and active tourism, but also evidences the use of the SMI persona to channel these ideas. In fact, presentation of the self is a key characteristic of influencer marketing [38]. It must be noted how two iconic attributes of Benidorm related to its mass 'sun and sand' model (the beach as the main attraction and skyscrapers as its distinctive urban model) are hardly present on the content, which unveils the intentions posed by the DMO when designing this influencer campaign. Regarding emojis as visual communication tools, their use by this SMI reflects several of the intentions identified by Ge and Gretzel [13], including: reinforcing arguments in this case related to destination characteristics(e.g. 🏝🌞🌊), emphasising emotions [e.g. 🤓] or providing further information about a given activity (e.g. 👟, 🚙).

Table 1. Description and classification of visual content. Source: Authors

Category	Description	*n*	%
Nature and natural landscape	**Depicts all types of natural resources, acting as scenery or main element of the image**	**39**	**24,07**
Beach		3	1,85
Ocean		27	16,67
Mountain		7	4,32
Wildlife		2	1,23
Outdoor activities	**Depicts any activity or sport practised in natural or urban landscapes**	**24**	**14,81**
Diving		6	3,70
Jeep driving		4	2,47
Hiking		6	3,70
Biking		1	0,62
Kayaking		1	0,62
Ambling		6	3,70
Urban landscape	**Depicts buildings, architectural sites, human-built elements**	**21**	**12,96**
Traditional architecture		10	6,17
Modern buildings/skyscrapers		11	6,79
Transport	**Represents different means of transport to get to and move around the destination**	**11**	**6,79**
Airplane		5	3,09
Car		4	2,47
Bike		1	0,62
Kayak		1	0,62
People	**Represents the own SMI, her team, locals, tourists, etc.**	**59**	**36,42**
Influencer only		34	20,99
Influencer + team		17	10,49
Influencer + other people		4	2,47
Other people		4	2,47
Accommodation	**Depicts any sort of accommodation or facilities related to it**	**5**	**3,09**
Other	**Promotional text, embedded images**	**3**	**1,85**
Total		162	100

Additional insights were derived from textual data, including the audio transcription of the video. In this regard, the SMI based her discourse on her passion for nature protection and adventure, but adjusted to the context of Benidorm. While acknowledging the bad reputation of Benidorm in terms of land use and its urban model ("Since the 50's Benidorm is unfortunately known for its many constructions. I'm going to show you another side of this city that you may not know"), the influencer highlights how the destination has different protected areas ("All this area of the sea is part of a reserve, it's an aquatic and earthly reserve. And you can't fish at all here, you just admire the nature") and emphasises the local sustainable initiatives (e.g. riding an electrical bike around the destination). Moreover, the performed activities at the destination fit with adventure as one of her core values and present Benidorm as an active and diverse destination. It is noteworthy that the main attraction of Benidorm (the beach) is barely mentioned. After allegedly discovering all the potential of the city, she argues her image of the destination has changed and recommends a visit to her conscious audience ("I had many prejudices when I arrived in Benidorm. If you have already been here or if you want to come, don't hesitate and go out of the beaten tracks. There are lots of pretty things, a great wildlife reserve, nice fauna and flora"). Additionally, this SMI interweaves destination marketing and sustainability as her brand storyline with glimpses of her feelings and personal life ("This picture represents everything you have allowed me to live until today. Everything that makes me try to be a better, conscious and open person every day"). This is a common practice among influencers, aimed at reinforcing a sense of authenticity and at connecting emotionally with the audience [38]. In terms of communicative style, the analysis reveals the constant use of humour in her posts, particularly in the video. This reinforces her connection with her followers and permits intermingling 'core content' with entertainment. Following DMO requirements, Léa includes in her posts the hashtag #visitbenidorm, mentions the professional movie maker who is part of her team and all service providers when applicable. Together with this, some space is also left for subtle self-branding and promotion of partners. In these moments, Léa adopts a position of naivety and alleged inexperience while introducing her message, thus reflecting a practice coined by Abidin [11] as "calibrated amateurism".

4.3 Impact of 'the Other Benidorm' Influencer Marketing Campaign

Data from the internal report [37] expose several important metrics of the 'The Other Benidorm' influencer campaign (Table 2). These data demonstrate how the YouTube video has been particularly fruitful, while Instagram has performed well, and actions on Facebook and Twitter have had a modest impact. Considering the specialization of this SMI in YouTube, the only post shared on this platform has had a high popularity among her audience and has rendered the destination high visibility on this channel. The overall impact in advertising equivalence terms is above 1 million of euros, which is a massive return considering the low cost for the DMO, partly explained by the collaboration with an airline (free tickets), accommodation offered by a luxury hotel, and excursions (diving, jeep riding, etc.) offered for free by local providers. In exchange for these services, the companies were tagged and named in the posts.

Table 2. Impact of 'The Other Benidorm' influencer marketing campaign. Source: Own elaboration based on Visit Benidorm (2018)

Number of posts (total)	31	**ROI YouTube**	**693.721,59€**
Potential reach (no. followers)	1.041.110	**ROI Instagram**	**77.992,54€**
Total engagement (any form)	243.370	**ROI Facebook**	**7.490,54€**
Campaign cost for DMO	3.308,40€	**ROI Twitter**	**2.469,73€**
Return of Investment (total)*	781.673,94€	**Cost per Interaction**	**0,013€**
Return/investment	236 points	**Cost per Visualisation**	**0,003€**

*Calculated with Ayzenberg Group's Earned Media Value Index 2.0 ([a]EMV Index).

5 Conclusion and Recommendations

Looking at the case of a mass coastal tourism destination, this research sheds light on the content and structure of a tourism-specific influencer marketing campaign. By focusing on the needs of the DMO, it introduces a perspective which had been heretofore overlooked [6, 7]. The findings reveal that influencer marketing provides DMOs with an opportunity to gain back control over branding and promoting a destination while taking full advantage of the power of social media-based eWOM. The case study illustrates that successful influencer endorsements occupy a new, advantageous space at the intersection of paid, earned, shared and owned media. Through these findings, this study widens our scarce knowledge of influencer marketing in the travel and tourism domain [5] and adds to our understanding of contemporary destination marketing practices.

While the specific findings from this case cannot be extrapolated to other destinations because of their high dependence on a particular context [29], the way the campaign was designed and implemented provides important practical insights. This campaign can be considered successful because of the reported results but also because of its focus on promoting sustainable tourism and alternative activities, leveraging this way influencers to foster responsible behaviors [19]. On another side, results show that influencer marketing for destinations needs to be part of a strategic vision and long-term planning. Selection of the influencer must respond to specific objectives and is an arduous process that entangles monitoring the appropriateness of each SMI and negotiating the conditions of the engagement. Formal contracts and specific guidelines should be given to SMIs beforehand and the process needs to be controlled as much as possible by the DMO. In order to ensure a maximization of benefits and reduction of costs, local service providers and external partners can be involved. Additionally, metrics about the process ought to be collected, particularly to measure the detailed results of each action within the campaign. Technological tools can assist the DMO in this endeavour. The findings also show that the future of influencer marketing is promising but also highly volatile, which requires that destinations keep their influencer marketing techniques and decisions updated. The current research represents a best practice case of a successful campaign implemented by an innovative DMO. Future research can build on it by investigating approaches to influencer marketing in DMOs with different levels of social media savviness. Also, exploring similarities and differences across campaigns with different levels of SMIs (from celebrities to microinfluencers) and across different travel and tourism sectors could provide important insights regarding the elements of tourism-related influencer marketing. Moreover, this paper has analyzed the impact of an influencer campaign using measures that reflect the earned media value. However, these measures only reveal part of the impact and need to be complemented with other types of data (e.g. followers, quality of produced content, generation of website traffic, relationship with bookings, users' reactions and sentiment analysis…), which is in line with the results and recommendations from similar studies [39]. Last but not least, expanding the content analysis to different tourism influencer campaigns could shed further light on the social media-afforded rhetoric of influencers.

Acknowledgement. Work supported by the Spanish National R&D&I Plan, funded by the Ministry of Economy, Industry and Competitiveness [Grant CSO2017-82592-R].

References

1. Bakshy E, Hofman J, Mason W, Watts D (2011) Everyone's an influencer: quantifying influence on Twitter. In: Proceedings of 4th ACM international conference on web search data Mining, SE-WSDM 2011, pp 65–74
2. Carter D (2016) Hustle and brand: the sociotechnical shaping of influence. Soc Med Soc 2 (3):1–12
3. De Veirman M, Cauberghe V, Hudders L (2017) Marketing through Instagram influencers: The impact of number of followers and product divergence on brand attitude. Int J Advert 36 (5):798–828
4. Glover P (2009) Celebrity endorsement in tourism advertising: effects on destination image. J Hosp Tour Manag 16(1):16–23
5. Gretzel U (2018) Influencer marketing in travel and tourism. In: Sigala M, Gretzel U (eds) Advances in social media for travel, tourism and hospitality: new perspectives, practice and cases. Routledge, New York, pp 147–156
6. Xu X, Pratt S (2018) Social media influencers as endorsers to promote travel destinations: an application of self-congruence theory to the Chinese Generation Y. J Travel Tour Mark 35 (7):958–972
7. Bokunewicz JF, Shulman J (2017) Influencer identification in Twitter networks of destination marketing organizations. J Hosp Tour Technol 8(2):205–219
8. Bergkvist L, Zhou KQ (2016) Celebrity endorsements: a literature review and research agenda. Int J Advert 35(4):642–663
9. Choi S (2015) The two-step flow of communication in Twitter-based public forums. Soc Sci Comput Rev 33(6):696–711
10. Ivars-Baidal JA, Rodríguez I, Vera JF (2013) The evolution of mass tourism destinations: new approaches beyond deterministic models in Benidorm (Spain). Tour Manag 34:184–195
11. Abidin C (2018) Internet celebrity: understanding fame online. Emerald Publishing Limited, Bingley
12. Freberg K, Graham K, McGaughey K, Freberg LA (2011) Who are the social media influencers? A study of public perceptions of personality. Public Relat Rev 37(1):90–92
13. Ge J, Gretzel U (2018) Emoji rhetoric: a social media influencer perspective. J Mark Manag 34(15–16):1272–1295

14. Uzunoğlu E, Misci Kip S (2014) Brand communication through digital influencers: Leveraging blogger engagement. Int J Inf Manage 34(5):592–602
15. Jerslev A (2016) In the time of the microcelebrity: celebrification and the YouTuber Zoella. Int J Commun 10:5233–5251
16. Djafarova E, Rushworth C (2017) Exploring the credibility of online celebrities' Instagram profiles in influencing the purchase decisions of young female users. Comput Human Behav 68:1–7
17. Khamis S, Ang L, Welling R (2017) Self-branding, 'micro-celebrity' and the rise of Social Media Influencers. Celebr Stud 8(2):191–208
18. Li SCHH, Robinson P, Oriade A (2017) Destination marketing: the use of technology since the millennium. J Destin Mark Manag 6(2):95–102
19. Gretzel U (2019) The role of social media in creating and addressing overtourism. In: Dodds R, Butler R (eds) Overtourism: issues, realities and solutions. de Gruyter, Boston, pp 62–75
20. Xiang Z, Gretzel U (2010) Role of social media in online travel information search. Tour Manag 31(2):179–188
21. Munar AM, Jacobsen JKS (2014) Motivations for sharing tourism experiences through social media. Tour Manag 43:46–54
22. Munar AM (2011) Tourist-created content: rethinking destination branding. Int J Cult Tour Hosp Res 5(3):291–305
23. Litvin SW, Goldsmith RE, Pan B (2008) Electronic word-of-mouth in hospitality and tourism management. Tour Manag 29(3):458–468
24. Hays S, Page SJ, Buhalis D (2013) Social media as a destination marketing tool: its use by national tourism organisations. Curr Issues Tour 16(3):211–239
25. Gunn CA (1972) Vacationscape: designing tourist regions. Bureau of Business Research, University of Texas at Austin, Austin
26. Lim Y, Chung Y, Weaver PA (2012) The impact of social media on destination branding: Consumer-generated videos versus destination marketer-generated videos. J Vacat Mark 18 (3):197–206
27. Pike S, Page SJ (2014) Destination marketing organizations and destination marketing: anarrative analysis of the literature. Tour Manag 41:202–227
28. Llodrà-Riera I, Martínez-Ruiz MP, Jiménez-Zarco AI, Izquierdo-Yusta A (2015) A multidimensional analysis of the information sources construct and its relevance for destination image formation. Tour Manag 48:319–328
29. Yin RK (2014) Case study research. design and methods, 5th edn. SAGE Publications, Thousand Oaks
30. Femenia-Serra F, Ivars-Baidal JA (2019) Do smart tourism destinations really work? The case of Benidorm. Asia Pacific J Tour Res (Forthcoming)
31. Decrop A (1999) Triangulation in qualitative tourism research. Tour Manag 20(1):157–161
32. Braun V, Clarke V (2006) Using thematic analysis in psychology. Qual Res Psychol 3 (2):77–101
33. Dimitrova N, Zhang H-J, Shahraray B, Sezan I, Huang T, Zakhor A (2002) Applications of video-content analysis and retrieval. IEEE Multimed 9(3):42–55
34. Li Y, Lee S-H, Yeh C-H, Kuo C-C (2006) Techniques for movie content analysis and skimming: tutorial and overview on video abstraction techniques. IEEE Sign Process Mag 23(2):79–89
35. Echtner CM, Ritchie JRB (1993) The measurement of destination image: an empirical assessment. J Travel Res 31(4):3–13
36. Stepchenkova S, Zhan F (2013) Visual destination images of Peru: comparative content analysis of DMO and user-generated photography. Tour Manag 36:590–601

37. Visit Benidorm (2018) France: final reports and activities summary
38. Audrezet A, de Kerviler G, Guidry Moulard J (2018) Authenticity under threat: when social media influencers need to go beyond self-presentation. J Bus Res (Forthcoming)
39. Wozniak T, Stangl B, Schegg R, Liebrich A (2017) The return on tourism organizations' social media investments: Preliminary evidence from Belgium, France, and Switzerland. Inf Technol Tour 17(1):75–100

Credibility in Question: Travel Information Adoption Among Chinese Consumers in Canada and Singapore

Si Ru Li[1(✉)], Yi Xuan Ong[1], and Naoya Ito[2]

[1] Graduate School of International Media, Communication, and Tourism Studies, Hokkaido University, Sapporo, Japan
siru.li@outlook.com, yixuanong@eis.hokudai.ac.jp
[2] Research Faculty of Media and Communication, Hokkaido University, Sapporo, Japan
naoya@imc.hokudai.ac.jp

Abstract. Drawing upon the dual-route theory of information processing, this study examined whether people from the same cultural origin would adopt online travel information differently, namely through the central or peripheral route, in consideration of the influences from their host societies as either being individualistic or collectivistic. Responses were collected from people of Chinese descent in Singapore (n = 133) and compared with data from Chinese people in Canada (n = 106). Results of the Structural Equation Modeling (SEM) indicate that cultural orientation might no longer explain differences in people's information processing as no significant peripheral route represented by source credibility was confirmed in either of the sample groups. Meanwhile, the present study examined the possibility of a single-route persuasion approach, where peripheral cue represented by source credibility would be used as a filter to select out credible information for further scrutiny. While prior research has demonstrated that both processing routes can be used concurrently, the order in which they are adopted is seldom discussed in the literature. Results of the multi-group invariance test suggest that the re-conceptualized single-route persuasion model might better explain online travel information processing for Chinese consumers in both Canada and Singapore in today's context.

Keywords: Travel information · ELM · Online reviews · Information adoption

1 Introduction

Online reviews posted by fellow consumers are highly influential in people's decision-making process and elicit greater interest than those of marketer-generated contents [1]. As people are inclined to rely more than ever on online user-generated contents (UCG) for travel planning, studies on the influence of online travel reviews have attracted increasing attention from researchers and practitioners [2, 3]. In particular, dual-process theories of information processing, such as the Elaboration Likelihood Model (ELM), have been actively drawn upon to understand individual's information adoption on travel websites [4, 5].

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 79–91, 2020.
https://doi.org/10.1007/978-3-030-36737-4_7

Developed by Petty and Cacioppo [6], the ELM interprets individual attitude change through a central or peripheral route to persuasion. It is one of the most widely used frameworks to study the persuasive power of online reviews [7] and explain how people are influenced in adopting such information [3, 8]. In a study by Zhang et al. [5], both the central and peripheral routes, represented by argument quality and source credibility, were found to affect Chinese consumers' cognitive processes, albeit source credibility appeared as a more important criterion for people in China to evaluate the usefulness of online travel information. However, a later study by Li and Ito [9] suggested rather different findings: Chinese people in Canada seem to rely solely on argument quality to evaluate online travel information usefulness, whereas source credibility as the peripheral route has no significant effect within the process.

Inconsistent results among previous studies necessitate further testing of the dual-route model, especially for geographically dispersed population that shares a common source culture. Hofstede's cultural dimension of individualism-collectivism has been widely employed to explain different persuasion approaches across cultures. Combined with the ELM, it is believed that the central route may be preferred by individualistic cultures whereas the peripheral route may be more prevalent in collectivistic societies [10, 11].

As part of a cross-national research project, this study attempts to validate the findings of Li and Ito [9] by comparing the Chinese Canadian sample with residents of Singapore who are also of Chinese ancestry. Although multiculturalism has been a central concept to both countries, it is argued that the prominence of nation is placed before racial diversities in Singapore, whereas liberal values of individualism are often pursued in Canada [12]. Moreover, based on Hofstede's cultural dimension, Canada is much more individualistic when compared to Singapore [13]. Hence, the present study aims to: (1) understand Chinese people's information processing of online travel reviews in distinctive socio-cultural contexts; and (2) discuss the applicability of the dual-route model when dealing with online travel information.

2 Theoretical Background

2.1 Information Adoption Model

The Elaboration Likelihood Model (ELM) is a dual-route theory that articulates individual attitude change based on elaboration likelihood states. In high elaboration states, a central route that involves thoughtful scrutiny of the information content will be adopted, whereas a peripheral route that requires little cognitive efforts but heuristic cues will be used in low elaboration states [14]. However, prior research has indicated that ELM cannot fully explain people's intention of adopting information and knowledge [3, 8]. In response to this limitation, Sussman and Siegal [15] integrated the ELM with the Technology Acceptance Model (TAM) [16], from which they developed an information adoption model (IAM) that posits perceived information usefulness as a mediator between argument quality (central route) and source credibility (peripheral route) leading to information adoption. Zhang et al. [5] proposed an extended IAM by incorporating technical adequacy as a predictor of both routes, from which the positive effect of source credibility on perceived information usefulness was found to be much higher than that of argument quality for people in China. However, when testing the same model with Chinese people in Canada, no significant effect was found from source credibility [9].

2.2 Individualism-Collectivism Orientation

As a paradigm for comparing cultures, Hofstede identified six dimensions of national culture, namely, power distance, uncertainty avoidance, individualism-collectivism, masculinity-femininity, long-short term orientation, and indulgence-restraint [13]. Among the six dimensions, individualism-collectivism is the most central one that has gained substantial attention in the field of cross-cultural studies [10]. Individualism (versus collectivism) is characterized by the extent to which people are incorporated into groups in a society [13]. On the individualism scale, Canada ranked 4th–6th of 76 countries with a score of 80 while Singapore ranked 58th–63rd with a score of 20 [13]. Building on this result, Canada and Singapore were considered to be sufficiently different on the individualism-collectivism dimension, which allows a test of their socio-cultural influences on Chinese people's adoption of online travel information.

3 Research Models and Hypotheses

3.1 Extended Information Adoption Models

From a dual-route persuasive viewpoint, previous research has found that argument quality and source credibility, mediated by perceived information usefulness, both effectively persuade people to adopt online travel information [3–5]. However, a more recent study questions the simultaneous effects of both routes in travel information adoption, since a significantly strong central route and a non-significant peripheral route were identified with the model [9]. Among the widespread application of the dual-process theory in tourism studies, peripheral routes represented by website design characteristics have been found non-significant in cases where people have high levels of involvement; however, such design features might foster people's engagement in thoughtful consideration of the website's information [17]. In a similar vein, source credibility is thought to be an unignorable factor in the persuasion process, which

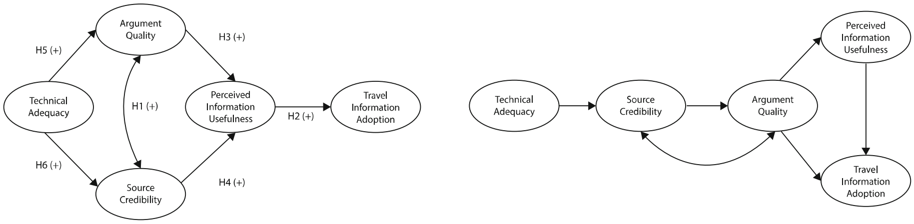


Fig. 1. Research model comparison. Left: adapted from Zhang et al. [5], p. 642. Right: adapted from Li and Ito [9], p. 115.

serves as a precondition for evaluating argument quality of online travel reviews [9]. Based on previous research, the present study aims to extend the analysis to people of Chinese descent in Singapore in order to examine the applicability of the two research models presented in Fig. 1.

3.2 Research Hypotheses

Argument Quality and Source Credibility. According to the ELM, individuals' elaboration likelihood states are determined by their motivation and ability to assess the central merits of the information [18]. In high elaboration likelihood, people's attitudes are mostly affected by argument quality; when the elaboration likelihood is low, attitudes tend to be affected by peripheral cues such as source credibility [6]. Previous studies have identified positive correlation between the two routes, suggesting that they both could form a basis of judgement on information adoption [19]. Therefore, the present study aims to ascertain whether this correlation would still hold true with the Singapore sample.

H1. Argument quality and source credibility of online travel reviews positively correlate with each other.

Perceived Information Usefulness and Information Adoption. Perceived usefulness was first posited by the Technology Acceptance Model (TAM) as a construct to explain people's intentions of adopting new technology [16]. Integrating the TAM with the ELM, previous studies have proven perceived usefulness as an important mediator of information adoption [2, 15]. To examine its mediating effect with the Singapore sample, the present study postulates the following.

H2. Perceived information usefulness positively influences information adoption on travel websites.
H3. Argument quality positively influences perceived usefulness of travel reviews.
H4. Source credibility positively influences perceived usefulness of travel reviews.

Technical Adequacy. According to the TAM, perceived usefulness can be affected by various external variables such as system characteristics [16]. Since intrinsic motivations such as subjective norms and social influence are not addressed in TAM, it has certain limitations when being employed beyond the workplace [20]. In order to improve the explanatory power of TAM in an online communication setting, technical adequacy has been adapted in previous studies as an influential predictor of trust and perceived usefulness towards websites [21, 22]. Technical adequacy can be represented by three crucial elements, namely, perceived interactivity, perceived personalization, and perceived sociability [5, 22]. Together they encourage users' participation and predict both argument quality and source credibility in online information adoption process [5]. Hence, the present study hypothesizes the following.

H5. Technical adequacy of a travel website positively influences the argument quality of travel reviews on that website.

H6. Technical adequacy of a travel website positively influences the source credibility of travel reviews on that website.

4 Methodology

4.1 Measurement

To enhance the comparability of the data across two sample groups, the same set of survey questions was employed from the Canada sample [9]. All variables were measured with items adapted from extant literature (Table 2). Participants were asked to choose one travel website that they most visited in the past 12 months and answer subsequent questions based on a seven-point Likert scale, ranging from "strongly disagree" to "strongly agree".

4.2 Data Collection

Canada Sample. In the previous study, a total of 106 valid responses were collected from people of Chinese descent in Canada who were also active users of travel websites. The average age of participants was 30.76 years and 57.5% were female [9].

Singapore Sample. Data were collected through an online survey software from March to April 2019. Survey invitations were sent to citizens and permanent residents of Singapore from the author's personal network as it consists primarily of Millennials who are more influenced by user-generated contents than other age groups [23].

Table 1. Demographics of respondents (compiled by authors)

Characteristics		Canada (n = 106) [9]		Singapore (n = 133)	
		Frequency	%	Frequency	%
Gender	Male	44	41.5	37	27.8
	Female	61	57.5	96	72.2
	Other	1	.9	–	–
Age	18–19	6	5.7	4	3.0
	20–29	62	58.5	100	75.2
	30–39	9	8.5	20	15.0
	40–49	13	12.3	5	3.8
	50–59	12	11.3	3	2.3
	60 and above	3	2.8	1	.8
	Unrevealed	1	.9	–	–
Education	High School	15	14.2	4	3.0
	College	9	8.5	29	21.8
	Bachelor's degree	69	65.1	91	68.4
	Master's degree/PhD	13	12.3	9	6.8

The sample was then expanded based on referrals from the primary data source. Respondents who had not referenced any online travel reviews in the past 12 months were excluded from further analysis. Overall, 133 valid responses were obtained from people who reported to have Chinese ancestry. Detailed demographic information is listed in Table 1.

5 Data Analysis

5.1 Singapore Model

Reliability and Validity. Out of the five proposed constructs, items measuring perceived information usefulness (PIU) and travel information adoption (TIA) loaded onto one factor based on the results of exploratory factor analysis (EFA) conducted in SPSS 25.0. The extant literature has suggested the merger of constructs into a more general measure as a way to address discriminant validity issue [24, 25]. Therefore, PIU and TIA were combined into one new factor named "perceived usefulness and adoption (PUA)".

Technical adequacy (TA) was initially measured with three different aspects. However, only two items pertaining to users' social interactivity were retained as a result of the EFA. It is believed that strong social ties between individuals tend to have greater influence on technology acceptance through knowledge exchange [26]. In a similar vein, it can be inferred that adequate technologies which support consumer-consumer interactions would become more important in shaping consumers' perception of other people's reviews. Thus, technical adequacy was renamed as "social interactivity (INT)" to better reflect the construct validity.

Confirmatory factor analysis (CFA) was performed using AMOS 25.0. Results of the CFA indicated that all factor loadings were statistically significant. Furthermore, Cronbach's α value, composite reliability (CR), and average variance extracted (AVE) for each construct were greater than the recommended cut-off values, confirming an adequate convergent validity [27]. Meanwhile, the square root of the AVE for each construct was larger than its correlations with other factors, suggesting a satisfactory discriminant validity.

Hypotheses Testing. Structural equation modeling (SEM) was performed using AMOS 25.0. The model fit indices reported $\chi^2(39) = 83.916$, $\chi^2/df = 2.152$, $p < .001$, CFI = .958, GFI = .907, AGFI = .842, NNFI = .941, RMSEA = .093, which suggested an acceptable model fit [28]. Significant correlation was confirmed between argument quality (AQ) and source credibility (SC), supporting H1. Since the results of the EFA suggested the merging of perceived information usefulness (PIU) and travel information adoption (TIA), H2 was invalidated. Significantly positive effect of argument quality ($\beta = .78$, $p < .001$) on the newly merged factor (PUA) was observed, validating H3. However, no significant effect of source credibility was found on the new factor, thus H4 was rejected. Social interactivity (INT) was found to have a positive effect on source credibility, but it did not exert any significant effect on argument quality. Thus, H6 was supported while H5 was rejected (Fig. 2).

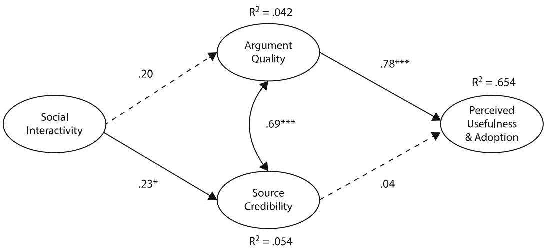


Fig. 2. Results of structural equation model. The dotted lines indicate non-significant relationships. **p* < .05. ***p* < .01. ****p* < .001. Compiled by authors.

5.2 Joint Canada-Singapore Model

Given that a non-significant peripheral route was confirmed with the Singapore sample, it is intriguing to find out whether the single-route model in Fig. 1 can be applied to Chinese people in both Singapore and Canada. In order to do so, measurement equivalence would need to be examined through multi-group confirmatory factor analysis (MGCFA) to ensure each items is perceived and interpreted in the same manner across sample groups [29–31].

Reliability and Validity. Convergent and discriminant validities of the model were tested once again with both the Canada and the Singapore samples. As shown in Tables 2 and 3, all indices had met the recommended threshold [27].

Table 2. Confirmatory factor analysis results (compiled by authors)

Items	Loading	Cronbach's α
Social Interactivity (CR = .823, AVE = .700)		.823
Adapted from Phang et al. [32]		
It is conducive to interact with other users through this website	.852	
It is easy to interact with other users through this website	.821	
Argument Quality (CR = .837, AVE = .632)		.835
Adapted from Tseng and Wang [4], and Zhang et al. [5]		
The online reviews on this website are accurate	.801	
The online reviews on this website are up-to-date	.753	
The online reviews on this website are convincing	.829	
Source Credibility (CR = .895, AVE = .741)		.889
Adapted from Tseng and Wang [4], and Zhang et al. [5]		
Users providing reviews on this website are knowledgeable in travel	.914	
Users providing reviews on this website are experienced	.893	
Users providing reviews on this website are trustworthy	.769	

(*continued*)

Table 2. (*continued*)

Items	Loading	Cronbach's α
Perceived Usefulness & Adoption (CR = .877, AVE = .644)		.871
Adapted from Sussman and Siegal [15], and Tseng and Wang [4]		
The online reviews on this website are informative	.861	
The online reviews on this website are valuable	.888	
The online reviews on this website motivate me to take action	.783	
I have followed the online reviews provided on this website	.657	

Note. All standard loadings are significant at $p < .001$.

Table 3. Results of discriminant validity assessment (compiled by authors)

Variable	*M*	*SD*	INT	AQ	SC	PUA
Social interactivity (INT)	4.38	1.33	**.837**			
Argument quality (AQ)	5.26	.94	.322	**.795**		
Source credibility (SC)	4.97	1.01	.437	.730	**.861**	
Perceived usefulness & adoption (PUA)	5.25	.97	.198	.723	.551	**.802**

Note. The boldface numbers are the square roots of corresponding AVE values.

5.3 Multi-group Analyses of Invariance

Table 4 indicates the results of the invariance tests, which supported configural invariance, full metric invariance, partial scalar invariance, and full structural weight invariance across the two sample groups. The estimated path coefficients for both samples are shown in Fig. 3 (Model fit indices: $\chi^2(102) = 211.039$, $\chi^2/df = 2.069$, $p < .001$, CFI = .941, GFI = .882, AGFI = .820, NNFI = .924, RMSEA = .067).

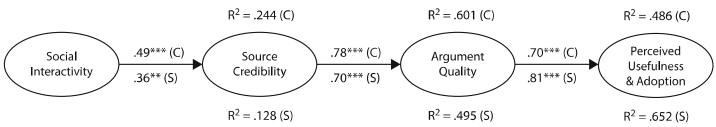


Fig. 3. Parameters estimates of the multi-group structural model. Letters in parentheses indicate country groups: C = Canada, S = Singapore. $^*p < .05$. $^{**}p < .01$. $^{***}p < .001$. Compiled by authors.

Table 4. Results of invariance tests (compiled by authors)

Model comparison	Δdf	$\Delta\chi^2$	p	CFI	RMSEA	ΔCFI	Decision
Configural invariance (baseline model)	–	–	–	.941	.067	–	Accept
Full metric invariance	8	10.931	.206	.940	.066	.001	Accept
Full scalar invariance	12	25.678	.012	.933	.066	.007	Reject
Partial scalar invariance (i1 free)	11	18.435	.072	.936	.065	.004	Accept
Full structural invariance	3	3.438	.329	.936	.064	.000	Accept

6 Discussion

6.1 A "Single-Route" Reconceptualization

The study results suggest that the dual-route theory is insufficient to explain online travel information adoption patterns as the peripheral route was found non-significant for both samples. On the other hand, the re-conceptualized single-route model appears to be a parsimonious model that explains 48.6% and 65.2% of PUA for the Canada and the Singapore sample, respectively.

Source Credibility as a Filter. Since the newly proposed model suggests a single-route approach to persuasion, a question arises as in what order argument quality and source credibility are adopted in people's cognitive processes. To verify whether source credibility will most likely precede argument quality, both the mediating and moderating effects of source credibility were tested on the relationship between argument quality (AQ) and PUA. While source credibility was found to have a significant direct effect on perceived usefulness and adoption in the unconstrained baseline model, the goodness-to-fit indices had dropped to a hardly acceptable level: $\chi^2(102) = 273.875$, $\chi^2/df = 2.685$, $p < .001$, CFI = .908, GFI = .846, AGFI = .764, NNFI = .881, RMSEA = .084 [28]. Moreover, the revised model could only explain up to 35.3% and 44.7% of PUA for the Canada and the Singapore samples, respectively. A moderation analysis was conducted in SPSS 25.0 following Dawson's [33] procedure. Based on the results of a two-way interaction analysis, no significant moderating effect of source credibility was found on the relationship between AQ and PUA ($t = -.879$, $p > .05$).

Overwhelmed with excessive information available on the Internet, credibility assessment has become more important than ever before for individual users [34]. It might be more reasonable to consider source credibility as a filter before moving on to evaluate the argument quality of online travel information that is considered to be from a credible source [9]. Based on existing research, Wathen and Burkell [35] proposed a staged assessment model for how users evaluate the credibility of online information. In their model, users will first make judgments about the surface characteristics of the website by looking at its presentation, usability and layout, after which they will assess the credibility of the source and the message before they finally come to evaluate the content of the information itself [35]. In a similar vein, the model proposed in the present study resembles some aspects of the staged assessment model, where external features of the travel website will be first evaluated, which is followed by the assessment of source credibility, and eventually the scrutiny of argument quality.

6.2 Absence of Cultural Orientation Effect

Building on the ELM with cross-cultural samples, previous studies have found that heuristic cues tend to have greater impacts on persuasion in collectivistic cultures than in individualistic cultures [10, 11]. However, participants from both sample groups in this study did not differ in their preferences for the central route. Moreover, even assuming that such consistency was due to their shared Chinese identities, participants' collectivistic cultural backgrounds did not influence them to undertake the peripheral route, which is in contrast to previous findings.

The expansion of the Internet enables people to connect beyond borders, which in turn reduces national cultural differences among younger generations [36]. Thus, socio-cultural characteristics might not be particularly important when using online services. In addition, it is believed that individualism would arise as a result of industrialization and economic growth, which allows people to be more independent [37]. Thus, Singapore's steady economic growth over the past decades might have triggered a tendency of transition from collectivism to individualism.

Another plausible explanation might be that cultural orientation has limited influence on people's perception of argument quality and source credibility. In a study that investigates the moderating effect of individualism-collectivism orientation (ICO) on eWOM reader's perception of information credibility, no moderating effect of ICO was found on argument quality and source credibility [14]. Thus, in order to fully understand the effect of cultural orientation on route selection, it is necessary to include more factors to represent the two routes in future studies.

7 Conclusion and Implications

The theoretical contribution of the present study is twofold. First, contrary to previous findings that individualism-collectivism orientation would impact persuasive effects of the central and peripheral routes, this study implies that people of Chinese descent seem to prefer the central route regardless of the host societies they happened to live in. Given that significant dual-route structures were attained with collectivistic samples in previous studies [4, 5], this study encourages researchers to consider what has changed and resulted in a predominant central route in today's context.

On the other hand, the present study re-examined a two-step single-route model that highlights a direct causal effect from source credibility to argument quality. Similar approach can be found in the continuum model of impression formation, which suggests that attribute-based processes only occur when categorization is difficult [38]. While the ELM would state that there are situations in which people high in need for cognition will engage in assessing category-based information along with attribute-based information [18], it is unable to explain movement along the elaboration continuum and between the central and peripheral route to persuasion [39]. Yet, little research has addressed the progression direction along the elaboration continuum, which makes it difficult to verify whether the peripheral route will be first taken before thoughtful processing in most cases. Therefore, the current findings warrant further investigation in future studies.

There are multiple practical implications can be drawn from the present study. First, since no cultural orientation effect was confirmed in this study, practitioners interested in persuading online users should allocate most attention to developing individual-based persuasive messages rather than culture specific contents. As the Internet has brought new ways of living and values, cultural principles are also subject to change [40]. Thus, any marketing strategy should reflect this change by providing personalized information to potential consumers. Second, the present study provided empirical evidence that source credibility and argument quality both serve as evaluation criteria in a successive order. In other words, online users might not start processing any travel information until they have validated its credibility. Practitioners would have to ensure their messages being delivered through credible channels in order to successfully reach their targets.

However, several limitations should be noted in regard to the present study. The relatively small sample sizes in both groups may lead to a coverage bias that limits the generalizability of the study results. The applicability of the original ELM has been questioned due to its use of college students as research subjects, who are considered to have greater cognitive abilities [41]. Similarly, with the majority of participants in this study holding a bachelor's degree or higher, it could be difficult to affirm that the study results are generalizable to other populations. In addition, the present study focused only on people of Chinese descent in order to compare the acculturation effects of their host societies. Thus, future studies should include a diverse sample of participants to test out whether the single-route approach is still valid in other socio-cultural contexts. Moreover, given that considerable criticism is directed against Hofstede's cultural dimension as it fails to reflect ethnic diversity [42], future studies should measure cultural orientation at the individual level in order to ascertain its effect on information adoption. Lastly, it remains unclear whether people with different elaboration likelihoods will all rely on argument quality over source credibility to evaluate travel information usefulness. Future studies should take into account the level of message elaboration while examining individuals' information adoption patterns.

References

1. Zhang K, Zhao S, Cheung C, Lee M (2014) Examining the influence of online reviews on consumers' decision-making: a heuristic-systematic model. Decis Support Syst 67:78–89
2. Ayeh J (2015) Travellers' acceptance of consumer-generated media: an integrated model of technology acceptance and source credibility theories. Comput Hum Behav 48:173–180
3. Chung N, Han H, Koo C (2015) Adoption of travel information in user-generated content on social media: the moderating effect of social presence. Behav Inf Technol 34(9):902–919
4. Tseng S-Y, Wang C-N (2016) Perceived risk influence on dual-route information adoption processes on travel websites. J Bus Res 69(6):2289–2296

5. Zhang J, Ito N, Wu W, Li Z (2017) “Don’t let me think!” Chinese adoption of travel information on social media: moderating effects of self-disclosure. In: Schegg R, Stangl B (eds) Information and communication technologies in tourism 2017, pp. 639–653. Springer, Cham (2017)
6. Petty R, Cacioppo J (1986) The elaboration likelihood model of persuasion. Exp Soc Psychol 19:123–205
7. Filieri R, McLeay F (2013) E-WOM and accommodation: an analysis of the factors that influence travelers’ adoption of information from online reviews. J Travel Res 53(1):44–57
8. Cheung C, Lee M, Rabjohn N (2008) The impact of electronic word-of-mouth: the adoption of online opinions in online customer communities. Internet Res 18(3):229–247
9. Li S, Ito N (2019) How valid are the dual-route theories? A transformed information adoption model. In: Conference proceedings: 25th Asia Pacific tourism association annual conference, pp. 107–119. APTA, Busan (2019)
10. Aaker J, Maheswaran D (1997) The effect of cultural orientation on persuasion. J Consum Res 24(3):315–328
11. Pornpitakpan C, Francis J (2000) The effect of cultural differences, source expertise, and argument strength on persuasion. J Int Consum Mark 13(1):77–101
12. Bokhorst-Heng W (2007) Multiculturalism’s narratives in Singapore and Canada: exploring a model for comparative multiculturalism and multicultural education. J Curric Stud 39 (6):629–658
13. Hofstede G, Hofstede GJ, Minkov M (2010) Cultures and organizations: software of the mind, 3rd edn. McGraw-Hill, Maidenhead
14. Luo C, Wu J, Shi Y, Xu Y (2014) The effects of individualism-collectivism cultural orientation on eWOM information. Int J Inf Manag 34(4):446–456
15. Sussman W, Siegal W (2003) Informational influence in organizations: an integrated approach to knowledge adoption. Inf Syst Res 53(9):1689–1699
16. Davis F, Bagozzi R, Warshaw P (1989) User acceptance of computer technology: a comparison of two theoretical models. Manag Sci 35(8):982–1003
17. Tang L, Jang S, Morrison A (2012) Dual-route communication of destination websites. Tour Manag 33(1):38–49
18. Petty R, Wegener D (1999) The elaboration likelihood model: current status and controversies. In: Chaiken S, Trope Y (eds) Dual process theories in social psychology. Guilford Press, New York, pp 41–72
19. SanJosé-Cabezudo R, Gutiérrez-Arranz A, Gutiérrez-Cillán J (2009) The combined influence of central and peripheral routes in the online persuasion process. CyberPsychology Behav 12(3):299–308
20. Taherdoost H (2017) A review of technology acceptance and adoption models and theories. Paper presented at the 11th international conference interdisciplinarity in engineering, Tirgu-Mures, Romania (2017)
21. Liao C, Palvia P, Lin H-N (2006) The roles of habit and web site quality in e-commerce. Int J Inf Manag 26:469–483
22. Zhang H, Lu Y, Gupta S, Zhao L (2014) What motivates customers to participate in social commerce? The impact of technological environments and virtual customer experiences. Inf Manag 51:1017–1030
23. Salem T, Twining-Ward L (2018) The voice of travelers: leveraging user-generated content for tourism development (2018). http://documents.worldbank.org/curated/en/656581537536830430/The-Voice-of-Travelers-Leveraging-User-Generated-Content-for-Tourism-Development-2018. Accessed 8 Sept 2019
24. Farrell A (2010) Insufficient discriminant validity: a comment on Bove, Pervan, Beatty, and Shiu (2009). J Bus Res 63(3):324–327

25. Henseler J, Ringle C, Sarstedt M (2015) A new criterion for assessing discriminant validity in variance-based structural equation modeling. J Acad Mark Sci 43(1):115–135
26. Kate S, Haverkamp S, Mahmood F (2010) Social network influences on technology acceptance: a matter of tie strength, centrality and density. Paper presented at the 23rd bled eConference - eTrust: implications for the individual, enterprises and society, Bled, Slovenia
27. Hair JF Jr, Black WC, Babin BJ, Anderson RE (2010) Multivariate data analysis, 7th edn. Pearson Prentice Hall, Upper Saddle River
28. Hooper D, Coughlan J, Mullen M (2008) Structural equation modelling: guidelines for determining model fit. Electron J Bus Res Methods 6(1):53–60
29. Teo T, Noyes J (2010) Exploring attitudes towards computer use among pre-service teachers from Singapore and the UK: a multi-group invariance test of the technology acceptance model (TAM). Multicultural Educ Technol J 4(2):126–135
30. Buil I, de Chernatony L, Martínez E (2012) Methodological issues in cross-cultural research: an overview and recommendations. J Target Meas Anal Mark 20:223–234
31. Chen H, Dai J, Gao Y (2019) Measurement invariance and latent mean differences of the Chinese version physical activity self-efficacy scale across gender and education levels. J Sport Health Sci 8(1):46–54
32. Phang C, Kankanhalli A, Sabherwal R (2009) Usability and sociability in online communities: a comparative study of knowledge seeking and contribution. J Assoc Inf Syst 10(10):721–747
33. Dawson J (2014) Moderation in management research: what, why, when, and how. J Bus Psychol 29:1–19
34. Metzger M (2007) Making sense of credibility on the web: models for evaluating online information and recommendations for future research. J Am Soc Inform Sci Technol 58 (13):2078–2091
35. Wathen C, Burkell J (2002) Believe it or not: factors influencing credibility on the web. J Am Soc Inform Sci Technol 53(2):134–144
36. Rettie R (2002) Net generation culture. J Electron Commer Res 3(4):254–264
37. Cao J (2009) The analysis of tendency of transition from collectivism to individualism in China. Cross-Cult Commun 5(4):42–50
38. Fiske S, Neuberg S, Beattie A, Milberg S (1987) Category-based and attribute-based reactions to others: some informational conditions of stereotyping and individuating processes. J Exp Soc Psychol 23(5):399–427
39. Kitchen P, Kerr G, Schultz D, McColl R, Pals H (2014) The elaboration likelihood model: review, critique and research agenda. Eur J Mark 48(11/12):2033–2050
40. Valaei N, Rezaei S, Ismail W, Oh Y (2016) The effect of culture on attitude towards online advertising and online brands: applying Hofstede's cultural factors to internet marketing. Int J Internet Mark Adv 10(4):270–301
41. Te'eni-Harari T, Lampert S, Lehman-Wilzig S (2007) Information processing of advertising among young people: the elaboration likelihood model as applied to youth. J Adv Res 47 (3):326–340
42. Jones M (2007) Hofstede - culturally questionable? Paper presented at the 2007 oxford business & economics conference, Oxford, England (2007)

An Efficiency Assessment of DMOs' Facebook Pages: A Benchmarking Study

Irem Onder[1(✉)], Bozana Zekan[2], and Nusret Araz[3]

[1] Hospitality and Tourism Department, University of Massachusetts – Amherst, Amherst, MA, USA
ionderneuhof@umass.edu
[2] Tourism and Service Department, Modul University Vienna, Vienna, Austria
bozana.zekan@modul.ac.at
[3] Pangea Digital, Husrev Gerede Cad.Tozan Apt. no 77/12, Istanbul, Turkey
nusret@pangeadigital.us

Abstract. Due to the ever-increasing importance of social media, destination management organizations (DMOs) are faced with the need to increase their presence on various digital platforms, which will ideally generate more interest in their destinations. Facebook is one such platform that is used by many DMOs nowadays, but clearly not with equal rates of success. The current study investigates this phenomenon by applying data envelopment analysis (DEA) to a sample of fifteen DMOs' Facebook pages. A contribution to robustness is also made by modifying the base DEA model both in terms of the variables and the sample and thus, inspecting the stability of the results across a number of models. As such, this study serves as a starting point for discussion for the affected DMOs and their proper/improper utilization of the resource variable. Ultimately, a chance is given to all inefficient units to learn from the suggested best practice peers in order to optimize their performance.

Keywords: Facebook · Destination management organization · Competitiveness · Benchmarking · Data envelopment analysis

1 Introduction

Nowadays, destination management organizations (DMOs) are no longer in a position to refuse to embrace social media as one of the main means of communication with their current and prospective visitors. One photo of the city walls and forts of Dubrovnik posted by the Croatian DMO may be a reason for someone to plan a visit to Dubrovnik for his/her next holiday. Moreover, many DMOs already use different social media platforms; however, not everyone is equally competitive within this domain.

Overall, the total number of social media users in the world has increased 13% between 2017 and 2018 and reached 3.196 billion users [1]. As one of the largest online social networks Facebook has 2.375 billion monthly active users (as of Q3 2018) and over 60 million active business pages [2]. The popularity of Facebook also makes it a practical marketing platform for companies. Majority of company websites also include links to their social media accounts on Facebook, Instagram, Twitter, and

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 92–102, 2020.
https://doi.org/10.1007/978-3-030-36737-4_8

YouTube. Considering the large number of users of these platforms, this is not surprising. Social media platforms such as Facebook are used as an information source by potential travelers [3], and therefore, tourism marketers use Facebook to interact with them and to improve the image of destinations [4, 5]. Especially in terms of business to consumer relations Facebook is considered to be the most attractive social media platform [6].

Any type of posting on social media related to a product or service is called electronic word of mouth (eWOM). This type of posting can appear in different formats such as texts, videos, and photos. Postings on Facebook that are related to destinations or other tourism products such as hotels and tours are also a type of eWOM. In the case of Facebook, these posts originate from both sides of the tourism system; meaning both the consumers (i.e., demand) and the tourism suppliers. The interactions between the consumers and the suppliers are visible on the destination's Facebook page and on the Facebook pages of suppliers such as hotels. These interactions are also quantified by the number of likes, shares, and comments they receive, which indicate the level of engagement of consumers/fans with the destination or brand. In light of this, it can be argued that some of the main goals of social media marketing are to increase engagement and a fan base. Thus, in this study, we use engagement metrics and the total number of fans as the measures of success of a given Facebook page, which are used to measure the efficiency/competitiveness of tourism-related Facebook pages.

Underlying premise is that the efficient page equates to the competitive one. In more detail, it was posited that "while 'competitiveness' and 'success' are clearly distinct concepts, they are nevertheless significantly related" [7 p. xiii]; same goes for efficiency, productivity, and performance. This strict distinction between the terms can be refuted since they were oftentimes treated as the synonyms in light of the tourism benchmarking research to date [e.g., 8–12]. In the same line, it was also argued that benchmarking and the efficiency level are inseparable terms [14], and that benchmarking and competitiveness are in a close relationship "… because the former is expected to bring about the latter" [14 p. 142].

Although the importance of Facebook pages for destination marketing is widely acknowledged, the efficiency of DMOs' Facebook pages has never been investigated in tourism research before. This study aims to bridge this gap in the existing tourism literature by assessing the efficiency/competitiveness of fifteen DMOs' Facebook pages. Data envelopment analysis (DEA) is applied, which computes the efficiency scores for each Facebook page in the study and differentiates between the efficient and inefficient ones. Moreover, best practice peers are identified for all inefficient units in order to give them a chance to optimize their performance. A contribution to robustness is also made by modifying the base DEA model both in terms of the variables and the sample and thus, inspecting the stability of results across a number of models. As such, this study serves as a starting point for discussion for the affected DMOs and their proper/improper utilization of the resource variable.

The paper is structured as follows: first, previous studies related to the topic are examined, followed by the methodology section in which the DEA model is explained. This section is followed by the results of the analysis and, finally, discussion and conclusive remarks are presented.

2 Literature Review

Social media networks, especially Facebook, are very popular all around the world. As a result of the increased use of mobile devices and social media, individuals' vacations can be monitored and tracked based on their updates on their social network accounts. Individuals do not only share, but they also react to the shared memories with comments and likes on Facebook [15]. This shows the amount of eWOM present on Facebook due to the fact that brands and destinations have Facebook pages. eWOM includes posts on Facebook and is defined as "all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers" [16 p. 461]. Moreover, Ben-Shaul and Reichel [17] indicate that communication on online social networks such as Facebook is also a form of eWOM.

The high amount of eWOM has been shown to influence consumer purchasing decisions; there is a positive correlation between eWOM and sales, and positive reviews have more impact on sales than negative reviews [18]. Negative reviews do not influence consumer purchasing decisions as much as positive reviews do, as consumers are unsure of whether the negative reviews are generated by a given company's competitor [19]. For the travel and tourism industry, eWOM is an important information source [20]. The influence of eWOM is determined by its credibility, which is based on previous knowledge about the eWOM writer, travel experience, and experience in the use of social media platforms [21]. In addition, viewing posts of luxurious vacations creates envy, which leads to increased intentions to visit the destination in the posting [22]. Furthermore, Marder et al. [23] find that although millennials feel envious of luxurious travel posts by their peers and would like to visit the destination in the posting, they may not be able to do it due to financial limitations.

Facebook is also used for travel-related purposes both by consumers and suppliers. Facebook offers business-specific options such as the Business Page or Fan Page where businesses can view the metrics related to the use of their Facebook page and thus, create targeted ads and engage with their customers. In addition, these Facebook pages are used as additional marketing and communication platforms through which businesses can connect with their current and prospective customers. After an individual becomes a fan of a Facebook page, for example, of a hotel, he/she starts receiving automated messages and updates from the hotel on his/her personal news feed, which are indicative of the promotional and marketing efforts made by companies [24].

By now travelers see Facebook as an information source for travel planning as well as sharing their travel experiences on their personal profiles [25]. Additionally, Facebook is also used for posting complaints related to tourism services and products [26]. Gretzel and Dinhopl [27] examined why users unlike destinations and travel-related companies. They found that for destinations a bad experience is enough to unlike it and for travel-related companies their online behavior based on frequency of postings or lack of promotions and contests are the reasons to unlike them on Facebook.

Moreover, Facebook is used by travel destinations as a communication tool to manage a destination's reputation. De Moya and Jain [28] analyzed the textual information on Brazil and Mexico's Facebook Fan Pages, and indicated that brand personality traits found in a destination's postings can improve its attractiveness. Additionally, Facebook is also suitable for reinstating a destination's image after a natural disaster such as an earthquake [29] as well as positively related to destination image formation [30].

Using Facebook as a marketing tool for DMOs is another topic that has attracted the attention of researchers. Uşaklı et al. [31] indicated that European DMOs use Facebook for marketing the destination rather than a customer service extension, based on their analysis of Facebook engagement measures, which is one of the success measures of social media marketing. Engagement includes all types of actions from the users towards the postings of the business (e.g., DMO) in the form of likes, shares, and comments. Thus, it is essential to post engaging content on DMOs' Facebook pages. In terms of Facebook engagement, photos and moderately long posts [32] as well as posting on the weekends have a positive impact [33]. In contrast, posting in the evening or early morning and a high posting frequency have a negative impact on DMOs' Facebook engagement [33]. DMOs can also use Facebook for destination brand building since potential travelers are influenced by the posts on these pages, thus marketers need to understand how to optimize Facebook pages [34].

In terms of tourism benchmarking, there are many performance analysis studies done concerning profit-oriented tourism businesses (i.e., organization benchmarking), and most notably within the hospitality sector, arguably due to ease of access to data. This also explains why destination benchmarking literature is scarce in comparison. Areas of research interest were: identification of the best practices for development of effective Internet marketing strategies in the Greek hotel sector [35]; use of benchmarking as a strategic tool for DMOs [36] and its role in optimizing the operations of DMOs [37]; DMOs website performance [38, 39]; influence of e-marketing on the hotel performance [40]; internal benchmarking for regional DMOs [41], and lastly, ICT efficiency and effectiveness in the hotel sector [42], to name a few examples of the benchmarking studies with the IT and/or DMO-related focus, as is the current study.

In summary, as the previous literature shows, the use of Facebook engagement metrics and the fan base as the primary measures of success of a DMO's Facebook page have not been investigated before. This research is the first to benchmark DMOs' Facebook pages, and thus, it fills the gap in the literature regarding the efficiency of the aforementioned pages. The next section introduces the methodology and proposes the model for this benchmarking endeavor.

3 Methodology

DEA is a non-parametric, multivariate technique, which is best described as "… a method for performance evaluation and benchmarking against best-practice" [43 p. 1]. Moreover, this method evaluates the relative efficiency of Decision Making Units (DMUs), examples of which are banks, hospitals, hotels, destinations, schools, and so forth [38, 44, 45]. The bottom line is that these units must be comparable [46]. What speaks in favor of employing this method in the current study is its ability to model multiple variables regardless of their individual importance or units of measurement [Herrero and Salmeron, as cited in 35, 38, 47]. Furthermore, it was also suggested that

"… the strength of its benchmarking analysis gives DEA a unique advantage over other methodologies of efficiency analysis" [13 p. 265].

There are many models that have been developed over time, from the basic CCR (Charnes, Cooper, Rhodes) also known as the CRS (Constant Returns to Scale) model, to the alternative ones such as BCC (Banker, Charnes, Cooper), referred to as the VRS (Variable Returns to Scale), models with restricted multipliers, allocation models, super-efficiency models, and so forth. The BCC model, which is used in the current study, is deemed appropriate when for instance, an increase in input variables does not lead to a proportional change in output variables, which the CCR model does not allow [49]. Or how Wöber [50 p. 74] explained, to account for the situations when not all units "… are operating at the optimal scale", which is the underlying condition of the standard formulation, and which also explains the popularity of the BCC model.

The current study evaluates the relative efficiency of fifteen DMOs' Facebook pages (=DMUs), all of which are listed below in Table 2 (name of a destination = DMO's page). As is evident, all DMOs included in the sample are national DMOs with the exception of Dubai. These units were chosen based on: (1) the content of the posts that the DMOs display on their Facebook pages in order to benchmark comparable units and (2) data availability. Since the data is from 2016, some of the Facebook page names may have changed; however, in the study we used the name of the page as it was in the year of the analysis.

With regards to the selection of variables, the authors aimed to include all variables deemed relevant to evaluate the performance of Facebook pages, conforming to the previously discussed goals of social media marketing, whilst respecting the methodological requirements (e.g., number of DMUs in relation to number of variables; discriminatory power). As a result, the DEA model consisted of one input (total number of page posts) and four output variables: (1) total number of fans, (2) total number of likes, (3) total number of comments, and (4) total number of shares, as shown below in Fig. 1.

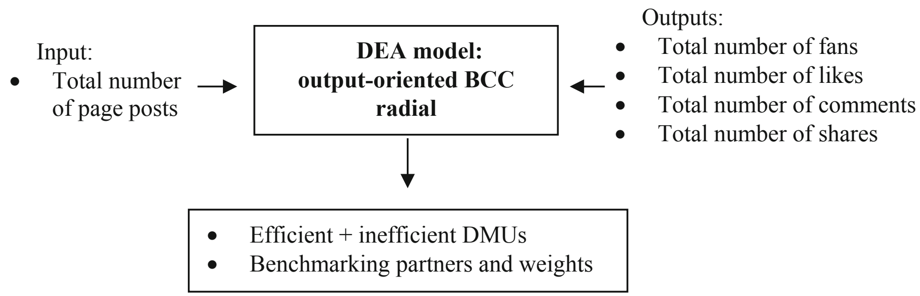


Fig. 1. The base DEA model source: Authors' elaboration from Bauernfeind and Mitsche [38 p. 250]

Thus, five variables were modeled, which is in line with a debatable 'rule of thumb' (sample size = twice/three times the sum of inputs and outputs), as elaborated in Cook et al. [43]. Moreover, it can be argued that the goal of any Facebook page is to increase the fan base and interactions (likes, comments, and shares); therefore, the output-oriented BCC radial model was employed as it aims to maximize the outputs [48]. All variables are averages for 2016 that have been sourced from Pangea. The Efficiency Measurement System (EMS) software version 1.3 was used to calculate DEA scores, which are presented in the subsequent section.

4 Findings

Table 1 summarizes the basic descriptive statistics of the input/output variables used in the DEA modeling (Fig. 1). It is evident that the units are very heterogeneous; however, this does not impact the analysis as the current study does not attempt to benchmark destinations, but rather the DMOs' Facebook pages.

Table 1. Descriptive Statistics of the Modeled Variables

	Maximum	Minimum	Mean	Standard deviation
Input				
Total number of page posts	120	7	55.47	28.71
Outputs				
Total number of fans	7122209	287003	2616871.03	2154520.47
Total number of likes	867608	534	145412.12	272416.36
Total number of comments	50400	32	5288.07	12862.93
Total number of shares	208220	43	23919.27	54434.06

Source: Table created by the authors based on authors' calculations

DEA results are presented below in Table 2. In more detail, column 1 indicates the number of the Facebook page analyzed, followed by the destination that it belongs to (column 2). As mentioned above, the name of the destination is used to proxy the DMO's page (e.g., Turkey = Turkey.Home). The table is sorted by the output-oriented efficiency scores, which are shown in column 3. Benchmarking partners and their associated weights are presented in column 4 for the inefficient units, whereas when it comes to the efficient DMUs, the number of times an individual page is suggested as a benchmark is noted in the same column.

The DEA results are rather interesting as only three pages were efficient (i.e., scores below 100%), whereas the remaining twelve were inefficient (i.e., scores above 100%) in the output-oriented DEA modeling. The Facebook page of the Egyptian DMO was the most inefficient unit in the sample, followed by those of Canada and Greece, all of which had extremely high inefficiency scores. Two benchmarking partners were proposed for these three units: the Facebook pages of the Australian and Turkish DMOs. However, the optimal benchmarking partner for all three units was unmistakably the Australian DMO's page, given the weights assigned (0.92 and 1.00, respectively). The pages of the Dubai and Mexican DMOs were the two least inefficient units, and yet they still showed quite a lot of room for improvement - their scores were 176.00% and 152.63% respectively - which implies that at least one of their output values could be

Table 2. DEA results: output-oriented BCC radial DEA model

	DMU	Score	Benchmarks & weights (Ineff.)/Benchmark appearance (Eff.)
Inefficient DMUs			
11	Egypt	2481.58%	15 (1.00)
14	Canada	1692.12%	5 (0.08) 15 (0.92)
3	Greece	1090.81%	15 (1.00)
10	Italy	805.00%	5 (0.23) 15 (0.77)
2	Portugal	607.11%	15 (1.00)
7	France	501.57%	15 (1.00)
13	Croatia	470.21%	15 (1.00)
6	Spain	427.45%	15 (1.00)
8	Malaysia	299.90%	15 (1.00)
9	UK	224.11%	15 (1.00)
4	Dubai	176.00%	15 (1.00)
1	Mexico	152.63%	15 (1.00)
Efficient DMUs			
5	Turkey	85.74%	2
15	Australia	4.35%	12
12	USA	big	0

Source: Table created by the authors based on authors' calculations

increased by 76% and almost 53%. This is also where the Australian page can be of benefit, considering the fact that it was the only and therefore, the most relevant benchmarking partner proposed for both inefficient units (i.e., weight of 1.00).

When shifting the focus toward efficient DMUs, the scores ranged from 'big' (page of the American DMO; a so-called 'infeasible solution' due to extremely high efficiency [Boljuncic, as cited in 47] to 85.74% (Turkish page). These results imply that the most efficient unit in the sample was the page of the American DMO. The Australian page was next in the line of best performers, yet heading the list with the numerical score (4.35%). Even though both pages could be classified as efficient, the Australian page still majorly outperformed the Turkish one by 81.39%.

In terms of benchmark appearances, the Facebook page of the American DMO had no appearances in spite of its extremely high efficiency. Therefore, if one unit is labeled as efficient, this does not automatically mean that inefficient units should learn from its practices; this would be the wrong approach for them to take. Instead, each inefficient unit should look toward its individually proposed best practice peers. The page of the Australian DMO was named as the benchmarking partner for all inefficient units, which is not a common occurrence in benchmarking endeavors. Thus, it can be argued that this particular DMU would be the best practice example for the entire sample, based on five modeled variables, understandably. The Turkish page was identified as the optimal benchmark for two DMUs (the Canadian and Italian pages), yet also here the allocated weights worked in favor of the Australian page (0.08 vs. 0.92 and 0.23 vs. 0.77, respectively). Hence, there is no doubt about the importance of this benchmark.

What should not be forgotten is that DEA evaluates relative efficiency. For this reason, the authors opted to go beyond a static model and inspect the stability of the aforementioned results and, by doing so, make a contribution to robustness. With this in mind, the base DEA model (Fig. 1) was modified both in terms of the variables and the sample. First, regarding variables, no changes could be made on the input side as there was only one variable; however, several alterations could be introduced concerning outputs. Five alternate models were run on the same sample of fifteen DMUs with anywhere from one input and two outputs (total number of fans; cumulative interaction instead of separate total numbers of likes/shares/comments) to one input and three outputs (combinations of three variables at the time in contrast to four of the base model). Interestingly, twelve to thirteen units could be classified as inefficient (scores between 104.62% and 26706.71%), depending on the modeling employed. These calculations corroborate the results of the base model (among others, the same twelve units as constant underperformers) as only one DMU (Turkey.Home) shifted between inefficient and efficient classification. Consequently, this had a direct impact on the allocation of the benchmarking partners for other inefficient units. There were no changes with regards to the most efficient units: the American DMO had the 'big' score and no benchmark appearances in spite of its extremely high efficiency, whereas Australia was with the numerical score and the absolute best practice example for the entire sample (twelve and thirteen benchmark appearances) regardless of the modeling.

Six more analyses were run (the base model and five alternate ones that are discussed above) with an additional change in the study sample. In this respect, the American page was the most apparent candidate for elimination (i.e., 'infeasible solution', no benchmark appearances), thus, resulting in fourteen DMUs. In this case, the calculations once again fully corroborate the results of the six previous models (with the American DMO), which merely implies that the introduced change in the sample made no impact. The only change that could be observed in the instance of exclusion of the American page was that the Australian page now had the 'big' score, and yet this made no impact in terms of its benchmark appearances; the Australian page was still the number one benchmarking partner for all inefficient units. Thus, the overall stability of the results across various models can be confirmed.

5 Discussion and Conclusive Remarks

Due to the ever-increasing importance of social media, DMOs are faced with the need to increase their presence on various digital platforms, which will ideally generate more interest in their destinations. Facebook is one such platform that is used by many DMOs nowadays, but clearly not with equal rates of success. The current study investigated this phenomenon by applying DEA to a sample of fifteen DMO's Facebook pages. Interestingly, according to the DEA calculations, even the least inefficient unit, the Facebook page of the Mexican DMO, still had about 53% room for improvement of its outputs. Therefore, the identification of relevant benchmarking partners is a crucial step in the envisioned improvement process. The absolute best practice for all inefficient units was the Facebook page of the Australian DMO based on five modeled variables, understandably. Thus, the implication of this benchmarking endeavor for the DMOs is clear: one should look closely at the practices of this particular benchmark in order to optimize performance. For instance, DMOs with inefficient Facebook pages such as Mexico can investigate what their benchmarking partner (Australian DMO) does differently with regards to page posts (e.g., what types of videos create most reactions from users) and consequently implement strategies that would result in a higher total number of fans, likes, comments, and/or shares. Moreover, the results indicate that all efficient units were not necessarily benchmarks for the inefficient ones.

One should be careful when interpreting these results. One limitation of the study is that the relative efficiency was calculated for only one time period (2016). Thus, the results could be different for the same Facebook pages today. Any change in the sample and/or variables can also lead to different DEA results. With this in mind, an attempt was made to inspect the stability of the DEA results by modifying the base model both in terms of the variables and the sample. This led to eleven additional analyses, which fully corroborated the results of the base model irrespective of the change introduced to the various models. Even with such a strong outcome, one cannot claim with 100% certainty that any change that may be introduced in the future would lead to the same results. This is where the importance of interactive and longitudinal DEA lies. Therefore, the focus of future studies should be placed on inspecting the stability of results not only over time, but also by further modifying the base DEA model employed in the current study, especially in terms of the sample. Subject to data availability, the inclusion of more pages in the current sample would be a welcome addition. Nonetheless, this benchmarking study makes a contribution by furthering the discussion on the efficiency analysis of Facebook pages used on a daily basis and by raising awareness about the proper/improper utilization of resource variable for DMOs.

References

1. Kemp S (2018) Digital in 2018: world's internet users pass the 4 billion mark. https://wearesocial.com/blog/2018/01/global-digital-report-2018. Accessed 6 Aug 2018
2. Brandwatch (2019) 53 incredible Facebook statistics and facts. https://www.brandwatch.com/blog/facebook-statistics/. Accessed 30 Jun 2019
3. Jacobsen JKS, Munar AM (2012) Tourist information search and destination choice in a digital age. Tour Manag Perspect 1:39–47
4. Yoo K-H, Gretzel U (2010) Web 2.0: new rules for tourism marketing. In: Proceedings of the 41st travel and tourism research association conference, San Antonio, TX, 20–22 June 2010. Travel and Tourism Research Association, Lake Orion
5. Lalicic L, Gindl S (2018) DMOs' Facebook success stories: a retrospective view. In: information and communication technologies in tourism 2018, pp 172–185. Springer, Cham
6. Cvijikj IP, Michahelles F (2013) Online engagement factors on Facebook brand pages. Soc Netw Anal Min 3(4):843–861
7. Ritchie JRB, Crouch GI (2003) The competitive destination: a sustainable tourism perspective. CAB International, Wallingford
8. Bosetti V, Cassinelli M, Lanza A (2006) Benchmarking in tourism destination, keeping in mind the sustainable paradigm (Fondazione Eni Enrico Mattei Working Paper). http://papers.ssrn.com/sol3/papers.cfm?abstract_id=879706. Accessed 20 Jul 2010

9. Cracolici MF, Nijkamp P, Cuffaro M (2007) Efficiency and productivity of Italian tourist destinations: a quantitative estimation based on data envelopment analysis and the Malmquist method. In: Matias Á, Nijkamp P, Neto P (eds) Advances in modern tourism research: economic perspectives. Physica-Verlag, Heidelberg, pp 325–343
10. Cracolici MF, Nijkamp P, Rietveld P (2008) Assessment of tourism competitiveness by analysing destination efficiency. Tour Econ 14(2):325–342
11. Botti L, Peypoch N, Robinot E, Solonandrasana B (2009) Tourism destination competitiveness: the French regions case. Eur J Tour Res 2(1):5–24
12. Barros CP, Botti L, Peypoch N, Robinot E, Solonandrasana B, Assaf AG (2011) Performance of French destinations: tourism attraction perspectives. Tour Manag 32(1):141–146
13. Baek C, Lee J (2009) The relevance of DEA benchmarking information and the least-distance measure. Math Comput Model 49(1–2):265–275
14. Kozak M, Nield K (2004) The role of quality and eco-labelling systems in destination benchmarking. J Sustain Tour 12(2):138–148
15. Hannam K, Butler G, Paris CM (2014) Developments and key issues in tourism mobilities. Ann Tour Res 44:171–185
16. Litvin SW, Goldsmith RE, Pan B (2008) Electronic word-of-mouth in hospitality and tourism management. Tour Manag 29:458–468
17. Ben-Shaul M, Reichel A (2018) Motives, modes of participation, and loyalty intentions of Facebook tourism brand page consumers. J Travel Res 57(4):453–471
18. Rosario AB, Sotgiu F, De Valck K, Bijmolt T (2016) The Effect of electronic word of mouth on sales: a meta-analytic review of platform, product, and metric factors. J Mark Res 53 (3):297–318
19. Ong BS (2011) Online shopper reviews: ramifications for promotion and website utility. J Promot Manag 17(3):327–344
20. Chung JY, Buhalis D (2008) Web 2.0: a study of online travel community. In: O'Connor P, Höpken W, Gretzel U (eds) Information and communication technologies in tourism 2008. Springer-Wien, New York, pp 70–81
21. Zeng B, Gerritsen R (2014) What do we know about social media in tourism? A review. Tour Manag Perspect 10:27–36
22. Liu H, Wu L, Li X (2018) Social media envy: how experience sharing on social networking sites drives millennials' aspirational tourism consumption. J Travel Res 58:355–369. https://doi.org/10.1177/0047287518761615
23. Marder B, Archer-Brown C, Colliander J, Lambert A (2018) Vacation posts on Facebook: a model for incidental vicarious travel consumption. J Travel Res 58:1014–1033. https://doi.org/10.1177/0047287518786465
24. Phelan KV, Chen H, Haney M (2013) "Like" and "Check-in": how hotels utilize Facebook as an effective marketing tool. J Hosp Tour Technol 4(2):134–154
25. Enter N, Michopoulou E (2013) An investigation on the acceptance of Facebook by travellers for travel planning. e-Review Tour Res (e-RTR) 4. http://hdl.handle.net/10545/601172
26. Pantano E, Di Pietro L (2013) From e-tourism to f-tourism: emerging issues from negative tourists' online reviews. J. Hosp Tour Technol 4(3):211–227
27. Gretzel U, Dinhopl A (2014) Breaking up is hard to do: why do travellers unlike travel-related organizations? In: Xiang Z, Tussyadiah L (eds) Information and communication technologies in tourism 2014. Springer International, Switzerland, pp 267–779
28. De Moya M, Jain R (2013) When tourists are your "friends": exploring the brand personality of Mexico and Brazil on Facebook. Public Relat Rev 39:23–29
29. Ketter E (2016) Destination image restoration on Facebook: the case study of Nepal's Gurkha Earthquake. J Hosp Tour Manag 28:66–72

30. Molinillo S, Liébana-Cabanillas F, Anaya-Sánchez R, Buhalis D (2018) DMO online platforms: image and intention to visit. Tour Manag 65:116–130
31. Uşaklı A, Koç B, Sönmez S (2017) How 'social' are destinations? Examining European DMO social media usage. J Destination Market Manag 6(2):136–149
32. Mariani MM, Di Felice M, Mura M (2016) Facebook as a destination marketing tool: evidence from Italian regional Destination Management Organizations. Tour Manag 54:321–343
33. Mariani MM, Mura M, Di Felice M (2017) The determinants of Facebook social engagement for national tourism organizations' Facebook pages: a quantitative approach. J Destination Market Manag 8:312–325. https://doi.org/10.1016/j.jdmm.2017.06.003
34. Chernysheva E, Skourtis G, Assiouras I, Koniordos M (2011) Social media and destination branding: how mediterranean tourism destinations use facebook. In: Academy of marketing conference, Liverpool, UK, pp 5–7)
35. Sigala M (2003) Developing and benchmarking internet marketing strategies in the hotel sector in Greece. J Hosp Tour Res 27(4):375–401
36. Xiang Z, Kothari T, Hu C, Fesenmaier DR (2007) Benchmarking as a strategic tool for destination management organizations: a proposed framework. J Travel Mark 22(1):81–93
37. Doussa M, Koutoulas D (2009) Benchmarking destination marketing organisations for the purpose of optimizing their operation: the case of convention bureaux. Paper presented at the 4th international scientific conference of the University of the Aegean, Rhodes Island, Greece. https://www.academia.edu/. Accessed 16 Jan 2016
38. Bauernfeind U, Mitsche N (2008) The application of the data envelopment analysis for tourism website evaluation. Inf Technol Tour 10(3):245–257
39. Stepchenkova S, Tang L, Jang S, Kirilenko AP, Morrison AM (2010) Benchmarking CVB website performance: spatial and structural patterns. Tour Manag 31(5):611–620
40. Shuai J, Wu W (2011) Evaluating the influence of E-marketing on hotel performance by DEA and grey entropy. Expert Syst Appl 38(7):8763–8769
41. Zins A (2014) Internal benchmarking for regional tourism organizations: a case example. Tour Anal 19(4):413–424
42. Scholochow C, Fuchs M, Höpken W (2010) ICT efficiency and effectiveness in the hotel sector—a three-stage DEA approach. In: Information and communication technologies in tourism 2010. Springer, Vienna, pp 13–24
43. Cook WD, Tone K, Zhu J (2014) Data envelopment analysis: prior to choosing a model. Omega Int J Manag Sci 44:1–4
44. Anderson DR, Sweeney DJ, Williams TA, Martin K (2008) An introduction to management science: quantitative approaches to decision making, 12th edn. South-Western, Mason
45. Cooper WW, Seiford LM, Zhu J (2004) Data envelopment analysis: history, models and interpretations. In: Cooper WW, Seiford LM, Zhu J (eds) Handbook on data envelopment analysis. Kluwer Academic Publishers, Norwell, pp 1–39
46. Cook WD, Seiford LM (2009) Data envelopment analysis (DEA): thirty years on. Eur J Oper Res 192(1):1–17
47. Wöber KW, Fesenmaier DR (2004) A multi-criteria approach to destination benchmarking: a case study of state tourism advertising programs in the United States. J Travel Tour Market 16(2/3):1–18
48. Scheel H (2000) EMS: efficiency measurement system user's manual. http://www.holger-scheel.de/ems/ems.pdf. Accessed 22 Feb 2015
49. Emrouznejad A (1995–2012) Ali Emrouznejad's data envelopment analysis. http://deazone.com/en/. Accessed 18 Jan 2016
50. Wöber KW (2002) Benchmarking in tourism and hospitality industries: the selection of benchmarking partners. CAB International, Wallingford

Projected and Perceived Destination Image of Tyrol on Instagram

Adriana Wacker and Aleksander Groth(✉)

Department Management Communication & IT,
Management Center Innsbruck (MCI), Innsbruck, Austria
aleksander.groth@mci.edu

Abstract. Alpine tourism destinations are highly dependent on their destination image. On Social Media, this perceived image relies heavily on user-generated content (UGC), which cannot be completely controlled by Destination Marketing Organizations (DMOs). Potential tourists prefer informing themselves about travel destinations online, as UGC provides an unbiased resource reflecting a tourist's perception. On Instagram, DMOs focus mainly on visual materials for projecting the intended destination image, affecting users' perceptions, attitudes as well as travel behaviour, thus, alignment between the projected and perceived destination image is beneficial. This study compares photos collected from Instagram adopting a comparative content analysis approach together with Chi-square tests and Co-occurrence analysis, in order to identify differences of the projected and perceived destination image between posts by the Tyrol Tourist Board and actual tourists with the *visittyrol* hashtag. Findings are visualized via aggregated destination image maps. Results identify Nature & Landscapes, People, Plants, Architecture & Buildings and Residents' Lives as the five predominant attributes of the projected Tyrolean destination image. However, tourists tend to be more interested in capturing nature, vegetation, leisure activities and domesticated animals, rather than lives of locals and their traditions. Similarities are found in illustrations of outdoor sports, other leisure activities and architecture.

Keywords: Destination image · Comparative visual content analysis · Destination image maps · Instagram

1 Introduction

Alpine tourism destinations are highly dependent on their destination image. This formed image relies on many attributes, which cannot be controlled completely by Destination Marketing Organizations (DMOs) and therefore leads to constrained alignments of their promoted attributes [1]. One important factor in modern destination image creation is user-generated content (UGC), which is only manageable to a limited degree, as tourists' perceptions and actions are not within the direct control of DMOs. Tourists share data, text and media of destinations voluntarily, because they want to earn recognition for their contributions within their personal circle, which makes this content especially useful to others, as they get access to an unbiased information source, which is perceived as more meaningful and trustworthy. Platforms focused on

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 103–114, 2020.
https://doi.org/10.1007/978-3-030-36737-4_9

UGC have been increasing over the last decade, thereby extending the information available to potential visitors [2]. The experience-based nature of tourism products sees the overall image of a destination as a construct of various integrated elements that are highly dependent on tourists' perceptions and not necessarily on the attributes themselves [3]. Stepchenkova and Zhan [4] see photographic content of a destination, distributed either by DMOs or by travellers, as a means of image communication to form and reform tourists' perceptions about a place. Naturally, tourism is regarded as a particularly visual field, focusing mainly on pictorial material for promoting the intended destination image [5]. When such visual material is combined with Social Media, enormous potential can be found in easy access, convenient search options, interactive real-time communication and convenient updating of content, thus, enhancing the effect of pictorial content on destination image formation [6]. Especially when tourists and their expectations are involved, DMOs realized that more authentic and real photographs result in a better congruence between expectation and reality, subsequently increasing re-visit intentions [7, 8]. Therefore, DMOs are confronted with the challenge to find the perfect balance between visually appealing and authentic photographs to promote their destinations, while considering a great variety of motives. Consequently, research on destination image in regard to visual Social Media channels (e.g., Instagram) is needed to establish a distinct framework for the evaluation of projected and perceived destination image [2, 9].

This study aims to build on the existing body of literature on visual destination image regarding the comparability of projected and perceived destination image, thereby, extending the influence of the field. Our objectives are (1) to determine the predominant attributes of the Tyrolean destination image on Instagram and (2) to confirm congruency between the pictorial material projected by the Tirol Tourist Board as a central destination marketing organization (cDMO) and UGC. Because of the scarce literature available in the field of destination image distributed on visual Social Media channels and the lack of an established framework for the evaluation, the study design is in line with a study by Stepchenkova and Zhan [4], applying a comparative visual content analysis. The following research questions are proposed:

- What are the predominant attributes representing the destination image of Tyrol deduced from Instagram as an image-sharing Social Media?
- What are the major differences between the holistic destination image projected by the Tirol Tourist Board and the destination image perceived by tourists?

2 Related Work

Destination image is one of the most researched fields in tourism [9]. The term *image* is defined as a combination of meanings "*by which an object is known and through which people describe, remember and relate to it. That is, an image is the net result of the interaction of a person's beliefs, ideas, feelings, expectations and impressions about an object*" [10]. Beerli and Martín [11] describe the term image as an idea that is constructed by a person's interpretation as an emotional and reasoned inference of perceptive-cognitive evaluations, meaning the consumer's personal knowledge and beliefs of an object including also the appraisal of all perceived attributes, as well as affective assessments concerning a consumer's feelings about the object. Gartner [3] sees the image of a product as a construct composed of several integrated elements including brand image and attribute perceptions of individuals, subsequently forming the overall image. Because the destination as a product of tourism is experience-based, it is more dependent on attribute perceptions than on the actual attributes. Therefore, *destination image* is an aggregation of impressions that is mentally condensed and can be used for efficient decision-making. Destination image, understood as an individual's mental destination representation, is deeply rooted in research done by or for the tourism industry, and has major implications for tourism marketing [12–14].

Xiang and Gretzel [15] understand Social Media websites as online applications that hold UGC, containing media content made by consumers about unique experiences, which are subsequently shared online to be accessed openly by interested readers. Social Media is mainly used for information search in travel planning, but trustworthiness is needed for the information to be actually used. Tourists are enormously active on Social Media, spreading their experiences and knowledge about travel-related topics. Actual tourists' experiences are trusted more by followers than official sources [16], thereby affecting destination-related travel decisions [17].

Perceived and projected image share a blurry relationship [4]. The projected image, also referred to as transferred image, defines an image created by various sources, ranging from promotional activities within the tourism industry, including also promotional activities of DMOs, to news about the destination. It illustrates the image that the tourism industry wants to establish in the minds of visitors. In tourist motivation research, the concept of push and pull factors is generally accepted, which states that travel behaviour is influenced by those forces [18, 19]. Push factors are socio-psychological motivations, which bring the potential tourist to travel. Once the decision to travel has been made, the pull factors attract the potential tourist to a certain destination [20]. The image can be transferred by several types of communication, ranging from DMOs promotional channels to the local and regional tourism boards and even to all available media channels. Consequently, the push element can be attributed to the perceived image, as it includes a tourist's needs, expectations, and the motivations behind the travel [19]. Several studies define perceived image as the image formed in the minds of potential tourists [21, 22]. Hu and Ritchie [1] argue that the perceived image can be viewed as a concept affected by previous familiarity and knowledge, perception of the image at the destination, and the subsequent existing preference of that information. Moreover, the perceived image is formed by information received through indirect sources and experiences at the destination; it represents the image a tourist forms in reality [23]. Nevertheless, there is no agreement on the precise factors that should be considered [11]. Hunt [24] assumes that consumers prefer destinations that evoke and reinforce their own self-image, whereby the actual and perceived destination image are not necessarily identical. Influential attributes are defined as landscape, climate, population and the perceived impressiveness of tourist attractions and tourist activities available. Urry [25] proposes the concept of the *tourist gaze*, arguing that the tourism industry is creating a certain imagery for a selected destination. This imagery is then forced on visitors as a distinct sort of view, resulting in a dependence between tourism as a producing force and photography as a tourist activity.

Kim and Stepchenkova [26] identify a photograph consisting of *manifest* and *latent* content, which are entirely different. Manifest content includes all types of signs depicted in the image (e.g. features of nature, people or buildings), whereas latent content is not tangible and deals with wider image implications that are not shown by the appearances alone. Because of the high subjectivity involved in deriving latent content, manifest content is more suitable to be interpreted quantitatively as done in surveys, such as proposed by Nixon, Popova, and Önder [27] to evaluate the most effective types of photos on Instagram for influencing the previous destination image, or content analysis. More recent publications used an image annotation approach as content analysis to distinguish the projected destination image focusing more on pictorial online sources, such as Instagram [25]. Quantitative visual content analysis is performed objectively and quantifies recorded visual representations using reliable and explicitly defined categories. Such an approach is used in order to identify representations of attributes like people, events, and situations. However, the selected scope of visual material needs to be set before the actual analysis starts, including a sample size and the exact domain. Thus, emerging questions about the possibility of generalizing the results should be posed and it must be emphasized that visual content analysis does not examine individual images, but the entire representation [27].

3 Methodology

This study builds on the existing literature of visual destination image regarding the comparability of projected and perceived destination image, to extend the influence of the field. The approach of comparative content analysis proposed by Stepchenkova and Zhan [4] is exploratively applied to Tyrol as a tourism destination. The objective is to compare images of Tyrol collected from the official Instagram account of the Tirol Tourist Board **visittirol** and from tourists' private accounts, under the hashtag *visittyrol*, in order to identify differences in pre-defined categories. Moreover, methodological limitations, which have been criticized before, were taken into consideration, such as the proposition to include a key performance indicator measuring awareness in the data collection process. Because of the persuasive power of photographs other people have already liked or commented on, only posts with more than 1000 likes were selected for the cDMO sample. Subsequently an overview of the various empirical research aims and the corresponding selected approaches is provided:

1. *What are the predominant attributes representing the destination image of Tyrol deduced from visual content on the Instagram account of the Tirol Tourist Board and from visual content on tourists' private accounts?*
   Based on published studies, a comparative content analysis methodology is adopted, to examine the collected visual samples of Tyrol. To establish congruity of the two visual samples, Chi-square tests are executed on the attribute frequency data.
2. *How does the aggregated image of Tyrol as an alpine tourism destination look constructed from the visual sample of the Tirol Tourist Board in contrast to the one constructed from the visual sample generated by tourists?*

Both image maps are constructed by building on statistical frequency and Co-occurrence analysis of destination attributes to construct those image maps [28].

3. *What are the major differences between the destination image projected by the Tirol Tourist Board and the destination image perceived and transferred by tourists? What destination attributes are likely to occur together on photographs?*
   We compare the aggregated image maps of Tyrol, including attribute frequency data as well as co-occurrences of certain categories, in order to find major differences within the two visual samples.

3.1 Data Collection and Category Development

The projected image of the alpine destination Tyrol, Austria was examined by utilizing photographs posted on the official Instagram account of the Tirol Tourist Board **visittirol**. The account covers a collection of 1250 posts, ranging thematically from nature in all seasons, architecture, people and sports to food, and has around 116.000 followers. Here, 333 photographs were selected and downloaded within one year, starting from April 1, 2018. For the perceived image of Tyrol, the visual content posted by tourists on Instagram with the hashtag *visittyrol* was utilized. This hashtag indicates that the posts were made by visitors of Tyrol instead of local residents. Overall, 11768 posts were collected, and 8007 images were chosen, posted also within a year, starting from April 1, 2018, in order to ensure consistency. Those visual posts were weighted according to monthly numbers and subsequently, two samples of 300 images each were randomly selected for analysis.

Pictures with less than 1000 likes were excluded as well as pictures from users, in which it seemed evident that they are company-related, promotional or from residents. The data collection was conducted on a single day. Starting from 20 categories developed for the features of Peru's destination image [4], 5% of the images were evaluated to establish major destination features illustrated on the photographs [29]. Hence, the categories *Tour*, *Other* and *Archeological Sites* were omitted, and the categories *Tourism Facilities* renamed to *Tourism Offers & Facilities*, *Way of Life* to *Residents' Lives* as well as *Food* to *Food & Drinks*, and the category *Historical Sites* added.

3.2 Data Coding and Reliability

Each single image and not each single feature was seen as a distinct unit of sample. However, Stepchenkova and Zhan [4] argue that especially photographs are complex structures, where it is not possible to simply reduce the content into reliable pieces as single units of analysis. Therefore, one of the authors coded each image into one up to four categories. Calculating raw agreement is understood as the simplest form of coding reliability, and therefor criticized, as coders might agree by mere coincidence. Still, we chose to verify reliability of the deduced categories by instructing another human coder to process a part of the content (300 images). The percentage of agreement was calculated by counting identical coding decisions in every category and dividing them by the overall image count [30]. For our sample, agreement percentage was above 94%, thus, each deviating image was discussed, and adaptations were made to the guidelines, in order to increase an unambiguous understanding.

3.3 Destination Image Maps

Li and Stepchenkova [28] state that the *"purpose of constructing perceptual maps is to visualize the links between images in respondents' collective mind"* (p. 253). As previously mentioned, each photographic unit within the selected sample was coded into four different categories. An aggregated image map is then constructed, in order to gain a better understanding for the tendencies of photographs to illustrate specific attributes together. These destination image maps aim at creating a meaningful visual summary of the content. By analysing the co-occurrence value for co-existing pairs of features within the photographic content, the existence of a true linkage between those categories can be uncovered. Hence, the probability of any destination attribute to occur in the image projected by the DMO or the UGC image was calculated. This can be assessed as the ratio of the attribute frequency and the corresponding size of the sample.

The probability p_X of the attribute X and the probability p_Y of the attribute Y to occur in a photograph have been approximated as f_X/N and f_Y/N with N = 300. However, the probability p_{XY} of two attributes appearing in the same photograph is not known, while the number of $X - Y$ co-occurrences for the random variable f_{XY}, has the probability p_{XY}. Therefore, with defined expectation as $E = N_{pXY}$ and variance $Var = N_{pXY}\ (1 - p_{XY})$ the random variable f_{XY} is binomially distributed. For better understanding, if attributes X and Y are independent, then the following formulas are valid under the assumption of independence: $p_{XY} = p_X\ p_Y$, $E = Np_X\ p_Y$, $Var = Np_X\ p_Y$ $(1 - p_X\, p_Y)$. To examine the existence of a significant difference between the actual co-occurrence value f_{XY}, which is counted within the data set, and the expected score received by assuming attribute independence, the formula $z = (f_{XY} - E)/\sqrt{Var}$ is applied.

4 Results

4.1 Predominant Attributes: Frequencies

All attribute frequencies were counted and coded, whereby the category *Nature & Landscapes* was represented most often (74%), followed by *People* (30.2%), and *Plants* (27%). The full list can be found in Table 1. Then congruence between the projected and perceived image of all categories was analysed. For categories of both samples, cDMO and UGC, a Chi-square test was performed with statistical differences in 12 out of 20 categories (see Table 1).

In general, cDMO photos tend to illustrate more *Residents' Lives*, *Food & Drinks*, *Architecture and Buildings*, *Traditional Clothing and People*, while tourists on Instagram posted more within *Nature & Landscapes*, *Leisure Activities*, *Festivals & Rituals*, *Plants*, *Country Landscapes*, *Domesticated Animals* and *Urban Landscapes*. Tourists are predominantly interested in all sorts of landscapes and the prevailing

Table 1. Attribute frequencies and Chi-Square Analysis (compiled by authors)

Categories	cDMO	cDMO (%)	UGC	UGC (%)	Total	Total (%)	p-value[a]
Nature & Landscapes	202	67.3	242	80.7	444	74.0	0.0002
People	101	33.7	80	26.7	181	30.2	0.0618
Plants	68	22.7	94	31.3	162	27.0	0.0168
Architecture & Buildings	94	31.3	58	19.3	152	25.3	0.0007
Residents' Lives	99	33.0	35	11.7	134	22.3	0.0000
Outdoor & Adventure	52	17.3	46	15.3	98	16.3	
Tourism Offers & Facilities	47	15.7	39	13.0	86	14.3	
Food & Drinks	57	19.0	12	4.0	69	11.5	0.0000
Country Landscapes	24	8.0	40	13.3	64	10.7	0.0343
Leisure Activities	14	4.7	35	11.7	49	8.2	0.0017
Transport & Infrastructure	19	6.3	27	9.0	46	7.7	
Urban Landscapes	11	3.7	21	7.0	32	5.3	0.0692
Art Objects	10	3.3	17	5.7	27	4.5	
Domesticated Animals	6	2.0	14	4.7	20	3.3	0.0688
Festivals & Rituals	4	1.3	14	4.7	18	3.0	0.0167
Wild Life	2	0.7	5	1.7	7	1.2	
Traditional Clothing	4	1.3	0	0.0	4	0.7	0.0448
Historical Sites	2	0.7	1	0.3	3	0.5	

[a]shown at significance level 0.1

vegetation together with leisure activities and domesticated animals, whereas they seem to be not so interested in the lives of people living at the destination. However, the cDMO illustrates primarily nature and landscapes, local people and their lives, the architecture of Tyrol, food and outdoor activities, which are not necessarily of interest by tourists.

4.2 Aggregated Image Maps: Co-occurrences and Differences

The aim of creating a perceptual map lies in visualizing the links between photographs in the viewer's mind. The aggregated image map of Tyrol constructed with the cDMO sample is presented in Fig. 1. Only categories with co-occurrence of two percent or higher are illustrated. The four destination attributes with the highest frequencies are illustrated with bold ellipses, while the other categories are represented by lighter ellipses. Occurrence frequencies are indicated within the ellipses. Solid, bold lines indicate a statistically significant co-occurrence of 10 or higher, solid lighter lines a co-occurrence smaller than 10 (z-score is positive and above 1.96). Dashed lines indicate a statistically significant, negative link. For example, *People* and *Outdoor & Adventure Activities* are shown together in 51 photographs of the cDMO sample with a z-score of 8.25. Hence, these two attributes tend to be presented together in images posted by the cDMO. In our sample, there are no positive, direct links between the four largest attributes, implying that there are no positive statistical associations between the attributes *Nature & Landscapes*, *People*, *Residents' Lives*, and *Architecture & Buildings*. Consequently, it is less likely to identify those attributes together in a cDMO photograph.

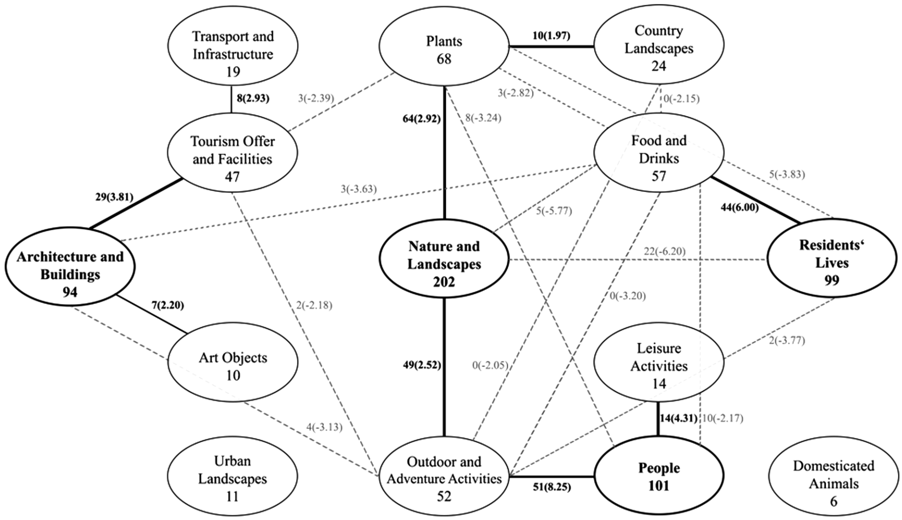


Fig. 1. Destination image map constructed from cDMO-generated photography (compiled by authors)

Furthermore, the map indicates the existence of three independent clusters. The largest cluster being *Nature & Landscapes*, linked through *Outdoor* and *Adventure Activities* to *People* (with *People* linked to *Leisure Activities*, *Nature & Landscapes* linked via *Plants* to *Country Landscapes*). Tyrol's landscape tends not to be illustrated alone but has either trees and flowers or people doing adventurous outdoor activities as a second focus. Furthermore, the cDMO tends to connect leisure with activities done by people; photographed villages and countryside tend to include plants. The second cluster comprises of *Architecture & Buildings* as the main category, loosely linked to *Art Objects* and *Tourism Offer & Facilities*, further loosely connected to *Transport & Infrastructure*. The cDMO tends to picture buildings that have an art component (e.g., the funicular stations of the Hungerburgbahn) with touristic components and tourism offers (e.g., mountain lodges, ski huts). The third cluster is formed by the category of *Residents' Lives*, which is only linked to *Food & Drinks*. Residents' lives tend to be photographed with traditional food and the associated preparation.

The aggregated image map constructed with UGC images is shown in Fig. 2. Its complexity shows that tourists create and share their photographs without an aligned strategy. The image map illustrates the 15 most frequent destination attributes with frequencies above two percent. The four destination attributes with the highest frequencies are *Nature & Landscapes*, *Plants*, *People*, and *Architecture & Buildings*. The four most frequent attributes are also not directly linked, but two negative associations can be identified; First, between *Nature & Landscapes* and *Architecture & Buildings* (z-score −2.35, expected and actual co-occurrences 49.79 and 32), and secondly, between *Plants* and *People* (z-score −2.52, expected and actual co-occurrence 25.10 and 13). Tourists tend to separate those categories when taking a photograph and it may be assumed that it is less likely to see those attribute pairs illustrated together than one would expect.

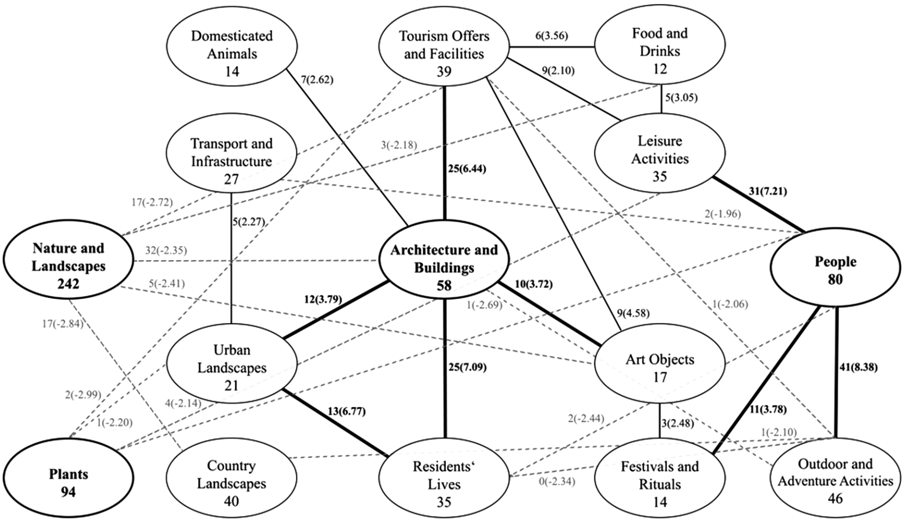


Fig. 2. Destination image map constructed from UGC (compiled by authors)

The UGC map cannot be distinguished into several clusters, as nearly all attributes seem to be linked indirectly. The category *Architecture & Buildings* is most widely connected, indicating that tourists photograph houses in urban settings as well as tourism facilities, which can also be viewed as art objects. Furthermore, houses are represented in UGC that show how residents are living, including domesticated animals like cows, sheep or dogs. The category *Urban Landscapes* itself has a strong link to *Residents' Lives* as well as a loose connection to *Transport & Infrastructure*, meaning that visitors of Tyrol tend to photograph how city people live including traffic and streets. The category *Tourism Offers & Facilities* incorporates three weak links to *Food & Drinks*, *Leisure Activities*, and *Art Objects*, indicating that pictures taken from obvious tourism activities are relatively scarce disregarding buildings like mountain lodges, huts, and others. *Food & Drinks* is loosely linked to *Leisure Activities*, meaning that tourists tend to take pictures of brunches or shared drinks. *People*, as one of the most frequent categories, is connected to *Leisure Activities* and *Outdoor & Adventure Activities*, which means that *People* can be positively associated with both activities and neither is preferred by tourists. The category of *People* is linked with *Festivals & Rituals*, indicating that tourists tend to take photographs including visitors at essential events (e.g., selfies at ski races or wedding pictures with the bridal couple). *Festivals & Rituals* has a weak link to *Art* Objects, showing that tourists tend to take pictures of decorative objects and art on festivities mainly on Christmas markets. *Nature & Landscapes* (co-occurrence of 242) does not have a significant link to any of the other categories, which means tourists tend to photograph Tyrol's unique landscape alone.

5 Conclusion

The five predominant attributes of the Tyrolean destination image, considering both the cDMO and the UGC frequency counts, were *Nature & Landscapes*, *People*, *Plants*, *Architecture & Buildings*, and *Residents' Lives*. In all predominant categories, we found a statistical difference in respect to the frequencies of those attributes, meaning the distribution of occurrences was significantly different between the samples (see Table 1). Tourists tend to be more interested in capturing all sorts of nature and landscapes including the prevailing plants, leisure activities and their domesticated animals, whereas they tend not to share the lives of locals and their traditions like food and clothing. In particular, the UGC map shows that tourists tend to capture pictures with the attribute *Nature & Landscape* alone, while the cDMO links this attribute with plants, and outdoor sports. This aligns Tirol Tourist Board's aim to project a broader image of the destination, placing emphasis on including people in most photographs to foster a certain thought process by viewing a photograph on Social Media[1]. For example, the impressive iconic photograph of lakes surrounded by mountains including no other category was illustrated in both the UGC (34 pictures) and the cDMO (13 pictures) sample. This can be explained with frameworks of destination image formation, that a tourist's perceived image of a destination is highly affected by the projected imagery induced by the Tirol Tourist Board and psychological characteristics of individual visitors, such as the motivation to prove to others that they have been to a location [11, 31]. Some pictures of specific locations (e.g., Seebensee) are even shot from the same angles, in order to succeed in retaking established promotional shots, thereby confirming similar findings of Stepchenkova and Zhan [4].

Secondly, tourists tended to photograph mountains without any other element of nature (31 pictures) nearly as often as the combination of lakes in front of mountains, whereas the cDMO numbers are lower (23 pictures). Furthermore, neither *Nature & Landscape* and *Architecture & Buildings*, nor *Plants* and *People* share a positive relationship in the UGC map. They are negatively linked and therefore, tourists do not tend to illustrate those pairs as pictorial foci together. The category *People*, as one of the predominant attributes, is pictured together with *Outdoor & Adventure Activities* as well as *Leisure Activities* in both samples. Outdoor sports in general has a higher co-occurrence frequency, with 51 cDMO pictures and 41 UGC pictures, therefore, it can be regarded as an iconic photograph, whereas the leisure activities have a lower co-occurrence frequency, but tend to be illustrated more on photographs of tourists (31

[1] Interview with Eckard Speckbacher, Head of Digital Communication, Tirol Tourist Board, on June 3, 2019.

pictures) than in the cDMO sample (14 pictures). Thus, it could be speculated, that it is not the single aim of tourists to include outdoor sports activities into their holidays, as indicated by promotional materials. Tourists value and enjoy their leisure time nearly as much, doing more relaxed activities (e.g., having brunch, visiting the spa), which is also linked to the attribute of *People* (11 co-occurring pictures in the UGC sample).

The adopted research methodology is highly dependent on the pictorial material chosen for examination; therefore, the permanently content-producing nature of Social Media together with the constrained usability of the platform itself limited the time-frame taken into consideration. Additionally, the chosen hashtag had an immense influence on the research outcome [3]. Other limitations are the compromise between reliable and accurate frequency data and the required manpower to execute the analysis, the subjectivity involved in the category development and coding, as well as the constrained comparison to already existing literature [5, 29].

Overall, the Tirol Tourist Board tends to project a strategically thought through destination image of Tyrol by illustrating beautiful landscapes, as well as Tyrolean architecture, outdoor sports, traditional food and impressive characters shown in their natural habitat. This study provides insights into the tourist perspective, which needs to be considered in a strategic destination image projection. Therefore, practical implications for DMOs could be to emphasize the unique Tyrolean landscape focusing on the attributes of nature alone, reducing the illustrations of locals in combination with their traditions, such as food and clothing, as well as including more representations of people doing leisure activities instead of outdoor sports.

References

1. Hu Y, Ritchie JB (1993) Measuring destination attractiveness: a contextual approach. J Travel Res 32(2):25–34
2. Bernkopf D, Nixon L (2019) The impact of visual social media on the projected image of a destination: the case of Mexico City on Instagram. In: Pesonen J, Neidhardt J (eds) Information and communication technologies in tourism 2019. Springer, Cham, pp 145–157
3. Gartner WC (1986) Temporal influences on image change. Ann Tour Res 13(4):635–644
4. Stepchenkova S, Zhan F (2013) Visual destination images of Peru: comparative content analysis of DMO and user-generated photography. Tour Manag 36:590–601
5. Ye H, Tussyadiah IP (2011) Destination visual image and expectation of experiences. J Travel Tour Mark 28(2):129–144
6. Frías DM, Rodríguez MA, Castañeda JA et al (2012) The formation of a tourist destination's image via information sources: the moderating effect of culture. Int J Tour Res 14(5):437–450
7. Chang J-H, Wang S-H (2019) Different levels of destination expectation: the effects of online advertising and electronic word-of-mouth. Telemat Inform 36:27–38
8. Pearce PL (1988) The ulysses factor: evaluating visitors in tourist settings. Springer, New York
9. Picazo P, Moreno-Gil S (2017) Analysis of the projected image of tourism destinations on photographs: a literature review to prepare for the future. J Vacat Mark 25(1):3–24
10. Chon K-S (1990) The role of destination image in tourism: a review and discussion. Tour Rev 45(2):2–9

11. Beerli A, Martín JD (2004) Factors influencing destination image. Ann Tour Res 31(3):657–681
12. Kock F, Josiassen A, Assaf AG (2016) Advancing destination image: the destination content model. Ann Tour Res 61:28–44
13. Josiassen A, Assaf AG, Woo L et al (2015) The imagery–image duality model: an integrative review and advocating for improved delimitation of concepts. J Travel Res 55 (6):789–803
14. del Bosque IR, Martín HS (2008) Tourist satisfaction a cognitive-affective model. Ann Tour Res 35(2):551–573
15. Xiang Z, Gretzel U (2010) Role of social media in online travel information search. Tour Manag 31(2):179–188
16. Yoo K-H, Gretzel U, Zach F (2011) Travel opinion leaders and seekers. In: Law R, Fuchs M, Ricci F (eds) Information and communication technologies in tourism 2011. Springer, Vienna, pp 525–535
17. Miller C (2017) How Instagram is changing travel. https://www.nationalgeographic.com/travel/travel-interests/arts-and-culture/how-instagram-is-changing-travel/. Accessed 23 June 2019
18. Andreu L, Bigné JE, Cooper C (2008) Projected and perceived image of Spain as a tourist destination for British travellers. J Travel Tour Mark 9(4):47–67
19. Schwaighofer V (2014) Tourist destination images and local culture. Springer Fachmedien Wiesbaden, Wiesbaden
20. Baloglu S, Uysal M (1996) Market segments of push and pull motivations: a canonical correlation approach. Int J Contemp Hosp Manag 8(3):32–38
21. Baloglu S, Mangaloglu M (2001) Tourism destination images of Turkey, Egypt, Greece, and Italy as perceived by US-based tour operators and travel agents. Tour Manag 22(1):1–9
22. Chen JS, Hsu CHC (2000) Measurement of Korean tourists' perceived images of overseas destinations. J Travel Res 38(4):411–416
23. Govers R, Go FM (2005) Projected destination image online: website content analysis of pictures and text. Inf Technol Tour 7(2):73–89
24. Hunt JD (1975) Image as a factor in tourism development. J Travel Res 13(3):1–7
25. Urry J (1990) The tourist gaze: leisure and travel in contemporary societies. Sage Publications, London
26. Kim H, Stepchenkova S (2015) Effect of tourist photographs on attitudes towards destination: manifest and latent content. Tour Manag 49:29–41
27. Bell P (2001) Content analysis of visual images. In: Jewitt C, van Leeuwen T (eds) Handbook of visual analysis. Sage Publications, London, pp 10–34
28. Li X, Stepchenkova S (2012) Chinese outbound tourists' destination image of America: part I. J Travel Res 51(3):250–266
29. Neuendorf KA (2002) The content analysis guidebook. Sage Publications, Thousand Oaks
30. Kirilenko AP, Stepchenkova S (2016) Inter-coder agreement in one-to-many classification: fuzzy kappa. PLoS One 11(3):e0149787
31. Cip T, Münch V, Pindzo J et al (2019) Conceptual process model for Instagram caption analysis in the case of the destination Ischgl. In: Maurer C, Siller HJ (eds) ISCONTOUR 2019 tourism research perspectives: proceedings of the international student conference in tourism research. BoD – Books on Demand, Norderstedt, pp 135–148

Recommendation and Decision Making

The Effects of Group Diversity in Group Decision-Making Process in the Travel and Tourism Domain

Amra Delic[1(✉)], Judith Masthoff[2], and Hannes Werthner[1]

[1] Research Unit of E-Commerce, TU Wien, Vienna, Austria
amra.delic@tuwien.ac.at
[2] Human-Centered Computing Group, Utrecht University, Utrecht, Netherlands

Abstract. In this paper, we present the results of a user study focusing on the impact of group diversity on the group decision-making process, in the travel and tourism domain, when a group is faced with a task to select a destination that they would visit together. Firstly, motivated by previous research, we introduce several measures that capture diversity with respect to group members' individual, explicit preferences. Next, we illustrate that group diversity in terms of preferences, in essence, has a negative effect on the group performance and the individual "well being". The analysis was conducted upon two data sets, one containing information about 200 participants organized in 55 groups, and the second about 150 participants organized in 41 groups.

Keywords: User modeling · Group diversity · Travel-related group decision-making · Group recommendations

1 Introduction

Group diversity is one of the key measures that provide essential information about a group at hand. According to [30], diversity is *"a characteristic of social grouping that reflects the degree to which objective or subjective differences exist between group members"*. Similarly, in [18,29,31], diversity is defined as variability between individuals in any attribute that potentially leads to individual perception of difference from another. Organizational diversity theory studies how group diversity impacts group performance, cohesion and social interaction, as well as, group members' individual commitment, satisfaction, etc. (i.e., "well being"). The main challenge for researchers is to understand which group processes are affected by diversity [30]. Group diversity is conceptualized into three types, (a) demographic diversity [31]; (b) informational diversity [18,19,21]; and (c) diversity in personality, attitudes, and values [3,16,19]. In this paper we focus on the third type - the diversity of group members' attitudes (i.e., preferences), and its impact on the group decision-making process in the travel and tourism

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 117–129, 2020.
https://doi.org/10.1007/978-3-030-36737-4_10

domain. The overall goal is to make use of the presented findings in the field of group recommender systems (GRSs).

Research has shown that group diversity might have positive, as well as, negative effects on the group performance, and group members' individual "well being" in the decision-making process. In the area of GRSs, only a couple of studies tackled the issue of diversity and its impact on the performance of a GRS, i.e., [1,5,27] showed that preference diversity decreased the effectiveness of group recommendations, while personality diversity increased the accuracy of a personality-based GRS. Moreover, it is not only that the objective (measured) diversity is relevant, in [6], it was shown that also the perceived diversity of group members' preferences is strongly related with their choice satisfaction. Our assumption is that how group members perceive themselves to be similar to each other in a certain discussion is influenced, to a great extent, by the flow of that discussion, and especially how the group members exchanged their preferences. For instance, given a set of ten destinations (i.e., a choice-set), group members would perceive their group as highly similar if they exchanged their individual top-three choices, and the same destination was found in the top-three choices of all members. However, if the group members discussed the full choice-set, they might discover that the group preferences are profoundly diverse, as they would found more inconsistencies in opinions about the destinations. Following this concept, and the previous research [11], we show that there are two basic approaches to measure group diversity, the first option is to consider the preferences of group members over the *full choice-set*, while the second option, would be to consider only a part of group members individual preferences. Accordingly, in order to evaluate the effects of group diversity on the group decision-making process, i.e., on the group performance and group members' individual "well being", we introduce three measures of group diversity: (1) Diversity of group members' top-choices, (2) Diversity of group members' preferences on the full choice-set, and (3) Maximum diversity of group members top-choices. The analysis is conducted on two data sets, i.e., DS-I (200 participants organized in 55 groups), and DS-II (150 participants organized in 41 groups), containing information about the group decision-making process, where a group is given the task to choose a destination, from a predefined set of destinations, to visit together.

The main contributions of this paper are: (1) Definition of diversity measures for group members' individual, explicit preferences; and (2) Analysis of the relationships, and influence that group diversity exerts on the group performance, and individuals' "well being" in the decision-making process.

The rest of the paper is organized as follows: Sect. 2 illustrates the related work; Sect. 3 provides an overview of the methodological approach; Sect. 4 presents the obtained results; and Sect. 5 discusses the results and conclusions of the work.

2 Related Work

Impact of diversity on group performance and individuals' "well being" has been extensively researched [30], with a highly inconsistent findings. In [20,26], it was proposed that demographic diversity, and diversity in personality, values and attitudes negatively affect group performance, and individuals' "well being", while information diversity might have a positive effect. Jehn et al. [20] then confirmed that information diversity did have a positive effect, and perceived value diversity did have a negative effect, but, opposite to the assumption, no evidence was found that demographic diversity had any influence on group performance, nor the individuals' "well being". In contrast to the findings of Jehn et al., Bantel and Jakson [2] found that demographic diversity has positive effects, while Simons et al. [28] identified a negative effect of information diversity. On the top of this, the authors of [4] found both, positive and negative effects of information diversity, depending on the form of the diversity. In our study, group members' explicit preferences about the travel destinations are equivalent to the diversity of values and attitudes in the organizational diversity theory. The field of our research are GRSs, thus, our perspective on the problem is adjusted accordingly.

The main question of GRSs is how to aggregate individual preferences into a group model in order to recommend items that would be accepted by a group as a whole. Here, only few works have investigated the impact of group members' preference diversity on the performance of a GRS. Baltrunas et al. [1] showed that the effectiveness of group recommendations is decreased for highly diverse groups compared to the individual recommendations, while for highly similar groups this was not the case. Pessemier et al. [5] confirmed these results. It is worth noting that in both works, a data set with synthetic groups (i.e., the groups were not real, but constructed from the MovieLens data set [15], containing item-ratings of individual users) was used. In this study we analyse real groups and their decision-making process. Research has shown that people in groups often change their opinions during the process, and therefore, they end up being satisfied with a group choice which was not their initially preferred option [7,8]. To this end, in our analysis we also evaluate the effects of group diversity on group members' "well being" in the decision-making process.

3 Methodology

In this section, we describe the data collection procedure, the relevant measurements, and definitions of the newly introduced constructs, i.e., the group diversity, group performance, and group members' individual "well-being" in the group decision-making process.

3.1 Data Collection and Data Description

The study was initiated in a cooperation with the International Federation for Information Technologies in Travel and Tourism (IFITT). The first study implementation (further referred to as DS-I) took place in 2015 and 2016, at four European universities; and the second one (further referred to as DS-II) in 2017, at two European universities. Both implementations were done as a part of regular lectures, and followed the same three-phases structure [7,9,10]: (1) a pre-questionnaire phase, (2) group discussions phase, and (3) a post-questionnaire phase. Prior to the first phase, the participants (students) were asked to form groups of their choosing with the only constraint that the size of the group should not exceed five members.

The pre-questionnaire tapped into participants' individual preferences (i.e., explicit and implicit), personality, experience, and social relationships. In this paper, we focus solely on the participants' explicit preferences. In DS-I, the participants were asked to rank ten destinations, i.e., ten large European cities, while in DS-II, they were actually asked to rate the ten destinations, on a 10-point scale (i.e., 10 represents the best score). The destinations, in DS-II, were selected to match ten types of vacation which were identified based on literature review [13,14,22–24,32], with the goal to try to increase the diversity and conflict of preferences in groups. **In the second phase**, the groups were asked to choose two top destinations that they, as a group, would like to visit together. **In the post-questionnaire**, the participants answered about: (1) First and second group choice; (2) Satisfaction with the group choice (CS); (3) Difficulty of the group decision-making process (Diff); (4) Group identity (Ident) (i.e., happiness with being a part of a specific group); and (5) Perceived preferences similarity within the group (Sim). Each of these constructs (i.e., 2–5), were related to multiple questionnaire items. The questionnaire items were evaluated on a five-point Likert scale, 1 - *"Strongly disagree"*, 5 - *"Strongly agree"*, and aggregated for each construct. Moreover, satisfaction with the group choice, group identity, and difficulty, all assess group members' happiness with the final choice, the group they belonged to, and the overall process (respectively), therefore, we consider that these three concepts capture participants' "well-being" in the group decision-making process.

DS-I consisted of 200 participants (i.e., 166 male, and 34 female; with age min 17, max 48, and mean 22.46), organized in 55 groups of two (7 groups), three (14), four (26) and five (8) group members. DS-II consisted of 150 participants (i.e, 75 male, 75 female; with age min 19, max 48, and mean 24.51) organized in 41 groups of two (6 groups), three (8), four (21) and five (6) group members. Descriptive statistics of the "well-being" constructs and the perceived group similarity is provided in Table 1 for both data sets.

Table 1. Descriptive statistics of "well being" constructs and perceived group similarity (authors' own table)

	DataSet-I					DataSet-II				
	Min	Max	Mean	MED	StDev	Min	Max	Mean	Med.	StDev
CS	1.75	5.00	4.07	4.00	.733	2.50	5.00	4.51	4.62	.514
Diff	1.00	3.83	2.30	2.33	.641	1.67	5.00	3.06	3.00	.484
Ident	1.5	5.00	3.85	4.00	.710	2.25	5.00	4.10	4.00	.647
Sim	1.00	5.00	3.61	4.00	.610	1.00	5.00	3.77	4.00	.758

3.2 Group Diversity

In a qualitative analysis presented in [11], the authors identified four types of preference disclosure techniques that were naturally adopted by groups. We assume, how group members perceive their group similarity/diversity mainly hinges on the flow of their discussion. Therefore, in accordance with the observations from [11], we introduce three group diversity measures.

Spearman Top-Choice Diversity (ST_DIV) measures the group diversity based on group members' ranks of each others' top-choices. The group diversity is therefore the average of group members' pairwise Spearman foot-rule distances on their individual top-choices. The Spearman function simply measures the difference between rankings provided by two users for a single item. Therefore, the formulation $\underset{TopChoice(user_i)}{Spearman}(user_i, user_j)$ measures the difference between $user_i$'s and $user_j$'s rankings of $user_i$'s top choices.

$$ST\_DIV = \frac{1}{n(n-1)} * \sum_{i=1}^{n} \sum_{j=1 \wedge j \neq i}^{n} \underset{TopChoice(user_i)}{Spearman}(user_i, user_j) \tag{1}$$

Spearman Full Choice-Set Diversity (SF_DIV) measures the average pairwise Spearman foot-rule distances between group members' individually ranked lists. In the first step, absolute differences between rankings over the ten destinations for each pair of members are calculated, and in the second step, the group diversity is obtained as the average of the pairwise differences. Here again, Spearman function simply measures the difference between rankings provided by two users for a single item.

$$SF\_DIV = \frac{2}{n(n-1)} * \sum_{j=1}^{n-1} \sum_{i=j+1}^{n} \underset{FullChoiceSet}{Spearman}(user_i, user_j) \tag{2}$$

Max-Min Diversity on the Top-Choices (MM_DIV) evaluates the diversity of a group on members' individual top-choices as well, but it is based on the maximum distance found for each group members' top-choice. To clarify, in the first step, for each group member and her top-choices, the maximum Spearman foot-rule distance to any other fellow group member is identified. In the second step, the group diversity is selected as the minimum of the previously obtained group members' maximum distance scores.

$$MM\_DIV = min(max(Spearman(user_i, user_j)))_{user_i \wedge user_j \in G} \tag{3}$$

Table 2 shows the descriptive statistics of the introduced diversity measures for the two data sets. Overall, the diversity scores for DS-II are higher than those of DS-I.

Table 2. Descriptive statistics of diversity measures (authors' own table)

	DataSet-I					DataSet-II				
	Min	Max	Mean	Med.	StDev	Min	Max	Mean	Med.	StDev
ST_DIV	.00	15.41	7.41	7.33	3.09	2.50	20.50	10.68	10.83	4.10
SF_DIV	9.33	42.00	29.55	31.00	6.68	15.00	44.00	30.13	30.50	6.20
MM_DIV	.00	5.00	1.40	1.00	1.27	.00	7.00	1.37	.00	1.99

3.3 Group Performance

In our case, the performance can be measured at the individual, and at the group level. At the individual level, we will use the "well-being" constructs, i.e., choice satisfaction (CS), difficulty of the group decision-making process (Diff), and group identity (Ident), as explained. Furthermore, we introduce another performance measure that is related to the individual preferences, and the actual group choice, i.e., Individual Loss (IL). It quantifies the difference between individual preferences and the group choice, and it is calculated as the absolute difference between group rank and individual rank of the chosen destination. This approach is equivalent to the ones defined in [1,5], that measured the efficiency of the group recommendations. Thus, $IL(user_n, G, i_G)$ is the distance between member's $user_n$ preferences and the first group choice i_G selected by group G, where $rank_{user_n}(i_G)$ is the rank position in the list of member $user_n$ for the first choice of group G:

$$IL(user_n, G, i_G) = |rank_{user_n}(i_G) - 1| \quad (4)$$

At the group level, the first set of group performance measures is based on the aggregated "well being" constructs, i.e., mean choice satisfaction (MCS), mean difficulty (MDiff), and mean group identity (MIdent). The perceived group similarity at the group level, is also aggregated with the mean function (MSim). In addition, to capture another dimension of the group satisfaction, we calculate the difference between maximal and minimal reported choice satisfaction in the group, i.e., Difference in Choice Satisfaction (DCS).

The second set of group performance measures, motivated by the work of Nguyen et al. [25], is based on the individual and group preferences: Mean Individual Loss (MIL) is the mean value of group members' Individual Loss scores; and Win-Loss Difference (WLD) is the difference between Individual Loss of the winner and Individual Loss of the loser in the group decision making process. The Mean Individual Loss (MIL), Win-Loss Difference (WLD), and Difference in Choice Satisfaction (DCS) variables are motivated by the idea of process loss in social psychology measuring the decline in performance caused by group settings [12]. In the context of GRSs, this is a valid measure, since the goal of group recommendations is to satisfy the preferences of all group members, which is hardly as good as recommendations tailored to satisfy individual users. Moreover, diverse preferences in the decision-making process often lead to one side winning, and the other side losing in the decision-making process. This motivates us to observe the difference in Individual Loss between the "winners" (i.e., those with the lowest Individual Loss) and the "losers" (i.e., those with the largest Individual Loss) of the decision-making process.

Descriptive statistics of the performance measures, for the two data sets are provided in Table 3. We can see that, in general, Individual Loss (IL) in DS-I was higher than in DS-II, together with Mean Individual Loss (MIL), and Win-Loss Difference (WLD). The groups from DS-II were more satisfied with their choices, and they reported higher group identity, even though they perceived the process as more difficult. Moreover, on average, the groups from DS-II, perceived their groups as more similar in terms of their travel preferences.

Table 3. Descriptive statistics of performance measures (authors' own table)

	DataSet-I					DataSet-II				
	Min	Max	Mean	Med.	StDev	Min	Max	Mean	Med.	StDev
IL	.00	16.00	5.35	5.00	3.79	.00	9.00	2.03	1.00	2.50
MIL	1.00	9.50	5.18	5.50	2.21	.00	4.25	1.95	2.00	1.32
WLD	.00	15.00	6.50	6.00	4.04	.00	9.00	4.09	4.00	2.83
MCS	3.11	5.00	4.08	4.10	.45	3.92	5.00	4.52	4.56	.30
DCS	.00	3.67	1.36	1.50	.73	.00	2.50	.85	1.00	.55
MDiff	1.50	2.92	2.29	2.33	.33	1.39	3.25	2.31	2.30	.43
MIdent	1.63	5.00	3.83	3.93	.54	2.67	5.00	4.11	4.06	.44
MSim	2.25	5.00	3.62	3.66	.57	2.33	4.75	3.77	3.75	.48

3.4 Analyses

In order to explore the relationship between the group diversity and group performance in the decision-making process, first we perform a simple Pearson's correlation analysis. In the next step, with the Kruskal-Wallis test (i.e., a non-parametric test) we evaluate the effects of group diversity on group performance, as well as group members' individual "well-being". The choice of the test was made based on the results of Kolmogorov-Smirnov and Shapiro-Wilk normality tests. They showed a significant deviation of our measures from the normal distribution. To employ the Kruskal-Wallis test, we split the data into diverse and non-diverse groups, based on the median score of the specific diversity measure. The data separation is done independently for the two data sets, and independently for each diversity measure. All the tables related to the Kruskal-Wallis, in the results section, test illustrate only the significant output.

4 Results

In the first part of this section, we present how group diversity is related, and affects the group performance, and in the second part, how it affects the group members' individual "well-being" and performance.

4.1 Group Level

Table 4 illustrates the results of the correlation analysis, i.e., Mean Individual Loss (MIL), and Win-Loss Difference (WLD) are positively and strongly correlated with the group diversity, for both data sets. This result is of course expected, i.e., the higher the diversity of preferences in a group, the more likely it is that the group decision will not satisfy everyone equally - some group members will lose more than the others. However, this result is not captured by all diversity measures that we introduced. As for the perceived group similarity, for DS-I, there is a moderate correlation captured by the diversity on group members' top-choices, but not the other diversity measures. This result might support our assumption that members' perception of group preference similarity is related to the discussion style that group adopted, but to confirm it, we would have to do an analysis that puts together similarity perception and discussion styles. Finally, even though previous research indicates that choice satisfaction (CS) is strongly related to group diversity, the analysis indicates no correlation at the group level at all. The same is observed for the group identity (Ident), and perceived difficulty of the decision-making process (Diff).

Table 4. Diversity correlations for DS-I and DS-II (authors' own table)

	DataSet-I			DataSet-II		
	MIL	WLD	MSIM	MIL	WLD	MSim
ST_DIV	.566**	.439**	−.339**	–	.387**	–
SF_DIV	.599**	.502**	–	–	–	–
MM_DIV	–	–	–	.351*	–	–

Table 5 shows the results of the Kruskal-Wallis test, at the group level. Again, Mean Individual Loss (MIL) and Win-Loss Difference (WLD) are significantly higher in diverse groups. Also, we can see that Spearman Top-choice Diversity (ST_DIV) captures how the group members perceive their group similarity, for DS-I, while for DS-II, the Max-Min Diversity measure provides the same functionality. Interestingly, for DS-I, the non-parametric test, showed that Mean Choice Satisfaction (MCS) is significantly higher in non-diverse groups, which follows the existing literature [20]. For DS-II, the test indicated that members of diverse groups perceived the decision-making process as significantly more difficult than those of non-diverse groups.

Table 5. Group level Kruskal-Wallis test results (authors' own table)

DataSet-I				
Diversity	Var.	Div	Non-div	p
ST_DIV	MIL	6.43	3.69	.000
	WLD	8.13	4.56	.001
	MSim	3.42	3.86	.002
SF_DIV	MCS	3.98	4.17	.043
	MIL	6.55	3.86	.000
	WLD	8.18	4.89	.003
	MSim	3.49	3.74	.041
MM_DIV	MCS	3.88	4.19	.006
DataSet-II				
Diversity	Var.	Div	Non-div	p
ST_DIV	MIL	2.48	1.40	.011
	WLD	5.52	2.60	.001
	MDiff	2.45	2.17	.020
MM_DIV	WLD	4.21	4.00	.019
	MSim	3.59	3.93	.042

Table 6. Individual level Kruskal-Wallis test results (authors' own table)

DataSet-I				
Diversity	Var.	Div	Non-div	p
ST_DIV	CS	4.00	4.29	.002
	Ident	3.87	4.00	.006
	IL	6.00	3.00	.000
	Sim	3.50	4.00	.000
SF_DIV	CS	4.00	4.25	.022
	IL	6.00	3.00	.000
	Sim	3.50	4.00	.005
MM_DIV	CS	4.00	4.25	.013
DataSet-II				
Diversity	Var.	Div	Non-div	p
ST_DIV	Diff	2.50	2.16	.001
SF_DIV	CS	4.5	4.75	.033
	Diff	2.50	2.16	.034
MM_DIV	IL	2.00	0.00	.001

4.2 Individual Level

At the individual level, for the DS-I data set, with the Kruskal-Wallis test, we obtain further insights in what actually happens within diverse and non-diverse groups (Table 6). Captured with the Spearman Top-choice Diversity, in non-diverse groups, group members are significantly more satisfied with the group choice (CS), they perceive their group similarity (Sim) as significantly higher, they are significantly happier with being part of their group (Ident), and they experience significantly lower Individual Loss (IL) in the decision-making process. Similarly, captured with the Spearman Full Choice-set Diversity, participants in the non-diverse groups are, also, significantly more satisfied (CS), they perceive their group similarity as higher (Sim), and their Individual Loss (IL) is significantly lower. As for the the Max-Min Diversity, group members were significantly more satisfied with the group choice (CS) in the non-diverse groups. In general, patterns observed within DS-I are as well found within the DS-II data set. Group members from non-diverse groups, as captured by the Spearman Full Choice-set Diversity, are significantly more satisfied with the group choice (CS). Moreover, captured by both, Sperman Full Choice-set and Spearman Top-choice Diversity, group members in diverse group perceive the decision-making process as significantly more difficult (Diff). Finally, members of the non-diverse groups, as captured by the Max-Min Diversity, had a significantly lower Individual Loss (IL), than the participants from the diverse groups.

5 Discussion and Conclusion

In the previous section, we have presented the results of the analysis focusing on the relationship and impact of the diversity of group members' explicit preferences on the group performance and group members' individual "well being". We have shown that diversity of group preferences has a negative effect on group members' individual "well being", i.e., (1) satisfaction with the group choice (CS); (2) happiness with being a part of a specific group (Ident) (i.e., group identity); and (3) difficulty of the decision-making process (Diff). This result is inline with the observations of Jehn et al. [20]. The same was confirmed for group "well being" (i.e., individuals' "well being" constructs aggregated at the group level). Moreover, in terms of Individual Loss (IL), Mean Individual Loss (MIL), and Win-Loss Difference (WLD), the individual and group performance is deteriorated, which is expected, and inline with the findings of Baltrunas et al. and Pessemier et al. [1,5]. In this section, we discuss the implications of these results.

First of all, even though we have shown that group members are significantly happier in non-diverse groups, results (Table 6) indicate that the difference in median values of choice satisfaction between diverse and non-diverse groups is only minor. Moreover the median choice satisfaction score in diverse groups is equal to four, which still indicates high satisfaction of the participants. This points out that, even in diverse groups, where some group members will, for sure, experience greater Individual Loss (IL), they do not necessarily end up being dissatisfied. The same holds for the group identity, i.e., happiness with being a part of a specific group. Secondly, the results show that different diversity measures display different effects on the group performance, and group members' individual "well being". Although, the patterns of the diversity effects are similar, the observed differences deserve a proper discussion. We believe that these differences can be explained by understanding "objective" (i.e., actual), and "subjective" (i.e., perceived) representations of group diversity, on the one side, and group performance and individuals' "well being", on the other. Namely, Individual Loss (IL), Mean Individual Loss (MIL), and Win-Loss Difference (WLD) are "objective" measures of individual and group performance in the decision-making process. For DS-I, these performance measures are affected by group diversity when the diversity is captured with the Full Choice-set Diversity, and Top-Choice Diversity, but not with the Max-Min Diversity. The probable explanation could be found in the way the group members expressed their individual preferences in the pre-questionnaire, i.e., absolute ranks of the ten destinations. Therefore, the "objective" diversity measure, in such a case, should compare individuals' ranking lists, either completely, or the individual top choices, in order to capture variations between individuals' preferences. This is not really what the Max-Min Diversity does, as it overlooks the group members' pairwise diversity (for details see Sect. 3). On the other side, for DS-II, the effect of diversity on the individual and group performance are captured with the Top-choice Diversity and Max-Min Diversity, but not with the Full Choice-set Diversity (see Table 5). Here, the group members expressed their preferences as ten-point ratings (i.e., the partial ranks of the ten destinations). If we measure the diversity over the full choice-set, the differences between individuals' partially ranked options might be diminished because of the ties, and this can decrease the overall diversity. However, Max-Min Diversity and Top-choice Diversity can capture exactly the required differences, and disregard all the similarities that might not affect group performance. Furthermore, the constructs of individuals' "well being" are all subjective measures, reported by participants as perceived. Hereby, we assume that group diversity affects individuals' "well being" mostly during the group discussion, more precisely, group diversity as individuals' perception of the group diversity (i.e., which does not have to be the same [17]). To explain the detected relationships, we would need to better understand which techniques the groups employed when they discussed their preferences. For instance, if the group members discussed all ten destinations, then we would expect to observe that the Full Choice-set Diversity, not Max-Min Diversity, affects group members' "well being".

To summarize, high diversity of group members' preferences has a negative effect on the individuals' "well being", and on the group performance in the travel-relate decision-making process. Nevertheless, it does not necessarily mean that members of highly diverse groups will be unsatisfied with the group choice. An important message, especially in the research of GRSs conveyed in this paper, is that we need different group diversity measures in order to be able to recognize different effects that diversity of group members' preferences might cause in the group decision-making process. Moreover, how we elicit members' individual preferences in the system, and how we support the group discussion, actually dictates the selection of the diversity measures that will provide relevant information about the group. Even more importantly, group discussion can lead to opinion shift, and therefore Individual Loss, and group diversity as usually defined in GRSs, as well as in this paper - based on the group members' initial preferences only, are not enough to make correct predictions of members' satisfaction with the group choice or group recommendations. Hence, future work in the GRSs should be dedicated to actually supporting and observing group decision-making process in order to truly help groups.

In our future work, we plan to explore the effects of other types of group diversity, such as informational diversity, cultural diversity, or diversity of group members' personality. In our two data sets, the necessary data is already contained, thus this seems like a natural next step in this research.

References

1. Baltrunas L, Makcinskas T, Ricci F (2010) Group recommendations with rank aggregation and collaborative filtering. In: Proceedings of the fourth ACM conference on Recommender systems, RecSys 2010. ACM, Barcelona, pp 119–126
2. Bantel KA, Jackson SE (1989) Top management and innovations in banking: does the composition of the top team make a difference? Strateg Manag J 10(S1):107–124

3. Bowers CA, Pharmer JA, Salas E (2000) When member homogeneity is needed in work teams: a meta-analysis. Small Group Res 31(3):305–327
4. Bunderson JS, Sutcliffe KM (2002) Comparing alternative conceptualizations of functional diversity in management teams: process and performance effects. Acad Manag J 45(5):875–893
5. De Pessemier T, Dooms S, Martens L (2014) Comparison of group recommendation algorithms. Multimed Tools Appl 72(3):2497–2541
6. Delic A, Neidhardt J (2017) A comprehensive approach to group recommendations in the travel and tourism domain. In: Adjunct publication of the 25th conferenceon user modeling, adaptation and personalization. ACM, Bratislava, pp 11–16
7. Delic A, Neidhardt J, Nguyen TN, Ricci F, Rook L, Werthner H, Zanker M (2016) Observing group decision making processes. In: Proceedings of the tenth ACM conference on Recommender systems, RecSys 2016
8. Delic A, Neidhardt J, Rook L, Werthner H, Zanker M (2017) Researching individual satisfaction with group decisions in tourism: experimental evidence. In: Information and communication technologies in tourism 2017. Springer, pp 73–85
9. Delic A, Masthoff J, Neidhardt J, Werthner H (2018) How to use social relationships in group recommenders: empirical evidence. In: Proceedings of the 26th conference on user modeling, adaptation and personalization. ACM, Singapore, pp 121–129
10. Delic A, Neidhardt J, Nguyen TN, Ricci F (2018) An observational user study for group recommender systems in the tourism domain. Inform Technol Tour 19(1–4):87–116
11. Delic A, Neidhardt J, Werthner H (2018) Group decision making and group recommendations. In: 2018 IEEE 20th conference on business informatics (CBI). IEEE, Vienna, vol 1, pp 79–88
12. Forsyth D (2014) Group dynamics, 6th edn. Wadsworth Cengage Learning, Boston
13. Gibson H, Yiannakis A (2002) Tourist roles: needs and the lifecourse. Ann Tour Res 29(2):358–383
14. Gretzel U, Mitsche N, Hwang YH, Fesenmaier DR (2004) Tell me who you are and i will tell you where to go: use of travel personalities in destination recommendation systems. Inform Technol Tour 7(1):3–12
15. Harper FM, Konstan JA (2016) The movielens datasets: history and context. ACM Trans Interact Intell Syst (TIIS) 5(4):19
16. Harrison DA, Price KH, Bell MP (1998) Beyond relational demography: time and the effects of surface-and deep-level diversity on work group cohesion. Acad Manag J 41(1):96–107
17. Harrison DA, Price KH, Gavin JH, Florey AT (2002) Time, teams, and task performance: changing effects of surface-and deep-level diversity on group functioning. Acad Manag J 45(5):1029–1045
18. Jackson SE (1991) Team composition in organizational settings: issues in managing an increasingly diverse work force. In: Symposium on group productivity and process, 1989, Texas A & MU, College Station, TX, US. Sage Publications, Inc
19. Jehn KA, Chadwick C, Thatcher SM (1997) To agree or not to agree: the effects of value congruence, individual demographic dissimilarity, and conflict on workgroup outcomes. Int J Confl Manag 8(4):287–305
20. Jehn KA, Northcraft GB, Neale MA (1999) Why differences make a difference: a field study of diversity, conflict and performance in workgroups. Adm Sci Q 44(4):741–763

21. Milliken FJ, Martins LL (1996) Searching for common threads: understanding the multiple effects of diversity in organizational groups. Acad Manag Rev 21(2):402–433
22. Moscardo G, Morrison AM, Pearce PL, Lang CT, O'Leary JT (1996) Understanding vacation destination choice through travel motivation and activities. J Vacat Mark 2(2):109–122
23. Neidhardt J, Schuster R, Seyfang L, Werthner H (2014) Eliciting the users' unknown preferences. In: Proceedings of the 8th ACM conference on recommender systems. ACM, pp 309–312. 2645767
24. Neidhardt J, Seyfang L, Schuster R, Werthner H (2015) A picture-based approach to recommender systems. Inform Technol Tour 15(1):49–69
25. Nguyen TN, Ricci F, Delic A, Bridge D (2019) Conflict resolution in group decision making: insights from a simulation study. User Model User-Adapt Interact 29(5):895–941
26. Pelled LH, Eisenhardt KM, Xin KR (1999) Exploring the black box: an analysis of work group diversity, conflict and performance. Adm Sci Q 44(1):1–28
27. Quijano-Sanchez L, Recio-Garcia JA, Diaz-Agudo B, Jimenez-Diaz G (2013) Social factors in group recommender systems. ACM Trans Intell Syst Technol (TIST) 4(1):8
28. Simons T, Pelled LH, Smith KA (1999) Making use of difference: diversity, debate, and decision comprehensiveness in top management teams. Acad Manag J 42(6):662–673
29. Triandis HC, Kurowski LL, Gelfand MJ (1994) Workplace diversity
30. Van Knippenberg D, Schippers MC (2007) Work group diversity. Ann Rev Psychol 58:515–541
31. Williams KY, O'Reilly CA III (1998) Demography and diversity in organizations: a review of 40 years of research. Res Organ Behav 20:77–140
32. Yiannakis A, Gibson H (1992) Roles tourists play. Ann Tour Res 19(2):287–303

Next-POI Recommendations for the Smart Destination Era

David Massimo(✉) and Francesco Ricci

Free University of Bolzano, Bolzano, Italy
{damassimo,fricci}@unibz.it

Abstract. A novel Recommender System exploiting behavioural users' data in order to identify and recommend relevant and novel points of interest (POIs) is here presented. The proposed approach applies clustering to users' sensed POI visit trajectories in order to identify like-behaving users and then it learns a distinct behaviour model for each cluster. The learnt behaviour model is used to generate novel and relevant recommendations for next POI visits that optimise the user reward, which is inferred from the data. In a live user study it is assessed, along different dimensions, how users evaluate recommendations produced by the proposed method in comparison with a traditional one. The results illustrate the differences between the compared approaches and the benefits of the proposed one.

Keywords: Recommender systems · Smart tourism · Behaviour learning

1 Introduction

Recommender Systems (RS) are software tools that aim at easing human decision making [1]. In the tourism domain some special dimensions of the recommendation process play an important role: the context of the traveller visit and the sequential nature of the typical tourist decision making process. In fact, a destination may be experienced in a totally different way when is visited, for instance, in summer vs. winter or by travelling alone or with the family [2,3]. Moreover, a travel is typically composed of several components (activities, events, locations) that are bundled at different times (before and during the travel itself) [4,5].

In a previous work [6,7], it has been developed a novel context-aware recommendation technology (here called *Q-BASE*) for helping travellers to sequentially choose Point of Interests (POIs). The proposed technique models with a reward function the "satisfaction" that a POI visit gives to a user. In order to overcome two major problem of tourism RSs, such as, scarce users' feedback about visited POIs and the absence of an extensive knowledge of the users' past travel choices, in *Q-BASE* the reward function is learnt by applying Inverse Reinforcement Learning (IRL) [8] on clusters of POI-visit sequences (trajectories) performed

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 130–141, 2020.
https://doi.org/10.1007/978-3-030-36737-4_11

by users. IRL is a behaviour learning approach that leverages solely observations of users actions. In our approach IRL is used to learn a generalized tourist behaviour model; one model common for all the users in a cluster. The results of an offline experiment showed that, while a state of the art session-based nearest neighbour algorithm, *SKNN* [9] generates more precise recommendations than *Q-BASE*, the latter suggests POIs that are more novel and higher in reward. Hence, it was conjectured that in reality *Q-BASE* recommendations may be more satisfying for the user. Additionally, it was conjectured that the better precision of *SKNN* is due to its bias to recommend popular items, which have been chosen often by the observed users, while *Q-BASE* is not influenced directly by the popularity of the items, but rather by the popularity of their features.

In order to test these conjectures, firstly, it is here introduced *Q-POP PUSH* a novel model that hybridizes *Q-BASE* with a popularity score: items more popular tend also to be recommended more. Secondly, an online study was conducted. In the study an ad-hoc designed interactive online system was used in order to measure the novelty and user satisfaction for the recommendations generated by *Q-BASE*, the hybrid model (*Q-POP PUSH*) and *SKNN*. In this online system, a user can enter the set of POIs that has already visited in a city (Florence) and can receive suggestions for next POIs to visit in the same city, after she has been automatically assigned to a pre-existing cluster of users.

By analyzing the users on-line evaluations of the recommended POIs it has been shown that *Q-BASE* suggests more novel items while *SKNN* and *Q-POP PUSH* offer suggestions that the users like more. But, by considering recommended items that have been evaluated as "liked and novel" by the users, it is found that *Q-BASE* is better than *SKNN* and *Q-POP PUSH* in suggesting novel and relevant items, which we believe is the primary goal of a recommender system.

The paper structure is as follows. In Sect. 2 the most relevant and related research works are presented. Then, in Sect. 3 it is described how IRL-based recommendations can be generated and the hybrid model *Q-POP PUSH* is introduced. In Sect. 4 the online system developed for the user evaluation of recommendations is presented. Then, the evaluation results are presented. Finally, in Sect. 6, the paper conclusions are stated.

2 Related Work

Identifying POIs to be suggested to a user given her preferences or past POI-visits has been already investigated in previous research. In [10], a POI recommendation method, which exploits POIs specific geographical information: the capacity of a POI to spread its visitors to other POIs; the propensity of a POI to attract visitors coming to other POIs; the POIs physical distance. The proposed model uses check-in data collected by Location Based Social Networks (LBSNs). The model computes the probability of a user to visit a POI by combining information about her preferences and the geographical influence, which is computed as the inner product of two low-level vectors representing the POI visitors' spread capacity and the POI visitors' attractiveness. This approach differs from the one proposed here in that it does not consider neither the POI content information nor the visit context. A personalized model for restaurant recommendations is proposed in [11]. A clustering technique that allows to identify in TripAdvisor groups of customers, groups of restaurants and how these groups relates is used. Recommendations for a user are generated by first identifying the customer group that is closer to the target user and then picking the related top ranked restaurants. This model requires explicit user feedback to generate recommendations while our approach uses implicit feedback data (behaviour).

The previously described approaches do not tackle the sequential choice dynamics of a typical tourist itinerary (trajectory). Instead, in [12], a next-POI recommendation approach is presented. The authors use check-in data as well as demographic data collected by LBSNs. Users' check-ins are clustered according to users' demographic and a Recurrent Neural Network is exploited to identify common visit patterns for a specific cluster. The authors suggest that relevant next-POIs can be identified from a database using the predicted POI category according to different strategies (e.g., popularity). Here, clustering solves the new user problem, but in contrast with the model presented in this paper, it is not based on learning the user's behaviour model. Another next-POI RS approach is presented in [13]. Similarly to our approach, the authors exploit observations of sequences of POI-visits made by users. However, visit context and POI specific information are not leveraged in the generation of the recommendations. The next-POI recommendations are generated by identifying, given the current POI of the target user, similar users that visited, after the current POI, POIs that are not already in the target user profile.

3 Recommendation Techniques

3.1 User Behaviour Modelling and Learning

User Behaviour Modelling. In this paper, user behaviour modelling is based on Markov Decision Processes (MDP). A MDP is defined by a tuple (S, A, T, r, γ). S is the state space, and in our scenario a state models the visit to a POI in a specific context. The contextual dimensions are: the weather (visiting a POI during a sunny, rainy or windy time); the day time (morning, afternoon or evening); and the visit temperature conditions (warm or cold). A is a finite set of actions: an action a represents the decisions to move to a POI. T are the probabilities to make a transition from state s to s' when action a is performed, i.e., the probabilities that a tourist moves from the current POI (and context) to another POI with a possibly different context. The (unknown) function $r : S \rightarrow \mathbb{R}$ models the reward a user obtains from visiting a state. Finally, $\gamma \in [0, 1]$ is used to weigth how future rewards are discounted with respect to immediate ones. In this study a user sequence of POI-visits (trajectory) is modelled as a temporally ordered list of states.

User Behaviour Learning. Given a MDP, the goal is to find an optimal (choice) policy π^* for the decision maker that maximises the cumulative reward that the decision maker obtains by acting according to it. The value of taking a specific action a in state s under the policy π, is denoted as $Q_\pi(s,a)$. It is the expected discounted cumulative reward obtained from a in state s and then following the policy π for choosing the next actions. The optimal policy π^* dictates to a user in state s to act with $\pi^*(s) = a$ in such a way that $Q_{\pi^*}(s,\cdot)$ is maximized.

Since it is here assumed that only the information about the user's POI-visits (user's trajectories) is available, then the MDP can be solved only via IRL methods [8]. In fact, these approaches are capable to learn both the reward function and the optimal policy that generate actions close to the demonstrated behavior. In this work Maximum Likelihood IRL [14] is used.

Moreover, it is hard to obtain complete knowledge of the user visit choices, which is necessary to learn the reward function of a single individual. Therefore, IRL is here applied to clusters of users' trajectories [6,7]. In this way, a generalised tourist behaviour model, which identifies the optimal POI visits that the users in a cluster should try next is learned. Clustering the users' trajectories is done here by applying Negative Matrix Factorization (NMF) to a document-like representation of the trajectories containing, as terms, the context and feature values of the POIs in a trajectory [6].

3.2 Recommending Next-POI Visits

It is here proposed a novel next-POI recommendations technique, *Q-POP PUSH*, that extends the pure IRL-based *Q-BASE* model, already introduced in [7].

Q-BASE. The behaviour model of the user's cluster is used to suggest the optimal action this user should take after the last visited POI. The optimal action is the action a with the highest $Q_{\pi^*}(s,a)$, given the user current state s [7].

Q-POP PUSH. This hybrid recommendation method introduces a popularity bias to the recommendations generated by *Q-BASE*. It is here conjectured that, because of that, *Q-POP PUSH* can obtain a precision close to that of *SKNN*. *Q-POP PUSH* scores the visit action a in state s as following:

$$score(s,a) = (1+\beta^2)\frac{Q_{\pi^*}(s,a)\cdot pop(a)}{(Q_{\pi^*}(s,a) + pop(a)\cdot\beta^2)}$$

This score is the harmonic mean of $Q_{\pi^*}(s,a)$ and $pop(a)$, where $pop(a)$ is the min-max scaled counts $c_Z(p)$ of the occurrences of the POI-visit p selected by the action a in the training data set of visit trajectories Z. The harmonic mean is widely used in information retrieval to combine scores, s.a., precision and recall in the F1-score. In our case the parameter β was set to 1 in order to give equal importance of the two contributing scores (Q and pop); alternative balances of Q and pop will be tried in future work. The recommended action a is the one with the highest final $score(s,a)$.

4 User Study Design

An online user-study was conducted in order to measure the users' perceived novelty and satisfaction of the recommendations generated by *Q-BASE*, the hybrid models *Q-POP PUSH* and *SKNN*, the baseline nearest neighbour method previously used in an offline study [7]. The developed online system first profiles users by asking them to elicit as many previously visited POIs (in Florence) as possible. Users are then asked to evaluate a list of recommendations generated by the aforementioned three models, without being informed which model recommends what. The data used by the system to generate the clusters, train the models and compute recommendations contains 793 items and 1668 trajectories [6].

4.1 Recommender System

Once the user accesses the system website[1] is asked whether has already been in Florence. If the reply is "no" the procedure ends. Otherwise, the user is considered to have some experience of the city and is asked to declare which POIs she visited already. This is supported by a user interface (Fig. 1) that enables to select as many POIs the user remembers to have visited in Florence. The selection can be performed in two non-exclusive modalities: by using a lookup bar with auto-completion, or with a selection pane that contains the most popular 50 POIs. When the user selects a POI as visited, this is added to an (editable) list. The selected POIs compose the user profile, which is then used to identify the cluster the user belongs to, among the clusters, 5 in our case, that were identified in the training data before the on-line experiment started (see Sect. 3).

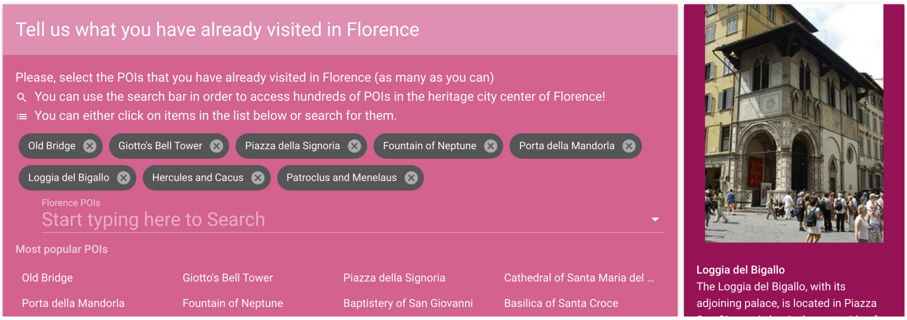


Fig. 1. User profiling by POI selection UI (Source: authors)

Then the system generates a short itinerary composed of a sample of 5 POIs, taken among those that the user previously declared to have visited. This is the

[1] www.experiment.inf.unibz.it.

itinerary that the user is supposed to have followed just before asking a recommendation for a new POI to visit. The context variables (time and weather) where not shown and not used in the recommendation generation in order to simplify the user's assessment of the recommendations. This fictitious itinerary is generated to avoid asking the user to remember any concrete previously conducted visit itinerary. Showing a hypothetical itinerary followed by the user is meant to reinforce the user understanding of the specific setting of the supported task: next-POI recommendation.

Then, the user accesses the recommendation generation and the evaluation interface (Fig. 2). At the top of the page there is an information box containing the hypothetical 5-POIs trajectory of the user. Below that box, there is an info box that explains to the participant to assume that she has so far visited the selected attractions, in the presented order. Finally, the participant is informed that the box below contains a list of POIs recommendations, worth to be visited next. The user is asked to mark the recommendations with one or more of the following labels: "I already visited it" (eye icon), "I like it" (thumb up icon) and "I didn't know it" (exclamation mark icon).

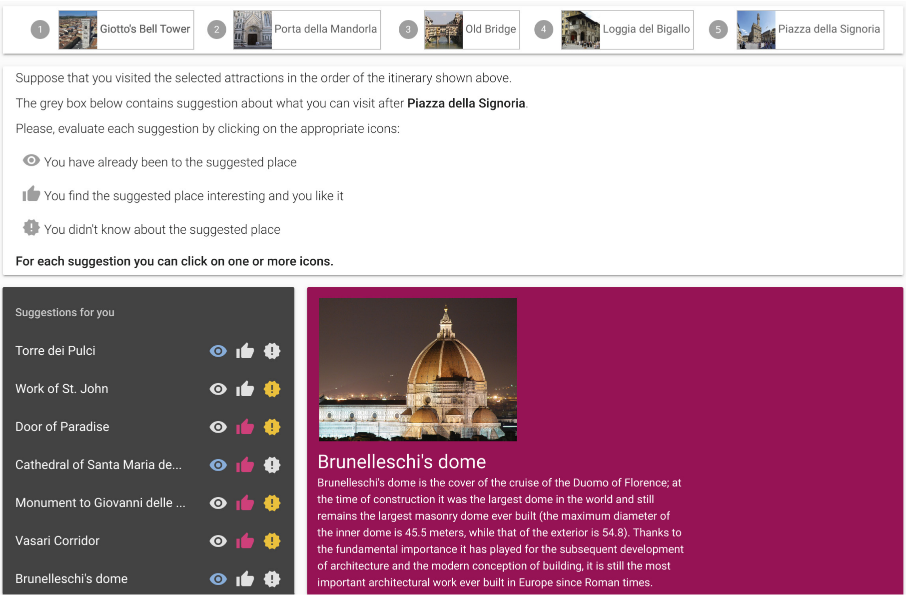


Fig. 2. Evaluation UI. From top to bottom: itinerary detail; info box; recommendations and item details (Source: authors)

Experiment participants were recruited via social media and mailing lists. Over 300 responses were collected; 202 of them were from users that visited Florence. After excluding unreliable replies (e.g., survey completed in less than 2 min) 158 users remained. The overall number of recommended next-POI visits shown to these users is 1119 (approximately three by each of the three methods per user, excluding the items recommended by two or more method simultaneously). Hence, on average, a user analysed 7.1 recommendations.

4.2 Recommendation List Generation

Matching a User to a Cluster. In order to generate recommendations, *Q-BASE* and *Q-POP PUSH* require an online user to be associated to one trajectories' cluster. To attain that goal, a tf-idf representation of the POIs (documents) that are in the user profile is built as in [6]. Then a k-nearest neighbor classifier (k = 8) where the training data are the trajectories in the data set, already classified in the 5 clusters, is ran. The classifier takes as input a user profile and returns the most likely representative cluster. The classification performance has been assessed by splitting the trajectories data set: 80% of the dataset was used for training the classifier and the remaining 20% was used as test set. In a tenfold cross-validation analysis the classifier showed an accuracy of 67%. Hence, the quality of this classifier is not very high. This may have penalised both *Q-BASE* and *Q-POP PUSH* in the online study.

5 POIs Fictitious Itinerary. Once the user is associated to a cluster, among all the trajectories in the cluster, the one with the highest overlap (intersection) with the POIs in the study participant profile is identified. Then, as it is mentioned above, in order to avoid information overload, an itinerary of at most 5 items, taken from the user profile, is shown to the user. These 5 POIs are ordered as in the matching itinerary found in the cluster to which the user is associated. The itinerary is shown to the user to represent her current (hypothesized) sequence of visited POIs. This information is provided to let the user to evaluate the next-POI recommendations as appropriate or not to continue this initiated itinerary.

Recommendations. Given the hypothesized 5 POIs itinerary followed by the user so far, next-POI recommendations are generated leveraging the models *Q-BASE*, *Q-POP* and *SKNN* and excluding from the recommendation list the POIs contained in the user profile. This is an important feature of our study: the system suggests POIs that the user has not yet visited.[2] Moreover, in order to avoid biases in the recommendation evaluation phase it is not revealed which recommendation model produced which POI recommendation.

The top-3 suggestions of each model are aggregated in such a way that no model is prioritized. At first, for each users, randomly, an order that is followed to pick items from the (model specific) 3 ranked lists of recommendations (with three items each) is generated. Then, the three ranked lists are aggregated by picking up, in turn, the items from the top to the bottom of the sorted lists. Moreover, if a POI is present in more than one of the three ranked lists, then this item is still shown only once.

[2] However, still some recommendations can be not novel because the user will never declare all the POIS that she previously visited in the city.

5 User Study Results

In Table 1, as an example, the recommendations offered to a user and her evaluations are shown. Each row shows: the suggested POI (in the order shown to the user); the POI popularity; the model that produced the recommendation; the participant's feedback as "visited", "liked" and "novel". The next-POI recommendations shown in this example have been generated for a user whose current 5 POIs itinerary is: "Giotto's Bell Tower"; "Old Bridge"; "Cathedral of Santa Maria del Fiore"; "Piazza della Signoria"; "Fountain of Neptune".

Table 1. Example of recommendations and evaluations of a user (Source: authors)

Recommendations			Models			User feedback		
Nr.	POI name	POI pop.	Q-BASE	Q-POP P.	SKNN	Visited	Liked	Novel
1	Baptistery of San Giovanni	0.53		✓	✓	✓	✓	
2	Spedale degli Innocenti	0.05	✓				✓	✓
3	Basilica of Santa Croce	0.47		✓		✓	✓	
4	Torre dei Pulci	0.60			✓			✓
5	Statue of Ferdinando I de 'Medici	0.08	✓				✓	✓
6	Door of the Mandorla	0.55			✓	✓		
7	Brunelleschi's dome	0.43	✓			✓	✓	
8	Santa Croce's Square	0.34		✓		✓		

In this example the mdoels' aggregation order is: *SKNN*, *Q-POP PUSH* and *Q-BASE*. The top ranked item in the list is suggested by both *SKNN* and *Q-POP PUSH*. The user evaluated that item as already visited and also liked. The second item, recommended by *Q-BASE*, has been judged as novel and liked by the user. The third recommendation, generated by *Q-POP PUSH*, is a POI that the user visited and liked. And so on for the other recommendations. We can observe that, for this specific user, all the next POIs suggested by *Q-POP PUSH* and *SKNN* are rather popular. For instance, "Torre dei Pulci" has 60% popularity. Whereas, recommendations generated by *Q-BASE* are less popular, e.g., "Spedale degli Innocenti" has 5% popularity. Moreover, this particular user liked more the items suggested by *Q-POP PUSH* and *SKNN*. Interestingly among the novel POIs the user liked only the least popular, but suggested by *Q-BASE*.

In order to show how the recommendations ranking correlates to the user assessment, the probability that a user expresses the three types of collected feedback, i.e., "liked", "visited" and "novel", for items shown at the i-th position of the recommendation list has been computed (see Fig. 3). The probability that a user mark an item as "liked" is around 40% in the first sixth positions of the recommendation list. Then, this probability drops. Differently, the probability to mark an item as visited decreases as the rank of the item decreases. Finally, the probability that a user mark an item as novel seems to be negatively correlated to the item rank. Hence, visited items tend to be found at the beginning of the list, whereas novel ones at the bottom.

Fig. 3. Probability that a user evaluates ("liked", "visited" and "novel") an item ranked at a specific position (Source: authors)

The results of the users evaluation of the recommended next POIs are shown in Fig. 4. Here, the probabilities that a user marks as "visited", "novel", "liked" or both "liked" and "novel" an item recommended by a model are shown. They are computed by dividing the total number of items marked as, visited, liked, novel and both liked and novel, for each model, by the total number of items shown by the model.

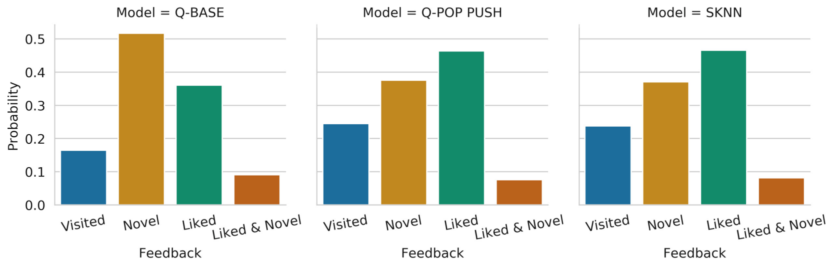


Fig. 4. Probability to evaluate a recommendation of a model as visited, novel and liked (Source: authors)

The POIs recommended by *SKNN* and *Q-POP PUSH* have the highest probability (24%) that the user already visited them, and the lowest probability to be considered as novel. Conversely, *Q-BASE* scores a lower probability that the recommended item be already visited (16%) and the highest probability that the recommended item be novel (52%). This is in line with the offline study results where *Q-BASE* excelled in recommending novel items.

Considering now the user satisfaction for the recommendations (liked), it was conjectured that a high reward of a model measured offline, corresponds to a high perceived satisfaction (likes) measured online. But, by looking at the results in Fig. 4 a different conclusion should be taken. *Q-BASE*, which has the highest offline reward, recommends items that the online users like with the lowest probability (36%). *Q-POP PUSH* and *SKNN* recommend items that are more often liked by the users (46%).

However, by observing the probability that a user likes a novel recommended POI, i.e., a POI that the user was unaware of ("Liked & Novel" in Fig. 4) one can see that *Q-BASE* recommends items that a user will find novel and also like with the highest probability (0.09%). *SKNN* and *Q-POP PUSH* perform slightly worse on that (0.08%). The small values of these probabilities signal that solving this problem is hard. However, we believe that this metric better matches the primary goal of a recommender system: to enable users to discover new and interesting items, not to suggest items that the user likes, but that she is already aware of, or she has already consumed.

A two-proportion z-test ($p < 0.01$) was used to check if the models were equally perceived, i.e., they perform equally in producing liked, novel and visited next POI suggestions. The test results are against the null hypothesis; there is a significant difference among all the three models.

In order to further analyse the user assessment of the recommended items, the probability that a user will like a recommendation, given that the item is known (but was not yet visited), visited or novel, have been computed (see Fig. 5).

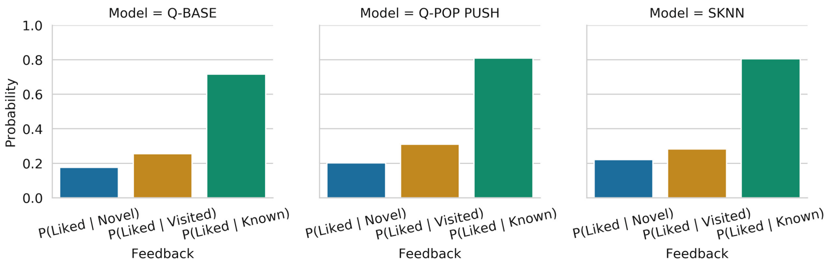


Fig. 5. Probability that a user likes a suggested item given that she visited, knew but not visited, or is unaware (novel item) of it (Source: authors)

The novel POIs recommendations generated by *SKNN* and *Q-POP PUSH* are liked more (20% and 22%) than those produced by *Q-BASE* (17%). This is likely due to the fact that often *Q-BASE* suggests unpopular items and users may find hard to evaluate them. For instance, *Q-BASE* often suggests "Porta della Mandorla", a door of "Duomo". This is a niche item and surely less attractive than "Duomo" itself.

Moreover, in the post experiment survey, participants declared that it is difficult to like something that is unknown. In fact, the probability that a user likes a recommended POI that she has visited tends to be much larger. This probability is 31% and 28% for *Q-POP PUSH* and *SKNN* respectively. *Q-BASE* also here performs worse (26%). The performance difference is likely to be due to the fact that both *SKNN* and *Q-POP* tend to recommend popular POIs (easier to judge), whereas *Q-BASE* recommends more "niche" items. The conclusion above is further supported by the measured probability that a user will like an item that she knows: *Q-POP PUSH* and *SKNN* suggest items that will be liked with a higher probability (81% and 80%) than *Q-BASE* (71%). Interestingly, users like known but not yet visited items much more than those already visited and even less the novel items. This further shows that users tend to like recommendations for items they are familiar with but they have not yet experienced.

6 Conclusions and Future Work

In this paper the results of an on line study aimed at assessing the performance of two IRL-based next-POI recommendation models are reported and discussed. The analysis started by hypothesising that users like more the recommendations produced by a specific IRL-based model (*Q-BASE*) and its poor offline precision, compared to KNN approaches, is because its recommendations are not influenced by item popularity. For that reason a new hybrid model called *Q-POP PUSH*, which deviates from the pure optimization of the reward used in *Q-BASE*, and suggests more popular items, was designed.

It is shown that *Q-BASE* excels in suggesting novel items, whereas *SKNN* and *Q-POP PUSH* suggest items that are generally “liked” more. It is also shown that if we consider the combined user's feedback “liked and novel”, i.e., recommendations that are liked and novel to the user, *Q-BASE* outperforms both *SKNN* and *Q-POP PUSH*. Hence, it is shown here that *Q-BASE* may be able to better accomplish the main task of a RS for tourism: suggesting interesting POIs that are unknown to the user.

Another conclusion of the experiments is that *Q-POP PUSH* can be used whenever the goal is to optimize the user satisfaction for the recommendations, if the suggested POIs should combine novel and known items. A specific advantage of this method relies on the fact that it is possible, by fine tuning the importance of the popularity score in the *Q-POP PUSH* POI scoring formula, to obtain recommendations with a desired level of popularity.

It is worth noting that the benefits and issues of the proposed models were identified by means of a web-based study where users evaluated a hypothetical scenario. But, it is necessary now to test the models integrated in a system accessed by tourists while they are at the destination. This will be accomplished next; we have developed a tailor made system that supports tourists on the move while exploring a smart destination.[3]

Acknowledgement. The research described in this paper was developed in the project Suggesto Market Space, which is funded by the Autonomous Province of Trento, in collaboration with Ectrl Solutions and Fondazione Bruno Kessler.

[3] www.wondervalley.unibz.it, https://beacon.bz.it/wp-6/beaconrecommender/.

References

1. Ricci F, Rokach L, Shapira B (2015) Recommender systems: introduction and challenges. In: Ricci F, Rokach L, Shapira B (eds) Recommender systems handbook, pp 1–34
2. Martín MBG (2005) Weather, climate and tourism a geographical perspective. Ann Tour Res 32(3):571–591
3. Ahn D, Park H, Yoo B (2017) Which group do you want to travel with? A study of rating differences among groups in online travel reviews. Electron Commer Res Appl 25:105–114
4. van Loon R, Rouwenda J (2017) Travel purpose and expenditure patterns in city tourism: evidence from the amsterdam metropolitan area. J Cult Econ 41(2):109–127
5. Xiang Z, Wang D, Fesenmaier DR (2013) Adaptive strategies to technological change: understanding travellers using the internet for trip planning. In: Xiang Z, Tussyadia I (eds) Information and communication technologies in tourism 2014. Springer, Cham, pp 411–423
6. Massimo D, Ricci F (2019) Clustering users' POIs visit trajectories for next-POI recommendation. In: Information and communication technologies in tourism 2019, ENTER 2019, Proceedings of the international conference in Nicosia, Cyprus, 30 January–1 February 2019, pp 3–14
7. Massimo D, Ricci F (2018) Harnessing a generalised user behaviour model for next-poi recommendation. In: Proceedings of the 12th ACM conference on recommender systems, RecSys 2018, Vancouver, BC, Canada, 2–7 October 2018, pp 402–406
8. Ng A, Russell S (2000) Algorithms for inverse reinforcement learning. In: Proceedings of the 17th international conference on machine learning - ICML 2000, pp 663–670
9. Jannach D, Lerche L (2017) Leveraging multi-dimensional user models for personalized next-track music recommendation. In: Proceedings of the symposium on applied computing - SAC 2017, pp 1635–1642
10. Wang HJ, Shen H, Ouyang W, Cheng X (2018) Exploiting poi-specific geographical influence for point-of-interest recommendation. In: IJCAI
11. Zhang C, Zhang H, Wang J (2018) Personalized restaurant recommendation method combining group correlations and customer preferences. Inf Sci 454–455:128–143
12. Palumbo E, Rizzo G, Baralis E (2017) Predicting your next stop-over from location-based social network data with recurrent neural networks. In: RecSys 2017, 2nd ACM international workshop on recommenders in tourism (RecTour 2017). CEUR Proceedings, vol 1906, pp 1–8
13. Huang H, Gartner G (2014) Using trajectories for collaborative filtering-based poi recommendation. IJDMMM 6:333–346
14. Babes-Vroman M, Marivate V, Subramanian K, Littman M (2011) Apprenticeship learning about multiple intentions. In: Proceedings of the 28th international conference on machine learning - ICML 2011, pp 897–904

From Pictures to Travel Characteristics: Deep Learning-Based Profiling of Tourists and Tourism Destinations

Mete Sertkan(✉), Julia Neidhardt, and Hannes Werthner

TU Wien, Research Unit of E-Commerce, Vienna, Austria
{mete.sertkan,julia.neidhardt,hannes.werthner}@tuwien.ac.at

Abstract. Tourism products are complex and strongly tied to emotions. Thus, it is not easy for consumers to explicitly communicate their travel preferences, needs, and interest, especially in the early phase of travel decision making. In the spirit of the idiom *"A picture is worth a thousand words"* we utilize pictures to characterize tourists as well as tourism destinations in order to build the foundations of a recommender system (RS). In this work all entities (i.e., users and items) are characterized using the Seven-Factor Model. Pre-labelled pictures are used in order to train convolutional neural networks (CNN) in a transfer learning manner with the goal to extract the Seven-Factors of a given picture. We demonstrate that touristic characteristics can be extracted out of pictures. Furthermore, we show that those characteristics can be aggregated for a collection of pictures, such that a representation of a user or a destination can be determined respectively.

Keywords: User modelling · Recommender systems · Tourism · Deep learning · Seven-Factor Model

1 Introduction

Tourism products are complex and strongly tied to emotions [25]. Thus, it is not easy for consumers to communicate their travel preferences, needs, and interest, especially in the early phase of their travel decision making process. In the spirit of the idiom *"A picture is worth a thousand words"* previous work has utilized pictures to characterize users and thus to counter those difficulties. In [17,18] pictures are used as a pivotal tool to elicit the travellers' preferences, needs and personality using a gamified way of picture selection and thus avoiding tedious questionnaires. Other approaches use low-level and/or high-level features of user generated pictures (e.g., Instagram, Flickr, etc.) to determine the users' personality traits or to classify a tourist within a basic taxonomy [6–8,21]. However, these works mainly focus on characterizing the user, i.e. determining a vector-representation of a user, where each dimension of the respective vector-space corresponds to a certain characteristic.

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 142–153, 2020.
https://doi.org/10.1007/978-3-030-36737-4_12

Ideally, such methods should be applicable universally and thus also to the pictures of the recommended items (i.e., tourism products) in order to characterize them, such that user and items are easily comparable. In other words, a vector-representation of the item (e.g., destination, attraction, etc.) and the user should be able to be determined by the same picture-based approach. Ultimately, this will enable to recommend a tourism product to a traveller based on some distance measure. To address this challenge, we present a novel concept to profile tourists and tourism destinations by utilizing pictures, e.g., a collection of images of a users' social media stream or a collection of pictures of a tourism destination provided by a destination management organization (DMO).

2 Background

In this section we briefly discuss the literature on tourist and tourism destinations characterizations. Furthermore, the Seven-Factor Model is introduced.

2.1 Characterization of Tourists

Taxonomies of tourists (i.e., preferences, needs, behaviour, and/or personality) have been of interest to researchers since decades [1,10,17–19,26]. Gretzel et al. showed that it is merit to use such taxonomies for recommending touristic activities and, in turn, tourism destinations [12]. In this context, a well-established taxonomy, capturing the preferences and needs of travellers, are the 17 tourist roles of Yiannakis and Gibson [10]. Another well-known widely used but domain-independent model, capturing the personality of users, is the Five-Factor-Model also known as "Big Five" personality traits [11]. Personality plays an important role in the decision-making-process and consequently for RS. It has been shown that personality correlates with user preferences [2]. Furthermore, personality traits tend to be stable over time (i.e., long-term behaviour), whereas preferences and needs might change occasionally (i.e., short-term behaviour). Neidhardt et al. [17,18] developed a Seven-Factor Model of travel behavioural patterns by combining both the "Big Five" personality traits and the 17 tourist roles via factor-analysis. Hence, the Seven-Factor-Model is capturing long-term and short-term behaviour of travellers. In this work users are represented by their Seven-Factor representation.

Traditionally, travellers are characterized, i.e., mapped onto a taxonomy, by filling out tedious questionnaires. But as already mentioned, people have difficulties in explicitly expressing their preferences and needs, especially in the early phase of the travel decision making [27]. In [17,18] also a picture-based approach to elicit a users preferences and needs (i.e., Seven-Factor representation) was introduced, where the user has simply to select pictures out of a pre-defined set of 63 pictures. In this way, they avoided tedious questionnaires and thus the difficulty of explicit preference stating. In comparison, the approach we propose is more flexible, since it is not restricted to a pre-define picture set. Instead, people can provide, for example, pictures of their last trip or a collection of images provided by a (travel) influencer they like. In the matter of characterizing tourists, the most similar approach to our work is introduced in [8], where CNNs are used to characterize users based on images of their social media streams. However, in this work we are considering preferences and personality of tourists by using the Seven-Factor Model as basis and furthermore we are treating tourists as a mixture of the Seven-Factors, whereas in [8] tourist are classified into five arbitrarily defined classes.

2.2 Characterization of Tourism Destinations

There is no common way of characterizing tourism destinations. In many cases tourism destinations are grouped by their geographical characteristics (e.g., rural, urban, coastal, etc.), with aggregated characteristics of the underlying attractions, and/or with aggregated characteristics and/or behaviour of their visitors. For example, one can use the travellers' mobility data gathered from social networks in order to characterize tourism destinations [4,5,22]. Another example closely related to this work is [13], where first steps into the direction of a comprehensive taxonomy of tourism products is set and later the taxonomy is used in order to map the products onto the Seven-Factor Model. In [23,24] a cluster analysis is conducted to group destinations with similar characteristics such as energetic cities, tranquil seaside resorts and more. Furthermore, in [23,24] similar to the aim of this work tourism destinations are described with the Seven-Factor Model, but by utilizing hard facts.

2.3 The Seven-Factor Model

In this work both tourists and tourism destinations are mapped onto the Seven-Factor Model, which can be summarized as following [17,18]:

Sun & Chill-Out (F1) - a neurotic sun lover, who likes warm weather and sun bathing and does not like cold, rainy or crowded places;
Knowledge & Travel (F2) - an open minded, educational and well-organized mass tourist, who likes travelling in groups and gaining knowledge, rather than being lazy;
Independence & History (F3) - an independent mass tourist, who is searching for the meaning of life, is interested in history and tradition, and likes to travel independently, rather than organized tours and travels;
Culture & Indulgence (F4) - an extroverted, culture and history loving high-class tourist, who is also a connoisseur of good food and wine;
Social & Sports (F5) - an open minded sportive traveller, who loves to socialize with locals and does not like areas of intense tourism;
Action & Fun (F6) - a jet setting thrill seeker, who loves action, party, and exclusiveness and avoids quiet and peaceful places;
Nature & Recreation (F7) - a nature and silence lover, who wants to escape from everyday life and avoids crowded places and large cities.

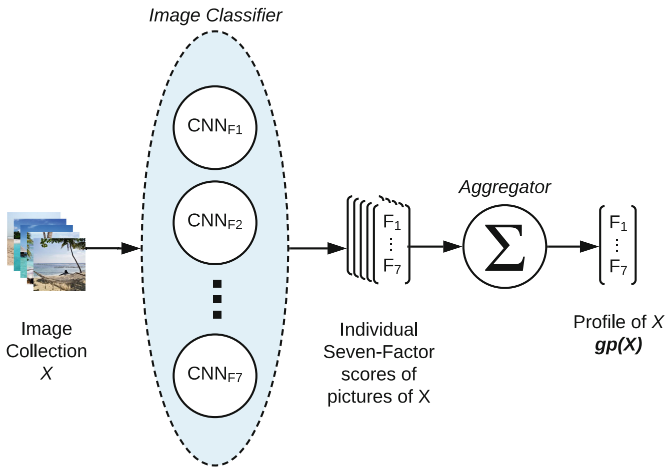


Fig. 1. Core concept - A *Generic Profiler* (authors' own figure).

3 Characterizing Tourist and Tourism Destinations

The core concept of our approach is depicted in Fig. 1. The main idea is, given any image collection (either of a user or of an item) to determine a vector-representation of the collection, i.e., a profile. In case the collection is provided by a user, the profile can be accounted as preferences and needs of the user (i.e., preference model). On the other hand, if the collection consists of images of an item, for example, a tourism destination, the profile can be seen as a description (i.e., characteristics) of the respective item. Such a *Generic Profiler* consist of two key components, namely an *Image Classifier* and an *Aggregator*, which are introduced and discussed in this section.

3.1 Image Classifier

In practice, very few researchers are training CNNs from scratch, since it requires a huge amount of pre-labelled images and much computational power (e.g., many GPUs over weeks, etc.). Instead, it is common to use pre-trained models in a Transfer Learning manner. There are two common ways two utilize pre-trained CNNs (i.e., two common Transfer Learning scenarios): (1) One can use existing CNNs as a feature extractor and replace only the last fully connected layer without touching the weights of the remaining network (2) One can replace the last fully connected layer and fine-tune the whole CNN for the respective purpose [15].

Also, this work utilizes existing pre-trained CNNs. More specifically, a pre-trained pytorch[1] implementation of ResNets which were introduced in [14] is used. In particular ResNet50, a 50 Layer implementation of ResNets, is adapted. This pre-trained model is capable to classify images into 1000 classes and was

[1] https://pytorch.org/hub/pytorch_vision_resnet/.

trained on ImageNet [3], a huge image data set with millions of labelled images. The data set used in this work is limited to 300 images per class (i.e., 300 pictures per factor of the Seven-Factor Model), but contentwise similar to the images of the ImageNet data set (e.g., pictures of everyday life, nature, urban areas etc.). In case of a limited but contentwise similar data set, it is recommended to use the first described Transfer Learning scenario [15]. Hence, in this work the ResNet50 model is used as a feature extractor and only its last fully connected layer, which outputs class probabilities for 1000 ImageNet classes is exchanged and trained.

The factors of the Seven-Factor Model were obtained via factor analysis and thus are independent of each other.Hence, for each factor an own CNN is trained, which takes an image as input and returns a score for the respective factor (i.e., a probability of an image belonging to the respective factor). In each case the last layer of the ResNet50 model is replaced by a linear layer with just one node, since only one class (i.e., factor) is considered per model. Furthermore, a SoftMax function is used in order to obtain a score between zero and one (i.e., a probability).Consequently, the depicted *Image Classifier* in Fig. 1 actually combines the seven individual CNNs (i.e., CNN_{F1}, CNN_{F2}, CNN_{F3}, CNN_{F4}, CNN_{F5}, CNN_{F6}, CNN_{F6}, and CNN_{F7}) and thus returns a vector of Seven-Factor scores (i.e., [*F1* score, *F2* score, *F3* score, *F4* score, *F5* score, *F6* score, *F7* score]) for a given picture.

The data set in use is provided by an Austrian Tourism company and consists of 300 images (i.e., 150 positively and 150 negatively associated images) for each factor. For example, a picture of sun bathing people on the beach is a positive example for the factor *Sun & Chillout* and a picture of a rainy day in an urban area is a negative one. Each model is trained with 200 images (i.e., 100 positive and 100 negative) and validated with 100 images (i.e., 50 positive and 50 negative). In addition, the training data is enriched by using data augmentation techniques (i.e., random crop and horizontal flip) [15]. Furthermore, stochastic gradient descent (SGD) is used as an optimizer in combination with cross entropy loss as the loss function [15].

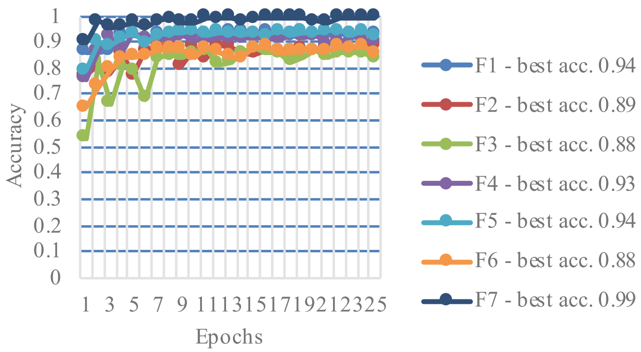


Fig. 2. Validation accuracies (authors' own figure).

Figure 2 shows the validation performance of each model. One can see that the pre-trained models are enabling a proper start performance with validation accuracies between 53% and up to 90% already after one epoch of training. Overall, all seven models show a good performance with best validation accuracies of greater or equal to 88%, in particular the CNN model of the factor *F7*, where 99% of the images in the validation set are correctly classified. The results are very promising, but we are aware that the used data set (i.e., the selection of pictures in the data set) also plays a big role, which will be discussed in more detail in Sect. 4.

3.2 Aggregator

For each image in a given collection the *Image Classifier* returns a vector f^p of Seven-Factor scores, i.e., the Seven-Factor representation of an image. Hence, the main role of the *Aggregator* is to aggregate the individual Seven-Factor representations f_i^p of a collection X with $i = 1...N$ images into one representation which characterizes the whole collection. In this work the aggregation is implemented as a simple mean and thus the *Generic Profile* of a collection X $gp(X)$ is defined as following:

$$gp(X) = \frac{1}{N} \sum_{i=1}^{N} f_i^p$$

Despite its simplicity, the *Aggregator* is modelled as an own component to enable flexibility for future work. For example, one might use the ordering of the images or other sources of information for the profile generation.

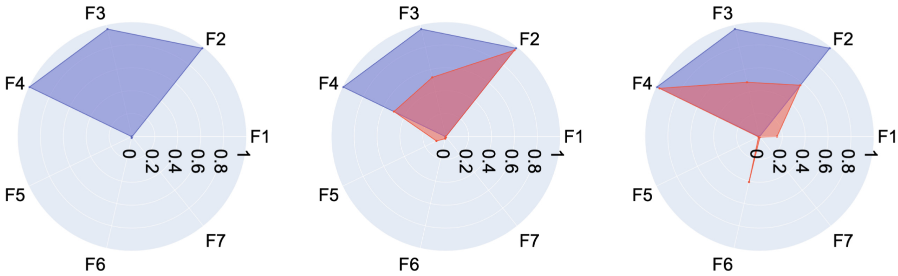
3.3 Profile Development and Validation

Figure 4 illustrates the development of a profile using the pictures listed in Fig. 3 as input. In Fig. 4a the output of the *Generic Profiler* for a single image collection, with Fig. 3a as its only entry, is shown. One can see that factors associated with culture, history, and knowledge (i.e., *F2*, *F3*, and *F4*) are scoring high. The remaining factors are scoring with almost zero, which is plausible, since there are no signals in the image for sports, sun, action, or nature.

(a) townhall [16] (b) hopon [20] (c) gourmet [9]

Fig. 3. Example pictures for profile development. Pictures are taken from *Wikimedia Commons* (https://commons.wikimedia.org) and *Flickr* (https://www.flickr.com).

The remaining sub-figures in Fig. 4 also present the same profile as in Fig. 4a in blue and in addition the output of the *Generic Profiler* for the image shown in Fig. 3a combined with the other images listed in Fig. 3 in red.



(a) townhall (b) townhall-hopon (c) townhall-gourmet

Fig. 4. Profile development (authors' own figures).

The profile of a collection, which consists of Fig. 3a and b, is presented in Fig. 4b. In comparison to the initial profile (Fig. 4a), one can see that the factors *F3* and *F4* have decreased. Such a change is in line with the description of those factors, since tour buses are negatively associated with independent travellers as well as with high-class travellers. On the other hand, the factor *F2* is still scoring high. This is reasonable, since hop-on-hop-off is positively associated with well-organized mass tourists.

Figure 4c presents the profile of a collection, which consists of Fig. 3a and c. Compared to the initial profile (Fig. 4a), one can observe a decrease in the factors *F2* and *F3*. This is in line with the respective factors' description, since both factors have mass tourism aspects and thus they are negatively associated with exclusivity and high-class. On the other hand, the factor *F4* is described as a high-class cultural traveller and thus shows a high score as expected. Furthermore, one can observe an increase in the factor *F6*, which is in line with its description as a jet setter, who likes exclusiveness.

Next, the proposed *Generic Profiler* is compared with the picture-based approach introduced in [17,18]. In [17,18] a user has to select three to seven pictures out of a predefined set of 63 pictures. Based on the selection, the respective user's profile is determined. Two different profiles are created using this approach. Then the selected images are used as an input for the CNN approach introduced in this work. Finally, the outcomes are compared.

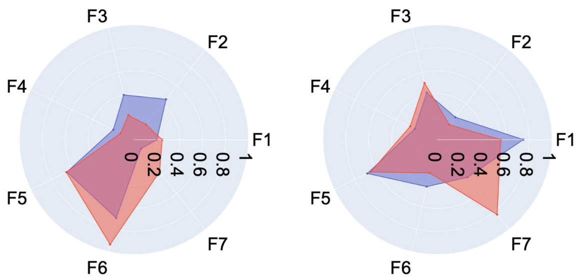
Figure 7 shows in red the outcome of the *Generic Profiler* if the image collection *Action* (Fig. 5) is used as input, whereas the baseline (i.e., the profile created with the approach introduced in [17,18]) is depicted in blue. As expected, the factor *F6* scores the best in both approaches and also the factor *F5* shows an increased score in both, since the considered collection contains two different kinds of sports, namely paragliding and snowboarding. With a *F7* score of 0.36

Fig. 5. Pictures of the example collection *Action* (authors' own pictures).

the proposed CNN approach also captures the nature aspect (i.e., mountains) of the images, whereas the corresponding score in the baseline is 0.08. On the other hand, the mass touristic aspect (i.e., carnival) is not covered compared to the baseline, where the factors *F3* and *F2* are scoring with 0.4 and 0.45 respectively.

Fig. 6. Pictures of the example collection *Sea* (authors' own pictures).

The resulting profiles of the image collection *Sea* (Fig. 6) are presented in Fig. 7b, where the result of the *Generic Profiler* is shown in red and the result of the picture-based approach introduced in [17,18] (i.e., baseline) is shown in blue. Overall, both approaches show similar results, except in case of the factor *F7*, where the CNN approach returns a score of 0.84 and the baseline approach only a score of 0.42. Since all pictures in the collection are related to nature and since there are no signals for crowdedness and mass tourism, a higher score in *F7* is reasonable.



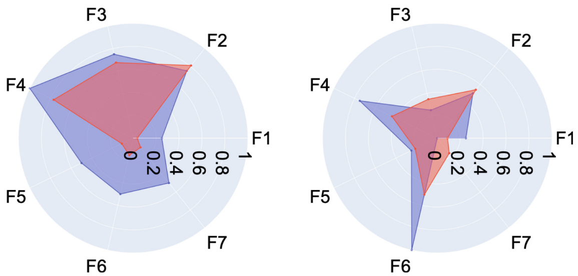
(a) action (b) sea

Fig. 7. Profiles of the example collections (authors' own figures).

Finally, we compare the experts' Seven-Factor scoring of two destinations, namely Vienna and Las Vegas, with the outcome of the *Generic Profiler*. The experts' Seven-Factor scorings are taken from [23,24], where experts of an Austrian eTourism company mapped more than 300 tourism destinations onto the Seven-Factor Model. As input for the *Generic Profiler*, all illustrations of the Things to do list in the Google travel guide[2] of each destination are used. The resulting profiles are presented in Fig. 8, where the experts' opinion is shown in blue and the results of our approach in red.

In case of Vienna (Fig. 8a), one can see that the experts' opinion of Vienna is more comprehensive, knowing that there is a lot of nature, possibilities for sports, and places to go out. This shortcoming of the introduced CNN approach is rather caused by the picture collection than by the model itself, since most pictures in the collection are about cultural, historical, and architectural sights.

In case of Las Vegas (Fig. 8b), the profiles are similar in shape, but relevant characteristics of the destination are clearly highlighted by the experts. Factors positively associated with high-class, exclusivity, luxury, thrill-seeking like *F6* and *F4* are scoring relatively higher in the experts' rating compared to the outcome of the proposed approach. Again, the used collection of pictures might not be reflecting the actual characteristics of the destination and the CNN approach heavily relies on the collection of pictures.



(a) Vienna (b) Las Vegas

Fig. 8. Profiles of the example destinations (authors' own figures).

4 Discussion

The *Image Classifier* shows promising results with validation accuracies between 88% to 99% depending on the respective factor. As already mentioned, this heavily relies on the data set used for training and testing the underlying models. In this work, experts of an Austrian eTourism company were asked to deliver positive and negative example images for each factor of the Seven-Factor Model. There was no other influence or information exchange regarding the picture selection or the labelling. Thus, it is not clear how the data set was built. The data

2 https://www.google.com/travel.

acquisition process should be done systematically in order to comprehensively capture the Seven-Factors and avoid bias. An approach could be to define a taxonomy of tourism related pictures or tourism products, which can be related to the Seven-Factors. Then the data acquisition can be conducted based on such a taxonomy. Work in this direction has already begun [13] and will be continued and improved in the future.

Our approach is closely related to the picture-based approach introduced in [17,18] and can be seen as a logical continuation in this direction, which uses recent advances in computer vision and neural network research. Compared to [17,18], the followed approach in this work offers more flexibility. The profile generation does not rely on a fixed set of pictures. Hence, users can upload pictures that they like or they can grant access to their social media streams, from which the respective user profiles can be extracted. The fixed set of pictures used in [17,18] and their relation to the (i.e., loading with the) Seven-Factors were developed via user studies, workshops and more. Thus, pictures of this set within that approach have also a symbolic character. For example, a picture of a carnival dancer in Rio de Janeiro is also associated with the factor *F1*, whereas our approach relies more on the content and thus cannot build such a relation.

We demonstrated that characterizing destinations using a collection of pictures is a reasonable approach. However, we also showed that this approach has its own challenges. A big challenge is to define (i.e., select) a proper collection of pictures which comprehensively characterizes the respective destination. A wrong selection of pictures might lead to misleading results. For example, taking only a collection of pictures from the social media stream of a nature loving influencer might lead to high *F7* scores in destinations, where it is not expected. In future work, it is planned to combine and compare different sources in order to extract a comprehensive view of the destinations.

5 Conclusion

In this paper we introduced a novel way to characterize tourist and tourism destinations out of a collection of pictures. The main aim was, given an image, to determine its Seven-Factors scores and furthermore to aggregate the individual Seven-Factor scores of a set of images into one Seven-Factor representation, which then can be accounted as the profile of the respective image collection (i.e., depending on the source of the collection, either user profile or destination profile). We trained seven CNNs, each for one factor of the Seven-Factor Model. Overall, the trained CNN models showed promising results, with validation accuracies between 88% up to 99% depending on the factor. Furthermore, we demonstrated the profile development process by combining different pictures and showing their individual influence. Finally, we compared the proposed approach with the picture-based approach introduced in [17,18] and with the Seven-Factor scoring of experts collected in [23,24].

To conclude, we demonstrated that the introduced concept is a feasible way of automatically profiling tourism destinations or a reasonable form of implicit preference elicitation. However, we are aware of the limitations and challenges of the followed approach. The trained CNNs were evaluated with a holdout test set, but the profile development and the resulting profiles are only exemplary demonstrated and discussed. Future work will consider a more thorough and comprehensive evaluation of the resulting user and destination profiles. For example, by analysing the correlation of the destination profiles generated by the proposed approach with the experts' opinion; or by conducting a user study and comparing the perceived profile with the user profile elicited by the proposed approach. As already mentioned, the data acquisition will be conducted more systematically by developing and using a taxonomy of tourism related pictures or tourism products and furthermore a relatively bigger data set will be used in future work. Finally, a more sophisticated *Aggregator* than the current naive approach is planed, where the order and/or the probability distribution of the pictures in a collection is utilized.

References

1. Cohen E (1972) Toward a sociology of international tourism. Soc Res 39:164–182
2. Delić A, Neidhardt J, Werthner H (2016) Are sun lovers nervous? e-Review of Tourism Research (eRTR) ENTER 2016 Special issue
3. Deng J, Dong W, Socher R, Li LJ, Li K, Fei-Fei L (2009) ImageNet: a large-scale hierarchical image database. In: 2009 IEEE conference on computer vision and pattern recognition. IEEE, pp 248–255
4. Dietz LW (2018) Data-driven destination recommender systems. In: Proceedings of the 26th conference on user modeling, adaptation and personalization. ACM, pp 257–260
5. Dietz LW, Weimert A (2018) Recommending crowdsourced trips on wondary. In: Proceedings of the RecSys workshop on recommenders in tourism
6. Ferwerda B, Schedl M, Tkalcic M (2015) Predicting personality traits with Instagram pictures. In: Proceedings of the 3rd workshop on emotions and personality in personalized systems 2015. ACM, pp 7–10
7. Ferwerda B, Tkalcic M (2018) Predicting users' personality from Instagram pictures: using visual and/or content features? In: Proceedings of the 26th conference on user modeling, adaptation and personalization. ACM, pp 157–161
8. Figueredo M et al (2018) From photos to travel itinerary: a tourism recommender system for smart tourism destination. In: 2018 IEEE fourth international conference on big data computing service and applications (BigDataService). IEEE, pp 85–92
9. Foodsters C (2019) Pinenut-herb crusted rack of lamb with portabella mushroom, brussels sprouts, and black garlic. https://www.flickr.com/photos/cityfoodsters/16468472701/. Accessed 19 Sept 2019. Licensed under CC BY-SA 2.0 (https://creativecommons.org/licenses/by-sa/2.0)
10. Gibson H, Yiannakis A (2002) Tourist roles: needs and the lifecourse. Ann Tourism Res 29(2):358–383 Kindly note that Refs. [9, 16, 20] are given in list but not cited in text. Please cite in text or delete from list
11. Goldberg LR (1990) An alternative "description of personality": the big-five factor structure. J Pers Soc Psychol 59(6):1216

12. Gretzel U, Mitsche N, Hwang YH, Fesenmaier DR et al (2006) Travel personality testing for destination recommendation systems. Destination recommendation systems. In: Behavioural foundations and applications. Oxfordshire: CABI, pp 121–136
13. Grossmann W, Sertkan M, Neidhardt J, Wethner H (2019) Pictures as a tool for matching tourist preferences with destinations. In: Personalized human-computer interaction. De Gruyter Oldenbourg
14. He K, Zhang X, Ren S, Sun J (2016) Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 770–778
15. Karpathy A (2019) CS231n convolutional neural networks for visual recognition. http://cs231n.github.io/. Accessed 20 June 2019
16. Ledl T (2019) Wien rathaus hochaufloesend. https://commons.wikimedia.org/wiki/File:Wien_Rathaus_hochaufl%C3%B6send.jpg. Accessed 19 Sept 2019. Licensed under CC BY-SA 4.0 (https://creativecommons.org/licenses/by-sa/4.0)
17. Neidhardt J, Schuster R, Seyfang L, Werthner H (2014) Eliciting the users' unknown preferences. In: Proceedings of the 8th ACM conference on recommender systems, RecSys 2014. ACM, New York, pp 309–312. http://doi.acm.org/10.1145/2645710.2645767
18. Neidhardt J, Seyfang L, Schuster R, Werthner H (2015) A picture-based approach to recommender systems. Inf Technol Tourism 15(1):49–69
19. Pearce P et al (1982) The social psychology of tourist behaviour
20. Photos ST (2019) Dscf8575. https://www.flickr.com/photos/fwc439h/3855936048/. Accessed 19 Sept 2019. Licensed under CC BY-SA 2.0 (https://creativecommons.org/licenses/by-sa/2.0)
21. Segalin C, Perina A, Cristani M, Vinciarelli A (2016) The pictures we like are our image: continuous mapping of favorite pictures into self-assessed and attributed personality traits. IEEE Trans Affect Comput 8(2):268–285
22. Sen A, Dietz LW (2019) Identifying travel regions using location-based social network check-in data. Front Big Data 2:12
23. Sertkan M, Neidhardt J, Werthner H (2018) Mapping of tourism destinations to travel behavioural patterns. In: Information and communication technologies in tourism 2018. Springer, pp 422–434
24. Sertkan M, Neidhardt J, Werthner H (2019) What is the "personality" of a tourism destination? Inf Technol Tourism 21(1):105–133
25. Werthner H, Klein S (1999) Information technology and tourism: a challenging ralationship. Springer, Wien
26. Yiannakis A, Gibson H (1992) Roles tourists play. Ann Tourism Res 19(2):287–303
27. Zins AH (2007) Exploring travel information search behavior beyond common frontiers. Inf Technol Tourism 9(3–1):149–164

Virtual and Augmented Reality

Enhancing Train Travel with Augmented Reality for Smartphones: The "Tales on Rails" Project

Heidrun Föhn(✉), Sonja Böckler, Fabio Baumgartner, René Bauer, and Ulrich Götz

Zurich University of the Arts, Zurich, Switzerland
heidrun.foehn@zhdk.ch

Abstract. The project "Tales on Rails" describes the research and development of an augmented reality game that can be played on trains with smartphones. The project addresses tourism changes in the digital age; the ubiquitous use of smartphones alters a tourist's travel experience, from accessing timetables to conveying cultural and historic information or transforming traditional souvenirs. "Tales on Rails" tested a smartphone application allowing tourists to play a game about a crime story on the route between the cities of Lucerne and Interlaken, which is operated by the Swiss railways company zb Zentralbahn AG. The game directly references the environment outside the train on this route as well as cultural themes about the region. The game's progress is linked to the position of the train, successively unlocking its content on the route. The game is tailored for use by 20 to 30-year-old leisure travellers, and optimized for a group experience in which two to four players collaborate on solving the game; thus, group dynamics during the gaming experience could be investigated. The game features a technologically ambitious program with augmented reality game elements, while minimizing negative impacts on playability by environmental influences such as seasonal and weather conditions. The technical complexity of the concept could be expanded in future iterations. The project "Tales on Rails" was released in July 2019 as fully functional game application in the Google Play Store and the Apple Store.

Keywords: Gamification in tourism · Tourism · Digital experience · Tourism · Augmented reality game · AR game · Digital souvenir

1 Introduction

Tourism is directly affected by digitization [10], including Augmented (AR), Virtual Reality (VR), the Internet of Things, and Artificial Intelligence, which are increasing technological complexity and changing the industry [9]. The greatest impact on tourism is associated with mobile technologies [10]. Through the emergence of an "experience economy," the use of play and games has become increasingly important [3, 4]. AR technology for smartphones has led to a comprehensive expansion of gaming into everyday life, as mobile AR devices add a digital layer to the physical world [5]. Such games can result in collaborative gameplay, strengthen personal contacts, and allow players to discover events, have fun, and learn together [5].

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 157–168, 2020.
https://doi.org/10.1007/978-3-030-36737-4_13

In order to benefit from these opportunities, the tourism sector needs to adapt its marketing strategies and plan to implement technological innovation [2]. For zb Zentralbahn AG (ZB), a subsidiary of Swiss Federal Railways (SBB), the question arose as to how the potential of mobile and location-based gaming could be used to create an incentive for increasing tourism travel on the ZB panorama routes. Such pervasive games extend into the physical realm in an exciting and commercially promising way [8], and they also appear to be especially suitable for addressing the target group of 20 to 30-year-olds, for whom social interaction, participation, and co-creation of experiences (also occurring in virtual worlds) play an important role in their leisure activities. The target group is familiar with internet-based technologies and spends significant time on their smartphones [16].

This paper presents the empirical results of the project “Tales on Rails,” which researched and developed an AR game application for tourists to use on their smartphones. An iterative design process between the Zurich University of the Arts (ZHdK) and ZB investigated how the travel experiences of the target group could be enhanced. The paper presents the design of a location-based AR game played inside ZB trains, which are in motion as the game progresses. It provides insight into the design process, as well as the limitations faced when optimizing the user experience of AR gaming in a moving train. It describes how the application was accepted by the target group, how the behavior of travelers in the train was affected, and where the challenges in the technical implementation lay. The results of iterative prototyping and playtesting were evaluated through surveys and interviews with laypeople and experts in a final analysis.

2 Related Work

Related work shows that the defined, limited spaces of compartments in moving trains appear to be an ideal frame for enhancing the experience of group tourism with location-based multiplayer games. “Tales on Rails” derived its design principles from:

Motivational Design. Competence, autonomy, and connectedness constitute the theory of self-determination [15], in which the increase or decrease in intrinsic and extrinsic motivation depends on an environment that promotes motivation through individual competences, solidarity, and autonomy [3]. Lazzaro [11] argues that games are played because of the emotions they generate. In research at XEODesign [20], the *Four Fun Keys Model* explains how a range of emotions can be identified and evoked. The model categorizes games that create *hard fun* by presenting challenges while providing the steps to get there; *easy fun* results from interaction, exploration, and imagination; the creation of real-world benefits, or changes in the players’ behaviors creates *serious fun*; integrating a community boosts *people fun* [11].

Cooperative Games. Cooperative Games are characterized by players forming a group to coordinate their actions and share their winnings [1]. In live escape games, a popular sub-genre of pervasive games, groups of players solve puzzles in order to escape enclosed spaces [19], relying on the players’ ability to cooperate. “Import-Export Rotterdam” [6] combines reality with VR, since the player’s real-world positions affect their positions in a game. “The Escape Train” [13] connects location-based cooperative gaming (solving a crime story during a train journey) with a live broadcast of the game's actions. Asymmetric gameplay demands collaborative communication between players who influence the game in separate but complementary ways, for example, as found in the game "Keep Talking and Nobody Explodes" [7].

AR-Based Games. Current AR-based games add a virtual layer upon the physical world with AR-technology, leading to a combination of physical and digital environments. Through this superimposition, real locations can become the background used to tell fictional stories [18] or to even make historical events visible once again [17]. This principle was effectively demonstrated by the location-based AR game "Pokémon Go" [14], in which players competitively collect AR-generated game characters in public spaces. It was also reported that AR learning games resulted in "the enhancement of learning performance and the learning experience," and that "social interactions were encouraged" [12].

Reflecting such design principles, the players of "Tales on Rails" have to decide whether they prefer to master challenges competitively and autonomously for a personal high score, or collaboratively in order to reach a common goal. Building on a wide range of aspects of game motivation design, the group of players explores virtual AR locations, collects information, and solves puzzles. An AR representation of the typical scenery around the train invites them to discover details in a digital world, as well as to compare these elements to their physical counterparts outside the train.

3 Creating "Tales on Rails"

"Tales on Rails" addresses the changes of railway tourism in the digital age by providing an optimized solution for a collaborative, multiplayer smartphone game, thus enhancing the travel experience. The game can be played on a scenic alpine train route between the Swiss cities of Lucerne and Interlaken, a connection operated by ZB. The first game of "Tales on Rails" was published as "Die Tote am Berg" [Death in the Mountains], a part of the newly founded ZB series "Crime Line," for which further games are planned. Providing a visually attractive experience of AR-gaming, the game's setting closely relates to the scenic and cultural context outside the train.

3.1 A Digital, Location-Based Game Concept for Group Tourism

"Tales on Rails" both condenses and enhances tourist activities on a train journey: fictional literature, entertainment media, and information about the route merge into an entertaining smartphone game telling a fictional detective story. Since communicative exchange during travel is an essential group tourist experience, the game concept established an AR setting which can be explored by up to four players simultaneously or consecutively, much like several detectives examine the same site. The incentives range from the search for hidden clues to mere narrative entertainment; the players each decide for themselves whether they reach the goal collaboratively, or whether every player aims for an individual high score competitively.

The initial AR concept for “Tales on Rails” suggested complementing the environment outside the train with a superimposed AR layer on the players’ smartphones, e.g. with precise position data or stickers on train windows as AR triggers. But in contrast to successful AR solutions based on fixed locations for AR triggers [17], the design process revealed that the constantly moving position of the train resulted in an unreliable representation of AR elements, for example, because of shifting lighting conditions. While AR was still identified as an attractive feature for the game, “Tales on Rails” had to ensure reliability for public use.

Consequently, the use of AR shifted from directly complementing the landscape to an indirect, more narrative application. The AR elements were designed to maintain a strong visual link to the scenery outside the train (e.g. through a thorough analysis of the predominantly traditional building styles), but to connect this loosely to the game rather than becoming a necessary condition at a particular time or position along the journey. While the game still relates to the landscape outside, the AR triggers could be placed at the seating groups, thus ensuring reliable AR visualization (Fig. 1).

Fig. 1. “Tales on Rails” played by scanning the AR marker on the train table (source authors)

Although this approach differs significantly from the original concept, it had positive effects for the further development of the game:

- The attractiveness of an AR game could be accurately maintained, allowing a group of players to explore an AR game location together.
- The indirect link allows for easy playability in both directions of the journey, without making a player’s individual progress dependent on the train’s exact position.
- Reliable AR visuals for a location-based game could be ensured, while the player’s position (i.e. the train) is in motion.

This use of AR therefore does not primarily extend physical reality, but instead enables a special group experience: several player “detectives” can examine a 3D level for clues by simultaneously pointing their smartphones at a virtual crime scene.

Accordingly, significant effort also went into relating the players' actions to one another, and into linking the game's current status to the train's position, in order to create a digital group experience that corresponds with the scenic context outside the train. However, initial testing showed three problems: (1) that an unstable mobile phone signal was to be expected, due to geographic and climatic conditions on the route. To remain reliable, the game could not rely solely on positioning systems (e.g. GPS) to retrieve data; (2) the direct exchange of multiplayer data was prone to technical glitches, potentially disrupting gameplay; (3) requiring players' smartphones to connect with each other could create a discouraging entry barrier for new players.

It has been stated that "current developments in localization technologies still fail to deal with positioning uncertainty" [8]. The framework of "Tales on Rails" was deliberately designed to be as robust as possible, "as not to frustrate players or compromise their trust in the game engine" [8]. Therefore, any data exchange during the gameplay was dispensed with in order to avoid player frustration due to such technical difficulties. After completing the initial installation, the game indicates its start with a tutorial sequence at the beginning of the trip and reaches its core action in the middle of the train journey. Similar to the indirect link to the environment of the AR concept, the exchange of information between players is not conducted through direct mutual data exchange, but instead, by motivating overall group communication. At the same time, close attention was paid to ensuring that the game would not create any disruptions for fellow travellers not participating in the game.

3.2 Game Narration, Usability, and Visual Design

The game features a criminal story based on local traditions and fictional events. It describes a rural family drama about the primary character, a wealthy farmer, as well as his son, daughter, and daughter's husband. Starting with the theft of the farmer's pride and joy—an unusually valuable bull—the story's multi-linear plot uncovers the motives of various suspects, and eventually leads to the accidental tragic death of the farmer's daughter. A police detective moderates the plot and directly addresses the players, who solve the case by collecting story-based evidence, exploring locations, and exchanging clues. The game features two main means of interaction: a multi-linear dialog system communicating the game's instructions and narratives, and an object-based visualization representing the scenic setting (Fig. 2):

- A 2D interface conveys all instructions and story elements, stores clues and information in submenus, and provides a structure similar to common chat applications for dialogues and interrogations with suspects. The text interfaces are triggered by looking up stored memos, or when a player interacts with a game character.
- 3D interactive game levels are displayed using an AR perspective. By focusing the smartphone's camera on an AR marker sticker placed at every seating group in the train, a 3D diorama of a game level is displayed.

The players solve the case by collecting story-based evidence, exploring locations, and exchanging clues. For this reason, the gameplay includes various aspects of search and combination games. A newly entered game level (a 3D AR diorama displaying a

Fig. 2. Three interface examples showing 3D dioramas, pop-up hints, and 2D story information (source authors)

game location) names a given number of clues that can be found in it, but does not indicate their exact position. Once a player has found a clue by closely searching the level (possibly in exchange with a fellow player), the new piece of evidence is marked in the AR diorama, saved as text input in the evidence submenu, and can trigger further dialogues and questions. This disclosure and storage of information lets players gradually combine the answers to the case (e.g. whether a violent quarrel between the farmer and his daughter could be connected with her death). If a player is able to find all clues to a diorama, this will have a positive effect on his or her ranking.

The game unlocks its content from the start of the train ride—either by the players' completion of a level, or by a countdown defining the maximum amount of time that can be spent on any given level. This time limit guarantees the story's progress and ensures a rough correspondence between the in-game action and the train's position. In order to gain useful information from AR levels or story elements, players need to distinguish relevant from non-relevant clues. To further strengthen the link between game and scenery, bonuses for observations on points of interest outside the train are awarded (either during or after the main gameplay). In multiple-choice interfaces, players are given one-time chances to select the correct answers to scenic observation questions. In doing so, players are able to improve their rank and to unlock optional game levels.

The seven game levels designed in total reflect the regional scenery and its architectural styles. In order to achieve a flawless rendering of the 3D models in AR, the scenes were implemented with reduced complexity, while strong color and object contrasts were used for high legibility. Each level diorama features interactive characters for dialogues, and hints which can be examined to discover hidden clues.

3.3 Technological Framework

Because of the unstable data connection during travel, all relevant game data was integrated into the application upon installation. Even though the gameplay suggests otherwise, the game's progress is not bound to the actual position of the train, but to the detection of the AR-marker, a sticker that is only available on the trains. Placing the stickers on the seating tables yielded the best results, as the AR detection and handling of the smartphones was better than, for example, on a window.

To run the game, operating systems must be equipped with basic AR technologies: ARKit for Apple OS and ARCore for Google. Devices should have a high battery level and performance. The implementation in the Unity AR Engine tested performance, and battery life in relation to the game's complexity, the constraints of AR display, and AR functionality. For optimal focus on game mechanics, the unity plugin Vuforia was used (https://developer.vuforia.com/). "Tales on Rails" was developed for mobile phones using iOS 9+ and Android 7+. Since July 2019, "Crime Line" offers an overview over the releases (https://playcrimeline.ch) on the AppStore[1] and Google Playstore[2].

4 Evaluation

The application development went through an iterative design process, during which the game was tested in different stages. Through playtesting, all components could be optimized. The tests resulted in continuous improvement and balancing of narration, game mechanics, gameplay, user interaction, usability, and AR stability (Table 1). Iteratively, the core idea of enhancing a tourist group's travel experience could be strengthened.

Participants. The participants (p) consisted of ZB employees (N = 6), ZHdK students (N = 28), and further volunteers from the relevant target group (N = 30), who registered after a public advertisement was conducted. Participants were divided into play groups (n = 2–4). Each participant only played once.

Measures. In order to control major phases of development, the project was set up in stages. Evaluation was scheduled at the end of each stage. Within four months, five tests were carried out on trains, and another two tests were done at ZHdK, with a total of 65 participants (N = 65).

Procedure and Data Collection. All participants were given an individual smartphone and played the game in groups of 2 to 4 people (except Playtest B, which was played alone and followed by an interview). After tests A, C, D, E, F, and G, a semi-standardized questionnaire collected quantitative and qualitative data, and had to be returned immediately after answering. During the tests, the participants' behaviors were also observed and recorded. For the subsequent qualitative analysis, the tests, the discussion, and the interview were transcribed. The questionnaires and protocols were

[1] https://apps.apple.com/us/app/crimeline/id1470944437?l=de&ls=1.

[2] https://play.google.com/store/apps/details?id=ch.zentralbahn.crimeline&gl=CH.

Table 1. Results of playtests and identified weaknesses (source authors)

Playtest session sample size & date	Method & Identified weaknesses
Playtest A N = 3 (m = 2; f = 1) p.: ZB Week 11/2019	*Methods:* Test on the train route, participatory observation, followed by questionnaire *Identified weaknesses:* – Story (shorten dialogues, harder puzzles) – Gameplay (more breaks, play time and rewards, integrate scenery) – Technology (stabilize AR, fix bugs) – Group experience (interaction, participation, competition) – Usability
Playtest B N = 1 (m = 1) p.: Expert Week 12/2019	*Methods:* Test at ZHdK, followed by interview with expert in dramaturgy & storytelling *Identified weaknesses:* – Story (strengthen dialogues, wrong story lines, harder puzzles) – Characters (profile characters, evoke more empathy) – Usability
Playtest C N = 16 (m = 9; f = 6; x = 1) p.: ZHdK Week 15/2019	*Methods:* Test on the train route, participatory observation, followed by questionnaire and discussion *Identified weaknesses:* – Gameplay (better feedback design and entertaining elements, shorten tutorial, bonus feature that relates to landscape) – Technology (stabilize AR, fix bugs, optimize point system) – Usability
Playtest D N = 9 (m = 5; f = 4) p.: target group Week 18/2019	*Methods:* Test on the train route, participatory observation, followed by questionnaire *Identified weaknesses:* – Story (simplify solution, shorten dialogues – Bonus feature (clear instruction at start, strengthen link to scenery) – Display max. reachable points – Gameplay (placement of clues in dioramas, timing) – Offer analog reward after game – Player interaction – Software bugs – Usability

(*continued*)

Table 1. (*continued*)

Playtest session sample size & date	Method & Identified weaknesses
Playtest E N = 11 (m = 6; f = 4; x = 1) p.: ZHdK Week 21/2019	*Methods:* Test on the train route, participatory observation, followed by questionnaire *Identified weaknesses:* – Story (ending abrupt/unclear) – Bonus feature (clear instruction at start, strengthen link to scenery) – Gameplay (placement of clues in dioramas, reduce focus on smartphone) – Shaking movements of train (enlarge trigger for clues to counter cause for nausea) – Software bugs – Usability
Playtest F N = 3 (m = 0; f = 3) p.: ZB Week 22/2019	*Methods:* Test on the train route, participatory observation, followed by questionnaire *Identified weaknesses:* – Bonus feature (clear instruction at start, strengthen link to scenery) – Gameplay (allow to return to tutorials, reduce focus on smartphone) – Shaking movements of train (enlarge trigger for clues to counter cause for nausea) – Software bugs – Usability
Playtest G N = 21 (m = 14; f = 7) p.: target group Week 26/2019	*Methods:* Test on the train route, participatory observation, followed by questionnaire *Identified weaknesses:* – Gameplay (too little linked to scenery, not location-dependent, reduced focus on smartphone) – Story (solution permits interpretations) – Bonus feature (user instructions too unclear) – Shaking movements of train (cause for nausea) – AR (impractical for more than 2 players)

evaluated, further development steps were derived from the results, and the game was improved iteratively on the basis of the results, from Playtest A to G.

Data Analysis. The quantitative data was analyzed, and the qualitative data was clustered into "Game/Tutorial/Resolution/Landscape/Story/Bugs-Usability/Train/Interaction/Dialogues/Bonus Features/AR/Graphics." Average values were determined, and weaknesses were identified and marked for improvement.

5 Results and Discussion

The ambitious setup of “Tales on Rails” has proven itself, both in its technology and as a game. All test players enjoyed the game and stated it enhanced the group’s tourist experience. All graphical elements (AR-dioramas, clues, 2D interface, etc.) were well accepted. Through seven consecutive playtests, design weaknesses could be identified iteratively, which led to substantial changes and improvements in all areas of the game. For a better understanding of the plot, the story of the game was significantly shortened and timed to fit into the core segment of the train’s journey: the length and amount of dialogue between game characters were reduced, and contrasts between the character profiles were accentuated. The changes in game mechanics resulted in adjusting and increasing the level of difficulty for puzzles, and in the introduction of a competitive ranking system. The usability of the game was constantly improved, both in terms of gameplay processes and the readability of graphical elements. Taking into account that players should be able to follow the course of the game without stress or frustration, the general changes reduced the complexity of the original concept but strengthened entertaining aspects of the game and social interaction among players. Due to these successive improvements, the testers’ critique shifted from the application itself to the situation in the train, in which shaking train movements were sometimes perceived as unpleasant (due to a narrow track width and rack sections, swinging and shaking movements of the train carriages can occur).

However, “Tales on Rails” disclosed the contradictory concepts of scenic observation outside a train, while simultaneously focusing on a smartphone application. Even though this contradiction was addressed from the start, the demand for an interesting plot in a high-quality AR game still preserves this conflict in the final result. In order to draw the players’ attention away from the smartphone and towards the scenery, various elements were added, such as a bonus feature that rewards observations made outside with a point system. Also, by extending the overall duration of the game’s core plot, pauses from the gameplay were introduced to stimulate group communication. It remains to be determined whether the initial conceptual contradiction can be overcome under the given circumstances, or whether introducing an additional experience could solve it: for example, a complementary guided hiking tour at the travel destination could embed a location-based multiplayer game for tourists into an even more intensive overall experience.

The development of “Tales on Rails” discussed the question as to whether an AR game application related to the surrounding scenery could become a digital souvenir, or even replace traditional forms of souvenirs. In game test questionnaires, the majority of the participants indicated that they would not yet recognize any parts of the game as souvenirs at this stage of development. Future extensions of the game could show whether certain game elements could either be digitally extracted from the game or even offered as analog counterparts, in order to function as souvenirs.

Technical tests revealed that neither the exchange of real-time data between players, nor the retrieval of online data for positioning (GPS, actual or stored train schedules, or a mix of both) were technologically feasible under the given circumstances. Such solutions were also found to negatively impact playability by shifting attention towards data connectivity, and away from the communicative aspects of a multiplayer game. The requirement for a direct reference to the train's position had to be reduced to an indirect reference, in order to avoid frustration in the event of a technical malfunction or if players missed the event. However, the consequent solution of indirect, communicative exchange among the players did not result in cooperative game-mechanic benefits.

Tests with groups of 2 to 4 participants showed that an AR sticker is best utilized for only 2 players. It was also found that long-term use of AR leads to high energy consumption of the devices.

6 Conclusion and Outlook

"Tales on Rails" enhances the group tourist experience of 20 to 30-year-old travelers with a location-based multiplayer game. The game's AR feature promotes individual exploration, as well as entertaining, collaborative, and communicative exchange within a group of tourists. At the same time, the project shows the complexity of combining the observation of scenery surrounding a moving train and simultaneously concentrating on the content of a narrative AR smartphone application.

Further assessment in 2019 will evaluate the success of "Tales on Rails" in different seasons and under other weather conditions, provide information on the composition of user groups, and gather detailed feedback on the reception of the story. The outcome of the assessment will define whether the project should be expanded into other parts of the ZB's network, or transferred into additional "Crime Line" stories with a series of alternative games.

It is planned to test a version of the game from which the AR components have been removed. This would make it possible to determine whether the developed AR concept is actually capable of reinforcing group dynamics in games for travelers. Additional extensions of the game could further strengthen the overlap of digital virtuality and physical reality, which is typical for pervasive games. This could implicate the transfer of elements from location-based multiplayer games to analog souvenirs, or vice versa, such as from a physical souvenir back into the game.

Acknowledgement. ZHdK wishes to thank Thomas Keiser, Christa Bieri, and Corina Schneider of zb Zentralbahn AG for the fruitful collaboration; Aleksandra Iakusheva for additional graphic design and programming; and Anna Martin-Niedecken for supporting the evaluation process.

References

1. Branzei R, Dimitrov D, Tijs S (2005) Models in cooperative game theory: crisp, fuzzy, and multichoice games. Springer, Heidelberg, p 3
2. Buhalis D, Law R (2008) Progress in information technology and tourism management: 20 years on and 10 years after the Internet – the state of eTourism research. Tourism Manage 29 (4):609–623
3. Bulencea P, Egger R (2015) Gamification in tourism. designing memorable experiences. BoD – Books on Demand, Norderstedt, p 35

4. Deterding, S.: The ambiguity of games: imaginaries, histories, and discourses of a gameful world. In: Walz P, Deterding S (eds) The gameful world: approaches, issues, applications. MIT Press, Boston, pp 23–64 (2014)
5. Horster E, Kreilkamp E. (2017) Gamification im tourimus. In: Landvogt M, Brysch A, Gardini M (eds) Tourismus – E-tourismus – M-tourismus. Erich Schmidt Verlag, Berlin, pp 215–230
6. Jahrmann M, Moswitzer M, Bauer R (2007) Import-export rotterdam. Performed at Dutch electronic arts festival, Rotterdam
7. Kane B, Fetter B, Pestaluky A (2015) Keep talking and nobody explodes. Steel Crate Games, Ottawa Ontario Canada
8. Kasapakis V, Gavalas D (2015) Pervasive gaming: status, trends and design principles. J Netw Comput Appl 55:213–236
9. Laesser C, Schegg R, Bandi Tanner M, Liebrich A, Lehmann Friedli T, Fux M, Stämpfli A (2018) Digitalisierung im Schweizer Tourismus: Chancen, Herausforderungen, Implikationen. Bericht im Auftrag des Staatssekretariats für Wirtschaft SECO. SECO, Bern
10. Landvogt M (2017) Technologische Treiber der Digitalisierung und ihre Auswirkungen auf die Digitalisierung im Tourismus. In: Landvogt M, Brysch A, Gardini M (eds) Tourismus – E-tourismus – M-tourismus. Erich Schmidt Verlag, Berlin, pp 13–34
11. Lazzaro N (2009) Why we play: affect and the fun of games, designing emotions for games, entertainment interfaces, and interactive. In: Sears A, Jacko JA (eds) Human-computer interaction: designing for diverse users and domains. CRC Press, Boca Raton, pp 155–176
12. Li J, van der Spek ED, Feijs L, Wang F, Hu J (2017) Augmented reality games for learning: a literature review. In: Streitz N, Markopoulos P (eds) Distributed, ambient and pervasive interactions. DAPI 2017. LNCS, vol 10291. Springer, Cham, pp 612–626
13. Marks G (2018) Mord im orient express – die längste Escape Room-Experience der Welt. http://digitaleleinwand.de/2018/02/05/mord-orient-express-escape-room-zug/. Accessed 7 Feb 2019
14. Niantic Inc (2016) Pokémon Go. https://nianticlabs.com/de/. Accessed 19 Jun 2019
15. Ryan RM, Deci EL (2000) Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. Am Psychol 55(1):68–78
16. Skinner H, Sarpong D, White GRT (2018) Meeting the needs of the millenials and generation Z: gamification in tourism through geocaching. J Tourism Futures 4(1):93–104
17. Spierling U, Winzer P, Massarczyk E (2017) Experiencing the presence of historical stories with location-based augmented reality. In: Nunes N, Oakley I, Nisi V (eds) Interactive storytelling. ICIDS 2017. LNCS, vol 10690. Springer, Cham, pp 49–62
18. Warpin Media: ARrrrrgh. https://warpinmedia.com/. Accessed 20 Jun 2019
19. Wiemker M, Elumir E, Clare A (2015) Escape room games: can you transform an unpleasant situation into a pleasant one? https://thecodex.ca/wp-content/uploads/2016/08/00511Wiemker-et-al-Paper-Escape-Room-Games.pdf/. Accessed 7 Feb 2019
20. XEODesign (2004) The 4 Keys to Fun. https://www.xeodesign.com/research/. Accessed 25 Jun 2019

Exploring the Impact of Multisensory VR on Travel Recommendation: A Presence Perspective

Jasmin Hopf(✉), Melina Scholl(✉), Barbara Neuhofer, and Roman Egger

University of Applied Sciences Salzburg, Puch/Salzburg, Austria
{jhopf.imte-m201, mscholl.imte-m2017}@fh-salzburg.ac.at

Abstract. The rapid development of Virtual Reality (VR) technology offers new opportunities for the promotion of tourism products and experiences. VR provides potential tourists with a compelling imagery and a chance to get a first impression of what it feels like to be at a destination. Previous studies have mostly focused on visual and auditory VR experiences and have rather neglected the possibility of adding additional sensory stimuli, i.e. haptic and olfactory feedback, to a VR experience. This study is novel in that it takes a multisensory approach to VR and examines its impact on the intention to recommend a destination through the lens of presence. A multi-stage laboratory experiment with 64 participants was conducted. The analysis reveals that the stimulation of additional senses does not lead to a significant enhancement of the user's sense of presence. However, a significant increase in the user's intention to recommend a destination can be observed. For destination marketers, this study proposes multisensory VR as a novel and effective tool to positively influence travel recommendations.

Keywords: Virtual Reality · Presence · Travel recommendation

1 Introduction

Virtual Reality as a novel and innovative tool to attract visitors to destinations has gained significant interest from researchers and tourism businesses over the last years [1, 2]. According to Guttentag [3], VR is defined as "the use of a computer-generated 3D environment – called a 'virtual environment' (VE) – that one can navigate and possibly interact with, resulting in real-time simulation of one or more of the user's five senses" (p. 638). In this regard, VR technology enables viewers to virtually experience and explore destinations by immersing them into an VE and triggering a feeling of 'being present'. From a marketing perspective, VR is expected to revolutionize tourism experiences as well as the promotion and selling of tourism products. Tourism products are intangible by nature. The reason VR has major potential lies in its ability to provide extensive sensory information and by doing so, allowing potential visitors to assess experiences before the physical visit [3, 4]. In fact, existing research discovered that image representations through VR enhance tourists' desire to experience sites since it

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 169–180, 2020.
https://doi.org/10.1007/978-3-030-36737-4_14

offers more compelling imagery of a tourism destination and gives the tourists a sense of what it is like to be there [5].

This subjective experience of being present in the VE is commonly defined as presence [5]. Research by Tussyadiah et al. [5] has revealed that an enhanced sense of presence in a virtual world leads to a higher level of interest, liking and preference of the real destination. Moreover, other researchers have found that the feeling of ‘being there’ positively affects tourists’ satisfaction, their intention to visit, and intention to recommend the real destination [6]. In addition, numerous studies have shown that the more human senses are engaged, the more immersive is the experience, which in turn leads to a higher level of presence in the VE [7]. Moreover, recent work suggests that presence in a VE enhances the intention to recommend the destination [2].

Whilst the body of literature on the use of VR in information sciences and marketing is growing rapidly [5, 8], VR is still a nascent area in tourism research [9]. In fact, only little research examined the impact of presence enabled by HMDs (head-mounted displays) on users’ intention to recommend the destination. Moreover, most of the existing studies have been limited to 3D VR experiences, i.e. to the visual and auditory representation, and have neglected other sensory dimensions. Based on this rationale, this study is the first to a) introduce the concept of 4D VR, namely multi-sensory VR experiences, and b) investigate the effect of multisensory VR experiences on the intention to recommend the destination based on the conceptual foundation of the sense of presence. This study aims to address the following research questions:

1. What effect does addressing more senses in a virtual experience have on the sense of presence compared to a 3D virtual experience?
2. How does the sense of presence affect the intention to recommend the destination?

In a first step, this paper offers an overview of the current literature on VR in tourism, multisensory dimensions of VR and the concept of presence. Next, the methodological approach through a laboratory experiment is explained to measure the differences in the degree of presence between 3D VR and 4D VR experiences as well as the impact of presence on the intention to recommend a destination. Finally, the results of this study, its limitations as well as suggestions for further research are discussed.

2 Literature Review

2.1 VR in Tourism

The main aim of VR applications is to create a virtual environment for users to experience that environment as if it were real [10]. The role of VR in tourism, hospitality and marketing has been discussed in the tourism literature for the past three decades [3, 5]. According to Tussyadiah et al. [11], VR can encourage destination marketers to create memorable experiences that can be integrated in their communication strategies in order to support tourists’ information search and decision-making processes.

Indeed, VR has the potential to revolutionize the way tourism companies promote, market and sell their products [5]. Due to the intangibility of tourism products, tourism companies have not been able to offer a 'try before you buy' experience to their potential customers as common in other sectors [12]. However, with the emergence of VR applications, tourism companies can provide an experience so similar to reality that it allows for better communication and generates positive attitudes towards a destination as well as a favorable behavior [5, 11]. Due to this similarity, some scholars even believe that VR will function as a substitute for real tours in the future. In this context, many situational and personal factors play a crucial role for tourists to accept VR as a substitute for traditional tours [3]. However, as Paquet and Viktor [13] noted that "most people want to see reality and not only virtuality" (p. 1), the majority of researchers focus on the great advantages of VR stimulating tourists' travel intention.

In this context, virtual tours of destinations with 360-degree videos are becoming increasingly popular for tourism marketing [14]. These videos allow users to experience a destination in 360-degrees by rotating around a certain angle [15]. This presentation facilitates the interaction with a destination before its actual consumption and enables capturing the user's attention, which can lead to more interest in a destination [5, 12]. Furthermore, a study conducted by McFee et al. [16] confirms the positive effects of VR on the image of a destination as users of VR experience a high level of involvement. In addition, by interacting with a destination and freely navigating through it, the loyalty of customers as well as their intention to recommend a destination to others can be strengthened [2]. In order to increase the effectiveness of VR as a marketing tool in tourism and to fully immerse users into an VE, it is suggested to engage the five human senses as the experience becomes closer to reality [10].

2.2 Multisensory VR Experience

Pan and Ryan [17] pointed out that "the touristic experience is multisensory" (p. 628) and the sensory dimension helps enhance the tourist experience. A recent study suggests that an experience tends to be more immersive if more human senses are involved in a VE [10]. Furthermore, an article published in Forbes by Porges [18] demonstrated that by implementing further sensory stimuli to VR experiences, designers could create a virtual environment that seems realistic, and could subsequently enhance the ability of the device to teleport. Hence, Porges [18] believes that multisensory VR could genuinely be a game-changer in the digital world.

The first multisensory VR system, known as Sensorama, consisted of a set of equipment, which was arranged with a seat and allowed viewers to sit and savor a multisensory experience. The system was designed to display 3D stereoscopic images, replicate stereo sound, stimulate wind and provide aromas. Although the outcomes were appreciated by the society, the system was not widely implemented as it failed to produce a credible experience. Since then, VR systems have been advanced, however they have been kept simpler [19]. Furthermore, with the advancement of technologies, VR-related systems are integrated with several senses that can stimulate to present users with a 'real' experience in the VE [10]. One example of such a system is the Multimodal Floor, which is comprised of a multimodal interface and allows users to experience an immersive virtual and augmented reality environment. The system is able to stimulate tactile, auditory and visual response to users' steps and deliver the feeling of walking on the natural floor, such as snow and ice [20].

2.3 The Sense of Presence

According to Martins et al. [10], multisensory cues are important to achieve credibility and a high level of presence in VEs, as humans experience the world through all their five senses. It has been widely argued in the literature that presence is the 'sense of being in the VE' instead of being in the place where the participant's body is situated. Gutiérrez et al. [21] propose that the feeling of presence is connected with a user's psychology and is indeed subjective. However, the quality of data delivered by a VR system influences the user's sense of presence. Witmer and Singer [22] suggest that the level of presence in a virtual environment depends on the degree to which the user feels transported from being physically in an existing environment to being immersed in a VE. Not surprisingly, according to Diemer et al. [23], the experience of presence is in fact a complex, multidimensional perception constructed by an interplay of multisensory information and several cognitive processes. The user's sense of presence is experienced when the existence of the medium (i.e. VR device) is not noticed and the user acts as if the medium was not there [5].

Antecedents of VR Presence. Previous literature has sought to explain what factors contribute to the formation of the feeling of presence [2]. Witmer and Singer [22] were among the first to investigate antecedents of presence and classify them into meaningful groups of similar items. In 2005, Witmer et al. [24] further refined the aspects underlying the concept of presence. This analysis led to four factors influencing the user to experience presence, namely (1) Involvement/Control, (2) Adaptation/Immersion, (3) Sensory Fidelity and (4) Interface Quality.

The sub-item Involvement/Control refers to a psychological state, which is experienced as a consequence of focusing one's attention on the VE (=involvement). Thereby, it addresses the perceived ability to control events in the VE as well as its responsiveness to user-initiated actions (=control) [24]. Regarding the sub-item Adaptation/Immersion, immersion characterizes a psychological state in which an individual perceives to be enveloped by, included in and interacting with the virtual environment. It can be stated that a higher sense of immersion produces a greater level of presence in the VE. For instance, a user will feel more immersed if the VR experience allows for isolation from the physical surroundings, thus avoiding distractions from external stimuli [22]. Additionally, users feel more immersed if they adapt quickly and readily to the VE, which Witmer et al. [24] describe as the term 'adaptation'. The third factor, Sensory Fidelity is defined as the degree to which the user's interactions feel natural and to what extent the VE is consistent with reality. Lastly, the factor Interface Quality describes the extent to which a user is distracted from the virtual environment by control devices or display devices, such as VR headsets and how well the user can concentrate on the virtual experience [24].

Measurement of Presence. When it comes to the measurement of presence, it is important to mention that different users can experience different levels of presence in the same VE since it is a subjective sensation, i.e. a product of the individual's mind.

To measure presence, it is necessary to conduct experimental research for subjective and objective measurement techniques to be applied. Previous research has mainly focused on subjective ratings, e.g. through questionnaires, which constitute the most commonly used method to measure presence. For the purpose of this study, the presence questionnaire by Witmer et al. [24] was used, as it has been tested and approved in a variety of settings.

In addition, objective, physiological measures, such as heart rate, heart rate variability, skin temperature or skin conductance can be applied to determine the level of presence [25, 26]. In particular, heart rate and skin conductance are considered to be reliable, objective and valid parameters to measure the sense of presence [26]. Concerning the relationship between presence and physiological response, it was found that the heart rate as well as skin conductance positively and significantly correlate with presence [26]. However, other researchers note that most physiological measures are not directly related to presence, but to emotional arousal [25]. To overcome these limitations, a combination of subjective and objective techniques is proposed in the literature and made use of within this study. More precisely, the objective data consists of the measurement of the participants' heart rate.

Based on the reviewed literature, it is suggested that a multisensory VR experience (4D) of a 360-degree destination video leads to greater levels of presence than a VR experience which is limited to visual and auditory sensory stimuli (3D). As a consequence, the following hypotheses and sub-hypotheses are proposed:

H1: The 4D VR experience shows greater reactions on the self-report measure of presence than the 3D VR experience.
- H1a: The 4D VR experience shows greater Involvement/Control than the 3D VR experience.
- H1b: The 4D VR experience shows greater Adaptation/Immersion than the 3D VR experience.
- H1c: The 4D VR experience shows greater Sensory Fidelity than the 3D VR experience.
- H1d: The 4D VR experience shows greater Interface Quality than the 3D VR experience.

H2: The 4D VR experience shows greater reactions on the Heart Rate measure than the 3D VR experience

2.4 Intention to Recommend the Destination

Presence in VR contexts has been widely explored to understand consumers' attitudes and future behavioral intentions [2]. The study carried out by Tussyadiah et al. [5] discovered positive impacts of the sense of presence on overall tourism destination experiences. For instance, a higher sense of presence positively influences the level of liking, preference and interest of users in the actual tourism destination. Furthermore, the sense of presence, which is created with the help of VR technology, positively affects overall satisfaction, intention to revisit as well as the recommendation of cultural heritage sites and museums [6]. Hence, considering the important role of multisensory VR influencing the sense of presence, this study suggests that multisensory VR, which leads to a higher level of presence, has a greater impact on the intention to recommend a destination. This leads to the following hypothesis:

H3: The 4D VR experience (higher level of presence) shows greater impact on the intention to recommend the destination than the 3D VR experience

3 Methodology

This study employed an experimental research design. A laboratory experiment in a contrived setting was conducted and participants were randomly assigned to two different groups, namely control and experimental group. This randomization was done using a website which created a random list with the numbers zero and one, whereby one represented the assignment to the experimental group and zero to the control group. A 360-degree video available on invirovr.com about the destination of Costa Rica was used and a 'multisensory VR cabin' was built for the purpose of this study. The control group watched the video through an HTC Vive headset, whereas the experimental group experienced the video with the same headset but in a multisensory VR setting addressing two more senses (olfactory, haptic) in addition to vision and auditory. In this regard, the 4D feedback was represented by temperature changes, wind, light drizzle as well as the typical smell of the ocean and the rainforest. These stimuli were matching with the different scenes of the video.

The video lasted for 6:03 min. Two measurement methods were applied, (1) a questionnaire for subjective measurement as well as (2) physiological data collection for objective measurement. In this context, the heart rate of the participants was measured with the iom Biofeedback-Sensor and the Alive clinical software of somaticvision.

A purposive convenience sampling strategy was applied to recruit participants via email and in person through proximity to the lab/university environment. A sample, largely comprised of students, was targeted, as a study conducted by Greenlight VR in 2015 showed that Millennials (aged 18–34) as well as Generation X (35–50) indicate the highest interest in travel related VR content [27]. Furthermore, it was proposed by Tussyadiah et al. [11] to select undergraduate and graduate students as they are an appropriate target group for VR studies in a tourism marketing context. To overcome the novelty effect of using VR the first time, participants were asked to attend a VR experience at least one day prior to the actual experiment. This is also suggested by Rooney et al. [28] since the test group is likely to be more fascinated and enthusiastic when experiencing a new technology for the first time.

Participants were scheduled an individual time slot, each procedure lasted between 20–25 min. Upon arrival, participants were explained the procedure and asked to sign a consent form. The experiment was divided into three phases. The first phase was a relaxation period of three minutes followed by the VR experience and completing the online questionnaire. Physiological measurement devices were put on the participants' fingertips during both the relaxation phase and the VR experience. Both groups answered the same questionnaire, which was adapted from Witmer et al. [24] and collected with surveymonkey. The presence questionnaire consisted of the four subscale-items, namely Adaptation/Immersion, Involvement/Control, Sensory Fidelity and Interface Quality and has been tested and approved to be suitable for measuring presence in a variety of settings [24]. All questions concerning presence could be answered on a 7-point Likert-scale. The overall presence score was the sum of the four subscale ratings. The questionnaire included a total of 38 questions, broken down into 28 presence questions, one question concerning the intention to recommend the destination as well as questions about participants' socio-demographic factors and general questions about VR. To compare the intention to recommend between the two groups, the Net Promoter Score (NPS) was applied [29] which was classified into detractors, passives and promoters using a scale from 1 to 10.[1]

The responses of the questionnaire as well as the physiological data were analyzed using SPSS Version 21. A total of usable 64 responses were gathered, of which all responses were complete and therefore none of the datasets had to be eliminated. The sample size of 64 is acceptable, whilst borderline, thus requiring a cautious interpretation of the results. In the following section, the sample profile is outlined, Cronbach's test for internal reliability is shown, and the results of the hypotheses are presented.

4 Results

4.1 Sample Description and Reliability Analysis

The tested sample consisted of 64 participants, 51.6% (n = 33) of these participants were assigned to the 4D VR experience (experimental group) whereas 48.4% (n = 31) were allocated to the 3D VR experience (control group). Most of the participants are between 18 and 24 years old (59%), 37.5% are between 25 and 34 years old and 2 respondents state to be between the ages 35 and 44. The sample is composed of 53% male and 47% female. To measure whether the applied questionnaire completely and consistently represents the constructs of presence, an internal reliability analysis with Cronbach's alpha was conducted. As a Cronbach's alpha of 0.922 was reached, the minimum value of $\alpha = .7$ is fulfilled, and therefore the presence questionnaire proved to be internally consistent.

4.2 Test of Normality and Hypotheses

As a first step, both the questionnaire and the physiological data were tested for normality with the Shapiro Wilk test. The heart rate proved to be normally distributed. On the contrary, the data of the questionnaire resulted to be abnormally distributed as the p-value was below 0.05. Thus, the authors chose to apply the Mann-Whitney U-test for nonparametric tests for both datasets.

[1] Further explanation and visualization under https://youtu.be/PYeruxMQagg.

Thereafter, the hypotheses were tested for differences between the 3D VR and the 4D VR group. A 7-point Likert-scale was used for the questionnaire, where the value of 1 represented the worst and 7 the best rating. Consequently, values between $4.5 \leq M \leq 7$ describe the more positive answers. With regard to the physiological data, the relaxation period was used to measure the baseline heart rate of each participant as physiological levels often vary widely between individuals. The change in heart rate was therefore calculated as follows: HR = HR Mean VR – HR Mean Baseline. Hereafter, the hypotheses mentioned above are tested for acceptance or rejection.

H1: The Mann-Whitney U-Test shows no significant difference between the 4D VR group (Mdn = 5.39) and the 3D VR group (Mdn = 5.04) ($U = 389.5$; $z = -1.64$; $p = .101$). Having a closer look at the mean values, it can be seen as well that the difference ($\Delta M = 0.19$) between the two groups is small. This indicates that the 4D VR experience did not lead to significantly greater subjectively experienced sense of presence for the experimental group, which suggests the rejection of H1.

H1a: Regarding the sub-scale item Involvement/Control, the Mann-Whitney U-Test shows no significant difference between the 4D VR group (Mdn = 5.1) and the 3D VR group (Mdn = 4.8) ($U = 437.5$; $z = -.995$; $p = .320$). When comparing the difference of the mean values between both groups ($\Delta M = 0.235$), the 4D VR experience shows greater Involvement/Control but no significant difference. Thus, H1a has to be rejected.

H1b: The 4D VR experience shows greater Adaption/Immersion (Mdn = 5.67) than the 3D VR experience (Mdn = 5.08). The mean values also show greater differences between the two groups ($\Delta M = 0.42$). Moreover, the Mann-Whitney U-test confirms that the two groups are significantly different ($U = 341.5$; $z = -2.287$; $p = .022$). Hence, H1b can be accepted.

H1c: The 4D VR experience reveals the same Sensory Fidelity (Mdn = 6.0) as the 3D VR experience. Comparing the means, the 4D VR experience shows higher Sensory Fidelity ($M = 5.91$) than the 3D VR experience ($M = 5.84$). However, there is no significant difference between the groups when looking at the Mann-Whitney U-Test ($U = 491.5$; $z = -.273$; $p = .785$), which results in the rejection of H1c.

H1d: The Mann-Whitney U-test displays no significant difference regarding the Interface Quality between the 4D VR group (Mdn = 5.25) and the 3D VR group (Mdn = 5.0) ($U = 432.5$; $z = -1.066$; $p = .286$). Having a closer look at the mean values, it can be seen as well that the difference ($\Delta M = 0.24$) between the two groups is only small. Therefore, H1d has to be rejected.

H2: On average, the heart rate measure for the 4D VR group ($M = 10.67$) is higher than the 3D VR group ($M = 9.56$). However, this difference is not significant ($U = 532.00$; $z = -.275$; $p = .783$) and therefore hypothesis 2 needs to be rejected.

H3: The 4D VR experience results in a Net Promoter Score of 39.3% (54,5%–15,2%), whereas the 3D VR experience indicates a Net Promoter Score of 0% (29%–29%). Due to the results of the Mann-Whitney U-test which show a significant difference between the two groups ($U = 361{,}0$; $Z = -2{,}066$; $p = .039$), hypothesis 3 can be accepted. These results implicate that a 4D VR experience has a greater impact on the intention to recommend the destination than a 3D VR experience.

4.3 Correlation Analysis

Spearman's Rho correlation was used to investigate possible relationships between the different parameters and constructs. The results of the full sample (Table 1) show that the antecedents of presence positively and significantly correlate with the overall sense of presence. Furthermore, the overall sense of presence positively and significantly correlates with the intention to recommend the destination. A correlation analysis was also conducted between the physiological reaction and the self-reported measure of presence. The results reveal that the heart rate does not significantly correlate with self-reported presence.

Table 1. Correlations (compiled by authors)

Full sample (N = 64)	Spearman's Rho
Involvement/Control → Presence	.929**
Adaptation/Immersion → Presence	.924**
Sensory Fidelity → Presence	.694**
Interface Quality → Presence	.588**
Presence → Intention to recommend	.582**
Heart rate → Presence	−.093

**correlation is significant at the 0.01 level (2-tailed)

In addition, the strength of the correlation between presence and intention to recommend was examined separately for each of the two groups. Both the 3D VR group (.360; $p = 0.046$) and the 4D VR group (.619; $p = 0.00$) show a positive correlation. To interpret the strength of correlation, the following classification for Spearman's rho (rs) is applied: 0 to 0.20 is negligible, 0.21 to 0.40 is weak, 0.41 to 0.60 is moderate, 0.61 to 0.80 is strong, and 0.81 to 1.00 is considered very strong [30]. Consequently, the 3D VR group only indicates a weak correlation while the 4D VR group presents a strong correlation. This leads to the conclusion that adding sensorial stimuli to a VR experience even enhances the positive relationship between the sense of presence and the user's intention to recommend the displayed destination.

5 Discussion

Previous research done by Wei et al. [2] found that visitors' feeling of presence in a VR experience is an essential factor driving the intention to recommend the destination to others. Moreover, research conducted by Chung et al. [6] suggests that the feeling of presence provoked by VR technologies positively affects the intention to recommend cultural heritage sites and museums. This study is in line with previous research in that it reveals a positive correlation between VR-induced presence and the intention to recommend the displayed destination. Adding to the existing research, this study found out that by addressing additional senses within the virtual experience (4D), the users' intention to recommend a destination increases significantly.

This study further reveals that the sense of presence is not significantly enhanced if additional human senses are addressed. This finding contradicts the results of previous research done by Jones and Dawkins [7], which states that added sensory stimuli to a 360-degree film leads to an increased level of presence in a virtual environment. However, having a closer look at the antecedents of presence, it can be outlined that the subscale Adaptation/Immersion results in a significant increase when experiencing a multisensory VR setting. Hence, it is assumed that adding sensory dimensions to the VR experience is the driving factor that isolates users from reality and enhances their immersion into the virtual environment. Moreover, the study reveals that concerning the physiological reaction, the heart rate does not appear to be a good measure of presence as it even shows a negative, yet not significant, correlation with presence. This result is also in line with previous research conducted by Wiederhold et al. [31]. What sets this research apart from its predecessors is that both the 3D VR as well as the 4D VR group received the exact same information and VR headset. Nevertheless, as the setting differed between the two groups, it is concluded that adding sensory stimuli significantly impacts the intention to recommend a given tourism destination.

6 Conclusion

This study aimed to explore multisensory VR and examine its impact on the intention to recommend a destination through the concept of presence. The results show that stimulating more senses during a VR experience has a positive impact on the intention to recommend a destination, while the sense of presence is not significantly affected. This study recommends VR as a useful marketing tool for the tourism industry. With 4D VR, tourists can better explore and more realistically experience the desired destination without actually visiting it. For tourism businesses adopting VR experiences, it is thus suggested to integrate at least two more senses (olfactory and haptic) in addition to vision and auditory feedback during the use of VR. Multisensory VR is particularly useful for DMOs to present their products and services in a more engaging way.

In terms of theoretical implications, the study is the first to tap into 4D multisensory VR and makes a contribution to VR research in a tourism context. The study stands in contrast with previous research on VR presence as it shows no significant increase in a multisensory VR setting. Nevertheless, adding additional sensory stimuli does in fact positively affect travel recommendation. For further research it is recommended to explore other factors, such as the users' enjoyment or emotional arousal, that could influence their intention to recommend a destination experienced through multisensory VR. In the course of the study, another physiological reaction, namely the participants' skin conductance, was measured. However, one limitation of this research is that the resulting data of the skin conductance could not be considered as the measurement device failed to record reliable data. For future research it is thus suggested to investigate presence through other objective measurement techniques, such as skin conductance.

Moreover, it is also acknowledged that the limited purposive sample (n = 64), with the majority of the respondents between 18 and 34 years, leads to a limited generalizability of the results. Future studies could conduct similar studies with a greater sample size and use different, high quality VR content. This study is novel in that it opened an investigation of multisensory VR experiences. Future research is encouraged to expand and replicate both subjective and objective measurement techniques to verify and confirm the results.

References

1. Rivera M, Croes R, Zhong Y (2016) Developing mobile services. Int J Contemp Hospitality Manage 28(12):2721–2747. https://doi.org/10.1108/IJCHM-02-2015-0052
2. Wei W, Qi R, Zhang L (2019) Effects of virtual reality on theme park visitors' experience and behaviors: a presence perspective. Tourism Manage 71:282–293. https://doi.org/10.1016/j.tourman.2018.10.024
3. Guttentag DA (2010) Virtual reality: applications and implications for tourism. Tourism Manage 31(5):637–651. https://doi.org/10.1016/j.tourman.2009.07.003
4. Xiang Z, Tussyadiah IIS (eds) (2014) Information and communication technologies in tourism 2014. In: Proceedings of the international conference in Dublin, Ireland, 22–25 January 2014. Springer, Cham
5. Tussyadiah IP, Wang D, Jung TH (2018) Virtual reality, presence, and attitude change: empirical evidence from tourism. Tourism Manage 66:140–154. https://doi.org/10.1016/j.tourman.2017.12.003
6. Chung N, Lee H, Kim J-Y (2018) The role of augmented reality for experience-influenced environments: the case of cultural heritage tourism in Korea. J Travel Res 57(5):627–643. https://doi.org/10.1177/0047287517708255
7. Jones S, Dawkins S (2018) The sensorama revisited: evaluating the application of multi-sensory input on the sense of presence in 360-degree immersive film in virtual reality. In: Jung T, Tom Dieck MC (eds) Augmented reality and virtual reality, vol 10. Springer, Cham, pp 183–197
8. Huang YC, Backman KF, Backman SJ (2016) Exploring the implications of virtual reality technology in tourism marketing: an integrated research framework. Int J Tourism Res 18 (2):116–128. https://doi.org/10.1002/jtr.2038
9. Griffin T, Giberson J, Lee SHM et al (2017) Virtual reality and implications for destination marketing
10. Martins J, Gonçalves R, Branco F (2017) A multisensory virtual experience model for thematic tourism: a port wine tourism application proposal. J Destination Mark Manage 6 (2):103–109. https://doi.org/10.1016/j.jdmm.2017.02.002
11. Tussyadiah IP, Wang D, Jia C (2017) Virtual reality and attitudes toward tourism destinations. In: Schegg R, Stangl B (eds) Information and communication technologies in tourism 2017: proceedings of the international conference in Rome, Italy, 24–26 January 2017, vol 74. Springer, Cham, pp 229–239
12. Gibson A, O'Rawe M (2018) Virtual reality as a travel promotional tool: insights from a consumer travel fair. In: Jung T, Tom Dieck MC (eds) Augmented reality and virtual reality, vol 11. Springer, Cham, pp 93–107
13. Paquet E, Viktor HL (2005) Long-term preservation of 3-D cultural heritage data related to architectural sites. In: Proceedings of the ISPRS Working Group, vol 4
14. Neuburger L, Beck J, Egger R (2018) Chapter 9 the 'Phygital' tourist experience: the use of augmented and virtual reality in destination marketing. In: Camilleri MA (ed) Tourism planning and destination marketing, vol 77. Emerald Publishing Limited, pp 183–202

15. O'Neil S (2016) Live, 360, or virtual video: Facebook's new video formats catch marketers' eyes. https://www.phocuswire.com/Live-360-or-virtual-video-Facebooks-new-video-formats-catch-marketers-eyes. Accessed 20 Jun 2019
16. McFee A, Mayrhofer T, Baràtovà A et al (2019) The effects of virtual reality on destination image formation. In: Pesonen J, Neidhardt J (eds) Information and communication technologies in tourism 2019: proceedings of the international conference in Nicosia, Cyprus, 30 January–1 February 2019, vol 16. Springer, Cham, pp 107–119
17. Pan S, Ryan C (2009) Tourism sense-making: the role of the senses and travel journalism. J. Travel Tourism Mark. 26(7):625–639. https://doi.org/10.1080/10548400903276897
18. Porges S (2016) Get Ready for Multisensory Virtual Reality That Goes Far Beyond Sight and Sound. https://www.forbes.com/sites/sethporges/2016/12/31/get-ready-for-multisensory-virtual-reality-that-goes-far-beyond-sight-and-sound/. Accessed 20 Jun 2019
19. Agapito D, Oom do Valle P, da Costa Mendes J (2013) The cognitive-affective-conative model of destination image: a confirmatory analysis. J Travel Tourism Mark 30(5):471–481. https://doi.org/10.1080/10548408.2013.803393
20. Law AW, Ip JW, Peck BV et al (2009) Multimodal floor for immersive environments. In: Wigdor D (ed) ACM SIGGRAPH 2009 emerging technologies. ACM, New York, p 1
21. Gutiérrez MAA, Vexo F, Thalmann D (2008) Stepping into virtual reality. Springer, London
22. Witmer BG, Singer MJ (1998) Measuring presence in virtual environments: a presence questionnaire. Presence Teleoperators Virtual Environ. 7(3):225–240. https://doi.org/10.1162/105474698565686
23. Diemer J, Alpers GW, Peperkorn HM (2015) The impact of perception and presence on emotional reactions: a review of research in virtual reality. Front Psychol 6:26. https://doi.org/10.3389/fpsyg.2015.00026
24. Witmer BG, Jerome CJ, Singer MJ (2005) The factor structure of the presence questionnaire. Presence Teleoperators Virtual Environ. 14(3):298–312. https://doi.org/10.1162/105474605323384654
25. Schuemie MJ, van der Straaten P, Krijn M (2001) Research on presence in virtual reality: a survey. Cyberpsychol Behav 4(2):183–201. https://doi.org/10.1089/109493101300117884
26. Meehan M, Razzaque S, Insko B (2005) Review of four studies on the use of physiological reaction as a measure of presence in stressful virtual environments. Appl Psychophysiol Biofeedback 30(3):239–258. https://doi.org/10.1007/s10484-005-6381-3
27. Dawson C (2015) What Americans Really Think About VR: Highlights from our 2015 U.S. Consumer Report. Virtual Reality Consumer Study by Greenlight Insights. https://de.slideshare.net/GreenlightVR/2015-us-consumer-report. Accessed 20 Jun 2019
28. Rooney B, Benson C, Hennessy E (2012) The apparent reality of movies and emotional arousal: a study using physiological and self-report measures. Poetics 40(5):405–422. https://doi.org/10.1016/j.poetic.2012.07.004
29. Satmetrix (2019) What Is Net Promoter? https://www.netpromoter.com/know/. Accessed 20 Jun 2019
30. Prion S, Haerling KA (2014) Making sense of methods and measurement: Spearman-rho ranked-order correlation coefficient. Clin. Simul. Nurs. 10(10):535–536. https://doi.org/10.1016/j.ecns.2014.07.005
31. Wiederhold BK, Jang DP, Kaneda M et al (2001) An investigation into physiological responses in virtual environments: an objective measurement of presence. In: Galimberti C, Riva G (eds) Towards cyberpsychology: mind, cognition and society in the internet age. IOS, Amsterdam

Augmented Reality Applications: The Impact of Usability and Emotional Perceptions on Tourists' App Experiences

Brigitte Stangl[1], Dandison C. Ukpabi[2(✉)], and Sangwon Park[3]

[1] School of Hospitality and Tourism Management, University of Surrey, Guildford, UK
b.stangl@surrey.ac.uk
[2] University of Jyväskylä, Jyväskylä, Finland
dandison.c.ukpabi@jyu.fi
[3] School of Hotel and Tourism Management, The Hong Kong Polytechnic University, Hong Kong, Hong Kong
sangwon.park@polyu.edu.hk

Abstract. There is a rising amount of research contributing to the knowledgebase of Augmented Reality (AR) application usage. However, up until now there is no sound understanding about how the emotional perception of AR application users impact on different types of experience. This paper aspires to contribute to this gap by analysing the link between usability, emotional perception (i.e. entertainment, playfulness and enjoyment), two types of experience viz. action- and emotional experience and users' intention to use the app in a travel context. 796 questionnaires show that emotional experience is driven by entertainment while action experience is mainly triggered by playfulness. However, only emotional experience impacts on users' intention to use the AR app. Action experience has no significant effect. Findings will be discussed in the light of previous literature and managerial implications will be provided.

Keywords: Augmented reality · Experience design · Usability · Emotional perception · Mobile applications

1 Introduction

Emerging technologies are changing consumers' perception of services. Specifically, augmented reality has introduced a new dimension to how services are accessed and consumed in several service sectors [1–4], including tourism services such as heritage tourism [5], tour guide [6] and hospitality [7]. A market report by [8] holds that currently, there are 1,684 companies in the augmented reality application business with a combined market value of 3.5 Billion US Dollars. Due to increasing consumer interest in AR applications, 67% of media planners are adopting it for their digital campaigns, with users estimated to rise to 1 billion in the year 2020. These statistics consistently stresses the potential effects of AR on tourism fields.

Current knowledge on AR apps has examined consumers' attitude from the viewpoint of the Technology Acceptance Model (TAM) [9], its use in retail frontline

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 181–191, 2020.
https://doi.org/10.1007/978-3-030-36737-4_15

operation [10] and positive brand attitude formation [11]. In the tourism domain, it has also been examined as a tool for improving destination engagement and satisfaction [2]. A critical missing link in extant knowledge is how the usability and emotional perception of AR apps impact experience and intention to use. This is particularly important as information system scholars have repeatedly echoed that the success in the diffusion of a piece of information technology is critically anchored on its cognitive (e.g., usability) and affective components [12, 13]. This study therefore adds to this gap by examining the role of usability and affective components (i.e., emotional perception) of AR apps on customer experience and intention to use. In order to address the research purposes, respondents were asked to experience an AR application (Layer) as a travel information source, containing travel attraction, destination and sports/leisure information. After their actual experiences to Layer, a set of survey was used to measure concepts of usability, enjoyment, entertainment, playfulness, action/emotion experiences and intention to use.

The paper starts with an overview about augmented reality. Next the development of the hypotheses is presented in two chapters. The first is dealing with usability and emotional app perception and the second one with emotional app perception, experience and intention to use. After the methodology the results will be presented. The paper closes with the discussion and managerial implications.

2 Literature Review

2.1 Augmented Reality

Increasing scholarly interest in augmented reality (AR) is underpinned by its role in improving customer experience [14]. [15, p. 20] defines AR as a "medium in which digital information is overlaid on the physical world that is in both spatial and temporal registration with the physical world and that is interactive in time." The difference between virtual reality (VR) and AR is that with VR, the use of special goggles separates and immerses the user in a virtual world, AR users are still in connection with reality, however, such reality is augmented via virtual information [11]. The use of AR has been applied in fields such as games and sports, education, entertainment, social networking and marketing [9] with different formats such as mirrors, smartphones and wearable devices [11]. With the ubiquity of smartphones present a vast potentials for the adoption of AR apps, however, there is limited understanding on how AR app usability and its emotional perceptions impacts tourists' experiences and intention to use.

2.2 Usability and Emotional App Perception

Several studies in the domain of information and communications technology have highlighted the importance of usability [16] and emotional components in user experience [17]. Usability implies the physical components of a piece of technology which enhances its use [16] and is for instance measured by efficiency, satisfaction, learnability, memorability and errors [18]. In the context of mobile applications, [19] developed and validated various measurements namely application design, application utility, user interface input, user interface output and user interface structure. While the physical features of mobile applications are a prerequisite for the success of an application, another consideration for users is the emotional perception such as fun, pleasure and enjoyment they derive from such applications [20]. Prior research has shown a positive relationship between usability of mobile applications and emotional aspects such as enjoyment [21, 22]. Similarly, [23] found that system quality and perceived playfulness are critical factors that influence consumers' decisions. AR apps contain images, interactive features and gaming functionalities that produce excitement and heightens the pleasure of the user [2]. [24] examined the physical and interactive features of AR apps and found a positive association between the physical properties and users' emotion (feelings of pleasure, feelings of control and arousal). We thus hypothesize that:

H1. AR app usability positively impacts on enjoyment
H2. AR app usability positively impacts on playfulness
H3. AR app usability positively impacts on entertainment

2.3 Emotional App Perception, Experience and Intention to Use

Studies have also established a relationship between usability and affective components of mobile applications and their influence on user experience [25]. There are different types of experience. In an offline context, [23] for instance look at emotional experience which is based on emotions and action experience Which is defined as experiences customers gain through participation in activities. Action experience positively influences behavioral intention. For emotional experience no direct link with behavioral intention could be found. In a study of mobile users in Taiwan, [26] found a positive and significant relationship between entertainment and customer experience. Similarly, [22] found a positive relationship between enjoyment and customer experience. The same study also establish a relationship between customer experience and positive emotions. Playfulness was also positively related to enjoyment [27]. Accordingly, we hypothesize that:

H4. AR app entertainment positively impacts emotional experience
H5. AR app enjoyment positively impacts emotional experience
H6. AR app playfulness positively impacts emotional experience
H7. AR app playfulness positively impacts action experience
H8. AR app entertainment positively impacts action experience
H9. AR app entertainment positively impacts action experience

Embedding affective components in mobile applications and its impact on user experience is strongly related to usage intention [28] and actual usage [29]. Pleasurable experiences strongly predict usage intention [30]. [31] found AR positively influences user experience which leads to higher user satisfaction and the willingness to buy more. However, [24] noted that only pleasure and arousal as emotional experiences positively influenced usage behaviour. Thus, we propose the following:

H10. Action experience has a positive impact on the intention to use an AR app
H11. Emotional experience has a positive impact on the intention to use an AR app

Figure 1 presents the proposed conceptual model reflecting the hypothesized relationships between usability, emotional perception, two types of experiences, and intention to use.

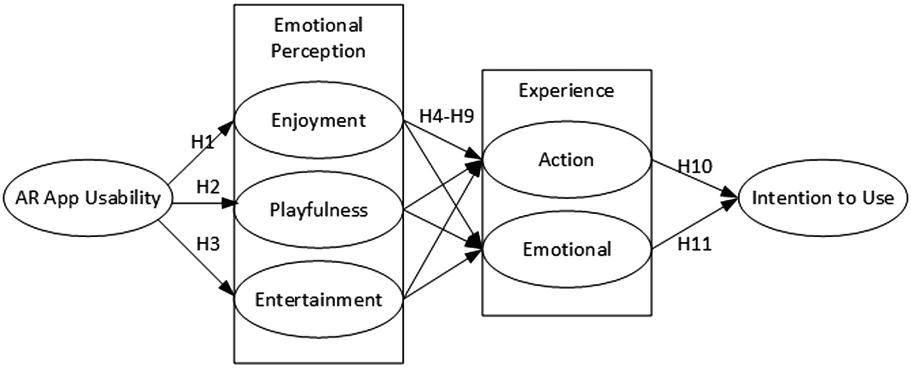


Fig. 1. Conceptual model (Source: authors' own figure)

3 Methodology

3.1 Research Context

There are numerous augmented reality app examples. For this research we used Layar. a Dutch organization who was founded in 2009. The Layar app gained international recognition as being one of the first augmented reality browsers. Today Layar is part of the Blippar group (headquarter is in London) with the reputation of being one of the world's leading augmented reality and interactive print apps. Interactive print basically bridges the gap between print media of all form and digital media. One way Layar accomplishes this is by linking flat two-dimensional images or text to videos, 360-degree pictures, audio or social media. Watching encoded print media through the Layar app then augments the printed version. The questionnaire designed for this research comprised examples study participants had to try before answering the survey.

3.2 Questionnaire Design and Data Collection

A questionnaire comprising four sections was designed. The first part comprised questions to reveal previous knowledge concerning augmented reality in general and Layar in particular. Example questions are whether they heard about augmented reality and/or Layar and which information sources they normally use to search for travel information. The second section introduced the app by showing a video about how Layar works (https://www.youtube.com/watch?v=ZR4eSmmPCxg) and it asked people to actually download the app to their phone. Then they had the chance to use Layar and actually experience how it works. They had to try at least one of the examples presented in Fig. 2. The way the examples are designed are all applicable and as such relevant in a tourism context.

Watch a video | Complete league tables | Slide through pictures

Fig. 2. Augmented print examples study participants experienced (Source: https://www.layar.com/)

Then, the third part of the questionnaire asked respondents about their experience with Layar and if they would like to use augmented reality sources such as the ones they just experienced in order to search for travel related information. They were asked about cognitive aspects looking at the augmented application usability, i.e. application design, application utility, interface in- and output and interface structure [19], affective aspects, i.e. enjoyment [32], playfulness [33], and entertainment [34]. Further, people responded concerning their experience with regards to action and emotional responsiveness [35]. Finally, they expressed their intention to use an augmented reality app in the future [36]. Table 1 provides an overview of all the items used. As an answer scale for all those items a 6-points Likert Scale from 1 (strongly agree) to 6 (strongly disagree) was used. The fourth and final part was about demographics.

The questionnaire was pre-tested among 43 people not only to reveal odds in terms of questions, spelling errors and language issues but also to check the feasibility of the actual usage of the augmented reality app with regard to the examples provided. Besides various typos and language issues the questionnaire turned out to be ready for the field. In order to control for confounding effects, the data was collected from a large student group from a UK university. That is, the researchers should be able to monitor the actual experiences of Layer by subjects and minimize any other environmental factors. Thus, the students registered a technology-related class are suitable to address the research questions. As a result, all of subjects have participated in the research as well as responded the survey. A convenience sample of 796 fully completed and usable questionnaires was collected.

Table 1. Constructs and measurement scales (Source: see sources added in this Table)

Construct	Items
Augmented reality application usability [19] (i.e. design, utility, interface input, interface output, interface structure)	– Overall, I think the Layar is designed well – In general, I believe that Layar has a great design – To me, Layar is very functional – Generally speaking, Layar serves its purpose well – In general, Layar allows me to scan print material easily – Overall, the user input mechanisms are designed effectively on Layar – In general, the multimedia content of the scanned print material is presented effectively – Overall, I believe that Layar presents the multimedia content of the scanned print material very well – Overall, I think Layar structures information effectively – In general, Layar is structured very well
Affective components – Enjoyment [32]	– I find Layar an entertaining app – Using Layar is an agreeable way of passing time – Overall, I find Layar enjoyable
– Entertainment [34]	– Layar was lots of fun to use – I thought Layar was clever and quite entertaining
– Playfulness [33]	– Please indicate how much Layar added to the following – Happiness, excitement, satisfaction, amusement
Experience [35] – Action experience	– Using the app makes me think about my search behaviour – Using the app influences my activities – Using the app makes me think about my usage of my mobile phone
– Emotional experience	– The app makes me feel more engaged in my search – The app is an emotional experience
Intention to use [36]	– I think I will use Layar in the future – I recommend that others use Layar – I intend to use brands that offer Layar in the future

3.3 Data Analyses

In order to analyse the Sructural Equation Model (SEM) the second generation software Mplus [37] was used. An advantage of the tool is that it provides estimators for data which is not normally distributed. For this study the robust estimator MLM was used [38]. First, one has to examine the measurement model with regard to discriminant validity and convergent validity [39]. Second, the evaluation of the structural model follows. In order to evaluate the structural model in a second step it is suggested to use a combination of stand-alone and incremental fit indices. We used the Satorra-Bentler scaled chi-square and the Root Mean Squared Error of Approximation (RMSEA) as stand-alone indices and the Tucker-Lewis Index (TLI) and the Comparative Fit Index (CFI) as incremental ones. Standardized solutions are reported.

4 Results

4.1 Sample Description

The data comprises 59.4% female and 40.6% male participants with an average age of 25.70 (STD = 11.44). 58.9% of the participants most of the time use an iOS system followed by 35.8% Android users. 49.9% have heard about augmented reality and 26.4% of Layar. On average people spend 5.68 h online (STD = 4.02) of which 5.63 h are on their smartphone (STD = 4.27).

With regards to their last holiday on average people stayed for 6.98 days (min = 1, max = 58, STD = 5.48). 8.5% travelled by themselves, 20.9% with their partner, 29.9% with their family (including child/ren), 32.3% with friends and the rest with others. The most important information sources used to search for travel information for that last trip are websites (81.0%), followed by travel guide books (32.8%), mobile applications (27.1%), online ads (25.4%), magazines/newspaper ads (21.0%), and brochures (20.9%). Only 2.6% used augmented reality applications.

4.2 Model Testing

The assessment of the measurement model reveals that the factor loadings are between 0.727 and 0.910 and as such they are well above the recommended threshold of 0.7 As all squared correlations between construct and its indicators are above 0.5 item reliability is achieved. The third column of Table 2 shows that Convergent Validity (CR) measures exceed the suggested threshold of 0.7 [39]. The [40] criterion requires all Average Variance Extracted (AVE) values to exceed 0.5. The diagonal in Table 2 shows that this criterion is met as the values range from 0.625 to 0.728. The comparison of the constructs' correlations and the AVE allows to further assess

Table 2. Discriminant validity and convergent validity (Source: compiled by authors)

				Affective components			Experience		
		CR	1	2	3	4	5	6	7
1	Usability	0.948	**0.648**						
2	Enjoyment	0.842	0.539	**0.728**					
3	Playfulness	0.896	0.284	0.432	**0.684**				
4	Entertainm.	0.832	0.332	0.452	0.561	**0.713**			
5	Action	0.856	0.310	0.317	0.406	0.276	**0.665**		
6	Emotional	0.768	0.448	0.464	0.531	0.487	0.781	**0.625**	
7	Use intent	0.869	0.296	0.384	0.561	0.684	0.412	0.516	**0.689**

discriminant validity. As required all AVE values are higher than the squared correlations. All seven constructs the model comprises discriminate well from each other. Furthermore, the measurements of all the constructs proof to be unidimensional which is a requirement determined by various researchers [41–43].

Based on a significant Satorra-Bentler scaled chi-square (χ^2 = 1380.45, $p < 0.001$) we examined the modification indices. However, no paths was added as there was no theoretical ground for it. An inspection of the fit indicators shows that all of them meet the essential level. With values of 0.905 and 0.916 respectively, both the TLI and CFI are above the required threshold of 0.9 [44]. RMSEA is at a satisfying level of 0.065.

Table 3 shows the details of the structural model results. The β-values show that Usability has the strongest impact on Enjoyment followed by Entertainment and then Playfulness. The Emotional Experience is driven by Entertainment and Playfulness. Enjoyment has a lower but also a significant impact. The main trigger for Action Experience is Playfulness followed by Enjoyment. Entertainment has the least impact. A striking insight is that Intention to Use is only driven by augmented reality users' Emotional Experience. Action Experience has no effect. So, we can confirm ten postulated hypotheses. The only one we must reject is that there is an impact of action experience on the intention to use an AR app.

Table 3. Standardized path estimates and significances (Source: compiled by authors)

Endogenous variable	Exogenous variable	R^2	β	p-value
Usability	Entertainment	0.390	0.625	<0.001
	Playfulness	0.331	0.576	<0.001
	Enjoyment	0.571	0.756	<0.001
Entertainment	Emotional experience	0.900	0.505	<0.001
Playfulness			0.495	<0.001
Enjoyment			0.199	<0.001
Entertainment	Action experience	0.461	0.172	<0.001
Playfulness			0.460	<0.001
Enjoyment			0.210	<0.001
Emotional experience	Intention to use	0.710	0.810	<0.001
Action experience			0.051	0.212

5 Discussion

5.1 Theoretical Contribution

This paper makes an effort to contribute to literature by examining the relationships between usability, emotional perception (i.e. playfulness, enjoyment and entertainment), action- and emotional experience and the intention to use an AR app in the future in a travel context. Previous literature suggests that usability is a crucial antecedent for the positive emotional perception of a technology [20–23]. Our results confirm that in the context of AR applications. Most of the previous studies looked at experience of a technology in general. We followed what [23] did in an offline context and analysed different types of experience namely action- and emotional experience. Action experience is mainly driven by playfulness while emotional experience is triggered by entertainment. In terms of the impact of action- and emotional experience on intentional behaviour our results contract with [23] findings. In an AR application context action experience has no significant impact on intention to use the AR app but it is all about the emotional experience that makes users want to use the app again.

5.2 Managerial Implications

From a management perspective the results show that usability of an AR app basically is the very basic requirement for positive emotional perceptions. While usability is crucial the app must comprise features that users find enjoyable, entertaining and playful. In order to succeed in terms of travellers' willing to use the app in the future the focus must be on the emotional experience of users. Indeed, this insight should be useful for mobile technology designers who create the contents for mobile users. With the advancement of mobile technology, the smartphones can be a catalyst for travellers to easily use an AR application. In this sense, the AR content that can induce emotional aspects can not only motivate adoption behaviours but also enhance the influences of AR on their user experiences for travel. Action Experience can be ignored. The most crucial design factor to focus on with an AR app to make its usage an emotional experience is entertainment followed by playfulness. So, depending on the context of the AR app relevant features must be identified and implemented.

5.3 Limitations and Future Research

This study is cross-sectional and focused on one AR app only. Future studies should examine different types of AR apps and examine effects over time. Further, it is worthwhile to look at differences regarding what service augmented reality provides. In our study this would be differences between using the AR app to watch videos, slide through pictures, or complete league tables. Other aspects such as looking at 360-degree pictures or showing versions of a place of different times in history should be considered too. Finally, it is suggested to add other potential emotional perceptions of an app and different types of experiences app users can have.

References

1. Chang SC, Hwang GJ (2018) Impacts of an augmented reality-based flipped learning guiding approach on students' scientific project performance and perceptions. Comput Educ 125:226–239
2. Koo C, Choi K, Ham J, Chung N (2018) Empirical study about the pokémonGo game and destination engagement. In: Information and communication technologies in tourism 2018. Springer, Cham, pp 16–28
3. Cruz E, Orts-Escolano S, Gomez-Donoso F, Rizo C, Rangel JC, Mora H, Cazorla M (2018) An augmented reality application for improving shopping experience in large retail stores. Virtual Reality 23:1–11

4. Errichiello L, Micera R, Atzeni M, Del Chiappa G (2019) Exploring the implications of wearable virtual reality technology for museum visitors' experience: a cluster analysis. Int J Tourism Res 21:590–605
5. Bec A, Moyle B, Timms K, Schaffer V, Skavronskaya L, Little C (2019) Management of immersive heritage tourism experiencs: a conceptual model. Tourism Manage 72:117–120
6. Aluri A (2017) Mobile augmented reality (MAR) game as a travel guide: insights from Pokémon GO. J Hospitality Tourism Technol 8(1):55–72
7. Ajibola D, Shafombabi V, Petrus P, Shilongo N, Thielen E, Sieck J (December 2018) Using augmented reality to enhance printed magazine articles about Namibian lodges. In: Proceedings of the second african conference for human computer interaction: thriving communities. ACM, p 57
8. Techjury (2019) Augmented Reality Stats to Keep You Sharp in 2019
9. Rese A, Baier D, Geyer-Schulz A, Schreiber S (2017) How augmented reality apps are accepted by consumers: a comparative analysis using scales and opinions. Technol Forecast Soc Change 124:306–319
10. Heller J, Chylinski M, de Ruyter K, Mahr D, Keeling DI (June 2019) Let me imagine that for you: transforming the retail frontline through augmenting customer mental imagery ability. J Retail 95(2), 94–114
11. Rauschnabel PA, Felix R, Hinsch C (2019) Augmented reality marketing: how mobile AR-apps can improve brands through inspiration. J Retail Consum Serv 49:43–53
12. Delone WH, McLean ER (2003) The DeLone and McLean model of information systems success: a ten-year update. J Manage Inf Syst 19(4):9–30
13. Tam C, Oliveira T (2016) Understanding the impact of m-banking on individual performance: DeLone & McLean and TTF perspective. Comput Hum Behav 61:233–244
14. Flavián C, Ibáñez-Sánchez S, Orús C (2019) The impact of virtual, augmented and mixed reality technologies on the customer experience. J Bus Res 100:547–560
15. Craig AB (2013) Understanding augmented reality: concepts and applications. Newnes
16. Nayebi F, Desharnais JM, Abran A (2012) The state of the art of mobile application usability evaluation. In: 2012 25th IEEE Canadian conference on electrical and computer engineering (CCECE). IEEE, pp 1–4
17. Cyr D, Head M, Ivanov A (2009) Perceived interactivity leading to e-loyalty: development of a model for cognitive–affective user responses. Int J Hum-Comput Stud 67(10):850–869
18. Nielsen J (1994) Usability engineering. Elsevier
19. Hoehle H, Venkatesh V (2015) Mobile application usability: conceptualization and instrument development. MIS Q 39(2):435–472
20. Merikivi J, Tuunainen V, Nguyen D (2017) What makes continued mobile gaming enjoyable? Comput Hum Behav 68:411–421
21. Lu J, Liu C, Wei J (2017) How important are enjoyment and mobility for mobile applications? J Comput Inf Syst 57(1):1–12
22. McLean G, Al-Nabhani K, Wilson A (2018) Developing a mobile applications customer experience model (MACE)-implications for retailers. J Bus Res 85:325–336
23. Wang K, Lin CL (2012) The adoption of mobile value-added services: investigating the influence of IS quality and perceived playfulness. Managing Serv Qual: Int J 22(2):184–208
24. Kourouthanassis P, Boletsis C, Bardaki C, Chasanidou D (2015) Tourists responses to mobile augmented reality travel guides: the role of emotions on adoption behavior. Pervasive Mobile Comput 18:71–87
25. Wilmer HH, Sherman LE, Chein JM (2017) Smartphones and cognition: a review of research exploring the links between mobile technology habits and cognitive functioning. Front Psychol 8:605

26. Sheng ML, Teo TS (2012) Product attributes and brand equity in the mobile domain: the mediating role of customer experience. Int J Inf Manage 32(2):139–146
27. Hung SY, Tsai JCA, Chou ST (2016) Decomposing perceived playfulness: a contextual examination of two social networking sites. Inf Manage 53(6):698–716
28. Hur HJ, Lee HK, Choo HJ (2017) Understanding usage intention in innovative mobile app service: comparison between millennial and mature consumers. Comput Hum Behav 73:353–361
29. Yang S, Jiang H, Yao J, Chen Y, Wei J (2018) Perceived values on mobile GMS continuance: a perspective from perceived integration and interactivity. Comput Hum Behav 89:16–26
30. Hsu CL, Chang KC, Chen MC (2012) The impact of website quality on customer satisfaction and purchase intention: perceived playfulness and perceived flow as mediators. Inf Syst e-Bus Manage 10(4):549–570
31. Poushneh A, Vasquez-Parraga AZ (2017) Discernible impact of augmented reality on retail customer's experience, satisfaction and willingness to buy. J Retail Consum Serv 34:229–234
32. Van der Heijden H (2004) User acceptance of hedonic information systems. MIS Q 695–704
33. Holbrook MB, Chestnut RW, Oliva TA, Greenleaf EA (1984) Play as a consumption experience: the roles of emotions, performance, and personality in the enjoyment of games. J Consum Res 11(2):728–739
34. Lastovicka JL (1983) Convergent and discriminant validity of television commercial rating scales. J Advertising 12(2):14–52. https://doi.org/10.1080/00913367.1983.10672836
35. Wang W, Chen JS, Fan L, Lu J (2012) Tourist experience and wetland parks: a case of Zhejiang, China. Ann Tourism Res 39(4):1763–1778
36. Davis FD (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology. Manage Inf Syst Q 13(3):319–340
37. Muthén L, Muthén B (2007) Mplus user's guide. statistical analysis with latent variables. Muthén & Muthén, Los Angeles
38. Satorra A, Bentler PM (1994) Corrections to test statistics and standard errors in covariance structure analysis. In: Eye A, Clogg CC (Eds) Latent variables analysis: applications for developmental research. Sage Publications, Thousand Oaks
39. Campbell DT, Fiske DW (1959) Convergent and discriminant validation by the multitrait-multimethod matrix. Psychol Bull 56:81–105
40. Fornell C, Larcker DF (1981) Evaluating structural equation models with unobservable variables and measurement error. J Mark Res 18(1):39–50
41. Anderson JC, Gerbing DW (1988) Structural equation modeling in practice: a review and recommended two-step approach. Psychol Bull 103:411–423
42. Gerbing DW, Anderson JC (1988) An updated paradigm for scale development incorporating unidimensionality and IST assessment. J Mark Res 25(2):186–192
43. Hattie JA (1985) Methodology review: assessing unidimensionality of tests and items. Appl Psychol Measur 9(2):351–362
44. Hu LT, Bentler PM (1995) Evaluating model fit. In: Hoyle RH (Ed) Structural equation modeling: concepts, issues and applications. Sage Publications, Thousand Oaks, pp 76–99

Technology

Impact of Free Wi-Fi on Guest Satisfaction and Price of Properties in Sharing Economy Accommodations

Jacques Bulchand-Gidumal(✉), Santiago Melián-González, and Beatriz González López-Valcárcel

University Institute for Tourism and Sustainable Economic Development (TIDES), University of Las Palmas de Gran Canaria, Campus de Tafira, 35017 Las Palmas, Spain
{jacques.bulchand, santiago.melian, beatriz.lopezvalcarcel}@ulpgc.es

Abstract. The purpose of this paper is to analyze the influence of offering free Wi-Fi on prices and guest satisfaction of accommodation properties in the sharing economy. To that aim, data on all the listings available on the Airbnb platform in Spain were automatically downloaded. These listings were classified in urban and non-urban ones. Based on a final sample of 74,722 apartments and houses, the impact of Wi-Fi and other property amenities was tested using linear regression analysis. Our results show that offering free Wi-Fi has a positive impact on both guest satisfaction and the price of properties. In the case of price, Wi-Fi was the most important amenity. Thus, property owners should seriously consider offering free Wi-Fi because it involves a daily price increase of 16.28 euros, therefore guaranteeing return-on-investment. To our best knowledge, this is the first study to investigate the importance of free Wi-Fi for guest satisfaction in sharing accommodations. It is also one of the first studies to take into consideration non-urban properties since most of the available research has analyzed properties in large cities. Results join the findings about the importance of free Wi-Fi in the traditional accommodation industry, confirming the importance of this technology for the tourism sector.

Keywords: Wi-Fi · WLAN · Sharing accommodation · Sharing economy · Peer-to-peer accommodation · Consumer behavior

1 Introduction

Sharing or peer-to-peer accommodation is one of the main activities that characterize what is known as collaborative tourism, that is, the set of sharing economy activities that pertain to the tourism industry. The rise of both the sharing economy and collaborative tourism is attributed to several factors, which include consumers' preferences [1], among many others. Consumers' motives for embracing sharing economy services are varied. Among these, individuals frequently mention factors referring to seeking some kind of utility [2].

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 195–205, 2020.
https://doi.org/10.1007/978-3-030-36737-4_16

From the guest point of view, there is evidence that sharing accommodation can be a substitute for hotels [3]. In this sense, data show that guests of sharing accommodations value some characteristics that hotels also have, such as the amenities [4] like AC, hair drier and personal items. However, and at the same time, sharing accommodation is also considered an accommodation service characterized by features that are not present in traditional accommodation options. For example, it has been suggested that sharing accommodation guests seek social experiences that are not available in traditional accommodation options [5], like socializing with locals and with other guests.

From the host point of view, property owners freely decide what equipment to offer in their homes. Similarly to what happens in any traditional economic activity, providers seek to offer attractive products that capture the consumer's attention. In fact, on Airbnb, all the properties provide detailed information about their characteristics and amenities, one of which is free Wi-Fi. The importance of this service has been demonstrated in the hotel industry [6]. Nevertheless, there is hardly any evidence about how relevant this amenity is in sharing accommodations, as will be commented in the literature section. It seems obvious that guests will prefer that properties provide free Wi-Fi. Nevertheless, what is not so evident is to what extent the price of properties and guest satisfaction depend on this particular amenity. Therefore, the objective of this research is to analyze the importance of providing free Wi-Fi as a property amenity in peer-to-peer accommodations. To that aim, an analysis is done using linear regression analysis based on all the properties offered through Airbnb in Spain considering both the price of properties and guest satisfaction.

The article unfolds as follows. We first present the literature review. The next section contains the research hypotheses, and the following one describes the methodological aspects. Then the results are described, and the conclusions and limitations are presented.

2 Literature Review

2.1 Collaborative Tourism

Tourism activities that fit under the sharing economy are usually referred to as collaborative tourism [7]. These activities are of different types and involve almost all the areas of tourism, from gastronomy to accommodation, including tourist guides and transportation. Out of these activities, transportation and accommodation are the two areas in which both the sharing economy and collaborative tourism have developed further. In the area of sharing accommodation, there are several digital platforms, out of which Airbnb stands out. It allows anyone who owns a property (the host) to offer it in the platform so that anyone (the guest) looking for a temporarily place to stay can find it. Thus, similarly to other digital platforms, Airbnb is a marketplace in which peers (the host and the guest) can find each other and reach an agreement [8].

Currently, Airbnb has 6 million units in almost every city and every country in the world [9]. It has become widespread due to several reasons, especially cost-savings, amenities available in the units, and the potential for more authentic local experiences [10–12].

2.2 Value in Collaborative Tourism Consumption

Consumers' use of sharing economy services draws on different motives. In this sense, it has been proved that social benefits (e.g., to have opportunities to start and maintain social relationships, being introduced in local communities) are an important aspect for collaborative tourism consumers [13–15].

At the same time, a more practical or utilitarian component has also been found [16]. In this sense, some authors [10] posit that as it happens with traditional services, in collaborative tourism consumers value the specific characteristics of the service, while [1] found that obtaining utility was the most important factor in the likelihood of choosing peer-to-peer services. In this sense, several works [2, 13, 16, 17] have found that economic benefits (i.e., cost-savings for better value) were an important reason for using sharing economy services. Also, other authors [18] mentioned the product variety available.

2.3 Sharing Accommodation and Wi-Fi

Getting a better value is not just an issue of cost. Sharing accommodations include a set of amenities that seek to meet clients' requirements. Air conditioning, access to a kitchen, heating, washers, and Wi-Fi are examples of the amenities that Airbnb hosts can mark when they offer their listings.

Free Wi-Fi has been shown to be an important amenity in the hotel industry. Previous research has found that offering free Wi-Fi was the most important hotel amenity in hotel rating results because it improved hotel ratings by up to 8% [6]. According to a TripAdvisor report [19] based on more than 44,000 hoteliers and travelers, 46% of travelers said that free in-room Wi-Fi was considered a must-have amenity. Li et al. identified Internet services as one of the hotel characteristics most appreciated by hotel guests, particularly business travelers and couples [20]. Eriksson and Fagerstrøm found that both Wi-Fi price and Wi-Fi reviews affect consumers' likelihood of booking a hotel [21].

Research has shown that sharing accommodation guests have similar preferences to those of hotels guests. In this regard, [3] showed that in Texas the rise of sharing accommodations negatively affected hotels' economic revenues, suggesting that consumers are increasingly substituting lower-end hotels for Airbnb. Likewise, [22] found that in Barcelona a high density of Airbnb activity has made hotel investment returns on equity fall. [23] found that two-thirds of a sample of Airbnb clients used this platform as a hotel substitute. Therefore, as Akbar and Tracogna [24] thoroughly analyze, some hotel clients find equivalent services in sharing accommodation. Thus, it could be derived that sharing accommodation guests will appreciate free Wi-Fi as hotel guests do and has been proven. However, literature has also mentioned that consumers may have different expectations when staying at sharing accommodations (e.g., social and environmental benefits) than when staying at hotels [13, 15]. Thus, it is not possible to guarantee that free Wi-Fi will be as important for sharing accommodations guests as it is for hotels' guests.

[11] suggested several research questions for the sharing accommodation phenomenon. One of them refers to the importance of the properties' attributes for clients

and how they compare to those of hotels. Based on previous studies, it is reasonable to hypothesize that for sharing accommodation clients, free Wi-Fi is also an important amenity. Wang and Nicolau [25] analyzed the relevance of different variables in the price of Airbnb's properties. Among them, two property amenities were considered: real beds and wireless Internet. Based on a sample of 33 cities, the authors found a positive and significant effect of both: real beds (15.5%) and free Wi-Fi (9.5%). However, the focus of this research was the price of properties, and guest satisfaction was not analyzed. Additionally, the aforementioned study was based on listings placed in large cities. Therefore, properties in places such as villages and smaller cities were not included. We believe it would be important to test if the importance of free Wi-Fi is as important outside major urban environments as it is in urban environments. The type of tourists that travel to both types of destinations are different, and their requirements and expectations regarding technological facilities could also be different. It could also be the case that mobile coverage is different in both settings (large urban areas vs. small urban areas, villages and country-side), thus making free Wi-Fi more important in one area than another.

3 Hypotheses

In the case of the hotel industry, there is evidence about the importance of offering free Wi-Fi [6]. Literature has also shown the importance of the amenities of properties for the sharing accommodation guests [20]. However, to the best of our knowledge, there is only one empirical study supporting the importance of providing this amenity in sharing accommodations [25]. This research did not consider a key variable for tourism and, especially, for sharing accommodation success, namely, guest satisfaction. In addition, listings out of large cities were not analyzed. In this sense, the literature has extensively recognized the existence of urban tourism [26], with distinctive characteristics from other forms of tourism. Thus, we think it would be valuable to provide more evidence about the extent to which it is relevant for sharing accommodations to offer free Wi-Fi. The relevance of this amenity will be determined by its impact on guest satisfaction and price, respectively, taking into account not only listings in large cities but also listings placed away from these. We propose two hypotheses.

H1. Offering free Wi-Fi positively contributes to sharing accommodations' guest satisfaction.

H2. Offering free Wi-Fi positively contributes to the prices of sharing accommodations.

4 Methodology

Spain is an important tourist destination. It was the second most visited country in the world in 2017 [27]. In January 2018, we downloaded from Airbnb data of all the units available in Spain on the platform. For each property, the following data were downloaded: GPS location, average daily rate, type of property (entire apartment and houses, private rooms, shared rooms), amenities, capacity, if the host was a superhost, number of reviews, and average guest rating. In order to obtain information from properties actually rented, the criterion of choosing only properties with at least one guest review was used, a similar criterion to that used in previous studies (i.e., [25]). Our initial sample was composed of 98,075 listings, among which 74,722 were entire apartments and houses, 22,819 were private rooms, and 534 were shared rooms. We decided to choose only entire properties because most of the private and shared rooms (more than 90%) offered free Wi-Fi, which hampered the analysis of this amenity influence. The data about the sample can be found in Table 1.

Table 1. Information about the sample (source: authors)

Source	Airbnb
Selection criteria	All entire units, that had received one or more reviews available in Spain
Data collection period	January 2018
Data collection method	Automated
Entire apartments and houses	74,722
Urban and non-urban	16,191 and 58,531
With free WiFi and without	53,308 and 21,414
Average max.number of guests	5.22
Average daily rate	97.89 euros
Average rating	4.75

According to the Spanish Statistical Office [28], the five largest cities in Spain are Madrid (3,182,981), Barcelona (1,620,809), Valencia (787,808), Seville (689,434), Saragossa (664,938) and Málaga (509,002). Thus, our sample is made up of cities smaller than those in the study by Wang and Nicolau [25], where the average size of the 33 cities they considered was close to 2 million people. Table 1 shows that the properties analyzed were located in urban contexts and outside of these locations. We considered a property to be in an urban context if it was within a radius of five kilometers from the center of a city of at least 50,000 people. With this specification, we wanted to determine possible differences from properties that are not located in areas that are usually more in demand by guests. In our sample, the properties' average rate was 97.89 euros (std: 103.78), and their average client rating was 4.75 (std: 0.28) on a scale from one to five.

Our alternative dependent variables are average pricing per day in euros and guest satisfaction. The latter was measured by the properties' average client rating, based on a five-star scale with the following values: 1; 1.5; 2; 2.5; 3; 3.5; 4; 4.5 and 5.

Although our hypotheses revolve around the impact of free Wi-Fi, we decided to include other properties' amenities in order to compare the relative importance of free Wi-Fi. This allows knowing not only whether guest satisfaction depends on free Wi-Fi, but whether this amenity is more or less relevant than others, such as a dishwasher, for example. We are not able to posit any hypotheses about the relative importance of the properties' amenities, but this comparison can contribute to better understand the role of free Wi-Fi. The amenities considered as explanatory variables were those included in the Airbnb platform's section where property owners list their services. All of them are treated as dummy variables and consist of the following: Wi-Fi, air conditioning, heating, kitchen, washer, dishwasher, laptop area, pets, and iron. We decided not to include the amenities kitchen and washer as independent variables in the analysis because they were present in almost all the properties (90% or more). Apart from Wi-Fi that is the main focus of this research, we also included the other amenities to test the relative importance of Wi-Fi.

As control variables, the following were taken into consideration: location (urban or non-urban), capacity (maximum number of guests allowed in the property), starting year in Airbnb (2009 to 2017), guest rating (when the price was treated as the dependent variable), and average daily rate (when guest satisfaction was treated as the dependent variable). When guest satisfaction was treated as a dependent variable, the category of Airbnb superhost was also included. The superhost category is awarded every three months by the platform to hosts that meet a series of criteria [29]: high ratings, high demand, low cancellation rate, and high response rate.

The data were analyzed by using linear regression analysis, and significance tests use a significance level of 5%. Calculations were performed with STATA v14.

5 Results

Wang and Nicolau's study showed the relevance of the listings' location. Our results revealed that, except for the kitchen, listings showed significant differences in all the characteristics when the properties' locations are considered (Table 2). Properties located in urban environments are smaller, better equipped (except for the kitchen), and less likely to admit pets than properties located outside a five-kilometer radius from the

Table 2. Properties' characteristics considering their location (source: authors)

Characteristics	Non-urban	Urban	Total	Significance
Free Wi-Fi	66.96%	87.18%	71.34%	0.00[a]
Kitchen	98.18%	98.19%	98.18%	n.s.[a]
Washer	90.80%	91.40%	90.93%	0.02[a]
Dishwasher	11.24%	12.11%	11.43%	0.02[a]
Laptop friendly area	42.36%	61.90%	46.60%	0.00[a]
Pets allowed	31.03%	17.03%	28.00%	0.00[a]
Air conditioning	43.10%	60.61%	46.90%	0.00[a]
Heating	69.08%	83.45%	72.20%	0.00[a]
Iron	67.29%	75.43%	69.05%	0.00[a]
Capacity (guests)	5.45	4.41	5.22	0.00[b]

[a]Chi2 probability; [b]T-test probability.

center of a city of more than 50,000 people. This result shows that there are differences in the characteristics of urban and non-urban properties, and thus, that it is important to verify the importance of amenities in both types of locations independently.

Table 3 shows that there are no significant differences in guests' ratings depending on the properties' locations. It also indicates that prices and the Airbnb category of superhost show significant differences between urban and non-urban properties. When the price per guest is used instead of the total price of the property, the differences become non-significant.

Table 3. Prices and superhost category considering properties' location (source: authors)

	Price		Price per guest		Superhost	Guest rating	
	Mean[a]	Std.	Mean[b]	Std.	%[c]	Mean[b]	Std.
Non-urban	103.48	111.45	19.13	17.18	16.64%	4.75	0.28
Urban	77.69	65.38	18.90	11.74	27.34%	4.74	0.28
Total	97.89	103.78	19.08	16.16	18.96%	4.75	0.28

[a]T-test probability: 0.00; [b]Non-significant; [c]Chi2 probability: 0.00

Hypothesis 1 states that Wi-Fi positively contributes to sharing accommodation client satisfaction. Table 4 collects the results of the linear regressions that analyze

Table 4. Impact of amenities on guest satisfaction[a] (source: authors)

	Total	Non-urban	Urban
n	74,722	58,531	16,191
Guest satisfaction			
Superhost	0.220*** (0.328)	0.205*** (0.294)	0.253*** (0.408)
Starting year	0.026*** (0.136)	0.025*** (0.132)	0.029*** (0.148)
Price	0.000*** (0.088)	0.000*** (0.086)	0.000*** (0.104)
Non-urban/urban	−0.044*** (−0.068)		
Capacity	−0.000^{ns} (0.054)	0.000^{ns} (0.010)	−0.005*** (−0.035)
Free Wi-Fi	0.023*** (0.034)	0.025*** (0.043)	0.020** (0.023)
Laptop area	0.014*** (0.026)	0.011*** (0.021)	0.024*** (0.041)
Pets	−0.032*** (−0.041)	−0.021*** (−.036)	−0.046*** (−0.062)
Air conditioning	0.003^{ns} (0.006)	−0.000^{ns} (−0.001)	0.019*** (0.033)
Heating	0.023*** (0.033)	0.025*** (0.042)	0.013* (0.016)
Iron	0.040*** (0.066)	0.038*** (0.065)	0.046*** (0.071)
Dishwasher	0.047*** (0.054)	0.045*** (0.051)	0.051*** (0.060)
F	1034.52	697.86	472.24
R^2	0.17	0.15	0.26
Adj. R^2	0.17	0.15	0.26

[a] Figures in brackets are the variables' standardized coefficients.
***p:0.00; $^{**}p < 0.01$; $^{*}p < 0.05$

guest satisfaction. Figures in brackets are the variables' standardized coefficients. The first column includes all the properties, the second column considers only the properties outside urban environments, and the third column collects properties located in urban areas. In the three regressions, being a superhost is the most important variable for client satisfaction. Regarding the amenities, when all the listings are considered, Wi-Fi positively contributes to client satisfaction, and it is the third most important amenity (β: 0.034), after the iron (β: 0.066) and the dishwasher (β: 0.054). The same thing is true for the properties located outside urban environments. For properties located in urban areas, the contribution of Wi-Fi is also positive, but less important: iron, dish-washer, laptop area, and air conditioning were found to be more important than free Wi-Fi.

Table 5 collects the results of the regressions of property prices and amenities (hypothesis 2). In the three regressions, the capacity (maximum number of guests allowed in the property) is the most important variable in the price. Regarding the amenities, when all the properties are considered, Wi-Fi (β: 0.081) is the most important service for the listings' price. Offering Wi-Fi involves an increase in the daily price of 16.28 euros. This increase is higher in the case of non-urban properties (17.22 euros) and lower in the case of urban properties (5.47 euros). The contribution of the second most important amenity (air conditioning, β: 0.045) entails a price increase of roughly half the previous amount (8.12 euros). For properties located in urban areas, only two amenities showed a significant and positive contribution to the price: heating (β: 0.072) and Wi-Fi (β: 0.032).

Table 5. Impact of amenities on price[a] (source: authors)

	Total	Non-urban	Urban
n	74,722	58,531	16,191
Price			
Capacity	18.890^{***} (0.512)	20.189^{***} (0.523)	11.980^{***} (0.417)
Clients rating	22.578^{***} (0.070)	23.319^{***} (0.066)	20.705^{***} (0.106)
Starting year	-2.539^{***} (0.040)	-2.842^{***} (0.042)	-1.563^{***} (−0.040)
Non-urban/urban	-8.935^{***} (−0.043)		
Free Wi-Fi	16.276^{***} (0.081)	17.229^{***} (0.082)	5.461^{***} (0.032)
Laptop area	0.403^{ns} (0.002)	1.694^{*} (0.008)	-4.438^{***} (−0.039)
Pets	-6.979^{***} (−0.034)	-7.808^{***} (−0.037)	-4.409^{***} (−0.030)
Air conditioning	8.122^{***} (0.045)	12.781^{***} (0.065)	-6.104^{***} (−0.054)
Heating	5.399^{***} (0.026)	3.26^{***} (0.015)	10.989^{***} (0.072)
Iron	-4.547^{***} (−0.023)	-4.951^{***} (−0.023)	-1.908^{ns} (−0.014)
Dishwasher	0.817^{ns} (0.002)	0.211^{ns} (0.000)	1.521^{ns} (0.009)
F	2228.24	1956.94	361.71
R^2	0.29	0.30	0.19
Adj. R^2	0.29	0.30	0.19

[a] Figures in brackets are the variables' standardized coefficients.
***p:0.00; $^{*}p < 0.05$

6 Conclusions

The main conclusion of this research is that, as in the case of hotels, free Wi-Fi is an important amenity in the sharing accommodation industry. Up to now, it was known that it was relevant for the price of units in cities, while our research shows that it is also important for guest satisfaction. These results are consistent with previous studies cited in the literature review about the importance of free Wi-Fi for hotel guest satisfaction and the substitution of hotels by sharing accommodation options, respectively. Our results also show that free Wi-Fi is even more important for properties located outside the urban areas. We believe this may be due to three reasons: first, the fact that urban areas usually have better mobile coverage than other areas; second, some cities in Spain have free public Wi-Fi available in certain areas, especially those with higher tourist interest; third, free Wi-Fi available in most restaurants and bars in major cities which could be used by sharing accommodation guests.

The influence of free Wi-Fi on properties' prices confirms the only result about this issue in the sharing accommodation sector [25]. In our research, if we consider the whole sample, Wi-Fi is the amenity with the most impact on price. The same thing is true of properties located outside the urban areas. Along with heating, Wi-Fi is the amenity that was relevant for any property, regardless of its location. Therefore, taking into consideration both the current Internet access prices and that Wi-Fi allows a daily price increase of 16.28 euros, providers who do not offer Wi-Fi are not maximizing their earnings. It must be taken into account that in Spain, the country in which all the properties in this study were located, most Internet providers charge less than 45 euros per month. Thus, with three nights per month of occupation, the Wi-Fi costs would be recovered.

Although it was not the main focus of our research, our results also provide additional interesting findings. First, being located outside the urban areas negatively impacts the property's price, which confirms the finding by Wang and Nicolau [25] who found that the farther the listing is from the city center, the lower its price. Second, we have found that allowing pets contributes in a significant way to guest satisfaction, but negatively: if a property allows pets, the guest satisfaction will be lower. We believe this can be due to the fact that guests travelling without pets will be less satisfied if previous guests have been in a property with pets, thus maybe leaving hair in the furniture or strong smells. Third, regarding air conditioning, and while it was not found to have a significant impact on guest satisfaction when all properties were considered, it did have a significant positive impact when only urban properties were analyzed.

An additional conclusion from the explaining power of the guest satisfaction regressions is that other important factors also influence guest satisfaction. They could be other property aspects not considered in this study (e.g., beds and furniture quality, decoration, room size, building characteristics) and/or aspects of the destination where the properties are located. The finding that staying in a property located in an urban area negatively affects guest satisfaction (β: −0.068) may provide a clue. For example, in a sample of guest reviews, previous research [30] found that 45% of the complaints refer to the environment where the property is located (e.g., street noise, problems with parking in the area). In addition, in the case of the hotel industry, there is evidence that the destination's characteristics (e.g., population qualification) significantly affect hotel client satisfaction [31]. We believe that probably a similar result to this one will happen in the case of sharing accommodations.

With regard to the negative role of some of the amenities on price (e.g., iron or air conditioning in urban properties), we do not find any reasonable explanation. It is probably an endogeneity problem of our variables.

7 Limitations

Although this study has used a very large sample of more than 74,000 properties, it is not free of limitations, some of which pave the road for future research. The main limitation that we must take into account when using pricing and amenities data that are directly inputted by the hosts, is that hosts may not use revenue management strategies that hotels usually do. There are many systems available to assist individual hosts with the revenue management of their properties; however, these systems are quite popular in markets such as the US, but they are less common in Spain. Thus, we assume that hosts change and manage the prices of their properties, but actually, this may not be the case. Instead, it may be the case that most hosts set a price for the whole year, with small variations for very specific timeframes. Also, some hosts will maybe not take the time to input all the amenities they offer, since they may think that they are not really relevant.

Another limitation is derived from the data we used, that did not allow us to analyze the specific type of property under analysis (e.g., detached house, apartment, isolated house), the type of neighborhood in which it was placed and the demographics of those renting the property.

References

1. Möhlmann M (2015) Collaborative consumption: determinants of satisfaction and the likelihood of using a sharing economy option again. J Consum Behav 14(3):193–207
2. Tussyadiah I (2015) An exploratory on drivers and deterrents of collaborative consumption in travel. In: Tussyadiah I, Inversini A (eds) Information & communication technologies in tourism. Springer, Switzerland
3. Zervas G, Proserpio D, Byers JW (2017) The rise of the sharing economy: estimating the impact of Airbnb on the hotel industry. J Mark Res 54(5):687–705
4. Lee D, Hyun W, Ryu J, Lee WJ, Rhee W, Suh B (2015) An analysis of social features associated with room sales of Airbnb. In: Proceedings of the 18th ACM conference companion on computer supported cooperative work & social computing. ACM, pp. 219–222
5. Belarmino A, Whalen E, Koh Y, Bowen JT (2019) Comparing guests' key attributes of peer-to-peer accommodations and hotels: mixed-methods approach. Curr Issues Tour 22(1):1–7
6. Bulchand-Gidumal J, Melián-González S, González López-Valcárcel B (2011) Improving hotel ratings by offering free Wi-Fi. J Hosp Tour Technol 2(3):235–245
7. Dredge D, Gyimóthy S (2017) Collaborative economy and tourism. Springer, Switzerland
8. Bulchand-Gidumal J, Melián-González S (2018) La revolución de la economía colaborativa, Lid, Madrid

9. Airbnb fast facts: https://press.atairbnb.com/fast-facts/. Accessed 10 July 2019
10. Chen Y, Xie K (2017) Consumer valuation of Airbnb listings: a hedonic pricing approach. Int J Contemp Hosp Manag 29(9):2405–2424
11. Guttentag DA (2015) Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. Curr Issues Tour 18(12):1192–1217
12. Gutiérrez J, García-Palomares JC, Romanillos G, Salas-Olmedo MH (2017) The eruption of Airbnb in tourist cities: comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. Tour Manag 62:278–291
13. Böcker L, Meelen T (2017) Sharing for people, planet or profit? Analysing motivations for intended sharing economy participation. Environ Innov Societal Transit 23(2):8–39
14. Jefferson-Jones J (2016) Shut out of Airbnb: a proposal for remedying housing discrimination in the modern sharing economy. SSRN scholarly paper no. ID 2772078. http://papers.ssrn.com/abstract=2772078. Accessed 10 July 2019
15. Kim J, Yoon Y, Zo H (2015) Why people participate in the sharing economy: a social exchange perspective. In: Proceedings of Pacific Asia conference on information systems 2015, p 76
16. Shaheen SA, Chan ND, Gaynor T (2016) Casual carpooling in the San Francisco Bay Area: understanding user characteristics, behaviors, and motivations. Transp Policy 51:165–173
17. Hamari J, Sjöklint M, Ukkonen A (2016) The sharing economy: why people participate in collaborative consumption. J Assoc Inf Sci Technol 67(9):2047–2059
18. Hawlitschek F, Teubner T, Gimpel H (2016) Understanding the sharing economy–drivers and impediments for participation in peer-to-peer rental. In: Proceedings of the Hawaii international conference on system sciences. HICSS, pp 4782–4791
19. TripAdvisor 6 key travel trends for 2016. https://www.tripadvisor.com/TripAdvisorInsights/w665. Accessed 10 July 2019
20. Li G, Law R, Vu HQ, Rong J, Zhao X (2015) Identifying emerging hotel preferences using emerging pattern mining technique. Tour Manag 46:311–321
21. Eriksson N, Fagerstrøm A (2017) The relative impact of Wi-Fi service on young consumers' hotel booking online. J Hosp Tour Res 42:1–18
22. Aznar JP, Sayeras JM, Rocafort A, Galiana J (2017) The irruption of Airbnb and its effects on hotel profitability: an analysis of Barcelona's hotel sector. Intangible Capital 13(1):147–159
23. Guttentag DA, Smith SL (2017) Assessing Airbnb as a disruptive innovation relative to hotels: substitution and comparative performance expectations. Int J Hosp Manag 64:1–10
24. Akbar YH, Tracogna A (2018) The sharing economy and the future of the hotel industry: transaction cost theory and platform economics. Int J Hosp Manag 71:91–101
25. Wang D, Nicolau JL (2017) Price determinants of sharing economy based accommodation rental: a study of listings from 33 cities on Airbnb.com. Int J Hosp Manag 62:120–131
26. Ashworth G, Page SJ (2011) Urban tourism research: recent progress and current paradoxes. Tour Manag 32(1):1–15
27. UNWTO tourism highlights 2018 highlights. https://www.e-unwto.org/doi/pdf/10.18111/9789284419876. Accessed 10 July 2019
28. Instituto Nacional de Estadística: Official population figures referring to revision of municipal register. http://www.ine.es/dynt3/inebase/en/index.htm?padre=517. Accessed 10 July 2019
29. Airbnb: Superhost: recognising the best in hospitality. https://www.airbnb.co.uk/superhost. Accessed 12 Sept 2910
30. Bulchand-Gidumal J, Melián-González S (2017) Relación entre sostenibilidad y turismo colaborativo a partir de las quejas recibidas en el alojamiento en vivienda vacacional. Cuadernos Económicos 93:91–106
31. Bulchand-Gidumal J, Melián-González S, Lopez-Valcarcel B (2013) A social media analysis of the contribution of destinations to client satisfaction with hotels. Int J Hosp Manag 35:44–47

Studying the Factors Influencing Customers' Intention to Use Self-service Kiosks in Fast Food Restaurants

Osman Ahmed El-Said[1,2(✉)] and Toleen Al Tall[2]

[1] Alexandria University, Alexandria, Egypt
Osman_ahmed12@yahoo.com
[2] German University of Technology (GUtech), Muscat, Oman

Abstract. Competition in the restaurant sector is intensifying. Therefore, restaurant brands that wish to win will be those that best use modern technology to respond to their customer needs. Recently, several restaurant brands have used self-service kiosks (SSKs) as a replacement to traditional point of sale. This study aimed to examine the different predictors of customers' behavioral intention to use SSKs. Data was collected from a sample of 316 customers who had previous experience in using SSKs. Results demonstrated that both effort expectancy and performance expectancy had a significant and positive impact of customers' perception of value and the impact of performance expectancy was stronger. In addition, facilitating conditions, social influence and perceived value served as strong predictors of behavioral intention toward the usage of SSKs. A set of recommendations were offered for fast-food managers on how to improve customers' intention to adopt SSKs.

Keywords: Self-service kiosks · Effort expectancy · Performance expectancy · Perceived value · Facilitating conditions · Social influence · Behavioral intention

1 Introduction

The growth and expansion of the information and communication technology (ICT) has been becoming a vital factor in the success of many industries, such as the tourism, hospitality and restaurant sector [1]. The expansion of ICT can eventually determine the outcome success of the organizations as it helps manage and control the business activities that are going on within an organization [2]. With the expansion of ICT, a new type of technology called self-service technologies (SSTs) has emerged. SSTs are defined as: "technological interfaces that enable customers to produce a service independent of direct service employee involvement" [3]. SSTs have been adopted by different organizations to ease the employees' jobs, motivate customers to manage their own service, decrease costs and to simplify the purchasing process for a customer [4]. Moreover, in order for organizations to invest in SSTs, they need to understand the impact of these SSTs on customers and evaluate customer's response towards them. The customer's response can eventually determine if the adoption of SSTs is going to be a failure or success in the organization [5]. Therefore, the current study will investigate the

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 206–217, 2020.
https://doi.org/10.1007/978-3-030-36737-4_17

factors that influence customers' intention toward the usage of one of the types of SSTs, which is self-service kiosks (SSKs) used in fast food restaurants.

More specifically, this research will investigate customers' acceptance and adoption of SSKs in fast food restaurants by applying the Unified Theory of Acceptance and Usage of Technology (UTAUT) which was developed by [6]. The importance of adopting SSKs in fast food restaurants was highlighted in previous research. For example, [7] stated that using SSKs in restaurants reduces the waiting in line queue thus customers will not have any complains when it comes to waiting in line. It also allows customers to create their own service without the need of help of employees [3]. Prior research has been done on the individual's interactions with new technology approaches such as SSTs specifically focusing on the adoption of SSKs. However, there is lack of research done on the focus of the individuals' overall perception of SSKs in fast food restaurants [5]. Therefore, it is essential for restaurants to understand the feedback given towards SSKs to further improve the adoption process [8]. Accordingly, the objectives of the current study are to investigate customers' perception toward SSKs in fast food restaurants, to understand the highest influential factors on customers' perception of the value of using SSKs and to study the factors that affect customers intention to use SSKs.

2 Literature Review

The restaurant sector in general and especially fast food restaurants are among the most successful examples for the application of SSKs. The main reasons for the use of SSKs in fast food restaurants are to reduce the waiting in line queue, reduce the number of employees and to increase the speed of service [9]. Moreover, the introduction of SSKs has given the customers an opportunity to be co-producers of the service [10]. On the other hand, some customers were found to be reluctant to the adoption of SSKs mainly because they perceive them as having flaws such as security and design flaws [11]. Some of the other reasons that cause customers to avoid the use of SSKs include: they may find it hard to navigate through the SSKs, they may worry about making a mistake when purchasing an order, they also may lack knowledge when it comes to using the SSKs and they may not trust it enough to place their credit cards as they may think it would steal data [12].

2.1 Theoretical Framework

The Unified Theory of Acceptance and Use of Technology (UTAUT). The following research adopted the UTAUT theory which was introduced by Venkatesh et al. [6] to understand the factors that influence people acceptance and use of new technologies. Venkatesh et al. [6] reviewed past models such as the Theory of Reasoned action (TRA), Theory of Planned Behaviour (TPB), Technological Acceptance Theory (TAM) and the Diffusion of Innovation Theory (DOI) and revealed that these models have some limitations such as being designed to work towards a simple environment and lack of empirical investigation on diversified samples. The UTAUT theory assumes that individual's intention to use technology is impacted by four main factors namely, performance expectancy, effort expectancy, social influences and facilitating conditions and this relationship is moderated by three factors which are, age, gender and experience [6, 13].

Conceptual Model and Hypotheses. The theoretical model of the current study is presented in Fig. 1. In our research, we added the construct perceived value as an outcome of the satisfaction of the performance of SSKs (performance expectancy) and its ease of use (effort expectancy). Previous studies have found that customers' perception of value is one of the most important determinants of satisfaction with the dining experience [14]. Also, we assumed that perceived value will be positively linked to intention to use SSKs. Similar to the original theory, we assumed that facilitating conditions and social influence are positively linked to intention to use SSKs.

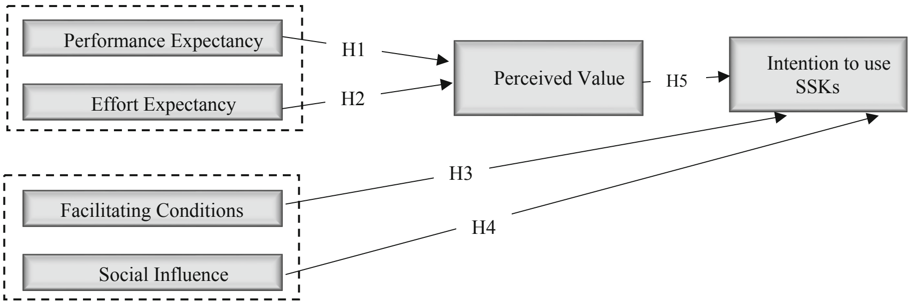


Fig. 1. Research model (Source: Authors' own figure)

Performance Expectancy and Perception of Value. Performance expectancy was defined as "the degree to which using a technology will provide benefits to consumers in performing certain activities" [15]. Various outcomes of SSTs usage such as improving consistency, increasing speed of service and increasing accuracy were linked to improving customers' performance expectancy which can enhance their perception of value [16]. For example, Gures, Inan and Arslan [17] found that functionality and speed level are among the key determinants of Y-Generation passengers' satisfaction with SSTs during the pre-flight services. Moreover, Setterstrom, Pearson, and Orwig [18] found that perceived usefulness is an important predictor of perceived value in web-enabled wireless technology. In the hotel industry, Wang and Liao [19] found that performance expectancy strongly and positively impacts customers' usage intention of mobile booking services. Thus, the following hypothesis is formulated:

> ***H1:*** *Performance expectancy has a significant positive impact on customers' perception of the usage value of self-service kiosks.*

Effort Expectancy and Perception of Value. Effort expectancy was defined as "the degree of ease associated with consumers' use of technology" [15]. This factor is similar to perceived ease of use [13], and it was found to be one of the antecedents of positive perception of value. For instance, Perdue [20] found that ease of navigation is significant predictor of tourists' perception of the quality of tourism suppliers' websites. Additionally, Wang and Wu [21] found that several factors including perceived ease of use and other factors such as perceived control and perceived usefulness were significantly affecting perceived value for restaurant customers using iPad as a menu card. Similarly, technicality which refers to the customers' perception of difficulty when using a new technology was found to have a negative impact on customers' perception of value in the context of web-enabled cell phones [18]. Therefore, we assume that customers will have a high-value perception of SSKs when they feel that it is easy to use. Thus, the following hypothesis is examined in this study:

> ***H2:*** *Effort expectancy has a significant positive impact on customers' perception of the usage value of self-service kiosks.*

Facilitating Conditions and Intention to Use SSKs. Facilitating conditions refer to "consumers' perceptions of the resources and support available to perform a behavior" [15]. This construct includes the presence of support factors such as training and supporting customers and providing online tutorials that help customers reduce the constraints of using technology [6, 15]. Facilitating conditions has been found to positively affect customers' behavioural intention to use new technologies in different contexts such as wireless internet services [22], e-government services [23], mobile banking [24], online educational platform and computer supported collaborative classrooms for hospitality and tourism education [25, 26] and service robots in hotels and restaurants [27]. Therefore, we assume that customers' intention to use SSKs will be positively affected by the presence of facilitating conditions such as staff support. Therefore, we formulated the following hypothesis:

> ***H3:*** *Facilitating conditions have a positive and significant impact on customers' intention to use self-service kiosks.*

Social Influence and Intention to Use SSKs. Social influence was defined as "the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology" [15]. An empirical justification for the significant effect of social influence on customers' intention to use different types of technologies was found in the literature. For instance, Ali et al. [26] found a significant relationship between social influence and students' intention to use computer supported collaborative classrooms. In another study, social influence was found to be one of the strong predictors of customers' acceptance to purchase online tickets for low cost airlines [28]. Accordingly, we proposed the following hypothesis:

> ***H4:*** *Social influence has a significant positive impact on customers' intention to use self-service kiosks.*

Perceived Value and Intention to Use SSKs. Perceived value was defined as "the consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given" [29]. Several studies have proved the significant impact of perceived value on attracting customers to adopt new technologies [18, 21]. For example, Wang and Wu [21] found that customers' behavioural intentions to patronize restaurants in Taiwan has been positively affected by the use of iPad menu, which has resulted in a better perception of value through the improvement of the dining experience. Similarly, Wang and Wang [30] found that customers' intention to adopt mobile hotel reservation was positively impacted by the perceived value of using mobile reservation compared to traditional reservation methods. Thus, the following hypothesis is examined in this study:

> ***H5:*** *Customers' perception of usage value has a positive and significant impact on their intention to use self-service kiosks.*

3 Methodology

The present study adopted an empirical research approach to test the research hypotheses by collecting quantitative data through a questionnaire.

3.1 Measures

The aim of this study was to explore and understand the acceptance and usage of the SSKs. To accomplish this, a questionnaire was developed to collect the data. The questionnaire included two main sections; section one included demographic and past experience questions. Section two included the six constructs that were included in the research model and they were all measured on a 5-point Likert scale ranging from "Strongly Disagree to Strongly Agree".

The constructs of the study were operationalized as follows. First, the performance expectancy construct was measured by five different attributes that were adopted from the study of [21]. An example of this construct is "the SSK provides accurate information such as prices, meal choices and offers". Second, the effort expectancy construct was measured by four different items which were adopted from the work Venkatesh et al. [6, 15], such as "it is easy to learn how to use McDonald's SSK". Third, the social influence construct was measured by two items which were adopted from the study of Lu et al. [22], such as "people who influence my behavior think that I should use the SSK". Fourth, four items adopted from the studies of Venkatesh et al. [6, 15] and Lu et al. [22] such as "resources needed for using the SSK are available" were used to measure the facilitating conditions construct. Fifth, the perceived value construct was measured by four items adopted from the work of Wang and Wu [21] and Wang and Wang [30], such as "compared to traditional cashiers, SSK requires less effort". The last construct which is the intention of customers to use SSKs was measured through four items adopted from the study of Venkatesh et al. [6, 15], such as "I intend to continue using the SSK in the future".

3.2 Sampling and Data Collection

The target population for the current study was customers in the Sultanate of Oman who visited McDonald's restaurants and used its SSKs before. McDonald's restaurants have been selected as they are the only restaurants that implement SSKs in the Sultanate of Oman. Data were collected from a convenience sample due to the impossibility of listing the study population and selecting a random sample. Two questions have been placed at the beginning of the questionnaire in order to determine the suitability of the participants to the survey. The first question was "Have you visited McDonald's before?" and the second question was "Did you try using the Self-service Kiosk? If the person answered no to one or both questions, the questionnaire ends and the participant does not complete the questionnaire, however if the answer is yes, the person can answer all the questionnaire questions.

An online questionnaire was designed using Google Forms which allows easy access and availability of the questionnaire 24/7 for the participants. The various social media sites in Oman were used as a means of disseminating the questionnaire link, in addition to inviting students, family members and friends to answer the questionnaire. Over a period of two months, 468 questionnaires were answered, of which 152 were incomplete because of the "no" answer to the first two questions. Therefore, the final sample included 316 valid questionnaires for the data analysis process.

4 Results and Discussions

The statistical analysis of the data was performed using SPSS V. 25. Firstly, the descriptive statistics was analyzed in order to develop a profile for the sample. Next, in order to determine the effect of the different independent factors on dependent factors, a multiple linear regression was conducted.

About 40% of the participants in the study were under the age of 30 years, followed by the age group of 30 to 40 years, representing 29%, while the age group > 40 to 50 years represented 20% and the age group > 50 years represented 11%. On the other hand, females represented 57% of the sample, while males represented 43%. As for the educational level, the majority of the participants were holders of the bachelor's degree (51%), followed by those who are still in the university education (21%).

Table 1 summarizes the descriptive statistics of the study. As can be deduced from the data in Table 1, customers believe that the SSKs are easy to use as the overall mean of all indicators is 4.21. Customers' evaluation for the performance of SSKs was measured through five indicators. The highest agreement was recorded for the indicator that was asking customers about the kiosk's provision of clear images for menu items ($M = 4.05$). Moreover, the overall mean the social influence dimension was below average ($M = 2.99$). Customers' perception of the existence of facilitating conditions recorded high agreement with an overall mean of 4.14. Finally, both the perception of value and the intention to use the SSKs scored a higher than average agreement score with an overall mean of 3.66 and 3.63 respectively.

Table 1. Means and standard deviations for study variables

Abbrev.	Constructs	Mean	SD
PE	*Performance Expectancy*	***3.95***	***0.84***
PE1	The SSK provides accurate information such as prices, meal choices and offers	3.94	0.99
PE2	The SSK provides high quality images of various menu items	4.05	0.92
PE3	I can browse the menu easily and conveniently through the SSK	3.84	0.98
PE4	I receive a quick response from the SSK when ordering meals	3.97	0.97
PE5	The SSK has better features compared to traditional cashiers	4.00	1.02
EE	*Effort Expectancy*	***4.21***	***0.81***
EE1	It is easy to learn how to use McDonald's SSK	4.21	0.87
EE2	I can easily use the SSK	4.30	0.86
EE3	The SSK has clear and understandable instructions	4.05	0.94
EE4	I find it easy to become skillful at using the SSK	4.28	0.87
FC	*Facilitating Conditions*	***4.14***	***0.90***
FC1	Resources needed for using the SSK are available	4.18	1.05
FC2	I have the knowledge necessary to use the SSK	4.11	0.96
FC3	The SSK is similar to other technologies I use	4.27	0.95
FC4	It is possible to get help from an employee in dealing with the SSK	4.06	0.96
SI	*Social Influence*	***2.99***	***0.76***
SI1	"People who influence my behavior think that I should use the SSK"	3.03	0.94
SI2	"People who are important to me think that I should use the SSK"	2.97	0.92
PV	*Perceived Value*	***3.66***	***0.81***
PV1	The purchase process becomes easier when using the SSK	3.87	0.99
PV2	Compared to traditional cashiers, SSK requires less effort	3.84	0.97
PV3	The use of the SSK enables me to get my food in a timely manner	3.54	0.97
PV4	"Using the SSK represent a good value for the paid money"	3.43	1.00
BI	*Behavioral Intention*	***3.63***	***0.90***
BI1	I intend to continue using the SSK in the future	3.95	1.01
BI2	I will always try to use SSK when it is possible	3.73	0.98
BI3	I plan to continue using SSK in all my purchases	3.81	1.00
BI4	I intend to use SSK in other restaurants implementing it	3.01	1.20

Source: Developed by the authors based on field survey data

4.1 Hypotheses Testing

A multiple regression analysis was conducted to test H1 and H2 using perceived value as the dependent variable and performance expectancy and effort expectancy as independent variables as shown in Tables 2 and 3. The two variables significantly predicted perceived value, $F = 61.419$, $p < .001$, $R^2 = .445$.

Table 2. Model summary of multiple regression analysis for predictors of perceived value

Model	R	R square	Adjusted R square	Std. error	F	Sig.
1	.667[a]	.445	.438	.60897	61.419	.000[b]

a. Predictors: (Constant), Effort Expectancy, Performance Expectancy
b. Dependent Variable: Perceived Value
Source: Developed by the authors based on field survey data

Moreover, data shown in Table 3 indicates that both performance and effort expectancy added significantly to the prediction, $p < .05$. By comparing the standardized coefficients, we can see that performance expectancy has a higher impact on perceived value than effort expectancy ($\beta = .391$ vs $\beta = .337$). This gives support for H1 and H2.

Table 3. Regression coefficients for the impact of predictors on perceived value

Model		Unst. coefficients		St. coefficients	t	Sig.
		B	Std. error	Beta		
1	(Constant)	.747	.270		2.769	.006
	Effort expectancy	.338	.082	.337	4.121	.000
	Performance expectancy	.377	.079	.391	4.781	.000

Dependent Variable: Perceived Value
Source: Developed by the authors based on field survey data

A second multiple regression model was tested to measure the impact of three independent variables, namely social influence, facilitating conditions and perceived value on behavioral intention to use SSKs. This model was employed to test H3 to H5. Table 4 shows that the three independent variables significantly predicted 59.4% of customers' behavioral intention toward the SSKs, $F = 74.249$, $P < .001$.

Table 4. Model summary of multiple regression analysis for predictors of behavioural intention

Model	R	R square	Adjusted R square	Std. error	F	Sig.
1	.771[a]	.594	.586	.57826	74.249	.000[b]

a. Predictors: (Constant), Perceived Value, Social Influence, Facilitating Conditions
b. Dependent Variable: Behavioural Intention
Source: Developed by the authors based on field survey data

Moreover, data shown in Table 5 indicates that the three variables added significantly to the prediction, $p < .05$. Among the three predictors, perceived value was the most influential on behavioral intention ($\beta = .539$, $p < .001$), followed by facilitating conditions ($\beta = .226$, $p < .01$) and finally social influence ($\beta = .192$, $p < .01$). Accordingly, H3 to H5 are supported.

Table 5. Regression coefficients for the impact of predictors on behavioural intention

Model		Unst. coefficients		St. coefficients	t	Sig.
		B	Std. error	Beta		
1	(Constant)	−.060	.265		−.227	.821
	Facilitating conditions	.224	.063	.226	3.551	.001
	Social influence	.192	.056	.192	3.434	.001
	Perceived value	.596	.075	.539	7.946	.000

Dependent Variable: Behavioral Intention

Source: Developed by the authors based on field survey data

4.2 Discussion

To understand the factors that impact customers' behavioural intention toward SSKs, the UTAUT theory was adopted and some modifications were made such as correlating both performance expectancy and effort expectancy with perception of value and then linking perception of value, social influence and facilitating conditions with customers' intention to use SSKs.

According to the results of the study, both effort expectancy and performance expectancy were found to be strong predictors of customers' perception of the value of using SSKs. These are similar to the results of previous studies which confirmed the importance of functional features such as improved consistency, increased speed of service and increased accuracy (performance expectancy) as strong predictors of customers' perception of the value [16–19]. Additionally, in line with previous studies, effort expectancy was reported to be a significant predictor of customers' perception of value [18, 20, 21]. These results revealed that most customers are concerned about the performance and ease of use of SSKs as an alternative to requesting the service from cashiers when placing their purchasing orders. From the customers' point of view, effort expectancy presented stronger impact on perceived value than effort expectancy. Previous studies have supported this finding and demonstrated that customers' perception of the performance of a new technology is more important than other features such as ease of use in determining the perception of value [21].

Moreover, facilitating conditions were found to have a strong influence on customers' intention to use SSKs. Previous studies have provided conflicting results in this regard. For example, Carlsson et al. [31] found that facilitating conditions did not have a significant relationship with behavioural intention. However, other researchers found a significant impact for facilitating conditions on behavioural intention [22–25]. Similarly, social influence was found to have a positive and significant impact on customers' intention to use SSKs. Previous studies have supported this finding and confirmed that customers' intention to use a new technology is influenced by surrounding persons such as family members and friends [26, 28]. Finally, among other predictors, it was found that the perception of value is the strongest predictor of customers' intention to use SSKs. This result confirmed previous findings in different contexts that emphasized the role of high perception of value as a strong positive predictor of behavioural intention [18, 21, 30].

5 Conclusion and Recommendations

The following study focused on customers' intention to adopt SSKs in fast food restaurants. The study adopted a slightly modified model adapted from the UTAUT theory. The first objective of the study which was related to investigating customers' perception toward SSKs was achieved through the descriptive data analysis, where it was found that customers have a positive attitude towards SSKs as shown in Table 1.

The second objective of the study was to investigate the influential factors on customers' perception of the value of using SSKs. This objective was achieved by testing a regression model which used performance and effort expectancy as predictors of perceived value. We found that both variables derived from UTAUT have a significant and positive impact on customers' perception of value. Therefore, we can conclude that when customers perceive that SSKs are performing well and are easy to use, their perception of value increases. In reality, compared to traditional point-of-sale, SSKs are distinguished by the following features that enhance customers' perception of value: (1) SSKs enhance the customer experience through fast order processing; (2) SSKs increase opportunities for growing sales through smart upselling and cross selling features; (3) SSKs prevent problems of poor communication that may occur between customers and employees because of different language, dialect or misunderstanding; (4) SSKs give customers a sense of full power and control over their orders; and (5) SSKs enable customers to browse all the menu items easily and customize the order as desired. Given these benefits, we recommend that in addition to the few restaurants that implement SSKs in Oman such as McDonald's, the rest of the restaurants should also start to apply SSKs as an alternative to traditional point-of-sale methods. We also recommend that restaurant managers purchase SSKs from reliable suppliers, ensure that they are easy to use and have functional features that enhance customers' value perceptions when using them.

The third objective of the study was achieved by testing a regression model where facilitating conditions, social influence and perceived value served as predictors of behavioral intention toward the usage of SSKs. According to the results, all the predictors were significantly and positively relevant to customers' behavioral intention and perceived value was the strongest predictor. According to that result, we offer a set of recommendations for fast-food managers on how to improve customers' intention to adopt SSKs. Firstly, since the perception of value has the strongest impact on intention, restaurant managers should adopt a number of practices associated with the use of SSKs that enhance customers' perceptions of its value, such as giving a discount to the customer in the case of the use of SSKs, increasing the number of SSKs to make it easier and faster to use them and creating an online simulation of SSKs that enables customers to browse and get used to them at any convenient time. Secondly, restaurant managers could improve customers' intention toward the usage of SSKs by providing support to customers who find difficulty in using them. This support can be provided through the help of an employee, or through the presence of a help feature in the kiosk supported by images and video illustrations. Finally, since the intention to use SSKs is influenced by other people, it is recommended to link the use of SSKs to something favored by family members such as giving a toy to children.

6 Limitations and Future Research

There were a set of limitations of the current study that presented opportunities for future research. First, the study included only a sample of SSKs users at McDonald's restaurants. McDonald's is the only fast-food restaurant in the Sultanate of Oman that implements SSKs and therefore it is not possible to generalize the results. Therefore, a larger sample from different sectors such as airlines, hotels and banks is necessary to generalize the results. Second, since SSKs were recently introduced in Oman, moderators were not included in our model. When SSKs become more popular, future researchers should investigate the impact of moderators such as gender, age and experience on the relationships established in our study model. Third, the current study adopted the original constructs of the UTAUT model; however future research could also consider other factors into account such as motivation. Fourth, the current study focused on the adoption of SSKs, however future research could analyze the acceptance and usage of other forms of SSTs. Finally, this study focused only on customers who used SSKs previously, while prospective studies may focus on customers who are reluctant to use the kiosks and study the reasons for such reluctance.

References

1. Croteau AM, Bergeron F (2001) An information technology trilogy: business strategy, technological deployment and organizational performance. J Strat Inf Syst 10(2):77–99
2. Powell TC, Dent-Micallef A (1997) Information technology as competitive advantage: the role of human, business, and technology resources. Strat Manag J 18(5):375–405
3. Meuter ML, Ostrom AL, Roundtree RI, Bitner MJ (2000) Self-service technologies: understanding customer satisfaction with technology-based service encounters. J Mark 64 (3):50–64
4. Dabholkar PA, Bagozzi RP (2002) An attitudinal model of technology-based self-service: moderating effects of consumer traits and situational factors. J Acad Mark Sci 30(3):184–201
5. Dabholkar PA (1996) Consumer evaluations of new technology-based self-service options: an investigation of alternative models of service quality. Int J Res Mark 13(1):29–51
6. Venkatesh V, Morris MG, Davis GB, Davis FD (2003) User acceptance of information technology: toward a unified view. MIS Q 27:425–478
7. Oh H, Jeong M, Baloglu S (2013) Tourists' adoption of self-service technologies at resort hotels. J Bus Res 66(6):692–699
8. Mozeik CK, Beldona S, Cobanoglu C, Poorani A (2009) The adoption of restaurant-based e-service. J Foodserv Bus Res 12(3):247–265
9. Kincaid CS, Baloglu S (2006) An exploratory study on the impact of self-service technology on restaurant operations. J Foodserv Bus Res 8(3):55–65
10. Auh S, Bell SJ, McLeod CS, Shih E (2007) Co-production and customer loyalty in financial services. J Retail 83(3):359–370
11. Curran JM, Meuter ML (2005) Self-service technology adoption: comparing three technologies. J Serv Mark 19(2):103–113
12. Meuter ML, Ostrom AL, Bitner MJ, Roundtree R (2003) The influence of technology anxiety on consumer use and experiences with self-service technologies. J Bus Res 56 (11):899–906

13. Davis FD (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q 13:319–340
14. Park C (2004) Efficient or enjoyable? Consumer values of eating-out and fast food restaurant consumption. Int J Hosp Manag 23(1):87–94
15. Venkatesh V, Thong JY, Xu X (2012) Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Q 36 (1):157–178
16. Baptista G, Oliveira T (2015) Understanding mobile banking: the unified theory of acceptance and use of technology combined with cultural moderators. Comput Hum Behav 50:418–430
17. Gures N, Inan H, Arslan S (2018) Assessing the self-service technology usage of Y-Generation in airline services. J Air Transp Manag 71:215–219
18. Setterstrom AJ, Pearson JM, Orwig RA (2013) Web-enabled wireless technology: an exploratory study of adoption and continued use intentions. Behav Inf Technol 32(11):1139–1154
19. Wang YS, Liao YW (2008) Understanding individual adoption of mobile booking service: an empirical investigation. Cyberpsychol Behav 11(5):603–605
20. Perdue RR (2002) Internet site evaluations: the influence of behavioural experience, existing images, and selected website characteristics. J Travel Tour Mark 11(2–3):21–38
21. Wang HY, Wu SY (2014) Factors influencing behavioural intention to patronise restaurants using iPad as a menu card. Behav Inf Technol 33(4):395–409
22. Lu J, Yu CS, Liu C (2005) Facilitating conditions, wireless trust and adoption intention. J Comput Inf Syst 46(1):17–24
23. Oechslein O, Fleischmann M, Hess T (2014) An application of UTAUT2 on social recommender systems: incorporating social information for performance expectancy. In: 2014 47th Hawaii international conference on system sciences. IEEE, pp 3297–3306
24. Püschel J, Afonso Mazzon J, Mauro C, Hernandez J (2010) Mobile banking: proposition of an integrated adoption intention framework. Int J Bank Mark 28(5):389–409
25. Chiao HM, Chen YL, Huang WH (2018) Examining the usability of an online virtual tour-guiding platform for cultural tourism education. J Hosp Leisure Sport Tour Educ 23:29–38
26. Ali F, Nair PK, Hussain K (2016) An assessment of students' acceptance and usage of computer supported collaborative classrooms in hospitality and tourism schools. J Hosp Leisure Sport Tour Educ 18:51–60
27. Lu L, Cai R, Gursoy D (2019) Developing and validating a service robot integration willingness scale. Int J Hosp Manag 80:36–51
28. Escobar-Rodríguez T, Carvajal-Trujillo E (2014) Online purchasing tickets for low cost carriers: an application of the unified theory of acceptance and use of technology (UTAUT) model. Tour Manag 43:70–88
29. Zeithaml VA (1988) Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. J Mark 52(3):2–22
30. Wang HY, Wang SH (2010) Predicting mobile hotel reservation adoption: insight from a perceived value standpoint. Int J Hosp Manag 29(4):598–608
31. Carlsson C, Carlsson J, Hyvonen K, Puhakainen J, Walden P (2006) Adoption of mobile devices/services-searching for answers with the UTAUT. In: (HICSS 2006), vol 6. IEEE, January 2006, p 132a

Pharmabroad: A Companion Chatbot for Identifying Pharmaceutical Products When Traveling Abroad

Boris Ruf[1], Matteo Sammarco[1(✉)], Jonathan Aigrain[1], and Marcin Detyniecki[1,2,3]

[1] Axa, Paris, France
{boris.ruf,matteo.sammarco,jonathan.aigrain,marcin.detyniecki}@axa.com
[2] Sorbonne Université, CNRS, LIP6, Paris, France
[3] Polish Academy of Science, IBS PAN, Warsaw, Poland

Abstract. Purchasing and taking unknown medications while abroad can be a stressful and even a dangerous undertaking. In this work we present Pharmabroad, which is a system able to convert pharmaceutical products sold in the visiting country to the more familiar products present in the travelers' home country market. Pharmabroad is based on computer vision (namely OCR coupled with Levenshtein distance) and its chatbot front-end guarantees a simple and effective human-machine interaction. Preliminary experiments about the effectiveness of the proposed system are reported.

Keywords: Travel chatbot · e-health · Mobile services · Human-computer interaction

1 Introduction

Despite the effort invested by institutions like the European Medicines Agency (EMA) to harmonize and standardize medicinal products at least in the European community [1,2], equivalent medicines are sold in different countries by diverse names and brands.

For instance, Tachipirina™ is the brand name for a widespread paracetamol-based medicine sold in Italy. It is mainly recommended to treat flu symptoms, headaches, neuralgia or other medium-low pains. The equivalent product in terms of active ingredient and diffusion sold in France is called Doliprane™ instead. An Italian tourist in France could be reluctant to accept a box of Doliprane™, and a French tourist in Italy would not be familiar with a box of Tachipirina™. The dilemma becomes trickier when dealing with different alphabets as both the brand name and the description are hard to interpret. It is therefore the task of Pharmabroad, our travel chatbot, to find correspondences between host and home countries medicines, independently from the alphabet and the language.

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 218–228, 2020.
https://doi.org/10.1007/978-3-030-36737-4_18

Even the most careful travelers carrying basic medicines with them, could face issues like the loss of medications during travel, not enough quantity for the entire stay, and unexpected needs. In such circumstances, travelers could take advantage of a travel chatbot which, with minimal interaction, given the image of a medicinal product box, provides the equivalent product sold in the traveler's home country. In this way, it becomes easier to demystify what the proposed medicine is for and the side effects it may cause. We stress the fact that the input accepted by the travel chatbot is just an image, as even writing the name of the medicinal in a different alphabet could result impracticable.

Recent breakthroughs in artificial intelligence (AI) have given rise to hopes for the development of useful digital agents which can help people to make their lives easier. The rapid expansion of smartphone ownership across the world has further contributed to the vision of such agents being mobile and always at hand, smoothly augmenting its owner's skills and knowledge when needed. In particular outside the familiar environment when traveling in foreign countries without knowledge of the local language, there are plenty of scenarios where a digital agent could be of useful support. However, research studies on the user perception and expectations from users of digital agents indicate that the systems still require significant improvements in order to provide a meaningful experience [3]. Also, demand analysis identified a need for specialized digital assistants, in particular in the insurance sector [4]. A promising approach to advance in this field are comprehensive knowledge engineering methodologies which back the digital agent and upgrade its abilities from small talk skills to domain expertise [5].

In this paper, we introduce Pharmabroad, a digital assistant which provides medical assistance when traveling. In particular, it offers to match a pharmaceutical product which is unknown to the user with a corresponding product from the user's home market. This way, a traveler in need of medicine can verify the purchase in a pharmacy when he or she is not familiar with the foreign language, or even the foreign alphabet.

To achieve this objective, we design a system architecture relying on off-the-shelf vision services, specific chatbot dialogues, and health data provided from existing public application programming interfaces (API). A smartphone equipped with camera serves as input device. Hence, the use of the digital agent is intuitive and simply consists of taking a picture of the foreign pharmaceutical product, and then reading the information about the similar local product found on the screen.

For the sake of clarity, in the rest of the paper we refer to medical products as medicine or medication or drug or pharmaceutical product and to their main ingredient as molecule or active constituent or principle.

The remainder of this paper is organized as following. We begin with a review of related work in image processing and digital agents in Sect. 2. Next, in Sect. 3 we give an overview of the system architecture. The image processing and text analysis components of our model are further explained and evaluated in Sect. 4. Finally, we conclude by providing insights in possible future fields of research.

2 Related Work

Conversational agents are becoming more and more present in the context of travel planning, reservation, and stay. In his work, Lino investigates the effectiveness of using a chatbot in replacement or complement to usual search engines for travel booking operations done by end users [6]. He shows, through a prototype, that looking for availability and prices results simpler and quicker if employing a chatbot as a proxy to multiple search engines. The same booking aid concept is applied to travel agents and companies for transverse reservations (train and airline tickets, hotel, theme park, and tour) [7]. Ivanov and Webster conduct an extensive cost-benefit analysis in terms of competitiveness, service quality, human resource management, service operation processes and standards, operating costs and revenues, especially for the use of chatbots by travel, tourism and hospitality companies [8]. In this direction, some reservation oriented online chatbot or mobile applications for both end users and travel agents are publicly available like Hello Hipmunk by Concur [9], Mezi by American Express [10], SnapTravel [11], or HelloGBye [12]. To enhance the reservation phase, authors in [13] propose and implement a chatbot for travel recommendations based on Restricted Boltzmann Machine and collaborative filtering. For longer stays abroad, chatbots are useful to assist in day-to-day life, for example helping learning foreign languages [14].

In parallel, chatbots are also employed in the context of e-Health for self-diagnosis [15–18] and medication advice [19–21]. The idea is to explain symptoms to a chatbot which will give back a diagnosis as long as a medication treatment relying on artificial intelligence, probabilistic-reasoning engine and a medical knowledge base covering many thousands of conditions, symptoms, risk factors and findings. If this aseptic approach is criticized [22], more emotionally conversational agent are developed, too [23]. Pharmabroad works as complement to such e-Health chatbots after obtaining a prescription abroad, or independently in case travelers already know what they are looking for.

In this direction, Pharmabroad joins chatbot capabilities in e-Health and computer vision to fill the gap for medication verification when traveling abroad. With respect to World Drugs Converter mobile application [24], Pharmabroad needs a minimal user interaction. This is especially necessary when the name is too difficult to write because written in a different language or alphabet. Taking just the image of the pharmaceutical box with the smartphone camera proves much more convenient from the user perspective.

3 System Architecture

The goal of our travel companion chatbot Pharmabroad is to help travelers decoding medical drug boxes sold in the host country, linking them with the corresponding and more familiar trade name sold in the traveler's home country.

This Section is divided into two parts. We first describe the interactions the tourist has with Pharmabroad and the high-level interface. Then we describe in

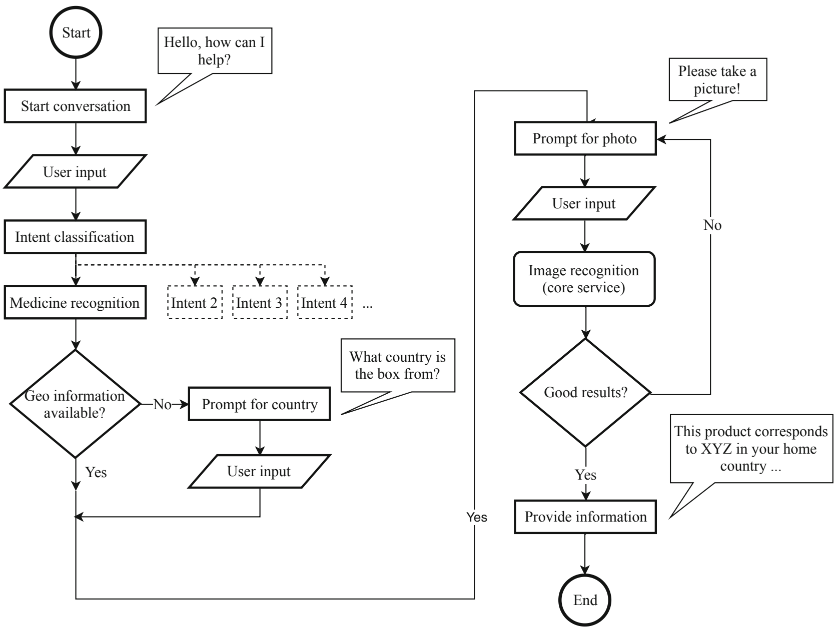


Fig. 1. The Pharmabroad dialog flow highlights the main steps from the user initial request to the final answer provided by the service (source: authors).

detail the core service behind Pharmabroad. A specific section dedicated to the image analysis is provided later in this paper.

Requirements include at least a home country database joining product names and active ingredients and the knowledge of geo-location for better OCR process and proper translation. In addition, we assume Pharmabroad running as a smartphone application for its pervasiveness, user interaction simplicity, and geo-location capability.

3.1 Dialog Flow

The conversational interface of a chatbot was chosen for this use case to facilitate the interaction of the traveler with the service and guide her through the process. Instead of typing the product's name we ask the user to take a picture of the medical box with the smartphone. In particular in geographical regions where the alphabet is different to the user's home country, this will lower the entry barrier to using the service.

A flow chart describing the dialog flow can be found in Fig. 1. After the chatbot has introduced itself, it asks the user for the matter of her request. In order to understand the intent, Natural Language Processing (NLP) methods such as the text classification library fastText can be applied to the user's answer [25]. Possible intents could be questions about symptoms, insurance coverage abroad,

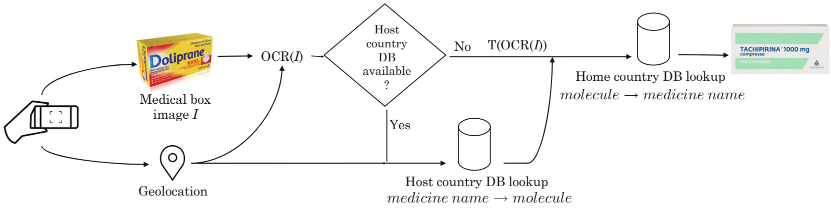


Fig. 2. Pharmabroad core service: home country drug name lookup starting from the host country pharmaceutical box image (source: authors).

or medicine lookup by brand name input. If the matter of the inquiry is about medicine recognition by image - the use case described in this paper - the application checks if the current geolocation can be determined. This information is used as country of origin of the medical box. If not, the user is asked to provide her location. In the next step, the user is requested to take a picture of the medicine. The image recognition process, described in detail in Sect. 3.2, tries to identify a corresponding medical product from the user's home market. If successful, the chatbot displays the brand name and additional information, and the dialog is finished. If no product could be matched, the user is requested to take another picture and the recognition process starts over.

3.2 Core Service

The core service is depicted in Fig. 2. Pharmabroad asks the user to take a picture of the medical box, front side. Such image I is then processed by an OCR engine to extract the text $OCR(I)$. The OCR engine can be embedded in the application or remotely called through an API. In both ways, the knowledge of the geographical position improves the text extraction as the right alphabet and dictionary is applied. For this reason, while taking the image, the geolocation is requested to the mobile operating system location service in parallel. At this point, Pharmabroad checks if a database joining the medicine name and the active ingredient for the host country is available. Also for this check, the geolocation is necessary. If so, $OCR(I)$ is iterated, word by word, and the host country drugs database is queried for the lookup $medicine\, name \rightarrow molecule$. The molecule returned is then, in turn, queried to the home country database for an inverse lookup $molecule \rightarrow medicine\, name$.

In case the host country database is not available or the first lookup described above does not return any result, the text $OCR(I)$ is translated to the traveler mother tongue $T(OCR(I))$ and iterated word by word trying to retrieve the molecule of the product. The home country drugs database is then queried for $molecule \rightarrow medicine name$. This last scenario could also be adopted in the case the user types directly the molecule she is looking for. Finally, an image of the correspondent drug is presented to the traveler.

Host and home country databases are complete lists of drugs on a specific country market. The Food and Drug Administration federal agency or the

Algorithm 1. Medicine name retrieval from an image

Require: Image I
Require: Medicine list L
Require: Threshold τ
Require: OCR
$text\_boxes \leftarrow OCR(I)$
if $text\_boxes$ is empty **then**
    return “”
end if
$candidate \leftarrow$ biggest box in $text\_boxes$
$name, distance \leftarrow$ closest name to $candidate$ in L using the Levenshtein distance
if $distance < \tau$ **then**
    return $name$
else
    return “”
end if

Agenzia Italiana del Farmaco, in United States and Italy respectively, are two examples of state agencies providing open data or API for medicines queries [26,27]. In case the database lookup does not return any result, it is plausible that $OCR(I)$ results are too inaccurate. In this case, it is asked to the user to take another picture of the medical box.

4 Image Analysis

The role of the image analysis part is to extract the medicine's name or molecule from a picture of its box, so that it can be used to query either the host country DB or the home one. In this section, we first describe the algorithms we developed to retrieve a medicine's name and molecule. We then present the database used to evaluate our algorithm and discuss the results obtained.

4.1 Medicine Name Retrieval

Depending on whether we have access to the host country DB, we either want to retrieve the name or the molecule of a picture of a medicine box. To retrieve the name, we use the following heuristic. We first run OCR on I to detect text boxes. These boxes must contain the recognized text as well as its size. Knowing that the name of a medicine is usually written with the biggest font on the box, we keep the biggest text box as a candidate. Then, we compare using the Levenshtein distance the text recognized by the OCR to the medicine names present in the host country DB and we keep the closest one. If the distance to the closest medicine name in the DB is lower than a threshold τ, we return the name. Otherwise, we consider that the name retrieval has failed. Algorithm 1 also presents this procedure.

To retrieve the molecule, the procedure is quite similar: L contains the molecule list instead of the medicine list, and instead of keeping only the biggest

Fig. 3. Examples of medicine boxes that compose the database (source: authors).

box as a candidate (i.e. line 5 of Algorithm 1), we go through all the text boxes and keep the one with the minimum distance to a molecule name in L.

4.2 Experiments

Database: In order to evaluate our proposed algorithm, we created a database of 343 pictures of medicine boxes. Starting from medicines that are in the ChEMBL database [28], we collected pictures on the internet that contained both the name of the medicine and the molecule. Some examples of the images composing the database are displayed in Fig. 3.

OCR: We use the API provided by OCR.space,[1] as it offers relevant features for our use case: OCR for several languages and automatic rotation based on the text direction.

Evaluation Metric: We measure the performance of our algorithm using 3 metrics: recall, precision and F1 score. The F1 score allows us to find a threshold τ that balances between "providing enough answers" and "providing good answers".

[1] https://ocr.space/.

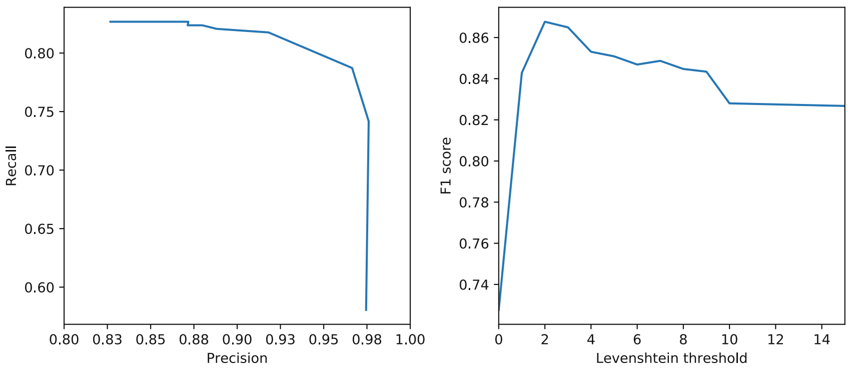


Fig. 4. Results for the title retrieval task. Left: Precision/Recall curve for different values of τ. Right: evolution of the F1 Score for different values of τ (source: authors).

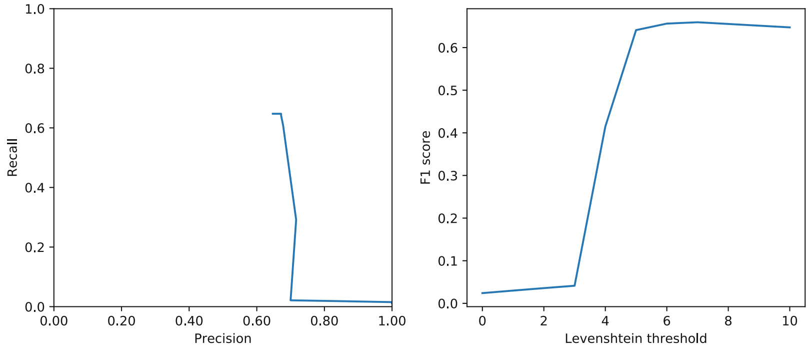


Fig. 5. Results for the molecule retrieval task. Left: Precision/Recall curve for different values of τ. Right: evolution of the F1 Score for different values of τ (source: authors).

Results: Figure 4 presents the precision/recall curve and the evolution of the F1 score for different values of τ for the retrieval of the name. Figure 5 displays the same information for the retrieval of the molecule. It might seem odd that we are not able to achieve perfect recall for the lowest threshold and perfect precision for the highest one, but it is important to remember that the threshold is applied on the Levenshtein distance between the OCR results and the medicine names in the DB. Thus, if the OCR results are really bad, it can be impossible to retrieve the correct name, even with a really high threshold τ. Similarly, if the OCR returns text that is really close to another medicine name present in the DB, we may retrieve the wrong name with a low distance.

For the name retrieval task, the best F1 Score - 0.87 with a precision of 0.97 and a recall of 0.79 - is obtained with $\tau = 3$. For the molecule retrieval task, the best F1 Score - 0.66 with a precision of 0.67 and a recall of 0.65 - is obtained with $\tau = 7$. As expected, we can observe that we get significantly better results for the retrieval of the name than for the retrieval of the molecule. It is thus preferable to have access to the host country medicine DB, as it leads to an overall much more reliable product.

However, it is important to note that the pictures in our database have a much lower resolution (405,000 pixels on average) than modern smartphone pictures (2,073,600 for standard HD). This could partly explain the performance gap, as the molecule is usually written in a smaller font than the name, which can become a problem when the resolution is too small. Thus, we could expect better results in real life settings.

5 Conclusion

In this manuscript we introduce Pharmabroad, which is a companion chatbot for travelers looking for adequate medications while being abroad. Pharmabroad accepts as input the image of a drug box, and proposes, as output, the equivalent drug sold in the user's home country. The user is guided through the process by a smooth and simplified dialog flow. To do so, Pharmabroad leverages computer vision techniques, namely OCR, chatbot capabilities and geo-location services.

Experiments show that we can get a good balance between precision and recall for medicine name extraction from drug boxes images (F1 score = 0.87) keeping a low Levenshtein distance ($\tau = 3$). Getting the molecule name from the image results more challenging, as the best F1 score achieved is 0.66.

It is worth to note that such results are achieved using only one image for each pharmaceutical box. In addition, the resolutions of the images composing the dataset are much lower on average than for smartphone pictures. These limitations might hinder the performances of our system, and we could expect better results in real-life settings.

Although we preliminary tested several OCR services, we would like to conduct a more extensive comparison, especially including services embedded in mobile devices to avoid users to connect to the local mobile network. Also, we plan to expand the dataset with pictures from other languages and alphabets in order to cover many other visiting countries.

References

1. European Medicines Agency (2018) Multiannual Work Program 2018–2020, EMA/73199/2018. Technical report, March. https://www.ema.europa.eu/en/documents/work-programme/multiannual-work-programme-2018-2020_en.pdf
2. World Health Organization (2017) Guidance on the Use of International Nonproprietary Names (INNs) for Pharmaceutical Substances. Technical report, WTO
3. Zamora J (2017) I'm sorry, Dave, I'm afraid i can't do that: chatbot perception and expectations. In: Proceedings of the 5th international conference on human agent interaction, HAI 2017. ACM, New York, pp 253–260. https://doi.org/10.1145/3125739.3125766
4. Koetter F, Blohm M, Kochanowski M, Goetzer J, Graziotin D, Wagner S (2018) Motivations, classification and model trial of conversational agents for insurance companies. CoRR, abs/1812.07339. http://arxiv.org/abs/1812.07339

5. Cameron G, Cameron D, Megaw G, Bond R, Mulvenna M, Neill SO, Armour C, Mctear M (2018) Back to the future: lessons from knowledge engineering methodologies for chatbot design and development. In: Proceedings of British HCI 2018, pp 1–5
6. Lino PMDB (2018) Travel booking chatbot. Master's thesis, Universidade do Porto
7. Purbowo AN, Yulia VYP (2018) Android based chatbot and mobile application for tour and travel company. IJCT - Int J Cult Technol 2:21–29
8. Ivanov SH, Webster C (2017) Adoption of robots, artificial intelligence and service automation by travel, tourism and hospitality companies-a cost-benefit analysis. In: Artificial intelligence and service automation by travel, tourism and hospitality companies-a cost-benefit analysis
9. Concur. Hello Hipmunk. https://www.hipmunk.com/hello
10. American Express. Mezi. https://mezi.com/
11. SnapTravel. https://www.snaptravel.com/
12. HelloGBye. https://www.hellogbye.com/
13. Argal A, Gupta S, Modi A, Pandey P, Shim S, Choo C (2018) Intelligent travel chatbot for predictive recommendation in echo platform. In: 2018 IEEE 8th annual computing and communication workshop and conference (CCWC), January 2018, pp 176–183
14. Jia J (2003) The study of the application of a keywords-based chatbot system on the teaching of foreign languages. CoRR, vol. cs.CY/0310018. http://arxiv.org/abs/cs.CY/0310018
15. Divya S, Indumathi V, Ishwarya S, Priyasankari M, Kalpana Devi S (2018) A self-diagnosis medical chatbot using artificial intelligence. J Web Dev Web Des. 3:1–7
16. Amato F, Marrone S, Moscato V, Piantadosi G, Picariello A, Sansone C (2017) Chatbots meet ehealth: automatizing healthcare. In: WAIAH@ AI* IA, pp 40–49
17. Ada. Your personal health guide. https://ada.com/
18. Your.MD. Your personal health guide and symptom checker. https://www.your.md/
19. Ahmad NS, Sanusi MH, Abd Wahab M.H, Mustapha A, Sayadi ZA, Saringat MZ (2018) Conversational bot for pharmacy: a natural language approach. In: 2018 IEEE conference on open systems (ICOS), November 2018, pp 76–79
20. Madhu D, Jain CJN, Sebastain E, Shaji S, Ajayakumar A (2017) A novel approach for medical assistance using trained chatbot. In: 2017 international conference on inventive communication and computational technologies (ICICCT), March 2017, pp 243–246
21. Microsoft. Healthcare Bot. https://www.microsoft.com/en-us/research/project/health-bot/
22. Ghassemi MM, Hanai TA, Raffa JD, Mark RG, Nemati S, Chokshi FH (2018) How is the doctor feeling? ICU provider sentiment is associated with diagnostic imaging utilization. In: 2018 40th annual international conference of the IEEE engineering in medicine and biology society (EMBC), pp 4058–4064
23. Fadhil A, Schiavo G (2019) Designing for health chatbots. CoRR, vol abs/1902.09022. http://arxiv.org/abs/1902.09022
24. TenTal Apps (2019) World drug converter 2019, Android mobile application
25. Joulin A, Grave E, Bojanowski P, Mikolov T (2017) Bag of tricks for efficient text classification. In: Proceedings of the 15th conference of the European chapter of the association for computational linguistics: vol 2, short papers. Association for Computational Linguistics, April 2017, pp 427–431

26. FDA. Food and drug administration federal agency. www.fda.gov
27. AIFA. Agenzia Italiana del Farmaco. www.agenziafarmaco.gov.it
28. Gaulton A, Hersey A, Nowotka M, Bento AP, Chambers J, Mendez D, Mutowo P, Atkinson F, Bellis LJ, Cibrián-Uhalte E, Davies M, Dedman N, Karlsson A, Magariños MP, Overington JP, Papadatos G, Smit I, Leach AR (2016) The ChEMBL database in 2017. Nucleic Acids Res 45(D1): D945–D954. https://doi.org/10.1093/nar/gkw1074

Hotels

Exploring the Use of Chatbots in Hotels: Technology Providers' Perspective

Dimitrios Buhalis(✉) and Emily Siaw Yen Cheng(✉)

Faculty of Management, Bournemouth University, Poole, UK
{dbuhalis, s5085050}@bournemouth.ac.uk

Abstract. Virtual assistants, also known as chatbot technology is getting more prominent and is applied widely in many industries. The use of chatbots, advantages, disadvantages, and future implication should be further understood; particularly from a technology provider' perspective. Previous studies, specialised in the hospitality context, focused solely on user's perspective. They have widely neglected the expert's point of view, which creates a gap in literature on the understanding of chatbot implications. The purpose of this study is to explore the use of chatbots in hotels by conducting semi-structured interviews with industry experts (technology providers). This study explores the use of chatbots and the key value the offer through interviews with chatbot experts. The findings show that the use of chatbots receive positive feedback and the benefits of chatbots outweigh the challenges. This will lead to further deployment of chatbot in the industry and the need to develop their abilities in order to achieve their full potential.

Keywords: Chatbots · Virtual assistants · Hotels · Tourism · Technology

1 Introduction

The implementation of technology in tourism and hotels improves competitive advantage as well as enhance guest experience [1, 2]. The ability for technology to create a unique experience and provide convenience to guests leads to guest satisfaction and possibly guest loyalty to the hotel or hotel brand [3–5]. Technology advancement has impacted every aspect of daily lives; changing how a person deals with a problem, how a person communicated, and also how a person travels. The use of technology contributes greatly to the hotel industry. This is generated by the desire to save cost while enhancing customer experience [3, 4, 6]. As AI technology advances to become more sophisticated and widely used, it will enable the delivery of a more personal service and unique travel experience [7]. Also, modern travelers are increasingly accept communication with the use of technology, compared to a decade ago when technology was regarded as too intrusive. Therefore, virtual assistants, also known as chatbots, is the focus of this study.

The chatbots have been studied by a number of researchers over the past 10 years [7, 8]. The existing literature on chatbots is limited, especially in the hotel context partly because of the fast-alteration of technology. Although there are several studies on chatbots and hotels, they primarily focus on the use of technology or artificial

The original version of this chapter was revised: The author name has been corrected to "Emily Siaw Yen Cheng". The correction to this chapter is available at https://doi.org/10.1007/978-3-030-36737-4_26

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 231–242, 2020.
https://doi.org/10.1007/978-3-030-36737-4_19

intelligence as a whole, rather than specific chatbot technologies. The hotel industry provides service to guests in hostile environments as tourists are often foreign and do not know the information as guests are distant from their language, culture and resources [9]. Chatbots can provide a flexible interface for guests to seek more information in order to maximise value for money and time. Having identified the gaps in literature, this study aims to contribute to the body of knowledge by understanding the technology supplier perspective on hotels chatbots. The research objectives are as listed below:

***RO*1** : To explore the use of chatbot adoption in hotels
***RO*2** : To study the functionality of chatbots in hotels
RO*3*a : To identify the benefits of chatbots use in hotels
RO*3*b : To determine the challenges for hotels with the use of chatbots
RO*4*a : To identify the benefits for hotels guests with the use of chatbots
RO*4*b : To determine the challenges for hotels guests with the use of chatbots
***RO*5** : To explore future opportunities for chatbots in the hotel industry

2 Background and Related Work

Technology leads developments in the tourism and hotel industries [9]. Technology trends appeal to the next generation travellers (millennials). Millennials are connected at all times of the day, which makes technology an important part on how they interact, shop and pay for travels [4, 9]. To enhance competitive edge of companies, financial performance, productivity, and guest service hotels implement smart technologies [6, 10]. Consumers also turn to social media to receive customer service. However, requests are usually not addressed at a timely manner or not addressed at all. Traditionally, organizations would have to hire dedicated customer service agents to respond to users on call centers or social media. This expensive, time consuming and often fails to meet expectations and demand.

Chatbots are programmed to work independently without a human. Human-chatbot communication is a broad field as it includes technical, human as well as psychological aspects. Chatbots answer questions based on formulated questions, in natural language, using a combination of predefined scripts and machine learning applications. Chatbots involve three modules: user interface, interpreter and a knowledge base and answer requests in near real time [11]. Data, with a blend of patterns and text are translated through natural language processing (NLP) to information through discovering applicable responses. Textually communication with technologies behind chatbots facilitate a range of functions, suchs as booking hotels, asking for sightseeing recommendations and planning trips.

2.1 Motivation for the Use of Chatbots

Hoteliers face a number of challenges daily; including servicing customers out of the office hours. As reported by Asksuite, 50% of the service requests is out of office hours, when customer service centers are closed. The inability to respond to guest enquiries may lead to loss of potential guests to other hotels or platforms. Instant guest gratification is crucial, especially when simple questions can be answered in real time with the use of chatbots. Hotels are keen to use chatbots to facilitate direct bookinges and reduce Online Travel Agents (OTAs) commissions. Hotels spend approximately 15–30% of their turnover on commissions for outsourcing sales. The use of chatbot aims to encourage direct bookings as guests can enquire and ask questions on hotel websites and book through chatbots. Guests can find the details of ongoing promotions or personalise their services through chatting with chatbots. Therefore, the use of chatbots in hotels may encourage more direct bookings, than booking through OTAs.

Customer service can also be improved. Guests prefer using mobile applications to get in contact with hotels to ask for information, directions, make reservations. They also use chatbots to request housekeeping, room service as well as other hotel services [12]. By implementing chatbots in the hotel's website or mobile application, guests are able to access information and make requests easily and from anywhere [12, 13].

2.2 Advantages and Disadvantages of Using Chatbots

Table 1 shows the advantages and disadvantages for the use of chatbots in hotels. In the current competitive hospitality industry, customer satisfaction is the key driver for sustaining competitive advantage. Understanding customers and designing services to attain customer satisfaction is critical. Chatbots have the ability to attend multiple guests at the same time and therefore can scale service. With the increasing number of users now relying on messaging and data applications for information, chatbots have a huge potential in the hotel industry. Chatbot has the ability to provide answers to user's queries instantly, which increases efficiency. The frictionless process enables users to get responses almost instantly. Chatbots' ability to recognize and response in a different language would be beneficial to hotels and guests, especially if the user is not fluent in English. The use of chatbot supports profitability by empowering more revenue generation, through smoother operations and by reducing labour cost. Encouraging and facilitating direct bookings, while guests are communicating live with chatbots, is one of the unique real-time direct sales opportunities. Guests demand real-time replies to their queries without delays. They expect personalized service as well as recommendations from hotels. A customised customer experience, delivered by chatbots, can also involve upselling and assisting with bookings, using information gathered from the digital conversation with a prospect guest. However, it can also potentially lead to disappointment if guests' questions are unanswered or problems unresolved. Chatbot technology currently is unable to detect sarcasm, humour or irony which may lead to misunderstandings and frustration [11, 12].

3 Methodology

3.1 Research Method

To address the research goal of exploring the use of chatbots in the hotel industry, semi-structured interviews were chosen as the data gathering method. The study was

Table 1. Summary of advantages and disadvantages of using chatbots in hotels. (Complied by authors)

	Advantages	Disadvantages
Hotels	–Attend to multiple guests simultaneously –Around the clock availability –Understand guest preference –Provide personalized experience –Real-time direct booking –Save labor costs –Constant quality of work –Communicate in multiple languages	–Unable to answer guests complicated questions –Unable to interpret sarcasm –Lack of acceptance and awareness from guests –Data protection –Image and reputation risks –Lack creativity, emotion and personal touch –May be perceived as threat to human employees
Guests	–Frictionless process with instant replies –Convenient for guests –Customise their stay –Provides anonymity –Communicate in different languages	–Unanswered questions causing distress and frustration –Privacy and data protection –Ethical concerns

conducted by interviewing industry experts (chatbot technology providers) to evaluate knowledge on chatbots. All the interviews were conducted through video/audio calls and they lasted between 25–40 min. Interviews were audio recorded and transcribed for analysis. Participants were recruited by contacting them, based on their web page and LinkedIn profiles. Participants' involvement was voluntary and the information provided was kept confidential. Seven semi-structured interviews were conducted to understand the use of chatbots in the hotel industry. Questions were designed based on the literature review. During the interview process, some further questions were asked to elaborate on participant responses.

Data Analysis: The data collected were analysed using the thematic analysis method. In the data coding process, the transcription was read several times to accurately code the data into several themes. Selective coding was used to identify responses only on the area or topic of interest and selecting unrelated responses out. This process refines and develops the topic of interest for the data analysis process.

3.2 Participants

A total of 7 industry experts were interviewed as shown in Table 2. In this paper, participants are labelled as 'P1' to 'P7' for analysis.

Table 2. Participants of the interviews. (Compiled by author)

Participant No.	Company Name	Position
P1	Zinc VC	Co-founder
P2	Cato Bot Company Limited	Founder & Managing Director
P3	IT Apps	Technical Consultant
P4	Humanise.AI	Co-founder & CEO
P5	Quicktext	VP Sales
P6	Bespoke Inc.	Head of Sales
P7	Asksuite Hotel Chatbot	Sales Representative

4 Findings and Discussion

Results from the semi-structured interviews were analyzed, using thematic analysis to achieve the five research objectives. Themes were identified according to the information gathered throughout the seven interviews.

4.1 Use of Chatbots and Acceptability from Hotels

Experts illustrated that hotels respond positively to the adaptation of chatbots. The effectiveness of chatbots is also improving. The use of technology in the hotel industry is prominent, with an average of 75% of bookings made through online systems. There is also an increase in the use of hotel technology to improve customer service. Besides Marriott International, several hotel chains, such as Hyatt Hotels, Accor Hotels, and Radisson Blu Hotels have successfully implemented the use of chatbots to benefit both their operations and guests. Chatbots primarily benefit hotels by responding to enquiries effectively at large scale. Entry-level chatbots can be implemented in most hotels, for answering FAQs and simple day-to-day questions, which can lead to improved customer service. The positive responses and the benefits introduced act as a catalyst to encourage other hotels to introduce chatbots. As mention by P4, chatbots are not suitable for every type of hotels. They primarily serve hotels that are digitally advanced and promote the use of technology in their service provision and customer engagement. P1 emphasized that budget hotels are often more suitable for the implementation of chatbots, compared to luxury hotels, due to its simpler and less complex nature of service. They also empower their guests to interact with their systems and serve themselves. Although chatbots contribute positively to the hotel industry, there are several factors that need to be taken into consideration when introducing chatbots. The most important factor is the target market, in terms of the type of traveler (family-oriented, business or leisure), age group and guests' level of knowledge, as well as acceptability of technology usage. Most hotels using chatbots have experienced positive results and feedback.

4.2 Functionality of Chatbots in the Hotel Industry

Communication. Online communications are increasingly made via chatbots, instead of call agents and they gradually replace traditional communication channels [12]. P4 mentioned that once guests make reservations via chatbots, hotels are able to send them messages pre-arrival, throughout their stay and post-check out to provide assistance and a unique experience. They can also maintain a direct communication line to support their visit through concierge services. For example, when a guest requires a late check out, a theatre recommendation or a restaurant booking, chatbots can facilitate.

P4: "I think, guests like to use chat as a medium to talk to a hotel… You get continuous contact with the chatbot throughout your experience with the hotel"

Customer Service. Besides communication, industry experts P2 and P7 explained the importance of chatbots to support customer service. According to P7, chatbots can improve customer service because they are readily available at any time of the day and from anywhere. When jet-lugged guests would like to interact in the middle of the night they are not embarrassed to engage in discussion. Even when guests are outside of the property, chatbots can still assist guests with their needs or requests when interactiong at the destination.

P7: *"We think the primary reason why chatbots are useful in improving customer service is that chatbots are available to help hotel guests anytime and anywhere. Even if a guest is outside the hotel, the chatbot can help, extending the hotel's customer service capabilities."*

Enhancing guest experience with the aid of continuous technological advancement is important for the hotel industry, as it would attract more guests and improve operational efficiency. Low cost, greater customer service, with minimal errors can be delivered by using chatbots. However, the use of chatbots can only improve customer service for guests who are willing and prefer to use chatbots and therefore a positive attitude to digital innovations is required. Chatbots maynot benefit guests who are technology challenged.

Direct Booking. Chatbots have the ability to encourage guests to make direct bookings through the hotel website, by providing quick clarifications, customizing the experience and providing efficient interactivity. P3, P4, and P6 discussed the ability for guests to book directly through chatbots, instead of OTAs, as a major advantage for hotels.

P6: "We create some things in our chatbot that influence the traveler to reserve with the chatbot and not with booking.com."

P3: "They definitely want the bot to be able do something simple like booking"

Textual communication between guests and hotel, using chatbot, can encourage direct hotel bookings. AI-powered chatbots are able to provide accurate and adaptive room rates and availability, compared to OTAs. It can support real-time, last-room availability and revenue management updates, supporting decision making. In addition, a range of gamification techniques can be applied supporting innovative revenue management [8, 14]. Direct bookings contribute to the profitability of hotels, as hotels are able to save 15–30% of their turnover on OTA commissions. However, some guests may not feel comfortable to disclose bank details or any personal information through chatbots. Therefore, hotels have to provide guests with assurance that data is used securely and data is protected.

4.3 Factors Encouraging the Use of Chatbots

Efficiency and Automation Contributing to Profitability. Chatbots are able to assist employees to deliver accurate information faster and more effectively. By using chatbots, employees can identify the exact information and check for real-time updates. With chatbots dealing with FAQs, employees can fully focus on guests and deliver higher customer satisfaction. Chatbots also serve multiple guests at the same time, which is not possible with human service.

P6: "Since hotel staff is no longer burdened with answering simple frequently-asked questions, they can devote more time and energy assisting guests with more complicated tasks that result in higher customer satisfaction rates."

Automation of all repetitive tasks, such as answering FAQs, can easily be automated to save time and effort to serve guests. However, hotels should consider the benefits of automation before deciding to adopt this technology. The suitability of chatbots for hotels depends on the clientele and the digital adoption.

P3: "There are definitely cost incentives to deploy chatbots. Ultimately, in the long run, you will save on the agent operation side. You want to reduce the number of agents. If the bot is really smart, it can answer 50% of what your agents are answering now- it's a huge saving cost really."

Efficiency and automation contribute to the profitability of organizations. The use of chatbots increases staff performance, optimizes sales funnels and reduces conversation times. With chatbots answering most of the FAQs and attending to guests, less members of staffs are needed, reducing labour cost. Although the implementation of chatbots inflict cost, it reduces costs in the long term. P6 also emphasized that less staff training is needed, as chatbots have the ability to answer and understand multiple languages. The assistance chatbots provide can reduce staff numbers and hotels can improve profitability.

Multilingual Chatbots and Usability. For guests who are not fluent in English, multilingual chatbots allow guests to obtain information and make requests in their native language. Although multilingual chatbots provide many opportunities, designing and implementing them comes with complications. Each language and region would have distinctive meanings, sentiments, abbreviations, written chat short hands, emoji usage and cultural considerations. Roman alphabets are not the standard writing system for multilingual users and therefore, the complexity of creating a multilingual chatbot needs careful design consideration to ensure appropriate guest experiences.

Personalization and Smart Marketing. Personalized content is important as it allows hotels to determine guest priorities in order to tailor information, recommendations and services for guests. Personalized content may include accommodation favourites, dietary restrictions or preference for certain services in the hotel. AI-powered chatbots also support guests to make real-time decisions and enable seamless communication.

By creating a platform, guests communicate through chatbots and send real-time information and requests to perspective departments.

P1: "Personalized content is definitely very important. For example, one of the features that we're running often is we learn over time what your preferences are… each piece of information is assigned to you and this also helps us with recommendation of products that meet your personal demands."

The use of chatbot also allows real-time marketing using location, context and proximity aware systems. Using real-time information chatbots ensure employees are equipped with related information to address the contemporary needs of guests. These supports them to carry out appropriate marketing action to capture guests or to upsell and upgrade products and services. By personalization, guests enjoy more value as products and services are based on their preference. Personalization aids guests in decision making process as they are exposed exclusively to relevant information that address their needs and preference.

Accessibility and Convenience Contribute to Guest Satisfaction Chatbots are available round the clock and allow guests to access hotel information and services at any time without having to call the hotel operator or through email. This saves time for guests and is a simpler way to obtain information.

P7: "the primary reason why chatbots are useful in improving customer service is that they are available to help hotel guests anytime and anywhere. Even if a guest is outside the hotel, chatbots can help, extending the hotel customer service capabilities. Guests feel as if they have a personal concierge with them at all times. Guests not only have a great experience while they are in the hotel, but even outside the hotel."

It is also convenient for guests to customize their stay through chatbots, leading to guest satisfaction. Chatbots ensure that product and service information are readily available and simplify the buying process. Chatbots also contribute customer satisfaction in hotels by providing 24 h a day front desk duty, controlling in-room temperature, prearranging check-in or check out processes, facilitating fast online reservations, and supporting 24-h service both in the hotel and outside.

Anonymity. Anonymity is an advantage, as chatbots allow guests to make requests anonymously, without revealing their intended itinerary or explain their requests and justify their choices. Some guests may be more comfortable communicating through a chatbot and looking for answers on their own, as they are able to make requests or ask questions without being judged.

P1: "The anonymity is great. You're in the hotel room and you don't want people to know what you're planning to do around the city or in your room. So, having anonymity to interact with chatbots is beneficial. Guests enjoy anonymity and users can just use chatbots without being judged about it in any way."

4.4 Challenges on the Use of Chatbots

Loss of Jobs. Repetitive jobs, such as answering simple FAQs, and requests from guests can be automated – which leads to the loss of certain jobs. Employees are afraid of losing their job and that chatbots will act like an emotionless robot. Low-level and repetitive jobs might be replaced by automated processes in order to save on labour cost. There are concerns on the loss of human touch, as chatbots lack empathy, personal touch, creativity and emotions. However, chatbot exist to assist and complement labour, instead of replacing staff in the hotel industry. Employees have the ability to focus on more complex requests and deliver better customer service.

P7: "…Staff are afraid of losing their jobs and they are afraid that making contact with a chatbots lacks the personal touch, "I have a small hotel in the tourist city and everybody that calls me, I make them feel welcome through warm contact. The chatbot will be like a robot, that's so cold."

Technical Knowledge. Technology might be complicated, especially for the older generation. Millennials tend to be more technologically savvy. One of the biggest challenges for hotels to adopt the use of chatbot is the technological knowledge behind system. Many of the internal legacy system used in hotels have to be integrated with the chatbots in order to provide an all rounded service. This is not always possible without serious investment. Hoteliers also need to hire suitable talent, with adequate technological knowledge to deal with chatbots related issues. They need to integrate chatbots with property management systems, booking, distribution channel and payment systems as well as housekeeping system to optimize the hotel performance.

P2: "Also ask about what the problems are in general and they don't use that much of system technology, or their system they have are connected. So, it's difficult to integrate something that's not digital… Hotels with less than 50 beds are more challenged in general, because they're not necessarily familiar with technology."

Guests may also face difficulty in using chatbots if they are not sure of what to do with the buttons presented to them. This may cause the chatbot to stall and not provide any answers. Guests can be unsure of chatbots capabilities and they might find using chatbots difficult; especially generations who grew up without smartphones. Chatbots can also cause frustration when conversations run in circles and guests are not presented with the answers they are looking for. Chatbots lose credibility and cause frustration when guests are unable to communicate efficiently.

Uncertainty. Guests may also be uncertain on the use of chatbots; not knowing how to respond, what to ask, or confused with the information given by the chatbot. Guests that are unsure of what to ask or do with it, tend to just ignore the chatbot. There are times guests are presented with option buttons in the chat but they do not click on any of the buttons leaving the conversation frozen. The kinds of conversational goals to anticipate from guests are (a) task goals, (b) communication goals, and (c) relationship goals. In order to achieve these goals effectively, menu options or voice inputs complement text to reduce error and recovery time. Lastly, using chatbots frequently increases the success rate of conversations, due to growth of customization to the types of command chatbot can respond to.

4.5 Future of Chatbots

The AI industry continues to move forward and companies automate and integrate as many processes as they can. Virtual assistants and chatbots are increasingly improving in understating requests and providing suitable answers and solutions. With the integration of AI and Machine Learning, P4 predicts that in the future, chatbots will have the ability to tailor guest's stay and experience. Based on interactions with guests over time and by recording preferences and choices, chatbots will develop their understanding of guest requirements, adding value in all. interactions. Chatbots will effectively offer a proactive, personalized and dedicated concierge assistant that is able to make suggestions dynamically and in real time, hence, adding value and enhancing guest satisfaction. P1 and P6 predicted that hotels might be heading towards the development of Smart Rooms, by using chatbots to control room amenities and tailoring rooms to suit guest preference. Smart rooms are effectively rooms powered by Internet of Things (IoT), which allows devices to interconnect and communicate with one another and also with all hotel facilities and services [6, 15]. Large international hotel chains, such as Hilton Hotels and Marriott International, have invested into implementing smart rooms in some of their hotels. It is a great way to personalize guest stay and create an enhanced guest experience. In addition, smart rooms can also support sustainability, as they can introduce environmentally friendly practices by monitoring and adjusting lighting, temperature and energy consumption. This can also reduce operational cosst by being energy efficient and by monitoring performance of electrical devices.

Although there are positive future prospects for the development of chatbots and hotel technology, P2 and P7 shows concern on the overuse of technology and the lack of human touch. Due to the nature of hotel industry, people may prefer to talk to another person, instead to a device. P7 states that hotels should never be 100% operated by robots and human interaction is crucial in the service industry; although many services may migrate from human interaction to technology substitutes.

Service delivery and service recovery in particular should avoid chatbots, as guests who are making complaints usually prefer to communicate directly with a person than through technological devices. Therefore, chatbots should be used with care to facititate some functions rather than totally replace customer service in the hotel environment.

5 Conclusion and Recommendation

Conclusion. The majority of hotel chatbot users have positive experiences and are willing to accept this technology. Chatbots are used in hotels for communication, customer service, direct booking and for answering guest FAQs. The benefits of using chatbots outweigh the challenges. Benefits include personalisation, smart marketing, automation, efficiency, profitability, language, accessibility, anonymity and guest experience. There are several challenges that both hotels and guests have to overcome, including: technical knowledge, threat on loss of jobs, guest negative experience and uncertainty. Chatbots are expected to change the end-user experience and the ways hotels advertise and do business. Not only do chatbots provide a platform for communication, they also supply hotels with a wealth of knowledge on guest preferences and experiences.

The growth of chatbots in the hospitality field is still in the early stages of development. With advanced technologies, machine learning techniques and improved algorithms, chatbots may be able to achieve realistic conversations, complete with emotions. Participants were optimistic with the positive growth and future for chatbots. Although chatbots are in the early stages of the product life cycle, they are improving rapidly by using AI and ML technologies. The implementation of chatbots in the hospitality industry will add value to all stakeholders and introduce benefits for both hotel and their guests. The future of chatbots will involve the use of smart rooms and virtual proactive chatbots and this has great opportunities.

Recommendations. One of the recommendations for future studies is to assess the existing literature by comparing views from end-user, experts and hoteliers. Future studies can also study the difference in views and preference of different types of virtual assistants, for instance, voicebots and chatbots. Voicebots may replace chatbots in the future, especially when guests are mobile. It is important, therefore, to understand the use of both chatbots and voicebots, as well as user preferences. Adding the voice component will expand the chatbots potential, allowing guests to have a more complete experience. Future research can look into how users view chatbots, specifically in the travel, tourism and hospitality industries. An understanding of employee's attitude towards the use of chatbots in hotels can also explore the value cocreated. Finally, research should explore the acceptability of chatbots and assist to find new ways that they can be incorporated in strategic and operational management.

References

1. Saratchandran V (2018) Fingent shaping the future. https://www.fingent.com/blog/how-hotels-are-using-technology-for-competitive-advantage
2. Buhalis D (2000) Information technology in tourism: past, present and future. Tourism Recreation Res 25(1):41–58
3. Paraskevas A, Buhalis D (2002) Information communication technologies decision-making: the ASP outsourcing model from the small hotel owner/manager perspective. Cornell Hotel Restaurant Adm Q 43(2):27–39
4. Neuhofer B, Buhalis D, Ladkin A (2015) Smart technologies for personalised experiences. a case from the hospitality industry. Electron Mark 25(3):243–254
5. Khazaei A, Manjiri H, Samiey E, Najafi H (2014) The effect of service convenience on customer satisfaction and behavioral responses in bank industry. Int J Basic Sci Appl Res 3 (1):16–23
6. Buhalis D, Leung R (2018) Smart hospitality-interconnectivity and interoperability towards an ecosystem. Int J Hospitality Manage 71:41–50
7. Ivanov SH, Webster C (2017) Adoption of robots, artificial intelligence and service automation by travel, tourism and hospitality companies–a cost-benefit analysis. Artificial Intelligence and Service Automation by Travel, Tourism and Hospitality Companies–A Cost-Benefit Analysis
8. Xu F, Buhalis D, Weber J (2017) Serious games and the gamification of tourism. Tourism Manage 60:244–256

9. Buhalis D, Harwood T, Bogicevic V, Viglia G, Beldona S, Hofhacker C (2019) Technological disruptions in services: lessons from tourism and hospitality. J Serv Manage. https://doi.org/10.1108/JOSM-12-2018-0398
10. Bilgihan A, Okumus F, Khal Nusair K, Joon-Wuk Kwun D (2011) Information technology applications and competitive advantage in hotel companies. J Hospitality Tourism Technol 2:139
11. Buhalis D, Sinarta Y (2019) Real-time co-creation and nowness service: lessons from tourism and hospitality. J Travel Tourism Mark 36(5):563–582
12. Zumstein D, Hundertmark S (2017) Chatbots–an interactive technology for personalized communication, transactions and services. IADIS Int J WWW/Internet 15(1):96
13. Ivanov SH (2019) Ultimate transformation: how will automation technologies disrupt the travel, tourism and hospitality industries? Zeitschrift für Tourismuswissenschaft 11(1):25–43
14. Xu F, Tian F, Buhalis D, Weber J, Zhang H (2016) Tourists as mobile gamers: gamification for tourism marketing. J Travel Tourism Mark. 33(8):1124–1142
15. Boes K, Buhalis D, Inversini A (2016) Smart tourism destinations: ecosystems for tourism destination competitiveness. Int J Tourism Cities 2(2):108–124

Brandjacking: The Effect of Google's 2018 Keyword Bidding Policy Changes on Hotel Website Visibility

Peter O'Connor(✉)

ESSEC Business School, Cergy Pontise, France
oconnor@essec.edu

Abstract. With travelers increasingly using search to help plan travel, visibility on search engine results pages have become a key issue. Intense competition makes it difficult to consistently appear in organic search results, pushing marketers to use paid search engine advertising. While in the past hotels could leverage this technique effectively thanks to exclusive use of their trademarks in the online environment, recent changes have eroded this advantage. Provided the third-party site is a reseller, as is the case with online travel agencies and other forms of online intermediaries, hotel trademarks can now be leveraged in both the trigger keywords and copy text of paid search adverts, threatening the online visibility of hotel websites. Using a web scrape of searches for 2200 hotel trademarks in Europe, this study sets out to establish if recent changes have affected hotel website visibility. Findings indicate that while trademark abuse has not increased, brandjacking remains common, with customers undoubtedly being diverted.

Keywords: Search · Trademark abuse · Brandjacking · Hotel sector

1 Introduction

As the hotel experience is intangible and in effect bought sight-unseen, brand plays an important role in the customer selection process. In the absence of physical signals, hotel brands act as a guarantee of quality to help guests better understand what they are about to purchase [17]. Multiple studies have shown that customers are more likely to book, and willing to pay a premium price for, their preferred brand, leading to increased occupancy and profitability [1, 23]. As such, brands, as potential sources of competitive advantage, have become important assets for hotel chains, with many maintaining multiple brands to potentially serve multiple markets [7].

However, online sales are threatening this brand equity [16]. Search engines has become central to the traveler search and booking process, making prominent positioning on search results pages vital [19]. Anecdotal evidence suggests that third parties (primarily online travel agents, metasearch sites and other online intermediaries) have been achieving this by abusing hotel tradenames in paid search engine marketing, a process known as 'brandjacking'. If potential customers searching for a particular hotel are intercepted, it results in, at best, the payment of an unnecessary commission for the

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 243–254, 2020.
https://doi.org/10.1007/978-3-030-36737-4_20

resulting booking, and at worst in the customer being diverted to an alternative property by the third-party intermediary concerned [11].

Registering the hotel's name as a trademark offers some protection in that the trademarked term, in theory at least, cannot be used by third parties without the expressed permission of the trademark holder [9]. However, what is acceptable in terms of trademark use in search engine marketing is subject to some debate. While in the past the unauthorized use of trademarks in the public ad-copy - the title, description and display URL shown when the ad is displayed in a search engine result page (SERP) – was prohibited, a worrying development has been Google's 2018 policy change that permits trademark use when the resulting landing page is a reseller of the product or service in question. In particular this will benefit online travel intermediaries. With now the ability to target their adverts specifically on hotel trademarks, this will make it harder, and more expensive, for hotels to feature prominently on SERP and drive traffic to their direct websites [28].

Given the importance of search positioning, and branded paid search in particular, in terms of driving direct bookings, this study sets out to establish whether this policy change has had an effect on the search visibility of both hotels and online intermediaries. By comparing findings from a web scape of the SERPs of the tradenames of 2200 randomly selected hotels in European destinations with the results of a similar 2007 study [21], this paper sets out to assess the implications for brand equity in the hotel sector.

The remainder of this paper is organized as follows. Firstly, the importance of direct distribution in hotel success is introduced. Secondly the role of search in driving direct bookings is discussed, with the importance of paid search engine marketing highlighted. The legal and contractual position regarding the use of tradenames by third parties is then discussed. The research methodology section provides more detail on how the question was empirically investigated, with a summary and assessment of the findings provided in the results section. Lastly implications for both industry practitioners and academia are presented.

2 Background

Over the past two decades online sales have gained increased significance for most hotels. Although figures vary by region, Phocuswright estimates that over 55% of hotel bookings now occur through online channels [25]. A key issue is whether a booking arrives through direct (i.e. the hotel's own website/app) or indirect (through a third party such as an Online Travel Agent (OTA), metasearch or other distributor) channels. In the latter case hotels must typically pay a commission or other form of customer acquisition fee, decreasing the resulting net revenue per booking generated [28]. Thus, for economic as well as strategic reasons, hotels should strive to drive as many direct bookings as possible.

Positioning the hotel well in search has emerged as a critical way of driving direct bookings. An estimated two out of three travelers consult Google when searching for and booking travel (WSJ, 2017). Search is regarded as highly relevant and useful in this context; with 82% of users either satisfied or very satisfied with their use of search for travel planning [5]. Travel shopping journeys that begin on search led to purchases more quickly than those that begin on suppliers or intermediary sites [8]. And search is thought to be particularly relevant in the European context, where the more fragmented nature of travel, combined with the more varied options available, typically result in a more intensive travel planning process [12].

A major challenge is that the average web user doesn't look further than the first few search results. According to a 2017 study, 67% of all clicks go to the top five listings, with 95% of users never going past the first results page [16]. Thus, gaining prominent positioning has become vital to exposure to potential customers searching for travel solutions. Marketers use two techniques to influence positioning. *Search Engine Optimization* (SEO) focuses on manipulating page structure/content to be naturally ranked highly, while *paid search engine marketing* instead allows advertisers to pay a competitive cost-per click for positioning [26].

Search engines use specialized software, known as *spiders*, to crawl websites to classify pages so that they can be added to their databases and subsequently displayed in SERPs (Search Engine Result Pages) in response to user queries. The SEO process tries to manipulate these classifications by adapting a page's code and/or content to convince the algorithm to rank that page higher for consumers search for a particular term [10]. This process suffers from multiple limitations, including that algorithms are complex, secret and change frequently, making it difficult to understand how to be better positioned [21]. Furthermore, each spider has specific preferences, meaning optimization on one may negatively affect positioning on others. Lastly, modifications must be reassessed to be taken into consideration making SEO an iterative, time consuming and costly process. Such limitations drive many towards instead using paid search engine marketing [21].

Instead of trying to manipulate the spider's classification algorithm, with paid search engine marketing the advertiser pays for prime positioning at the top of a specific SERP, usually on a pay-per-click basis [18]. Google, for example, allows up to four paid search listings to precede its organic search results. Using paid search engine marketing overcomes the challenges of SEO, guaranteeing instant visibility under a desired set of keywords independently of the ranking algorithm, meaning adverts can be precisely targeted to deliver high quality, highly targeted traffic. As a result, paid placement has become the search engine marketing strategy of choice for most advertisers [2].

Paid search ads are positioned by competitively bidding on specific keywords, usually on a pay-per-click basis. As a simplistic level, if an advertiser wants to appear in top position for "boutique hotel London", he might bid 50 cents per click. If no one else bids more, the advert would appear in the number one spot. In practice this is complicated by a factor known as the quality score, with Google selecting auction winners based not just on price but also on an assessment of the likelihood that users will click on the ad. This assessment is based on the relationship between the content of the ad-copy and the resulting landing page, with the degree of match resulting in a bonus or malus on the amount paid [29].

Paid search adverts are undoubtedly effective. In addition to being in prime position and thus having the highest visibility, the click-through rates for the subsequent organic listings fall drastically when paid listings are display. For SERPs without any adverts, the average CTR of the first organic result is 30%. When paid search ads take over the top of the results listing this falls further to just 17% [24].

Thus, simply engaging in SEO is unlikely to be sufficient to gain necessary visibility. Marketers need to use paid search engine marketing if they wish to gain visibility with the highly qualified audience using search to find solutions for their accommodation needs. However, with the exception (perhaps) of the largest hotel chains, few have the budget or expertise to extensively play the paid search marketing game. For example, in July 2019 gaining visibility on 'boutique hotel London' in paid search would require a commitment of at least €2.30 per click. Applying a typical hotel website conversion rate of 2% would result in an acquisition cost of €115.00 per booking, undoubtedly too expensive for most hotels [22]. Online travel agents (OTAs), with their recognisable brands, experienced marketing teams and deeper commitment to driving online sales resulting in higher conversion rates, can successfully and more economically drive business through paid search [28]. As a result, the majority of hotel-related SERPs are dominated by OTA-linked results [13].

2.1 Trademarks and Paid Placement

Paid placement works by encouraging advertisers to competitively bid on keywords under which they wish to be displayed, which subsequent are used by the search engines as triggers when users search for these terms [21]. For example, a clothing retailer might wish to appear whenever users enter "little black dress" as a search criterion. The critical question is, however, whether these same advertisers should be allowed to bid on another company's trademarks. For example, can that third party online retailer bid on the keyword "Chanel" and/or use the trademark "Chanel" in the copy of their advert, thus potentially diverting shoppers who might otherwise have bought directly from the trademark owner?

Generically an estimated twenty percent of searches are for trademark terms [3]. However, brand use becomes more prominent as the customer moves closer to purchase, peaking in the session in which the sale actually occurs. DoubleClick concludes that buyers start searches with generic terms, but rely on branded searches to find sites in the period immediately leading up to purchase. In addition, there is evidence that branded searches may be more effective, with 16% of searchers who made a supplier related search making an instant purchase compared to only 5% of general searchers [27].

Trademark owners argue that when consumers specifically search for a trademark, they are seeking information about, or to purchase, their company's products [14]. For example, when a customer searches for the brand name of a particular hotel into a search engine, they want to book and stay in that hotel and should therefore be taken directed to the hotel's direct booking website [4]. Unfortunately, with paid search engine marketing, this is not always the case. When trademarks are used as trigger keywords by third parties, customers may be diverted to third party sites. Furthermore, if trademarks are also included in the ad-copy of these resulting ads, this can be a highly effective way to bait-and-switch consumers to alternative products, resulting in the hotel at best paying an unnecessary commission, or alternatively losing the sale completely if the customer is diverted to competitors by the third party.

To combat such practices, in the absence of trademark protection hotels would be obliged to themselves participate in paid search engine marketing, engaging in costly bidding wars with competitors to protect what are effectively their own trademarks, thus increasing their sales, marketing and customer acquisition costs. Such so called 'brandjacking' represents a considerable challenge that can have substantial implications for hotels wishing to drive bookings directly.

2.2 Trademark Law

One of the key challenges is that the legal position on how tradenames can be used is unclear, with controversy raging as to who should be able to use such terms both in copy text as well as in the underlying keywords driving paid search adverts. In case law, precedent comes from *Brookfield Communications Inc v. West Coast Entertainment Corp,* where the courts found that use of third-party trademarks in meta-tags was unacceptable based on the principle of 'initial interest confusion'. This was defined as "the diversion of potential customers from the website they were seeking to another site, based on the belief that the second site is associated with the original one sought" [18]. Other courts have broadly followed this argument, making the unauthorized use of trademarks (registered or not) actionable in circumstances where they are being used to lure searchers away from the owner's website [15].

Where trademark terms are being used in the copy text of paid search adverts, it is comparatively easy to claim initial interest confusion as there can be little doubt that the advertiser is intentionally trying to present themselves as being associated with the trademark owner. However, the situation is less clear when third parties bid on trademarks as keyword triggers. In *GEICO v. Google Inc & Overture Services*, the plaintiff claimed that search engines infringed upon its trademarks when it sold them as keywords to competitors, leading to confusion as to an implied association between the company and the adverts displayed [20]. However, GEICO failed to prove conclusively that such trademark use was likely to confuse an ordinary reasonable consumer, in effect allowing the search engines to continue such practices. In the European context the courts have followed similar reasoning, in general allowing third parties to bid on trademarks as keywords as long as the trademark does not appear in the advert text [21].

A recent development is that some companies have been penalized under antitrust regulations for trying to prevent subsidiaries from bidding on their brand names, by defacto implying that the use of tradenames as keyword triggers by third parties is permissible in certain circumstances. For example, in 2019 Guess Jeans was sanctioned for prohibiting distributors from bidding on the Guess brand name in search. As with hotel companies, this was part of an e-commerce strategy designed to route online sales through Guess's direct online website. The European Commission found this to be a violation of EU antitrust rules as it gave the company a significant competitive advantage over retailers [6]. Thus, from the EU perspective, trademark use in keyword bidding is permissible, at least when there is a contractual sales relationship between the trademark holder and the advertiser.

2.3 Google's 2018 Change of Policy

With third parties now allowed to bid on trademarked terms as keyword triggers if they are retailers or distributors of the brand in question (as is the case for most OTAs and other online travel intermediaries) the last line of defense would seem to be the protection against trademark usage in the ad copy of the advert itself. If the tradename appears in the advert, not only does this increase the chances that the ad in question will be clicked on (the initial interest confusion argument discussed earlier), but it also positively affects the landing page's quality score as there would be a closer link between the advert copy and the contents of the landing page, in effect allowing the ad to appear higher for cheaper. By having exclusive use of their own branded terms, hotels are able to maintain their search positioning at a reasonable cost because of this quality score bonus, forcing third parties to bid substantially more to appear higher than the hotel itself.

However, another blow to trademark protection has been the recent change in policy by search giant Google. In the past, hotels could prevent resellers from using the hotel brand in the ad titles, text or display URL of paid search adverts simply by submit an infringement complaint to Google, who would then disqualify the resulting ads. However, citing arguments of comparative advertising and fair use, in October 2018 the search network revised its policies, permitting trademark use in the copy text of adverts if the advertiser is a reseller of goods and services related to the trademarked term.

Under this new policy OTAs and other third parties can now use a hotel's trademarks as part of their advert copy text, as long as the resulting landing page has commercial information about the hotel, such as prices, availability or a booking mechanism, which is usually the case with an OTA site. Thus, the trademark owner's quality score advantage discussed above has been eliminated and competitive pressure within the search space increased. In addition, it drives up the cost of participating in paid search for hotels. Preventing the use of the hotel name in third party adverts negatively affected their quality score, allowing the hotel site to appear higher for cheaper. With this advantage removed, hotels will need to pay more for the same positioning, increasing their cost of participating in paid search.

This change in policy has significant implications for hotels as it will make it more difficult, and costlier, to gain visibility in the online space. As pure play online companies, OTAs typically have extensive expertise in online marketing as well as extensive marketing budgets. As highlighted earlier, OTA listings already dominate the search space, both organic and paid. As resellers and/or distributors of hotel rooms, they are sure to exploit this newfound ability to combine trademarks in the ad-copy with their existing trademark bids, making it even more challenging for hotels to protect/gain visibility in the online space.

3 Research Methodology

Given the importance of positioning in SERPs for hotels' direct distribution and resulting profitability, assessing the effect of these recent changes is important and served as a motivation for this study. The objective therefore was to establish whether

Google's policy change has had an effect on the search visibility of both hotels and OTAs.

The tradenames of a random sample of 2200 hotel properties in European destinations was used to investigate the issue. Investigated properties were located in France (23%), Germany (16%), Italy (19%), Spain (18%) and the U.K. (24%). These ranged from two-star (2%) to five-star (10%), with the most common being three-star (49%). Nearly half (45.2%) were branded and part of a hotel chain, with the average overall size of 46 bedrooms.

Automated searches were performed for each brand name in Google.co.uk during May 2019. Web scrapping software (Apify.com) was used to perform a one-time scrap to extract the title, copy text and landing page URL of the first SERP in each case. Search were carried out in private mode and histories were cleared between each session to prevent cross contamination of searches. Paid search adverts were identified using the "Ad" identifier preceding the landing page URL, and analyses performed to establish if each advert was for the trademark holder or a third party. Results were compared with findings from a similar 2007 study [21] to assess the effect of the new policy changes.

The study suffers from a variety of limitations, not least of which is that the algorithm used by Google to position listing both paid and organic search on results pages is both secret and constantly changing. As a result, how positions are allocated may have changed between the initial and the current study, making comparisons questionable. In addition, the current paper is based on a data scrap at a particular moment in time. Search is highly dynamic and using data from multiple scrap would increase confidence in the findings.

4 Selected Findings

4.1 Evolving Search Positioning

As discussed earlier, Google's SERPs are typically made up of a series of organic listings preceded by up to four paid listings. While in the previous study, when searching specifically for hotels' tradenames, the hotel's official web sites performed well in organic search, appearing in first position in nearly two-thirds of cases, in the 2019 study this had dropped to just one in twenty (see Table 1), with top organic positioning being taken by third party distributors in 28% of cases. Inclusion on the first page similarly dropped, from 83% to 53% respectively. This we can clearly see that visibility in organic search results has fallen, making participation, and strong performance, in paid search all the more essential to be visible in front of potential customers specifically searching for their property.

In addition, the prominence of paid search has increased, with at least one paid search advert appearing on 71% of SERP displayed, as opposed to only in two-thirds of cases in the previous study. The mean number of adverts displayed was 1.21, with a standard deviation of 1.08 and a skewness of 0.84.

Table 1. Search result overview (compiled by author)

Topic	2007	2019
Hotel in 1st position in organic listings	67%	6%
Hotel in positions 2 to 10 in organic listings	16%	47%
OTA site in 1st position in organic listings	11%	28%
Sponsored links appear	64%	71%
with hotel in 1st position in organic listings	65%	76%
with hotel in position 2–10 in organic listings	18%	77%
Hotel appears first in paid listings	20%	0%
Paid links include hotel site	38%	1%

Digging deeper, when the hotel site appeared in first position in organic search listings, it was preceded by a sponsored link in 76% of cases, while when the official site appeared elsewhere on the first page of search results, it was preceded by a paid link 77% of the time. Both reflect major increases in the prominence of paid search adverts on hotel trademark terms compared to the previous study, where the corresponding metrics were 65% and 18% respectively. In terms of the relative positioning of these adverts, OTAs clearly dominate the paid search listing, with at least one OTA advert appearing in 87% of searches, as opposed to just 57% of hotel adverts.

Both of these findings suggest that OTAs are making more extensive use of trademarks in their keyword bidding strategies, and as a result gaining increased visibility in front of the highly qualified audience of consumers searching for a specific hotel. A key question is whether they are leveraging their newfound ability to use trademarked terms in the ad-copy of these adverts and in effect engaging in brandjacking of the hotel's brand assets?

4.2 Brandjacking of Hotel Trademark Terms

For brandjacking to occur, the advertiser must be both bidding on the trademarked term as a keyword trigger (which, if they appeared in one of the SERPs analyzed, by default was the case) and also using the hotel's trademark in the title, description and/or display URL of the resulting advert. Overall, when searches were carried out for hotel trademarks, nearly two-thirds of the paid search adverts that appeared were for third parties, primarily online intermediaries. Given how paid search functions, the only way these adverts could be displayed is if advertisers expressly specified the trademark term as a keyword trigger so as to appear in the SERP of consumers searching for the hotel in question.

At least one paid advert was displayed on every search, with adverts appearing in second and third positions in 33% and 13% of cases respectively (see Table 2). Looking specifically at the content of these adverts, trademarks were extensively used within the ad-copy displayed. As can be seen from Table 2, the hotel's trademark was included in the title, copy text or display URL in 52% of cases. Of these, clicking on the advert in question would take the user to third party (primarily OTA) landing page in 41% of cases. With the comparable figure from the 2007 study sitting at 37%, this does not represent a major increase in the use of trademark terms in paid search advertising by OTAs. Thus OTAs seem, for the time being at least, to have not as yet exploited their newly granted ability to use brand names in their paid search engine marketing.

Table 2. Brandjacking analysis (compiled by author)

Advert position	Are adverts displayed?	Brand mentioned in advert copy text	OTA landing page	Percentage Brandjacking
1	100%	46%	36%	77%
2	33%	67%	55%	83%
3	13%	62%	46%	75%
4	4%	47%	47%	100%
Summary	100%	52%	41%	79%

5 Conclusion

The use of trademarks as both keyword triggers and as part of the copy text of adverts in paid search is clearly a controversial topic. From the study, it's clear that hotels are performing less well in terms of organic search positioning than in the past. As a result of more intense competition, when searching for the hotel's trademark, the hotel's official website now only appears in top position in organic listings in 20% of cases, and on the first page of search results in 53% of cases. This drop in organic search visibility makes paid search positioning more important for hotels wishing to appear in front of potential customers specifically searching for their property.

However, hotels' participation, and potential success, in paid search is being compromised by third party sites paying for placement on the hotel's trademarks and using these trademarks in the advertising copy of the adverts. While in the past third parties were prohibited from leveraging trademarks in such situations, recent developments have removed this protection. In particular the EU's move to prevent anti-competitive behavior by brands, which has in effect legitimized the use of trademarks as keyword triggers, coupled with Google's recent change in policy as regards use of trademarks in ad-copy when the sponsoring site is a reseller of the product/service in question, has effectively changed the rules of the paid search game. These developments have important implications for hotel distribution where OTAs already dominate the paid search environment and can now leverage improved quality scores to gain higher levels of visibility at a cheaper cost.

Interestingly, the study shows that, despite this opportunity, OTAs and other third parties have not, at least to date, increased their use of trademarks in paid search. Although nearly two-thirds of the paid search adverts that appeared were for third parties, brandjacking (where the hotel's tradename is used in both the keyword triggers and ad-copy of the resulting advert) has not increased significantly. Brandjacking only occurred in 41% of the cases where an advert lead to a third-party site, suggesting that OTAs have yet to exploit the recent changes in policy, a surprising finding given the speed at which these online companies usually react to change.

However, it is also worth noting that brandjacking is occurring in nearly 80% of cases where an OTA has positioned themselves on the SERP based on a hotel's trademarked term. Although permitted by Google, and used by the OTAs under arguments of comparative advertising and fair use, such usage represents a major challenge to hotel brands, who effectively no longer exclusively leverage their brand equity in the search environment. Given the importance of brands for the hotel chains, this will sure be the subject of legal action in the near future as the global chains act to protect one of their key assets from exploitation by third parties. It's also clear that hotel companies are largely failing to take advantage of the potential of paid search to reach out to their customer base. The study shows that only a small percentage are using paid search advertising, and an even smaller number using it effectively. Although these developments mean that competition has increased and (although this was not directly investigated in the study) costs undoubtedly increased, bidding on the hotel's own trademarks remains essential as it overcomes the uncertainty of search engine optimization, insuring that the hotel website is always presented in relevant consumer searches.

The study's findings clearly show that hotels have lost visibility both in the organic and the paid search domains. As a result, potential customers searching specifically for a specific hotel are being diverted, resulting in the payment of additional commissions or the loss of a potential sale. And the recent developments discussed in this paper imply that this trend will continue, or perhaps even accelerate. This, if hotels wish to compete, and insure that they continue to drive direct bookings, hotels need to specifically up their search game and engage more fully in positioning themselves favorable in the paid search environment.

References

1. Aaker DA (1991) Managing brand equity. Free Press, New York
2. Andersen C, Cheng M (2017) Multi-click attribution in sponsored search advertising: an empirical study in hospitality industry. Cornell Hosp Q 58(3):253–262. https://doi.org/10.1177/1938965516686112
3. Bechtold S, Tucker C (2014) Trademarks, triggers, and online search. J Empir Leg Stud 11 (4):718–750. https://doi.org/10.1111/jels.12054
4. Beldona S, Morrison A, O'Leary J (2005) Online shopping motivations and pleasure travel products: a correspondence analysis. Tour Manage 26(4):561–570. https://doi.org/10.1016/j.tourman.2004.03.008
5. Beldona S, Lin K, Chen M (2012) hotel trademarks in organic search: a longitudinal cross-national study. J Travel Res 51(2):227–238. https://doi.org/10.1177/0047287511400612

6. Crowell & Moring LLP (2019) https://www.lexology.com/library/detail.aspx?g=564dac6a-2d19-4721-a813-418e200ea33d. Accessed 20 June 2019
7. Damonte LT, Rompf PD, Bahl R, Domke DJ (1997) Brand affiliation and property size effects on measures of performance in lodging properties. J Hosp Res 20:1–16
8. Dichter A (2018) How to serve today's digital traveller. McKinsey & Company. https://www.mckinsey.com/industries/travel-transport-and-logistics/our-insights/how-to-serve-todays-digital-traveler. Accessed 27 June 2019
9. Dogan S, Lemley M (2004) Trademarks and consumer search costs on the internet. Houst Law Rev 41:777–838
10. Evans M (2007) Analyzing Google rankings through search engine optimization data. Internet Res 17(1):21–37. https://doi.org/10.1108/10662240710730470
11. Ferenczuk K (2018) Brand hijacking in the hospitality industry. https://insights.ehotelier.com/insights/2018/04/17/brand-hijacking-hospitality-industry. Accessed 20 June 2019
12. Floater G, Makie L (2016) Travel distribution: the end of the world as we know It?. London School of Economics and Political Science, London
13. Garcia M (2018) TripAdvisor takes a lead but most of travel search is up for grabs. https://www.phocuswire.com/TripAdvisor-takes-a-lead-but-most-of-travel-search-is-up-for-grabs. Accessed 20/7/19
14. Gerhardt D (2010) Consumer investment in trademarks. North C Law Rev 88(2):427–500
15. Hung W (2012) Limiting Initial Interest Confusion Claims in Keyword Advertising. Berkley Technology Law Journal. 27(4), Article 16. https://doi.org/10.15779/z38m40r
16. Jacobson M (2017) How Far Down the Search Engine Results Page Will Most People Go? https://www.theleverageway.com/blog/how-far-down-the-search-engine-results-page-will-most-people-go/. Accessed 19 June 2019
17. Jones J, Slater JS (2003) What's in a name? Advertising and the concept of brands. M.E. Sharpe, New York
18. Lastowka FG (2002) Search engines under siege: do paid placement listings infringe trademarks. Intellect Prop Technol Law J 14(7):1–7
19. Law R, Hsu C (2006) Importance of hotel website dimensions and attributes: perceptions of online browsers and online purchasers. J Hosp Tour Res 30(3):295–312. https://doi.org/10.1177/1096348006287161
20. Mirchin D (2005) Google wins U.S. keyword case. Inf Today 22(9):1–5
21. O'Connor P (200) An analysis of hotel trademark abuse in pay-per-click search advertising. In: Sigala M, Mich L, Murphy J (eds) Proceedings of the international conference on information and communication technologies in tourism 2007, Ljubljana, Slovenia, pp 377–388. Springer, Vienna (2007): https://doi.org/10.1007/978-3-211-69566-1_35
22. O'Connor P (2009) Pay-per-click search engine advertising - are hotel trademarks being abused? Cornell Hosp Q 50(2):232–244. https://doi.org/10.1177/1938965509332961
23. O'Neill JW, Carlback M (2011) Do brands matter? A comparison of branded and independent hotels' performance during a full economic cycle. Int J Hosp Manage 30:515–521. https://doi.org/10.1016/j.ijhm.2010.08.003
24. Petrescu P (2014) How Ads Influence Organic Click-Through Rate on Google. https://searchengineland.com/different-types-ads-influence-organic-ctr-google-204676. Accessed 19 June 2019
25. Phocuswright. Rethinking hotel distribution with attribute-based selling 2019. Accessed 8 June 2019

26. Ramos A, Cota S (2008) Search engine marketing. McGraw-Hill, New York
27. Search Engine Land. How Search Engines Impact Online Sales (2005). https://www.searchenginejournal.com/how-search-engines-impact-online-sales/1350. Accessed 1 Mar 2019
28. Tooke-Marchant R (2015) Online travel agents (OTAs) and their dominance of search engine results: Can independent hotels compete? J Direct Data Digit Mark Pract 16(3):154–156. https://doi.org/10.1057/dddmp.2015.3
29. Wordstream. Quality Score: What Is Quality Score & How Does it Affect PPC? (2018). https://www.wordstream.com/quality-score. Accessed 27 June 2019

Blockchain Implementation in Hotel Management

Mª Dolores Flecha-Barrio[1](✉), Jesús Palomo[1], Cristina Figueroa-Domecq[2], and Mónica Segovia-Perez[1]

[1] Business Department, Rey Juan Carlos University, Móstoles, Spain
{mariadolores.flecha, jesus.palomo, monica.segovia}@urjc.es

[2] School of Hospitality and Tourism Management, University of Surrey, Guildford, UK
c.figueroadomecq@surrey.ac.uk

Abstract. The relevance and future prospects of blockchain technology in the tourism industry are not backed up by an important research corpus. Furthermore, the concept of blockchain is still blurred, not fully understood, and there is limited information around the knowledge and implementation level of blockchain in the hospitality industry. Consequently, the aim of this article is to identify the current gap in blockchain implementation in the hotel industry. Through a survey to managers in the Spanish hospitality industry, one of the most important tourist destinations in the world, the study shows the very low level of implementation and knowledge concerning blockchain and, hence, room for improvement in the future. Finally, professional and managers in the hospitality industry confirm that blockchain is an emerging technology with tremendous implications for the tourism industry.

Keywords: Blockchain · Tourism · Hospitality · Technology · Emerging technologies

1 Introduction

Blockchain technology is receiving global attention [1] and in the tourism industry, its application is considered as fifth out of the seven emerging trends with more challenges and opportunities for the hotel sector [2].

The first known reference concerning Blockchain came from its unknown creator Satoshi Nakamoto [3]. In 2008 he published a research describing the Bitcoin cryptocurrency design on the cryptography mailing list metzdowd.com [4]. The blockchain technique may be defined as a distributed public ledger, highly encrypted, that is shared among its users and that allows them to do transactions in a public and anonymous way without the reliance on an intermediary or central authority [5]. This decentralized registry links all records by consensus of the participants in the network, relying on an open-source highly encrypted system, and allows transparent, trusty, secure, validated, stored and shared contracts [6–8]. Hence, it differs from a traditional database, where a single entity has a centralized copy with all the records, in that every node of the

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 255–266, 2020.
https://doi.org/10.1007/978-3-030-36737-4_21

blockchain network keeps a complete copy of the ledger [9]. Within the blockchain, the information can only be added if there is an agreement between the majority of the parties. After a certain period of time, it can be assumed that the added information in a block will no longer be modified (immutability) [10]. This process prevents the data from being altered. Its first consequence is the creation of trust environments where two parties can do business without the need for an intermediary to verify the transactions.

Research on blockchains has largely focussed on financial and trading transactions [11] and initially 80% of its research were focused on Bitcoin [12]. However, as a disruptive technology, the potential uses of blockchains could transcend the financial industry [13]. Indeed, the impact of the blockchain technology may affect organizations, their business models, and how they create and deliver value [14]. Nowadays the research and use of this technology is not limited to financial aspects, and it includes all types of innovative implementations from healthcare, real estate or the government sector [15, 16]. Blockchain is associated to sharing economy [17]; software license to ameliorate software piracy [18]; agri-food supply chain traceability system [19]; electricity [20]; platform governance [21]; autonomous vehicles [22]. At a transparency level, it is related to trustworthy digital record [23]; transparency to verify the electoral register and vote count while protecting the secrecy of the votes [24]; data transparency in clinical trials [25]; educational record [26]; medical data access [27]. Finally, there is an important field of application related to supply chain operations, logistics and operations management: smart contracting, product authentication and certification, ethical sourcing and supply chain transparency, fighting against counterfeits, product lifecycle management, product information disclosure [28].

Important applications have been identified in the tourism industry, but as we will see in the following sections, literature review shows a limited adoption of this technology and limited research around it. Reasons might be technological immaturity of the tourism companies to handle business transactions related requirements through coins/tokens but also to a behavioural issue and attitudes of the consumers that needed to be expanded [29, 30].

Since blockchain is nascent in academic research on tourism and the hospitality industry is at the early stages of its application, the aim of this article is to perform an exploratory analysis around the implementation of blockchain technology in the hotel industry. These reasons make this study relevant and timely. The exploratory analysis will be based in Spain and focused on hotel management strategies around this technology. Based on this aim, the following Research Objectives (RO) have been defined:

RO1. Understand the gap in blockchain implementation in the Spanish hotel industry, through the evaluation of current and future interest in this technology and its level of execution.

RO2. Based on previously identified limitations and benefits of blockchain, evaluate managers' perception in the Spanish hospitality industry.

2 Literature Review

2.1 Blockchain and Tourism: A Bibliometric Analysis

The undoubted interest of the industry on this technology has not driven the attention of the academic community. Blockchain application in the tourism industry is still at its early stages [31] even though it has a huge potential to transform the way tourism industry 'exchange value'.

In order to identify its importance as a research field, a bibliometric analysis has been performed around blockchain and tourism literature. To the best of our knowledge, the review of the retrieved articles is the first attempt to shed light upon the academic research on this subject. A search based on the combination of keywords "blockchain & tourism" or "blockchain & hospitality" in one of the biggest database of academic production (Scopus) resulted in twenty-three related articles, conference or informative reports; only eleven are dedicated specifically to the tourism industry: two seminal papers published in 2017, five documents in 2018 and four in 2019.

Such small academic productivity, compared to the 5,654 published documents about blockchain since 2010, shows the delay in the application of blockchain on tourism research. Such situation could be justified by the novelty of the topic, the difficulties to integrate it into the existing research agendas and the dearth of understanding in the improvement of blockchain solutions [1, 31]. However, many academics agree that it is now an emerging topic with strong implications that needs to be further investigated [6, 29, 31, 32].

Thematically, due to the novelty of the blockchain concept in the tourism realm, the vast majority of the documents includes a fairly extensive definition and explanation of the technical concept. Some in a more informative way [29–31, 33, 34] and others in a much more technical fashion [10, 35, 36]. Some articles also include a reference to the beginning of the technology, through the seminal bitcoin work in 2008 [3].

The most frequent tourism-related keywords are: smart tourism, crowd detection, cryptocurrency, internet of things, product traceability, supply chain management, tourism development, transparency, eco-tourism, local economy, rural tourism industry, tourism promotion and services. The tourism journal with highest number of articles published are: the African Journal of Hospitality, Tourism and Leisure (2), Annals of Tourism Research (1), Asia Pacific Journal of Tourism Research (1), Current Issues in Tourism (1), and Journal of Environmental Management and Tourism (1). Besides the academic publications, there are two reports, [30] for a more international approach and [34] for a Spanish perspective. In both reports, the technical characteristics of the blockchain are reported with an eminently explanatory language. The latter also involves nine institutions to show how to begin incorporating this technology into the business management process.

The implications of the blockchain technology for the business context are highlighted in most of the publications. This argument is supported in some cases through market figures. For example, [30] estimates that approximately in 2017 it has been invested $1.8 billion in blockchain start-ups and the overall cryptocurrency market was worth over $150 billion. The blockchain is recognized as a disruptive technology that will generate a new economic paradigm that impacts the tourism industry [34]. The most outstanding positive characteristics of blockchain emphasized in the literature are disintermediation, efficiency, automation, data integrity, immutability, trust, cost reduction, cryptographically security, transparency and traceability, decentralized, share ledger and smart contracts [29, 37, 38].

2.2 Blockchain Implementation in the Tourism Industry

Important applications have been identified in tourism. Generically, the advantage of the Digital ID is highlighted as a practical solution to privacy concerns, meaning that blockchain keeps confidentially and authentication [34, 36] providing a solution to identity theft. The application of Digital ID is also indicated as an opportunity to use loyalty points without friction between suppliers and allowing consumers an easy way to redeeming loyalty point [30]. Also, it helps to create a more trustworthy rating systems with the use of a unique private key, avoiding duplicate opinions [31] in client's platforms. Another of the most showed applications is the simplification of contracting [29, 30] between hotels and intermediaries. The contracts based on blockchain technology can automatically execute transactions that are traceable, unchangeable and irreversible. And in this respect, authors consider that Blockchain could promote disintermediation and creates a new distribution network in which anybody can participate [29–31] and in which there would be a cost saving [8, 33]. Also, [29] point out that instead of reducing intermediaries, there could be a possibility to increase the number of them offering various types of coins/ tokens to travellers and sellers. Also, literature stressed cryptocurrency as one of the main benefits of blockchain [29, 31, 39] allowing a saving in the exchange of currency. Nevertheless, prior researches [8, 40] highlighted that the absence of regulation over blockchain and cryptocurrencies could create a problem for tax evasion or, even more important, to exchange rate fluctuation in case of an unpredictable shock to the economy.

Researchers also have shown specific applications of blockchain for tourism industry [35] based on the adaptive neural network algorithm and from the perspective of blockchain, developed the theoretical basis for the convergence and development of tourism industry and cultural industry. Several authors [8] point out how small island economies could boost tourism through crypto-payment. The DApps for smart tourism is one of this application available for consumers. As DApps have the potential to better connect/ interact with customers. Nam et al. [29] identify nine solutions that are already available (Globaltourist, LockTrip, Winding Tree, Trippki, DeskBell Chain, Roomdao, Travel Block, and TravelCoin, Trippago). Finally, tracking food is identified among the best advantages of the blockchain [29, 38, 39]. Thus, tracking and monitoring of food allow to understand the true origin of production and authentication of the acquisition as organic or local for restaurant and hotels.

Nevertheless, the potential application of blockchain to the hospitality and tourism industry has not been fully implemented by them yet, due to relevant limitations that will need to be identified and overcome [10, 12].

3 Methodology

The exploratory concept given to these studies leads to the use of surveys to obtain the participation and involvement of as many professionals (hotel managers as a target) as possible, and evaluate the level of importance and current and future implementation of blockchain technology in the hotel industry. In order to do so, the most important services related to tourism and blockchain have been identified so as the be evaluated through a likert-scale (1-5): criptocurrency [8, 30, 31, 34, 41], tracking guest [34, 39], loyalty programs [30, 34, 39, 42], Digital ID [8, 30, 34, 39, 42], smartcontract [10, 29, 39, 43], disintermediation reviews [31, 34, 35, 43], providers process management [34], disintermediation [30, 31, 34], inventory management [8], reservation management [8]. Benefits and limitations have also been identified through (1-5) likert-scale. Benefits: Fully privacy [10], cost reduction [10, 14], the possibility of making transaction anytime [10], security and control of money [29, 41], immutability and permanent ledger [10], automatization of processes [14, 29] trust [14, 29, 42], traceability [29, 42], transaction irreversibility [41], speculative opportunities [41], lower transaction fees [29, 41, 43], security money [10], faster transaction speeds [14, 41, 42]); Limitations: Possibility of interference, different competing platforms [10, 14], various regulatory implications [10, 14], tech & source complexity [10], transactions vs. content. [44], traffic level [44], hotel legacy technology [44], uncertain legal and regulatory status of Bitcoin [41], linking Bitcoin addresses to real identifiers [41], potential vulnerabilities in the protocol design [41], security incidents (e.g., forgotten or stolen passwords) [12, 41, 44], potential blacklisting of bitcoins of dubious origin [41], possible cancelation of a confirmed transaction [41], irreversibility of transactions [41, 44], security breaches or malfunction of exchanges/ wallet providers [41, 44].

Snow-ball sampling was applied, through the initial identification of professionals and experts working at the most important hotel chains and hotel industry in Spain and the collaboration of two very important organizations in this industry: Spanish Confederation of the Hotel Industry (Confederación Española de Hoteles y Alojamientos Turísticos) and Technological Institute for the Hotel Industry (Instituto Tecnológico Hotelero). Although the initial objective was to obtain the participation of 100-150 middle-managers and managers in the hotel industry, the final sample comprises 97 responses, that after a revision. were unfinished surveys were deleted, ended up with 49 full responses from managers and middle managers in the Spanish hotel industry. Though it is a limited sample, it is relevant due to the professional level of its respondents.

This sample includes more men (57.1%) than women (36.7%), and the distribution shows equality among ages. These managers and middle-managers work mainly in hotel chains, with 38.8% working at headquarters and 36.7% at hotels managed or owned by those hotel chains. Finally, only 6.1% of the participants work at independent hotels and 16.3% at other types of organizations related to the hotel industry. The size of this hotel chains is also very varied, with 5 participants working in hotel chains with 1-10 hotels, 1 with 11-25 hotels, 6 with 26-50 hotels, 2 with 51-100 hotels, and finally 6 hotel chains with more than 100 hotels. Finally, through a statistical analysis, using SPSS and R software, descriptive statistics and relations between variables have been performed.

4 Results

It has been found that the majority of managers and middle-managers that participate in this survey do not really understand blockchain technology: only 36.7% (18 out of 49 participants) of the respondents have answered positively to the question about their understanding of blockchain. This result itself has important implications at a research and management level.

The level of implementation of this technology in the evaluated hotel chains and hotels is extremely limited. According to the participating managers, just a minority of hotels and hotel chains have implemented, at different levels, this technology in their management process. The most relevant level of implementation (between 5 and 2 in likert-scale) is found in Fidelity Programs (55.6.5%), clients monitorization (50%), Digital ID (50%) and reservations management (44.4%), while cryptocurrencies are employed at a very low level (Fig. 1).

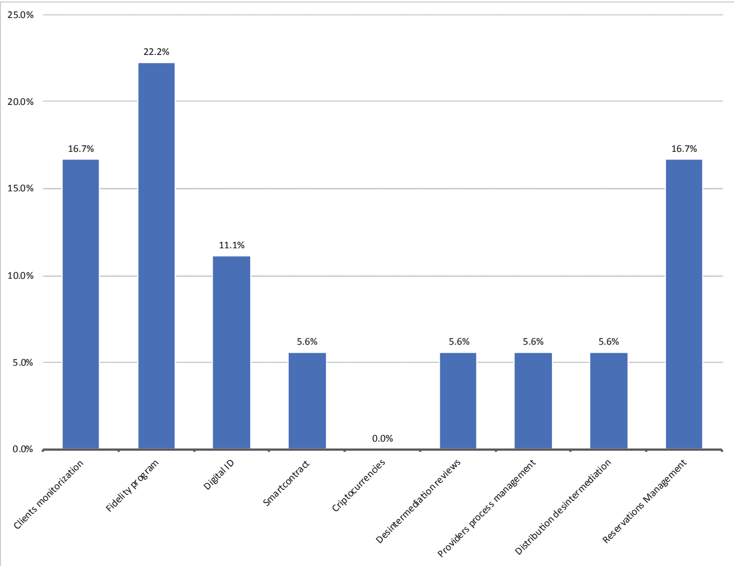


Fig. 1. Percentage of managers informing about the complete implementation of blockchain specific technologies in their organizations (authors' own figure)

The other side of the same story (Fig. 2) is that participants inform about a very low level of complete implementation (5 likert-scale). There is no implementation of blockchain for cryptocurrencies, and only 5.6% of managers inform about a total implementation on distribution intermediation, providers process management, disintermediation reviews and smartcontracts. The highest level of implementation is found in Fidelity Programs (22.2% of informants consider this technology totally implemented in their organizations) and reservations management (16.7%).

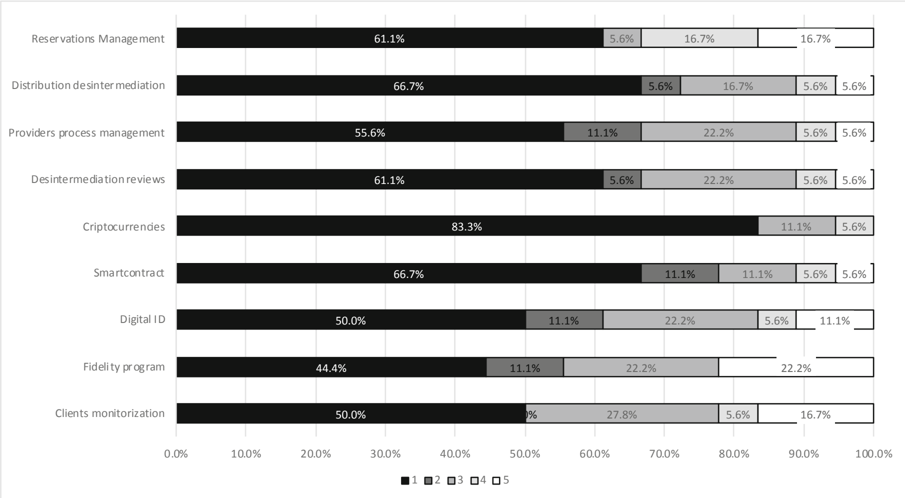


Fig. 2. Level of implementation of blockchain technologies, (1 not important, 5 very important) (authors' own figure)

Blockchain means talking about a technology that is still evolving and adapting to its own and tourism idiosyncrasies, so future prospects are as important as current ones. The evaluation of the current and future implementation intention shows a clear gap of implementation, positive in the future as the majority of blockchain services are expected to improve in the next 5 years (Table 1); some of the most important ones will be cryptocurrencies, providers management and reservations management. Also, the higher level of interest of the participants and the level of implementation of the technologies support an important increase of blockchain technology in the future, in cryptocurrencies and distribution des-intermediation.

Figure 3 presents the histograms corresponding to the 'Importance' of each of the applications of blockchain in Hospitality. The perceptions about the importance of the use of blockchain for 'Smart contracts', De-intermediation reviews' and 'Digital ID' are quite neutral (neither in favour nor against). In the case of 'clients monitorization' the perception is more in favour. When applied to 'Reservation Management', 'Dis-intermediation distribution' and 'Procurement process management' the perception is also in favour.

Benefits and limitations of this technology are highly influential on their current and future implementation level of blockchain. The most relevant benefits (Fig. 4) identified by the participants are the possibility of making the transaction process much faster (64.7% of the participants consider this benefit very important), security in money transfers (70.6%) and privacy (64.7%). Reduced costs, the possibility of making

Table 1. Interest, implementation and future implementation of blockchain services (compiled by author)

	Clients monitor	Fidelity program	Digital ID	Smart contract	Cripto currencies	Disinterm reviews	Prov. process mnge	Distr disinterm	Reserv Manag
Complete level of implementation	16.7%	22.2%	11.1%	5.6%	0.0%	5.6%	5.6%	5.6%	16.7%
Extremely important	27.8%	38.9%	38.9%	33.3%	38.9%	33.3%	33.3%	38.9%	44.4%
Future total implementation	22.2%	11.1%	11.1%	22.2%	22.2%	16.7%	27.8%	11.1%	38.9%
Gap current-future implementation	5.6%	−11.1%	0.0%	16.7%	22.2%	11.1%	22.2%	5.6%	22.2%
Gap importance-current implementation	11.1%	16.7%	27.8%	27.8%	38.9%	27.8%	27.8%	33.3%	27.8%

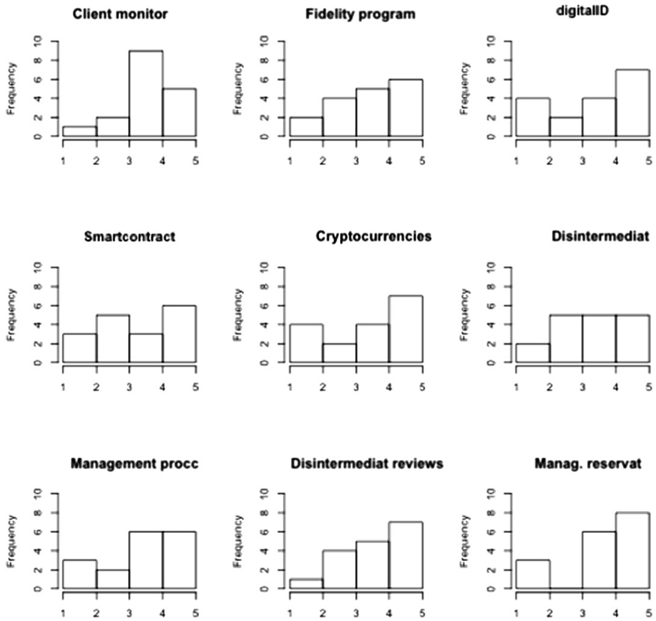


Fig. 3. Histogram Importance Blockchain services (authors' own figure)

transaction anytime, security, automatization of processes, and trust in the process (58.8%) are also very important. The lowest levels of importance are found in the following benefits: speculative opportunities, irreversibility, automatization and immutability.

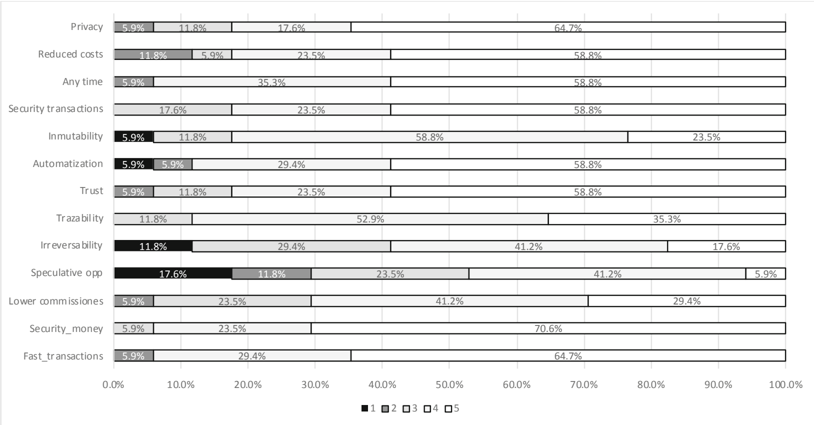


Fig. 4. Set of benefits attached to blockchain (1 not important, 5 very important) (authors' own figure)

In regard to limitations (Fig. 5), the list is important, which is probably the reason attached to such a low level of implementation of blockchain in tourism. The most relevant limitations are Security failures (64.7% of the participants consider it very important) and security gaps in cryptocurrencies (52.9%). Technological incompatibilities, protocol vulnerabilities, complexity, traffic level and link with cryptocurrencies (47.1%) are also extremely relevant.

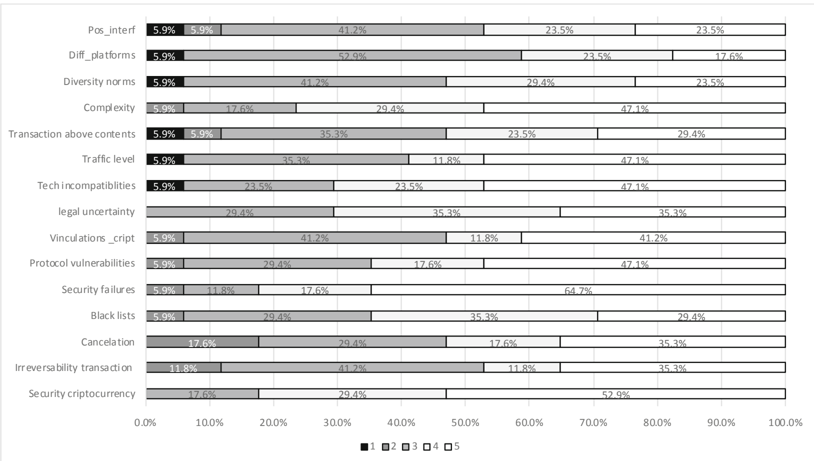


Fig. 5. Set of limitations attached to blockchain (1 not important, 5 very important) (authors' own figure)

5 Conclusions

Blockchain technology will increasingly be developed in the future and its impacts will be relevant for the tourism industry. Nevertheless, two main pending issues have been highlighted in our research: a current limited adoption of this technology by the industry and a limited academic research around it.

Literature review has highlighted that this topic has obtained a very small academic productivity, compared to the much higher number of publications about blockchain since 2010. Likewise, many academics recognise that it is an emerging topic that needs to be further investigated.

On the industry side, professional and managers have confirmed that blockchain is an emerging technology with tremendous implications for the tourism industry, however it has had limited implantations so far. Managers explain the slow establishment of this technology on the fact that the industry does not really understand it. Nevertheless, the participating managers informed that the most relevant level of blockchain implementation is on Fidelity Programs, clients monitorization, Digital ID and reservations management. On the contrary, the lowest level is on cryptocurrencies. For the future, the expected blockchain services to improve its application are 'clients monitorization', 'Reservation Management', 'Disintermediation distribution', 'Procurement process management'.

The identified positive benefits of blockchain are in line with the literature: the faster and anytime transaction, the security, privacy, reduced costs, automatization and confidence in the process. Also, professionals have considered some limitation as security failures or security gaps in cryptocurrencies, technological incompatibilities, protocol vulnerabilities, complexity, traffic level, cryptocurrencies.

In the future, this topic is worthy of investigation in order to build frameworks to expand our knowledge and to boost the development of this technology in the tourism industry.

References

1. Calvaresi D, Leis M, Dubovitskaya A, Schegg R, Schumacher M (2019) Trust in tourism via blockchain technology: results from a systematic review. In: Information and communication technologies in tourism 2019, pp 304–317. Springer, Cham
2. Micrometrics (2018) The future of Hospitality 2018. Research report. https://goo.gl/8re8ob
3. Nakamoto S (2008) Bitcoin: A peer-to-peer electronic cash system. https://bitcoin.org/bitcoin.pdf
4. Singh S, Singh N (2016) Blockchain: future of financial and cyber security. In: 2016 2nd international conference on contemporary computing and informatics (IC3I), pp 463–467. IEEE
5. Glaser F (2017) Pervasive decentralisation of digital infrastructures: a framework for blockchain enabled system and use case analysis (2017)
6. Iansiti M, Lakhani KR (2017) The truth about blockchain. Harv Bus Rev 95(1):118–127
7. Avital M, Beck R, King J, Rossi M, Teigland R (2016) Jumping on the blockchain bandwagon: lessons of the past and outlook to the future

8. Kwok AOJ, Koh SGM (2019) Is blockchain technology a watershed for tourism development? Curr Issues Tour 22(20):2447–2452
9. Hawlitschek F, Notheisen B, Teubner T (2018) The limits of trust-free systems: a literature review on blockchain technology and trust in the sharing economy. Electron Commer Res Appl 29:50–63
10. Rakic D (2018) Blockchain and tourist data interoperability. In: Proceeding in XII international conference of tourism and information & communication technology, pp 80–98. Facultad de Turismo – Universidad de Málaga
11. Andrian HR, Kurniawan NB. Suhardi (2018) Blockchain technology and implementation: a systematic literature review. In: 2018 international conference on information technology systems and innovation (ICITSI), pp 370–374. IEEE
12. Yli-Huumo J, Ko D, Choi S, Park S, Smolander K (2016) Where is current research on blockchain technology? A systematic review. PLoS ONE 11(10):e0163477
13. Wang Y, Singgih M, Wang J, Rit M (2019) Making sense of blockchain technology: how will it transform supply chains? Int J Prod Econ 211:221–236
14. Morkunas VJ, Paschen J, Boon E (2019) How blockchain technologies impact your business model. Bus Horiz 62(3):295–306
15. Ølnes S (2016). Beyond bitcoin enabling smart government using blockchain technology. In: International conference on electronic government, pp 253–264. Springer, Cham
16. Christidis K, Devetsikiotis M (2016) Blockchains and smart contracts for the internet of things. IEEE Access 4:2292–2303
17. Killeen A (2015) The confluence of bitcoin and the global sharing economy. In: Handbook of Digital Currency, pp 485–503. Academic Press
18. Herbert J, Litchfield A (2015) A novel method for decentralised peer-to-peer software license validation using cryptocurrency blockchain technology. In: Proceedings of the 38th Australasian computer science conference (ACSC 2015), vol 27, p 30
19. Tian F (2016) An agri-food supply chain traceability system for China based on RFID & blockchain technology. In: 2016 13th international conference on service systems and service management (ICSSSM), pp 1–6. IEEE
20. Tai X, Sun H, Guo Q (2016) Electricity transactions and congestion management based on blockchain in energy internet. Power Syst Technol 40:3630–3638
21. Fenwick M, McCahery JA, Vermeulen EP (2019) The end of 'corporate'governance: hello 'platform'governance. Eur Bus Organ Law Rev 20(1):171–199
22. Saranti PG, Chondrogianni D, Karatzas S (2018) Autonomous vehicles and blockchain technology are shaping the future of transportation. In: The 4th conference on sustainable urban mobility, pp 797–803. Springer, Cham
23. Lemieux VL (2016) Trusting records: is blockchain technology the answer? Rec Manage J 26(2):110–139
24. Noizat P (2015) Blockchain electronic vote. In: Handbook of digital currency, pp 453–461. Academic Press
25. Nugent T, Upton D, Cimpoesu M (2016) Improving data transparency in clinical trials using blockchain smart contracts. F1000Research 5:2541
26. Sharples M, Domingue J (2016) The blockchain and kudos: a distributed system for educational record, reputation and reward. In: European Conference on Technology Enhanced Learning, pp 490–496. Springer, Cham
27. Azaria A, Ekblaw A, Vieira T, Lippman A (2016) Medrec: Using blockchain for medical data access and permission management. In: 2016 2nd international conference on open and big data (OBD), pp 25–30. IEEE

28. Choi TM, Wen X, Sun X, Chung SH (2019) The mean-variance approach for global supply chain risk analysis with air logistics in the blockchain technology era. Transp Res Part E: Logist Transp Rev 127:178–191
29. Nam K, Dutt SS, Chathoth P, Khan MS (2019) Blockchain technology for smart city and smart tourism: latest trends and challenges. Asia Pac J Tour Res 60:1–15
30. Amadeus (2017) Blockchain: harnessing its potential in travel. An Amadeus Innovation foresight paper, Research Report. https://amadeus.com/en/insights/research-report/blockchain-harnessing-its-potential-in-travelRetrieved, 17 June 2019
31. Önder I, Treiblmaier H (2018) Blockchain and tourism: three research propositions. Annal Tour Res 72:180–182
32. Sigala M (2017) Collaborative commerce in tourism: implications for research and industry. Curr Issues Tour 20(4):346–355
33. Wolfe F (2017) Is blockchain technology another Y2K for hospitality? Hotel Management. https://www.hotelmanagement.net/tech/blockchain-technology-another-y2k-for-hospitality. Retrieved 17 June 2019
34. Thinktur (2019) Blockchain: casos de uso en turismo, Thinktur, Madrid
35. Liu Y (2019) Cognitive diagnosis of cultural and rural tourism convergence. Transl Neurosci 10:19–24
36. Zhou H, Niu Y, Liu J, Zhang C, Wei L, Fang Y (2018) A privacy-preserving networked hospitality service with the bitcoin blockchain. In: international conference on wireless algorithms, systems, and applications, pp 696–708. Springer, Cham
37. Alhadhrami Z, Alghfeli S, Alghfeli M, Abedlla JA, Shuaib K (2017) Introducing blockchains for healthcare. In: 2017 international conference on electrical and computing technologies and applications (ICECTA), pp 1–4. IEEE
38. Baralla G, Ibba S, Marchesi M, Tonelli R, Missineo, S (2018) A blockchain based system to ensure transparency and reliability in food supply chain. In: European conference on parallel processing, pp 379–391. Springer, Cham
39. Dogru T, Mody M, Leonardi C (2018) Blockchain technology and its implications for the hospitality industry. Boston Hospitality Review, Boston University School of Hospitality Administration
40. Polasik M, Piotrowska AI, Wisniewski TP, Kotkowski R, Lightfoot G (2015) Price fluctuations and the use of bitcoin: an empirical inquiry. Int J Electron Commer 20(1):9–49
41. Abramova S, Böhme R (2018) Perceived benefit and risk as multidimensional determinants of bitcoin use: a quantitative exploratory study. In: Thirty Seventh International Conference on Information Systems, Dublin 2016. https://informationsecurity.uibk.ac.at/pdfs/Abramova2016_Bitcoin_ICIS.pdf
42. Revfine. (2018) How blockchain technology is transforming the travel industry. https://www.revfine.com/blockchain-technology-travel-industry/
43. Tozzi C (2018) How Blockchains Are Changing the Hotel Industry. https://www.nasdaq.com/article/how-blockchains-are-changing-the-hotel-industry-cm963808
44. Starkov M (2018) Debunking the impact of blockchain on hotel distribution. https://www.phocuswire.com/Debunking-blockchain-hotel-distribution

Self-service Technology Preference During Hotel Service Delivery: A Comparison of Hoteliers and Customers

Chun Liu[1,2](✉) and Kam Hung[3]

[1] School of Tourism Sciences, Beijing International Studies University, Beijing 100024, China
sinoliuchun@163.com
[2] Research Center of Beijing Tourism Development, Beijing 100024, China
[3] School of Hotel and Tourism Management, The Hong Kong Polytechnic University, Hong Kong SAR, China
kam.hung@polyu.edu.hk

Abstract. Although previous studies have paid attention to customers' intention to use self-service technology (SST), there is a limited understanding of individual and organizational preferences for SSTs compared with traditional human services during hotel service delivery process. To fill this gap, this study investigated and compared individual and organizational preferences between SSTs and human services by dividing hotel service delivery process into eight service encounters. 601 customer questionnaires and 504 hotelier questionnaires were collected and analyzed. Findings revealed a service-channel-fit conceptual framework and indicated that customers' and hoteliers' preferences are rather a sequence of channel choices during hotel service delivery. Overall, customers showed more preferences for SSTs than hoteliers. This study further notified that customers' and hoteliers' preferences were distinct across service delivery stages except for service delivery at restaurants or bars. Customers expressed a greater preference for smartphone-based SSTs, whereas hoteliers favored kiosks for check-in/-out.

Keywords: SST · Preference · Customer · Hotelier · Service delivery

1 Introduction

For the sake of efficiency, cost-saving, service quality, and customer satisfaction, hoteliers have constantly invested in technology, including self-check-in/check-out systems, self-service ordering gadgets, and robots [1, 2]. Among the similarities of these diversified technology-based services is that they all emphasize customer involvement and self-service. Self-service technology (SST) refers to technology that allows consumers to create or receive services without employees' direct involvement [3]. With the development of technology, SST-based services show the trend to supplement or replace people-delivered [4, 5].

Looking back on the research background and previous research on SSTs, prior studies have paid attention to how customers' intentions to use SSTs are influenced by

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 267–279, 2020.
https://doi.org/10.1007/978-3-030-36737-4_22

their attitudes toward SSTs, SST characteristics (e.g., perceived usefulness), individual demographics (e.g., age), situational differences (e.g., perceived waiting time) and psychological factors (i.e., anxiety), mainly based on technology acceptance model (TAM) and technology readiness [1, 2, 6]. However, these studies ignored the standpoints of the supplier, and separated technology from workforce, thus, neglecting their possible interaction. According to consumer theory, substitute goods and complementary goods have great effects on the demand for the good they replace and complement. Reference-dependent preference further reveals that individuals' decision making is related to a reference point [7]. That is, whether people adopt SSTs hinges on the channel it substitutes. In this respect, it is necessary to consider human service that is substituted by SST, and explore how does it affect decision making, instead of exclusively focusing on the "intention to use" SST [8]. This underscores the need to explore preferences for SSTs compared with human services, which is regarded as the essence of intentional behavior [9]. However, people maybe unclear about their own preferences [10]. Therefore, more attention should be paid to customers' and hoteliers' preferences between SSTs and human services.

Additionally, hotel service delivery is much more complicated than the delivery process of a check-out service at a supermarket, or a check-in service at an airport. Aside from check-in, hotel service delivery involves room service, restaurant, and check out [11, 12]. The acceptance of self-check-in technology does not necessarily mean a preference for SST-based room service. Nevertheless, studies on SSTs in hospitality and tourism either examined customers' adoption of hotel SSTs in general [13, 14], or on the basis of a single service encounter (i.e., check-in) [2, 15]. This argument, thereby, heightens the necessity to explore preferences for specific SST in a corresponding hotel service delivery phase, on account of the different antecedents of and attitudes towards dissimilar SSTs in different sectors [14, 16]. Considering the lack of research in this direction, this study aims to explore customers' and hoteliers' preferences during hotel service delivery and compare the possible disconfirmations among the preferences of the two groups. Aside from filling the research gap, this study contributes to the industry. Armed with these abundant findings, hoteliers can make more rational decisions around SST adoption and service delivery management and marketing, and tailor their services to meet customers' needs.

2 Literature Review

Albeit prior studies have paid attention to customers' intention to use SSTs and contributed valuable insights into SST adoption [1, 2], they neglected the multiple nature of service [17]. Little work has been done to investigate customers' and hoteliers' preferences between SSTs and service employees. Despite the increasing technology application, there was no autonomous decline in the utilization of traditional channels (e.g., face to face) [18]. For example, although waiting to turn to service staffs for help was frustrating, it did not motivate consumers to forgo a live service employee [19]. Customers are usually multi-channellers, which means that they adopt more than two channels to satisfy their needs [18, 20]. In this endeavor, service providers (e.g., retailers and government) have growingly tapped diversified channels to contact with customers [17, 20–22]. SST ought to be considered in a multi-channel setting since customers and service providers do not isolate it from other channels [23]. Consequently, the simplistic nature of a model based on a single service delivery channel is questionable. It is necessary to take another channel into account to explore the preference rather than the intention to use SST [8].

In the domain of hotel, Kattara and El-Said [25] proved that five-star hotel customers' preferences for human services to SSTs vary during different guest cycle stages from preregistration to after departure, whereas neglecting organizational preferences [25]. Kaushik and Rahman [24] illustrated the mediating effects of need for interaction on the relationship between technology readiness and customers' choice between SSTs and service staffs [24]. Yet, Kaushik and Rahman [24] used intention to adopt SSTs to refer to the choice between SSTs and service personnel [24]. That is, their study is rather a research on intentions to use SSTs than choices between the two service delivery channels. Another drawback of their research is that they regarded choice between SSTs and staffs as a one-off event, thus neglecting that customers are repeatedly faced with a choice during the service delivery process.

Service delivery process is usually divided into dissimilar service encounters to enhance the understanding of hotel performance and the whole service process [26]. Hotel service process comprised of more than one service encounter [11, 12] is much more complicated than the exclusive and single check-in/check-out service encounter at a supermarket or airport. In the past literature, the delivery process of hotel service has been segmented into five or six service categories, as shown in Table 1 [11, 12, 25, 27]. Accordingly, this study further divides the service delivery process into eight phases, namely, check-in, room service order, room service delivery, service order at restaurants/bars, service delivery at restaurants/bars, check-out and invoice obtaining.

Table 1. Hotel service delivery process (compiled by author)

Author (Year)	Hotel service delivery process
Bitran and Lojo [27]	Access, Check-in, Diagnosis, Service Delivery, Check out, Follow-up
Danaher and Mattsson [11]	Check-in, Room, Restaurant, Breakfast, Check-out
Yung and Chan [12]	Check-in, Room, Restaurant, Business center, Check-out
Kattara and El-Said [25]	Room reservation, Check-in, Room service order, Information seeking, Service order at restaurants, Complaint, Wake up, Check out, Contact after check-out

In short, the usage of various channels during a service delivery process is not a one-off event but a question of channel sequencing [28, 29]. Previous studies on SSTs in the hotel context are accused of exploring SSTs without taking other channels into consideration but taking the service delivery as a whole or exclusively focusing on a single service encounter (e.g., check-in encounter) [2, 13–15, 30]. This study, thus, argues to explore customers' and hoteliers' preferences by dividing the service delivery process into different service encounters to enhance knowledge of individual and organizational technology behaviors in a hospitality context. Accordingly, two hypotheses warrant further consideration:

H1: Customers' preferences for SSTs differ by service delivery stage.
H2: Hoteliers' preferences for SSTs differ by service delivery stage.

Moreover, customer adoption and acceptance lay the foundation for hoteliers' decisions on deploying technologies [31–33]. Although previous studies have identified that organizational technology adoption is influenced by firm-related ingredients (e.g., top management support), environmental factors (e.g., pressure from industry), technologies characteristics [34, 35], their investment in SST application might incur negative consequences if they do not take customers' preferences into consideration [36]. In this sense, the discrepancies between hotels' preference and customers' preference for SSTs during hotel service delivery process warrants exploration. The following hypotheses are thus proposed:

H3: Overall, customers' and hoteliers' SSTs preferences are different.
H4: Customers' and hoteliers' preferences for SSTs differ by service delivery stage.

3 Methodology

To test the aforementioned hypotheses, two rounds of surveys were conducted. Ultimately, two samples were derived. The data collection targeting customers was labeled Sample 1. The data collection targeting hoteliers was referred to as Sample 2. This research is set in the context of China given its special situations (e.g., the rapid development of SSTs) and the lack of academic research compared with SST research conducted in western countries such as USA [6].

Preferences in the present study were measured in two ways. Firstly, four items borrowed from behavioral intention measures were used to obtain the respondents' general behavioral intention to use either SSTs or human services [2, 37]. The seven-point Likert scale ranged from 1 (strongly disagree) to 7 (strongly agree) was adopted to guarantee discrimination and to avoid overwhelming response options. Preferences were obtained by subtracting the rating scores of behavior intention to use human services from the scores of intentions to use SSTs. Secondly, the respondents were asked to make multiple choices among various SSTs and conventional service employees at each service delivery phase (i.e., check in, control room amenities, order room service, deliver room service, order service at restaurants/bars, deliver service at restaurants/bars, check out and obtain an invoice). Available SSTs in the delivery of hotel services were identified via literature review. These identified innovative SSTs were listed on the questionnaires and were allocated to the corresponding service delivery phases (e.g., check-in, room service order, and check-out).

Before the formal data collection, pre-tests and pilot studies were conducted to check the validity of the questionnaire. Modifications were made on question types, wording, and online screen configurations. Questionnaires were distributed via Wenjuanxing (www.wjx.cn), which is a professional and the largest online survey platform in mainland China. A web-based survey has valuable merits, such as reduced costs, enhanced response time and maximized respondents who meet the requirements.

3.1 Customer Data: Sample 1

Between February and March 2019, a total of 2307 questionnaires targeting customers were handed out and 773 respondents passed the screening process (respondents have used SSTs in hotels in mainland China at least once in the past 12 months). Customer respondents were from different hotels all around China, including economy hotel, midscale hotel, luxury hotel, business hotel and resort hotel. These criteria were to underpin respondents' knowledge of SSTs and the hotel service delivery process and eliminate the limitations of examining only one type of hotel. A total of 601 valid questionnaires were retained for further analysis according to attention filters (reverse and homogeneous items), which had a validity rate of 77.8% and were labelled as Sample 1. 57.4% of the 601 respondents were female. 77.4% of the respondents were no older than 35 years old, while only 0.7% were between the ages of 55–64 years. More than half of the respondents had bachelor's degrees (64.7%), followed by postgraduate degrees or higher (28.6%). 19.6% of the respondents have used SSTs more than 5 times in hotels in the past 12 months.

3.2 Hotelier Data: Sample 2

2,102 questionnaires targeting hoteliers were distributed and returned from March 9 to 12, 2019. A total of 2,020 respondents passed the screening process. Specifically, managers from hotels with the SST application were selected given their knowledge of the hotel's service practices and performance and SSTs. Hotel respondents were also from different hotels, departments, and positions all around China. 481 valid questionnaires were retained for further analysis based on attention filters (reverse and homogeneous items) with a validity rate of 23.81%. A total of 504 questionnaires were used for further analysis after the 23 valid questionnaires from the pilot studies were added. The hotelier data were named Sample 2. The female respondents (55.8%) outnumbered their male counterparts (44.2%). The majority age group was 25–35 years, comprising approximately 57.3% of the respondents. The majority of the hotel managers had a 2–3 year college degree (58.9%). The most common number of years of experience at a management level position was 6–10 years (41.5%).

3.3 Data Analysis

Customers' and hoteliers' preferences for different SSTs and traditional service delivery channels in associated service delivery stages were derived from the descriptive analysis of the multiple responses (H1 and H2). The overall SST preferences differences between customers and hoteliers were tested via independent-sample t-tests (H3). The preference differences between hoteliers and customers by hotel service delivery stage were compared via crosstabulation analysis (H4).

4 Findings

With respect to intentions to use SSTs in the future, customers' ratings (Mean = 6.118) were significantly higher than those of hotels (Mean = 6.009), with much lower ratings for human services (3.196 vs. 4.870), as illustrated in Table 2. In terms of differences between intentions to use SSTs and human services, discrepancies among customers were significantly larger than among hotels (t = 18.477, p = .000), indicating that overall, customers showed more SST preferences than hoteliers.

Table 2. Independent-samples *t*-tests: customers' and hoteliers' general preferences (source authors)

		Mean	SD	*t*-value	Sig.	Mean differences
Intention to use SSTs	Customer	6.118	0.644	2.090	.037*	.109
	Hotelier	6.009	0.925			
Intention to use human services	Customer	3.196	0.883	−21.362	.000***	−1.673
	Hotelier	4.870	1.460			
Intention discrepancies (Preferences)	Customer	2.922	1.274	18.477	.000***	1.782
	Hotelier	1.140	1.638			

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Regarding preferences for SSTs compared with human services in specific service encounters, customers and hotels displayed similar preferences (Table 3). Nearly all preferred SSTs for checking in (customers: 87.2%; hoteliers: 77.8%); controlling room amenities (customers: 92.5%; hoteliers: 94.6%); ordering room service (customers: 93.7%; hoteliers: 95.0%) and restaurant service (customers: 92.3%; hoteliers: 88.9%) and checking out (customers: 89.5%; hoteliers: 88.7%); and obtaining an invoice (customers: 92.0%; hoteliers: 96.6%). In terms of room service delivery, 47.6% of customers, and more than half of hoteliers (56.3%) preferred service employees to SSTs. Similarly, more than half of customers (56.6%) and hoteliers (56.2%) showed preferences for staffs to deliver room service or service at restaurants/bars.

Table 3. Percentages of preferences for SSTs by hotel service stage (%) (source authors)

	Check-in	Control room amenities	Order room service	Deliver room service	Order service at restaurant/bars	Deliver service at restaurant/bars	Check-out	Obtain an invoice
Customer	87.2	92.5	93.7	52.4	92.3	43.4	89.5	92.0
Manager	77.8	94.6	95.0	43.7	88.9	43.8	88.7	96.6

In terms of preferences for specific SSTs across service delivery phases, customers' and hotels' preferences were significantly different except for service delivery at restaurants/bars (Table 4).

Table 4. Results of cross-tabulation analysis: customers' and hotels' preferences (source authors)

	Check-in	Control room amenities	Order room service	Deliver room service	Order service at restaurant/bars	Deliver service at restaurant/bars	Check-out	Obtain an invoice
df	2	4	3	1	2	1	2	2
Sig.	.000***	.000***	.000***	.004**	.004**	.936	.000***	.000***

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

As shown in Fig. 1, about two-thirds (66.1%) of customers preferred to use mobile check-in, whereas only 30.8% of hotelier respondents did. Instead, hotels' preferred SST was facial recognition self-service kiosks (SSK) (47%). In terms of in-room amenities control, smartphones ranked first among customer and hotelier respondents. However, fewer customers (34.4%) mentioned them than hoteliers (49.4%). Customers' preferences for AI management systems and control panels exceeded those of hotelier respondents (Fig. 1). With respect to ordering service at room or restaurants/bars, the most popular service channel was smartphones as reported by 71.2% and 59.6% of customers and 79.4% and 64.5% of hoteliers, respectively. Notably, preferences for smartphones were lower for restaurants/bars than for room service. Conversely, mobile tablets and human services were more preferred in restaurants/bars than for room service. As for room service delivery, slightly more than half of the customers preferred robots to service staff (52.4%), whereas more than half of hotels preferred depending on service employees to deliver room service (56.3%). Regarding service delivery at restaurants, customers' and hotels' preferences were similar: approximately 56% preferred staffs over robots. Similar to check-in, nearly half (50.1%) of customers preferred mobile check-out, while most hotels favored self-service check-out kiosks (61.7%). As for invoicing, many more hotel respondents preferred SSKs (81.5%) compared with customer respondents (52.4%). By contrast, customers' preferences for QR codes (39.6%) outweighed hotels' (15.1%).

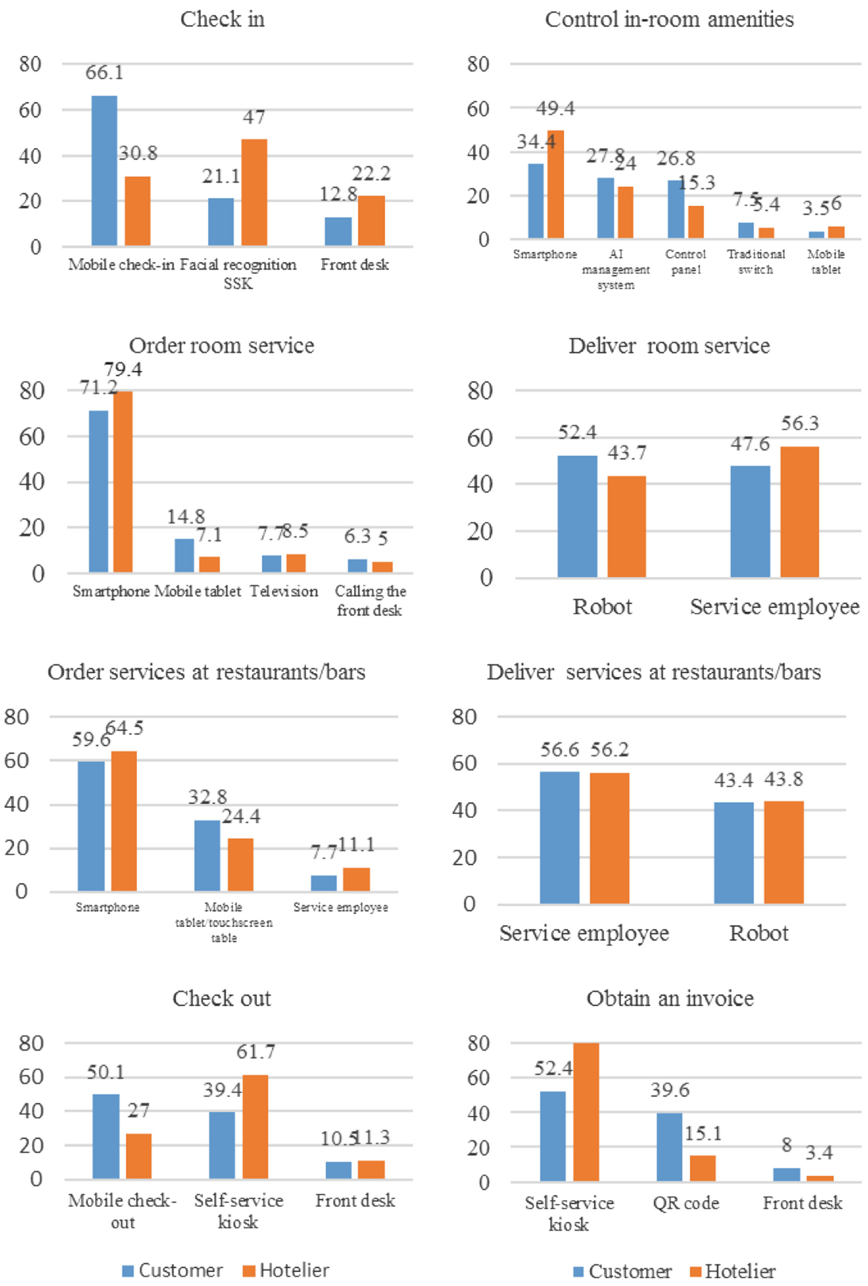


Fig. 1. Percentage of preferences for specific channel by hotel service stage (source authors)

5 Discussion and Conclusion

In summary, this study revealed variations in customers' and hotels' preferences across hotel service stages (H1 and H2 supported). Customers and hotels preferred using SSTs to check in, control room amenities, order service at room/restaurants/bars, check-out, and obtain invoices, while both were more reluctant to use SSTs for room and restaurant/bar service delivery. Furthermore, customers' and hoteliers' behavioral intentions to use SSTs differed (H3 Supported). Overall, customers indicated more preferences for SSTs than hoteliers. The SSTs preferences of the two groups at different service delivery stages were significantly distinct except for service delivery at restaurants or bars (H4 partially supported). The most popular SSTs among customer, in general, were smartphone-based SSTs. Although hoteliers showed preferences for smartphone-based SSTs for in-room facilities control and service order, they generally preferred SSKs to help customers with check-in/-out and invoice.

The finding that customers generally preferred SSTs to service employees, is contrary to Kattara and El-Said [25] who suggested that hotel guests prefer to be served by service employees instead of innovative technologies in majority service encounters [25]. These differences may be explained through the following reasons. First of all, the study contexts were different (China vs. Egypt). The literature has revealed that nationality significantly affects SST adoption [38]. Second, respondents in Kattara and El-Said's [25] study were five-star hotel guests, whereas respondents in this study were guests of one-, two-, three-, four-, and five-star hotels. Besides, Kattara and El-Said's [25] research was conducted in 2011, when hotel SSTs were much less popular. The popularity of SSTs probably contributed to SST adoption.

The finding that customers' and hotels' preferences vary across hotel service stages underscores the necessity of deconstructing the hotel service delivery process into service encounters consisting of the main parts of the service process [11]. This provides supports for prior research in government service that different service delivery channels provide specific advantages in specific task completion [18], wherein citizens' channel selection is a question of channel sequencing rather than a binary preference [29]. One reason for this trend may be explained by task-technology fit (TTF), which refers to the fit among task requirements, customers' abilities, and the functionality of technology (Fig. 2) [39]. Task-technology fit asserts that individual performance will be enhanced if technology matches well with the task [39]. In this sense, the adoption of a specific channel may follow from enhanced assistance in handling a particular service. Overall, the specific features of different service stages and the fit among service requirements, customer capability, and technology functionality likely informed customers' preferences at different service delivery stages. The same situation may apply at the organizational level.

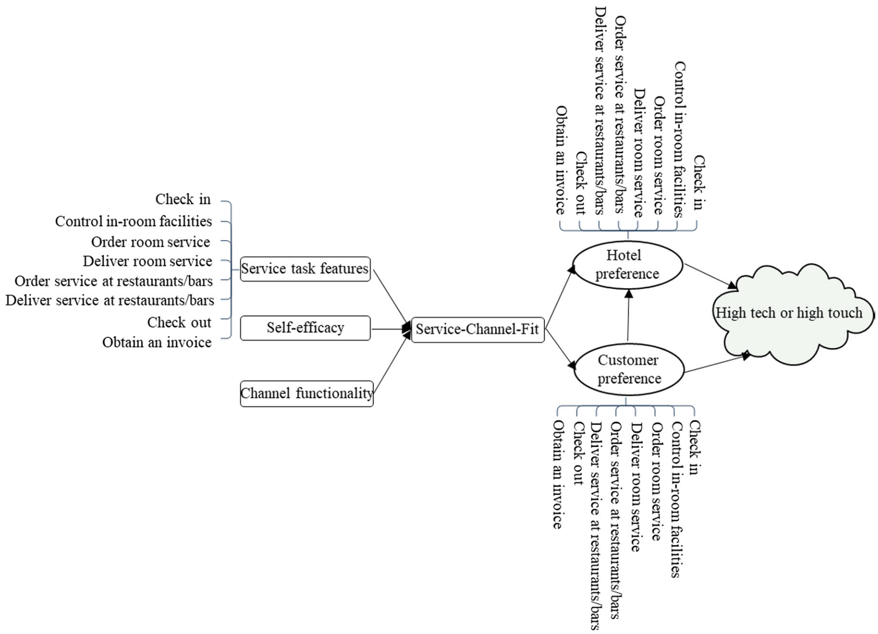


Fig. 2. Service-channel-fit conceptual framework (Adapted from TTF [39])

Given the crucial roles of customer responses and practitioners' opinions in successful application and promotion of new technologies [34, 40], the exploration of customers' and hoteliers' preferences for SSTs compared with human services and preference discrepancies of the two groups contribute to our understanding of individual and organizational behaviours and in turn do a favour to handling the debate over human-touch versus tech-focus in a hospitality domain [36].

5.1 Theoretical Implications

These results offer an in-depth understanding of guests' and hotels' technology behaviors. Conveying preferences via choices and decision making is the essence of intelligent and intentional behavior [9]. However, in the limited literature, academia has mainly concentrated on customers' intention to use SSTs, neglecting the influences of human services and suppliers' opinions. Besides, albeit exploring service from the perspective of service delivery is as important as service outcomes [41, 42], prior studies have largely ignored the differences among service stages. The past literature either explored customers' intention to use hotel SSTs in general [13, 14] or within a single service encounter (i.e., check-in) [2, 15]. The findings of this study suggest that customers' and hoteliers' SSTs preferences vary during hotel service delivery. Customers and hoteliers were identified as multi-channelers. Their preferences between SSTs and service employees were not binary but involved channel sequencing. These results, thus, offer a new avenue of investigating customers' and hotels' technology behaviors. Exploration of customers' and hoteliers' SST preferences via anatomizing service delivery into distinct service encounters consisting of main parts of the entire process is more detailed than studies only focusing on "intention to use", check-in encounters or overlooking distinctions among encounters. The results, therefore, contribute to academic expertise around individual and organizational technology adoption in a hotel context and unveil new research directions.

5.2 Practical Implications

Armed with the findings, hoteliers can wield better strategies to manage and deploy multiple channels rather than simply making a decision regarding whether to implement SSTs [43]. Effective management of service delivery channels increases a hotel's likelihood of being profitable and successful within a growing competitive marketplace [3]. The awareness of preferences variations across different phases of service delivery help hoteliers decide the extent of SST applications in their settings. For example, the results of this study revealed the customers and hoteliers preferred SSTs for checking in, controlling room amenities, ordering room or restaurant service, checking out, and obtaining invoices, while service employees were favored for service delivery. These differences imply that hotels should begin incorporating SSTs for check-in, in-room amenities, service orders, checking out, and invoicing but perhaps not yet for service delivery. Furthermore, hotels should adjust their preferences and select SSTs that customers prefer. The identified discrepancies between customer preference and the hotelier preference help hotels modify their service delivery strategies to satisfy customer needs and enhance customer loyalty [28]. For example, the findings indicated that customers generally prefer smartphone-based SSTs such as mobile check-in/-out. By contrast, hotels showed greater preferences for self-check-in kiosks. Hence, if hotels tailor their service channel arrangement according to customers' preferences, money and time will be saved and used efficiently, and customer loyalty will be elevated to promote future success.

5.3 Limitations and Future Research

Couples of limitations were admitted with suggestions for future research. Firstly, this study was conducted in China. Customer and hotelier respondents from diverse cultures should be recruited in future research for potentially better generalizability. Besides, only eight service phases were examined in the quantitative survey considering time and money. Other service encounters (e.g., taking an elevator and opening the door) exist. Academia and industry are suggested to pay attention to the division of hotel service delivery process and SSTs application in associated stages. Besides, the service-channel-fit conceptual framework needs further verification.

References

1. Shin H, Perdue RR (2019) Self-service technology research: a bibliometric co-citation visualization analysis. Int J Hospitality Manag 80:101–112
2. Kim M, Qu H (2014) Travelers' behavioral intention toward hotel self-service kiosks usage. Int J Contemp Hospitality Manag 26:225–245

3. Meuter ML, Ostrom AL, Roundtree RI, Bitner MJ (2000) Self-service technologies: understanding customer satisfaction with technology-based service encounters. J Mark 64:50–64
4. Ba S, Stallaert J, Zhang Z (2010) Balancing IT with the human touch: Optimal investment in IT-based customer service. Inf Syst Res 21:423–442
5. Romps NG (2007) Where Hi-tech and the human touch intersect. (cover story). Am Gas 89:16–23
6. Kokkinou A, Cranage DA (2013) Using self-service technology to reduce customer waiting times. Int J Hospitality Manag 33:435–445
7. Kahneman D, Tversky A (1979) Prospect theory: An analysis of decision under risk. Econometrica 47:263–291
8. Gelderman CJ, Ghijsen PWT, van Diemen R (2011) Choosing self-service technologies or interpersonal services—The impact of situational factors and technology-related attitudes. J Retail Consum Serv 18:414–421
9. Slovic P (1995) The construction of preference. Am Psychol 50:364–371
10. Piccoli G, Lui T-W, Grün B (2017) The impact of IT-enabled customer service systems on service personalization, customer service perceptions, and hotel performance. Tourism Manag 59:349–362
11. Danaher PJ, Mattsson J (1994) Customer satisfaction during the service delivery process. Eur J Mark 28:5–16
12. Yung E, Chan A (2002) Business traveler satisfaction with hotel service encounters. J Travel Tourism Mark 11:29–41
13. Oh H, Jeong M, Baloglu S (2013) Tourists' adoption of self-service technologies at resort hotels. J Bus Res 66:692–699
14. Rosenbaum MS, Wong IA (2015) If you install it, will they use it? Understanding why hospitality customers take "technological pauses" from self-service technology. J Bus Res 68:1862–1868
15. Kokkinou A, Cranage DA (2015) Why wait? Impact of waiting lines on self-service technology use. Int J Contemp Hospitality Manag 27:1181–1197
16. Beatson A, Coote LV, Rudd JM (2006) Determining consumer satisfaction and commitment through self-service technology and personal service usage. J Mark Manag 22:853–882
17. Sousa R, Voss CA (2006) Service quality in multichannel services employing virtual channels. J Serv Res 8:356–371
18. Pieterson W, Ebbers W (2008) The use of service channels by citizens in the Netherlands: Implications for multi-channel management. Int Rev Adm Sci 74:95–110
19. Cassab H (2009) Investigating the dynamics of service attributes in multi-channel environments. J Retail Consum Serv 16:25–30
20. Berry LL, Bolton RN, Bridges CH et al (2010) Opportunities for innovation in the delivery of interactive retail services. J Interact Mark 24:155–167
21. Lin J-SC, Hsieh P-L (2011) Assessing the self-service technology encounters: development and validation of SSTQUAL scale. J Retail 87:194–206
22. van den Boer Y, Arendsen R, Pieterson W (2016) In search of information: investigating source and channel choices in business-to-government service interactions. Gov Inf Q 33:40–52
23. Eriksson K, Nilsson D (2007) Determinants of the continued use of self-service technology: the case of Internet banking. Technovation 27:159–167
24. Kaushik AK, Rahman Z (2017) An empirical investigation of tourist's choice of service delivery options: SSTs vs service employees. Int J Contemp Hospitality Manag 29:1892–1913

25. Kattara HS, El-Said OA (2014) Customers' preferences for new technology-based self-services versus human interaction services in hotels. Tourism Hospitality Res 13:67–82
26. Yang SY (2008) The resort hotel experience: Conceptualization, measurement, and relation to antecedents and consequences. The Hong Kong Polytechnic University
27. Bitran G, Lojo M (1993) A framework for analyzing the quality of the customer interface. Eur Manag J 11:385–396
28. Buell RW, Campbell D, Frei FX (2010) Are self-service customers satisfied or stuck? Prod Oper Manag 19:679–697
29. Reddick CG, Turner M (2012) Channel choice and public service delivery in Canada: comparing e-government to traditional service delivery. Gov Inf Q 29:1–11
30. Mäkinen O (2016) Self-service technology in hotel reception: finnish customer perceptions. University of Lapland
31. Hansen HR (1995) Conceptual framework and guidelines for the implementation of mass information systems. Inf Manag 28:125–142
32. Sahadev S, Islam N (2005) Why hotels adopt ICTs: a study on the ICT adoption propensity of hotels in Thailand. Int J Contemp Hospitality Manag 17:391–401
33. Wünderlich NV, Wangenheim FV, Bitner MJ (2013) High tech and high touch: a framework for understanding user attitudes and behaviors related to smart interactive services. J Serv Res 16:3–20
34. Ozturk AB, Hancer M (2014) Hotel and IT decision-maker characteristics and information technology adoption relationship in the hotel industry. J Hospitality Tourism Technol 5:194–206
35. Leung D, Lo A, Fong LHN, Law R (2015) Applying the technology-organization-environment framework to explore ICT initial and continued adoption: an exploratory study of an independent hotel in Hong Kong. Tourism Recreation Res 40:391–406
36. Wei W, Torres E, Hua N (2016) Improving consumer commitment through the integration of self-service technologies: a transcendent consumer experience perspective. Int J Hospitality Manag 59:105–115
37. Zeithaml VA, Berry LL, Parasuraman A (1996) The behavioral consequences of service quality. J Mark 60:31–46
38. Fisher G, Beatson A (2002) The impact of culture on self-service on technology adoption in the hotel industry. Int J Hospitality Tourism Adm 3:59–77
39. Goodhue DL, Thompson RL (June 1995) Task-technology fit and individual performance. MIS Q 19(2): 213–236
40. Zhang C, Dhaliwal J (2009) An investigation of resource-based and institutional theoretic factors in technology adoption for operations and supply chain management. Int J Prod Econ 120:252–269
41. Parasuraman A, Zeithaml VA, Berry LL (1985) A conceptual model of service quality and its implications for future research. J Mark 49(4):41–50
42. Mohr LA, Bitner MJ (1995) Process factors in service delivery: what employee effort means to customers. Adv Serv Mark Manag 4:91–117
43. Wang C, Harris J, Patterson PG (2012) Customer choice of self-service technology: the roles of situational influences and past experience. J Serv Manag 23:54–78

Review Helpfulness: The Influences of Price Cues and Hotel Class

Erin Yirun Wang[1(✉)], Lawrence Hoc Nang Fong[1], and Rob Law[2]

[1] Avenida da Universidade, University of Macau, Taipa, Macao, Special Administrative Region of China
erin.wang@connect.um.edu.mo, lawrencefong@um.edu.mo

[2] The Hong Kong Polytechnic University, 17 Science Museum Road, TST East, Kowloon, Hong Kong, China
rob.law@polyu.edu.hk

Abstract. In the digital age, online reviews are increasingly used by consumers to understand product features and make purchase decisions. Despite the benefit brought to consumers, the popularity of reviews also causes information overload. To deal with this issue, consumers rely on hints to decide the reviews to read. A widely adopted hint is helpfulness of the reviews. Therefore, plenty of research efforts have been devoted to study the predictors of review helpfulness. To our best understanding, however, the effect of price cues on review helpfulness remains unknown. Since price is a crucial factor in product/service evaluations, online reviews with price cues are supposed to be helpful in a consumer decision-making process. Furthermore, consumers' emphasis on price information is supposed to vary with product class. Based on Cue Utilization Theory and Elaboration Likelihood Model, this study examined the effect of price cues on review helpfulness and the moderating role of hotel class. By analyzing 24,537 TripAdvisor reviews of hotels in New York City, we found that presence of price cues led to more helpful votes. However, it happened only for low-class hotels, but not for high-class counterparts. The study contributes to literature about determinants of review helpfulness, as well as provides implications for online travel review platforms to enrich their filtering function and for hoteliers to attract bookings.

Keywords: Price cue · Review helpfulness · User-generated content · Hotel class · Online review

1 Introduction

The introduction of web 2.0 has evolved the way to communicate marketing information on the web. Besides allowing marketers to advertise their products to a larger market, the digital age is empowering consumers to disseminate electronic word of mouth (eWOM) instantly through social media. As one form of eWOM, online reviews consist of customer experience and can be an alternative information source for consumers [1]. When making purchase decisions, consumers are increasingly relying on online reviews to learn about product attributes [2]. In particular, online reviews are

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 280–291, 2020.
https://doi.org/10.1007/978-3-030-36737-4_23

especially useful when buying tourism products, which cannot be evaluated before purchase [3]. Therefore, online consumer reviews related to hotel, attraction, and restaurant experience are available on numerous online travel communities (e.g., TripAdvisor, Yelp), supplementing marketers' information to help consumer make purchase decisions.

Although online travel review platforms provided valuable references for consumers, a huge amount of online reviews leads to information overload and increases cognitive cost for consumers [3]. To cope with this issue, some online travel platforms allow users to evaluate the helpfulness/usefulness of a review. Taking TripAdvisor as an example, if users consider a hotel review providing valuable information for hotel booking process, they can vote this review as helpful. Accumulated helpful votes assist potential tourists to identify the useful reviews and make booking decisions efficiently [4]. The helpfulness voting mechanism not only is instrumental to potential consumers, but also benefits website managers [5]. Specifically, it is useful for online travel review platforms to identify reviews that will potentially receive helpful votes. By identifying potentially influential reviews, platform managers can offer an effective review filtering system to improve user experience [6]. Therefore, it is crucial to investigate the characteristics of reviews that will draw more helpful votes [7].

To identify the determinants of helpful reviews, researchers primarily investigated two major streams which are review and reviewer characteristics [8, 9]. Among various review characteristics, review textual features are the core part of online reviews, but research related to the effect of these features on perceived helpfulness is relatively scant [10]. In the hospitality and tourism industry, price cues (referring to monetary words in this study) have been shown prevalent in online hotel reviews [11]. That is reasonable since customers generally evaluate service quality and value according to the price they paid [12]. However, the effect of price cues in hotel online reviews on users/potential customers' responses, in particular helpfulness of the reviews, remains unknown. Compared to market price, which is an objective indicator of monetary cost, price cues in online reviews encompass richer information. The cues allow users to evaluate the value of a hotel as customers' experience is assessed simultaneously. Since value has a significant impact on consumer decision [12], it is possible that price cues strengthen the helpfulness of a review, which is yet to be examined.

Factors that determine review helpfulness are well-documented in the literature [13, 14]. Product characteristic is one of the factors [15]. In particular, depending on the products that the consumers intend to buy, perceived helpfulness of reviews can differ even though the reviews consist of identical cues [16]. For example, consumers who seek high-price products considered contents of reviews more helpful; whereas low-price seekers emphasized on review rating [15]. The findings hint that interaction of price cues and product class (e.g., high-class versus low-class hotels) may result in different review helpfulness. This conjecture remains unexplored.

In the present study, grounded in Cue Utilization Theory which explains the influence of observable cue on an observer's judgment [17, 18], we first investigated if price cues draw more review helpful votes. Second, we further examined the effect of price cue by investigating the moderating role of hotel class, based on the Elaboration Likelihood Model (ELM), which suggested that information processing effort varies with the cognitive paths that people used [19]. These objectives were achieved by analyzing hotel review data extracted from TripAdvisor.

This research contributes to the literature on review helpfulness in two major aspects. First, this study extends previous research on review helpfulness by adding price cues as the antecedent. Focusing on the effect of online review semantic features, we are able to better understand the characteristics of helpful reviews. Second, our study suggests and demonstrates that effect of price cues on review helpfulness is not robust across situations, such as when the hotel class is different.

2 Theoretical Background

2.1 Online Reviews and Review Helpfulness

Online reviews, as a form of user generated content, consists of product evaluations delivered by experienced consumers [20]. Since tourism product is experiential in nature, online travel reviews are especially valuable for consumers in decision making process [21]. Reviewers describe their experience in online hotel reviews, which allow consumers to predict their experience in the hotel. The review reduces uncertainty of consumers and increases their confidence in their booking decisions [20]. Empirical evidences show that travelers strongly rely on online reviews during information search and hotel comparison processes [15]. Online reviews also shape purchase behavior and sale performance [16].

Given the large volume of reviews written by millions of customers, reviews vary in quality and are not perceived equally helpful in consumer decision making [22]. The unequal helpfulness leaves rooms for a plethora of research on antecedents of review helpfulness. In general, the antecedents are divided into two major aspects which are review and reviewer characteristics [23]. With regard to the effect of review characteristics, prior studies revealed that both rating on the product/service providers and review contents impact perceived helpfulness [22]. For example, reviews with extremely high and low product/service ratings are considered less helpful [24]; reviews which are readable, self-explanatory, and have certain emotional contents receive more helpful votes [25]. With respect to reviewer characteristics, reviewer expertise, which is measured by their total number of published reviews and helpful votes received, is a positive predictor of review helpfulness [23].

Among the predictors of review helpfulness mentioned above, we focus on the influence of review content features. Compared to review ratings, review contents offer more detailed information for potential customers since the text contains vivid evaluation of product and consumer individual experience [2]. To examine the influence of review contents on perceived helpfulness, some research has performed linguistic analysis (e.g. readability, length) and sentiment analysis (e.g. valence) [26]. However, research on the impact of semantic aspect in review contents was relatively limited. Review semantic refers to topics and meaning encoded in review contents [26]. In the context of hospitality and tourism, a recent study has found temporal cues and explanatory cues in contents significantly affect review helpfulness [25]. Besides semantic features mentioned above, price cues have been found prevalent in online reviews. For instance, Pantelidis [27] analyzed contents of restaurant reviews and found that consumers considered price in describing service experience; Berezina et al. [11] found value-for-money was a theme frequently described by unsatisfied hotel customers; Xiang et al. [26] identified value as salient topics in reviews across three major platforms (i.e. TripAdvisor, Yelp, and Expedia). Yet, little is known about the effect of price cues on review helpfulness.

2.2 Price Cues in Online Reviews and Review Helpfulness

Although research on price cues in online reviews has received little scholarly attention, insights can be drawn from studies on the relationship between market price and online reviews. In the context of hospitality and tourism research, researchers have found that market price influences e-satisfaction and online purchase behavior [28, 29]. Other studies have shown that the effects of market price on review helpfulness rest upon reviewer expertise [30] and review rating [31]. The basic assumption of these studies is that market price acts as an indicator of consumption or cost [12, 30]. Actually, consumers not only considered price cost, but also concerned about the value of product when making purchase decisions [12]. This kind of value judgement is manifested in online reviews containing price cues. To illustrate, when reviewers mentioned about price or money, it is usually accompanied with value judgement (e.g., 'The resort fee is worth the price'). A joint evaluation of price and personal experience can assist consumers to perceive the product value and then make purchase decisions [32].

The reasons for investigating price cues can be summarized into two aspects. First, price cues in online reviews are prevalent but their effects are less understood; second, price cues in online reviews can provide value reference for potential consumers. Therefore, we propose to examine the effect of price cues in online reviews to further understand information processing of consumers. In this regard, Cue Utilization Theory has theoretical implications.

Cue Utilization Theory connects the relationship between the observable cue and an observer's judgment [17, 33]. This theory has been adopted by psychology and marketing researchers to make inferential judgements [17, 18]. Taking product quality as an example, this theory was used to explain the product quality perception influenced by available information cues (e.g. market price) [18]. Regarding online information quality, if online reviews provide sufficient and relevant information for consumers to evaluate the product, potential consumers will consider this review helpful in decision making. For example, reviews containing explanatory cues are featured with specified reasons and elaborated arguments, and these contents enable readers to better assess the product [34]. Reviews containing product assessment, which are influential references for consumers to make decisions, can be considered helpful. Thus, explanatory cues can be predictors of review helpfulness [25]. In a similar way, if online reviews contain price cues, consumers will be aware of product value information which is crucial in decision making, then the reviews will be considered helpful. Therefore, we assume that the presence of price cues will generate more helpful votes to the online review and thus hypothesize that:

H1. In online reviews, the presence of price cues has more helpful votes than the absence of price cues.

2.3 The Moderating Role of Hotel Class

As review helpfulness is subjective, it varies by individual situations. According to Baek et al. [15], review helpfulness is perceived differently depending on the readers' situations when they search information or evaluate alternatives. For instance, temporal distance and risk-benefit tendency of a person were found to moderate the impact of review concreteness on review helpfulness [10]. A prior study examined the effect of personal objectives as a situational factor [15]. Depending on how much consumers aim to pay, Baek et al. [15] divided product into high-priced and low-priced goods and found features of helpful reviews are different under these two situations. Taken together, review helpfulness is affected by the situations that the review readers are exposed to.

Among various situations, relevance to readers can make them evaluate review helpfulness differently, and this can be explained by Elaboration Likelihood Model (ELM) [35]. Focusing on persuasion, ELM proposes that information processing travels through two different routes based on personal relevance [19]. One is the central route, in which presented information is relevant to readers, and consequently individuals expend cognitive effort on information processing. The other is peripheral route, in which individuals deem the available information as low relevancy to themselves, so people are less motivated to devote effort to process this information. ELM has been widely applied in online review research, and particularly in investigating the features of helpful reviews [36]. Previous research has categorized review length and review readability as central cues, whereas peripheral cues comprise emotions in review, review rating, reviewer credibility and so on [23]. Reviews that are relevant to and hence require great cognitive effort of readers (i.e., using central route) earn more helpful votes [37].

In the context of hotel, relevancy of online review can vary based on what hotel class consumers intend to book. Considering the price level consumers aims to pay, hotels can be categorized into low-class and high-class groups [31]. For consumers who intend to book low-class hotels which are assumed to charge a lower price, price information is highly relevant to them due to their limited budget; while consumers seeking high-class hotels are more concerned about quality and less sensitive to price information in decision making [38]. In the case of price cues in online reviews, since consumers who intend to book low-class hotels are more concerned about monetary cost and value-for-money experience, they are expected to devote more cognitive effort using the central route to process reviews with price cues and cast more votes on review helpfulness. By contrast, since high-class hotel seekers may focus more on the hotel quality, monetary information is less relevant to them and expend less cognitive effort to process the price cues when they read the review. Therefore, the presence of price cues may not be helpful to their decision making. Taken together, we hypothesize that:

H2. Hotel class moderates the relationship between presence of price cues in online reviews and helpful votes. Specifically, for low-class hotels, the presence of price cues has more helpful votes than the absence of price cues, whereas for high-class hotels, the presence/absence of price cues has equal helpful votes.

3 Method

3.1 Data Collection

The data were collected from TripAdvisor, the leading travel online platform worldwide. TripAdvisor provides hotel reviews and helpfulness voting functions, which are the data source of this study to test the hypotheses. New York City ranks the top destination in the US according to 2019 ratings from TripAdvisor, and it has hotels of different classes. Hence, we deem New York City representative and suitable for our study.

We crawled reviews of hotels in New York City from TripAdvisor in June 2019. The data contain 545,519 reviews of 201 hotels in high-class and 323,958 reviews of 195 hotels in low-class. To control effect caused by language difference, we only included English reviews. As the variation of helpful votes are our research focus, reviews without helpful votes were excluded. Therefore, a total of 24,537 reviews, including 16,955 reviews for high-class hotels and 7,582 reviews for low-class hotels, were retained for analysis. The review data contain review rating, review date, review contents, and helpful votes received. The reviewer information such as the number of published reviews and total helpful votes the reviewer received are also included.

3.2 Variables

Table 1 displays hotel review information extracted from TripAdvisor, which summarizes the dependent variable, independent variable, moderator variable, control variables, and their measurements. The descriptions and measurement of these variables are explained as follows.

Dependent Variable. The dependent variable is review helpfulness and measured by counting the helpful votes received by each review.

Independent Variable. The independent variable, price cues, was operationalized by the presence or absence of money-related words (e.g., affordable, spend, and cheap) in a review. We identified money-related words based on the dictionary from Linguistic Inquiry and Word Count (LIWC) 2015. Adopting binary coding, we coded reviews with money-related words as “1” and coded reviews without money-related words as “0”. For example, reviews contain statements “Great hotel and Great service worth the money spent” or “The resort fee including breakfast and free drink from 5 pm to 7 pm is not worth the price” were considered presence of price cues and coded “1”.

Moderator. Hotel class is universally categorized according to hotel facility and service quality. In this study, the hotel class was divided into low and high levels.

Table 1. Variable description (source authors).

Variable	Description
Helpful votes	Number of "helpful" votes for a review
Price cues	Money-related words in a review (presence versus absence)
Hotel class	Grades of hotel establishments (low-class versus high-class)
Time length	The time elapsed since the review being posted (difference between data collection month and review posting month)
Review rating	The hotel rating in each review in a 5-point scale (from 1 to 5). Higher rating denotes stronger positive evaluation on the hotel
Reviewer contribution	The total number of reviews published by the reviewer
Reviewer helpful votes	The total number of helpful votes received by the reviewer

TripAdvisor has four categories of hotel class ranging from 2-star to 5-star. We operationalized high-class hotel with 5-star and 4-star hotels, and low-class hotel with 3-star and 2-star hotels.

Control Variables. This study took into account the effects of several variables at review level and reviewer level. Regarding the review level, time length and review rating were included as control variables. Normally, reviews posted earlier tend to receive more helpful votes due to accumulation effects. Therefore, time length was measured by calculating the difference between the data collection time and the review posting time. On TripAdvisor, the available review posting time is based on month unit, we calculate the month elapsed from data retrieving time to review posting time. Another factor of review level was review rating, which was measured by one-star to five-star in TripAdvisor. Regarding the reviewer level, we controlled reviewer expertise in our data analysis. Reviewer expertise contains two aspects, namely reviewer contributions and reviewer helpful votes. Reviewer contributions was measured by the number of total written reviews, while reviewer helpful votes were measured by counting total helpful votes the reviewer had received.

4 Results

Among the 24,537 reviews included in the analysis, the helpful votes each review received have a mean value of 1.42. As price cues and hotel class are binary variables, their value includes 0 and 1. Reviews with price cues occupy 58.85% whilst high-class hotels occupy 69.10% of the samples. The time length between data collecting and review posting is 9.31 months on average. Ranging from 1-star to 5-star, review rating on average scores 3.65. For each reviewer, the median numbers of contributed reviews and received helpful votes are 11 and 6 respectively.

We utilized model 1 of PROCESS tool for SPSS to perform the analysis. PROCESS is an add-on tool that can be used in SPSS to analyze the interactive effect of independent variable and moderator on dependent variable; besides, model 1 of the PROCESS tool can examine the simple moderation model (conditional effect of X on $Y = b_1 + b_3M$). Since we aim to examine whether the effect of price cues on review helpfulness is influenced by hotel class, model 1 of PROCESS tool in SPSS is suitable to test the relationship. Table 2 presents the result of the effect of price cues on review helpful votes moderated by hotel class. In hypothesis 1 we investigated whether the presence of price cues in online reviews has more helpful votes. This hypothesis is supported (coefficient = 0.067, $t = 3.430$, $p < 0.01$). Hypothesis 2 examines the moderating role of hotel class on the relationship between presence of price cues and helpful votes, which is also supported by our results given the significant interaction effect of price cues and hotel class (coefficient = −0.080, $t = -2.086$, $p < 0.05$) (see Table 3). The R-square change of this interaction effect was significant ($F(1,24,529) = 4.350$, $p < 0.05$). As Table 3 and Fig. 1 show, for low-class hotels, more helpful votes were recorded for reviews with price cues (effect = 0.108, $t = 3.324$, $p < 0.01$); for high-class hotels, the presence or absence of price cues in review contents makes no statistical difference on helpful votes (effect = 0.027, $t = 1.257$, $p = 0.209$).

Table 2. Results of variables predicting helpful votes (source authors).

	Coefficient	SE	t-statistics	p-value
Constant	1.594	0.029	54.457	0.000
Price cues (A)	0.067	0.020	3.430	0.001
Hotel class (B)	0.015	0.030	0.491	0.623
A × B	−0.080	0.039	−2.086	0.037
Time length	−0.011	0.001	−14.353	0.000
Review rating	−0.039	0.006	−6.628	0.000
Reviewer contribution	0.000	0.000	−14.822	0.000
Reviewer helpful vote	0.002	0.000	74.163	0.000

Table 3. Conditional effects of price cues on helpful votes by hotel class (source authors).

Hotel class	Effect	SE	t-statistics	p-value
Low-class	0.108	0.032	3.324	0.001
High-class	0.027	0.022	1.257	0.209

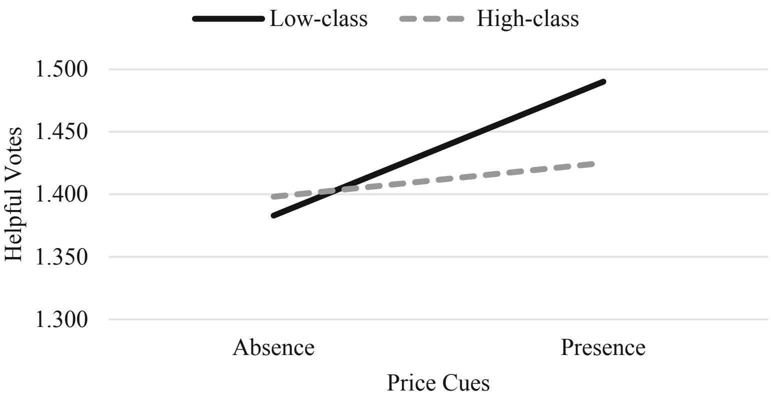


Fig. 1. Conditional effects of price cues on helpful votes by hotel class (source authors).

5 Discussion

This study aims to explore the effect of price cues in online reviews on review helpfulness and the moderating role of hotel class. Based on the Cue Utilization Theory, we found that TripAdvisor hotel reviews with price cues received more helpful votes than the counterparts without the cues. In addition, grounded in the Elaboration Likelihood Model, we revealed that hotel class significantly moderate the relationship between price cues and review helpfulness. To be specific, reviews of low-class hotels with price cues received more helpful votes than those without price cues; price cues in reviews of high-class hotels did not make a difference on helpful votes.

5.1 Theoretical and Practical Implications

This study adds knowledge to the antecedents of review helpfulness. Echoing to the call for research on predicting review helpfulness, the present research focuses on price cues, an aspect of review semantic features which is under-researched. The findings allow us to gain a better understanding of review helpfulness based on review content features. Previous research has devoted effort into the influence of review content features on review helpfulness using linguistic [39], semantic [10, 25], and sentiment analysis [25, 40] respectively. Semantic features were suggested to provide explanatory benefits in understanding perceived helpfulness [10]. However, empirical evidence that connects semantic features and review helpfulness is limited. Our findings about price cues as a semantic feature to attract helpful votes in hotel context are worthwhile for additional effort in this line of review helpfulness research.

Another major contribution of this study is the conclusion that price cues effect on review helpfulness is dependent on hotel class. In this regard, relevancy of the review contents to readers' concerns has to be considered. If readers find a review with certain topics (i.e., semantic features) related to their concerns, they will devote greater cognitive effort to process the review through central route of ELM and are likely to find the review helpful. Therefore, consumers who seek low-class hotels (high price sensitivity) use central route to process price cues, whereas high-class hotel seekers who are less sensitive to price would pay less attention to the price cues and find the cues less helpful in making their booking decision. This is somehow inconsistent with Baek et al.'s [15] conclusion that high-priced product demands greater cognitive effort of review readers than low-priced product. However, their study has not considered the relevancy of the review content based on the situations that readers are exposed to (e.g., hotel class in this study).

In addition to the theoretical implications mentioned above, this research provides practical insights to hotel managers and online review stakeholders. First, price cues in review featuring customers' experience are useful information for consumers to judge if the hotel is value-for-money. Our findings on the effect of presence of price cues on review helpfulness for low-class hotels indicate that value-for-money is something that their potential customers would stress on. Managers of low-class hotel need to ensure that their customers will receive value-for-money service and incorporate it into their marketing scheme. Second, as helpful reviews induce consumers to choose the hotel [41], managers of low-class hotel may encourage and remind their customers to add price cues when writing online reviews. Third, as price cues are valued by consumers, TripAdvisor and other review platforms may allow users to filter their search by displaying the reviews with price cues in the first-page results. This function is especially useful for consumers who are looking for low-class hotel (e.g., 2-star and 3-star hotels on TripAdvisor).

5.2 Limitations and Future Research

Several limitations in this study should be addressed for future research. First, we studied the relationship in the context of hotel reviews. Since consumers have different price perceptions with respect to different products, our findings drawn from hotels may not be generalizable to other service or products, leaving rooms for replications of this research using different service and products in the future. Second, the data were extracted from a review website, and in this case the variables were restricted to online available data. Numerous other factors, for example individual differences, may have influence on the results. Future research can adopt experimental design so that alternative explanations can be ruled out. Third, we used hotels in New York City as the study sample, the distinct characteristics of New York hinder generalization of our findings to other cities, especially those beyond US. Future studies can be conducted using reviews for hotels in other destinations. Finally, the price cues may not be related to the hotel experience (e.g., related to the area near to the hotel). Future research can develop and use a more sophisticated dictionary.

References

1. Yang Y, Park S, Hu X (2018) Electronic word of mouth and hotel performance: a meta-analysis. Tour Manag 67:248–260
2. Chan ICC, Lam LW, Chow CW, Fong LHN, Law R (2017) The effect of online reviews on hotel booking intention: the role of reader-reviewer similarity. Int J Hosp Manag 66:54–65

3. Liu Z, Park S (2015) What makes a useful online review? Implication for travel product websites. Tour Manag 47:140–151
4. Gottschalk SA, Mafael A (2017) Cutting through the online review jungle—investigating selective eWOM processing. J Interact Mark 37:89–104
5. Schindler RM, Bickart B (2012) Perceived helpfulness of online consumer reviews: the role of message content and style. J Consum Behav 11:234–243
6. Black HG, Kelley SW (2009) A storytelling perspective on online customer reviews reporting service failure and recovery. J Travel Tour Mark 26:169–179
7. Wang P, Li H (2019) Understanding the antecedents and consequences of the perceived usefulness of travel review websites. Int J Contemp Hosp Manag 31:1086–1103
8. Fong LHN, Lei SSI, Law R (2017) A symmetry of hotel ratings on TripAdvisor: evidence from single-versus dual-valence reviews. J Hosp Market Manag 26:67–82
9. Hong H, Xu D, Wang GA, Fan W (2017) Understanding the determinants of online review helpfulness: a meta-analytic investigation. Decis Support Syst 102:1–11
10. Shin S, Chung N, Xiang Z, Koo C (2018) Assessing the impact of textual content concreteness on helpfulness in online travel reviews. J Travel Res 58:579–593
11. Berezina K, Bilgihan A, Cobanoglu C, Okumus F (2016) Understanding satisfied and dissatisfied hotel customers: text mining of online hotel reviews. J Hosp Market Manag 25:1–24
12. Ye Q, Li H, Wang Z, Law R (2014) The influence of hotel price on perceived service quality and value in e-tourism: an empirical investigation based on online traveler reviews. J Hosp Tour Res 38:23–39
13. Kwok L, Xie KL (2016) Factors contributing to the helpfulness of online hotel reviews. Int J Contemp Hosp Manag 28:2156–2177
14. Lee HA, Law R, Murphy J (2011) Helpful reviewers in TripAdvisor, an online travel community. J Travel Tour Mark 28:675–688
15. Baek H, Ahn J, Choi Y (2012) Helpfulness of online consumer reviews: readers' objectives and review cues. Int J Electron Commer 17:99–126
16. Zhu F, Zhang XQ (2010) Impact of online consumer reviews on sales: the moderating role of product and consumer characteristics. J Mark 74:133–148
17. Gosling SD, Ko SJ, Mannarelli T, Morris ME (2002) A room with a cue: personality judgments based on offices and bedrooms. J Pers Soc Psychol 82:379–398
18. Rao AR, Monroe KB (1988) The moderating effect of prior knowledge on cue utilization in product evaluations. J Consum Res 15:253–264
19. Petty RE, Cacioppo JT (1986) The elaboration likelihood model of persuasion. In: Petty RE, Cacioppo JT (eds) Communication and Persuasion. Springer, New York, pp 1–24
20. Mudambi SM, Schuff D (2010) What makes a helpful online review? A study of customer reviews on Amazon.com. MIS Q 34:185–200
21. Fong LHN (2017) The effect of user-generated content on consumer responses in hotels and restaurants: a social communication framework. In: Gursoy D (ed) Routledge Handbook of Hospitality Marketing. Taylor & Francis, New York, pp 551–561
22. Purnawirawan N, Eisend M, De Pelsmacker P, Dens N (2015) A meta-analytic investigation of the role of valence in online reviews. J Interact Mark 31:17–27
23. Fang B, Ye Q, Kucukusta D, Law R (2016) Analysis of the perceived value of online tourism reviews: influence of readability and reviewer characteristics. Tour Manag 52:498–506
24. Filieri R, Raguseo E, Vitari C (2018) When are extreme ratings more helpful? Empirical evidence on the moderating effects of review characteristics and product type. Comput Hum Behav 88:134–142

25. Li H, Wang C, Meng F, Zhang Z (2018) Making restaurant reviews useful and/or enjoyable? The impacts of temporal, explanatory, and sensory cues. Int J Hosp Manag https://doi.org/10.1016/j.ijhm.2018.11.002
26. Xiang Z, Du Q, Ma Y, Fan W (2017) A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism. Tour Manag 58:51–65
27. Pantelidis IS (2010) Electronic meal experience: a content analysis of online restaurant comments. Cornell Hosp Q 51:483–491
28. Kim J, Franklin D, Phillips M, Hwang E (2019) Online travel agency price presentation: examining the influence of price dispersion on travelers' hotel preference. J Travel Res https://doi.org/10.1177/0047287519857159
29. Kim WG, Ma X, Kim DJ (2006) Determinants of Chinese hotel customers'e-satisfaction and purchase intentions. Tour Manag 27:890–900
30. Zhu L, Yin G, He W (2014) Is this opinion leader's review useful? Peripheral cues for online review helpfulness. J Electron Commer Res 15:267–280
31. Hu Y-H, Chen K (2016) Predicting hotel review helpfulness: the impact of review visibility, and interaction between hotel stars and review ratings. Int J Inf Manag 36:929–944
32. Matzler K, Teichmann K, Strobl A, Partel M (2019) The effect of price on word of mouth: first time versus heavy repeat visitors. Tour Manag 70:453–459
33. Easterbrook JA (1959) The effect of emotion on cue utilization and the organization of behavior. Psychol Rev 66:183
34. Moore SG (2015) Attitude predictability and helpfulness in online reviews: the role of explained actions and reactions. J Consum Res 42:30–44
35. Guo B, Zhou SS (2017) What makes population perception of review helpfulness: an information processing perspective. Electron Commer Res 17:585–608
36. Filieri R, Mcleay F, Tsui B, Lin ZB (2018) Consumer perceptions of information helpfulness and determinants of purchase intention in online consumer reviews of services. Inf Manag 55:956–970
37. Srivastava V, Kalro AD (2019) Enhancing the helpfulness of online consumer reviews: the role of latent (content) factors. J Interact Mark 48:33–50
38. Rajaguru R, Hassanli N (2018) The role of trip purpose and hotel star rating on guests' satisfaction and WOM. Int J Contemp Hosp Manag 30:2268–2286
39. Wang X, Tang L, Kim E (2018) More than words: do emotional content and linguistic style matching matter on restaurant review helpfulness? Int J Hosp Manag 77:438–447
40. Chua AYK, Banerjee S (2016) Helpfulness of user-generated reviews as a function of review sentiment, product type and information quality. Comput Hum Behav 54:547–554
41. Ghosh T (2018) Predicting hotel book intention: the influential role of helpfulness and advocacy of online reviews. J Hosp Market Manag 27:299–322

Activities

Semantic Data Models for Hiking Trail Difficulty Assessment

Jean-Paul Calbimonte(✉), Simon Martin, Davide Calvaresi, Nancy Zappelaz, and Alexandre Cotting

Institute of Information Systems, University of Applied Sciences and Arts Western Switzerland (HES-SO), Sierre, Switzerland
{jean-paul.calbimonte,simon.martin,davide.calvaresi,nancy.zappelaz, alexandre.cotting}@hevs.ch

Abstract. Hiking is a popular outdoor activity that if practiced regularly, can bring significant health benefits. Moreover, considering that hikers range from expert mountaineers to older adults with limited physical capabilities, it touches a large target audience, and is strategically included in several tourism packages across the globe. Thus, a precise characterization of the tracks, especially regarding their points of difficulty, is crucial to effectively cope with the challenge of identifying the best-suited hiking trails for heterogeneous users. This paper introduces a semantic model for representing and integrating the main characteristics of a track, including their different types of difficulties, using Semantic Web ontologies. The construction of knowledge graphs that use such a model may constitute a first step towards a system for personalized recommendations of trails based on difficulty-classification criteria.

Keywords: Hiking tourism · Difficulty assessment · Semantic models · Semantic Web · Tourism knowledge graph

1 Introduction

Pedestrian tourism comprises a set of increasingly popular outdoor activities, accessible to people of all ages, physical, and economic conditions [3,7]. In this sector, the demand for routes and trails is growing drastically. In particular, in countries with a long tradition such as Austria, Italy, and Switzerland, this demand boosted interest in providing more efficient, personalized, accessible, and accurate information (in particular, supporting digital applications). In this context, different complementary actors have been actively contributing to the emergence of both public and private resources, and applications that partially address the information and usage needs of pedestrian tourism. For example, in the region of Vorarlberg[1] in Austria, the local tourism office holds an online

[1] https://www.vorarlberg.travel.

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 295–306, 2020.
https://doi.org/10.1007/978-3-030-36737-4_24

database of hiking trails offered to potential visitors. As another example, in the Swiss canton of Valais, the management of official hiking trails is governed by Valrando[2], offering online descriptions and maps, relying on geographic information sources managed by the federal government. At the same time, SuisseMobile[3] provides online apps that allow discovering and tracking pedestrian trails, offering additional technical information. Complementary to these services, in each location or region, tourism offices provide detailed and curated information about local pathways, including cultural or thematic offers, sometimes through 3rd party exploitation companies such as Outdooractive[4] or Snukr[5]. The collection and maintenance of these information knowledge bases about hiking trails is costly, and requires on-site interventions by local guides, but can also benefit from crowd-based feedback. This detailed information is crucial afterwards, as it provides hikers with essential indications of which trails (or parts of trails) are adapted to their preferences, context, time constraints, and limitations. Given the heterogeneity of these information sources, potential hikers have to deal with complex analysis to choose among existing pathways. Such complexity escalates if hikers have certain limitations, such as fear of heights, climbing constraints, reduced mobility, walking aids, or terrain preferences.

In this paper, we explore the use of semantic data models for representing features of hiking trails, especially those that may constitute an obstacle or a difficulty for specific users. The presence of such features has a direct impact on the user experience. Hence, an "apparently" mild difficulty may completely block a hiker in some circumstances (e.g., a hanging bridge for a person with the fear of heights). Moreover, the objective representation of the path features and the modeling of their perception (users-wise) is not trivial. In particular, besides the intrinsic characteristics of the difficulty points, it depends on the user's context. This work elaborates on the principles of a methodology that considers three main aspects: effort, technique, and risk. Using semantic representations to link these aspects together with the geometry information of a hiking trail, we provide a solid base for the development of location-based services related to hiking recommendations.

The remainder of the paper is structured as follows. Section 2 presents related work. Section 3 presents the main principles behind the model. Section 4 explains the methodology chosen for describing the difficulties and information needs. Section 5 describes the semantic model itself, while Sect. 6 provides a discussion about the potential use of this model and its extension as a knowledge graph for recommendation purposes. Finally, Sect. 7 concludes the paper.

2 Related Work

Hiking is an outdoor activity that has shown extensive adoption in heterogeneous segments of the population and has proven to be particularly beneficial

2 https://www.valrando.ch/.
3 https://www.schweizmobil.ch.
4 https://www.outdooractive.com.
5 https://www.snukr.com.

for people with limited mobility. The economic interest of maintaining and promoting hiking sites has been shown to increase and gain in terms of market value [15,16]. Moreover, it has also received the attention of health promotion bodies and institutions, who, over the years, collaborated in improving existing guidelines and making more accessible scientific recommendations [6,9,10]. In this context, several initiatives promoting awareness about hiking trail difficulties (e.g., updating tracks conditions according to their situation) arose. For instance, in [12], a chatbot-based approach is described, aiming at providing recommendations of tourism offers. Other efforts, as in [5], considered recommendations for groups of users, taking into account combinations of preferences. Some of the early experiences to assess difficulty in terms of energy expenditure have been reflected in works such as [8]. Other efforts have focused on the analysis of preparedness [11] of hikers, or collaborative annotation of tourism objects[6]. Regarding the suggestion of hiking trails, several works have partially addressed the problem. For example, Boerger et al. [2] and Pitman et al. [14] proposed recommendation algorithms and tailored hiking time estimations, and Calbimonte et al. [4] have tried to use questionnaires to estimate the users' physical condition.

Although some of these works introduced certain elements which are relevant for the evaluation of track difficulties, none of them considers the different aspects included in the model below presented, and do not comply with existing Semantic Web modeling techniques. Concerning standards for representation and modeling of tourism and travel concepts and objects, several initiatives and resources for different scopes and purposes can be acknowledged. For example, the Open Travel Alliance (OTA)[7] has developed standard models for travel objects, such as the Open Travel Schema. This model is restricted mostly to booking information and do not conform to current ontology modeling standards. Another relevant resource is the Thesaurus on Tourism and Leisure Activities published by the WTO (World Tourism Organization) [13], used mainly for indexing concepts in the tourism realm. On the same line, the Travel Technology Initiative[8] provided a set of standards, including different messaging and tourism agent specifications.

Such standards offer given structural guidance and technological means for integration of information in the tourism domain. Nevertheless, they focus mainly on booking operations and availability, and less on the content specified for outdoor activities. In particular, there are no data description models for representing pedestrian roads and the different aspects that analyzed in this paper (e.g., description and specification of difficulty types are entirely neglected by the aforementioned previous works).

3 Hiking Trail Difficulties

This section elaborates on the challenges underlying the difficulty-based trail characterization of hiking trails. One of the reasons causing such complexity is

[6] https://www.apidae-tourisme.com/.
[7] https://opentravel.org.
[8] https://www.tti.org/.

the degree of subjectivity that the difficulty may entail, linked to the relative perception of a trail user. Each person may have entirely different notions of difficulty, associated with their previous experiences, background, fitness level, age, etc. For example, a rocky mountain trailing path may be mildly difficult for a young hiker, but extremely hard for an aged user. Moreover, difficulties can be related to different orthogonal aspects. For instance, a bridge crossing may not be associated with physical difficulty, but if it is located over a deep canyon, it may cause vertigo or other psychological effects on certain hikers. Similarly, a scarped rocky trail may require a specific technique level, although it may not be physically demanding.

In particular, the Swiss hiking offer, reflected in the information available in web sites of local tourism offices and public organizations, includes some information relative to trail difficulties. This information includes basic but essential data, such as the elevation, generally perceived difficulty, total estimated time, and distance (see Fig. 1).

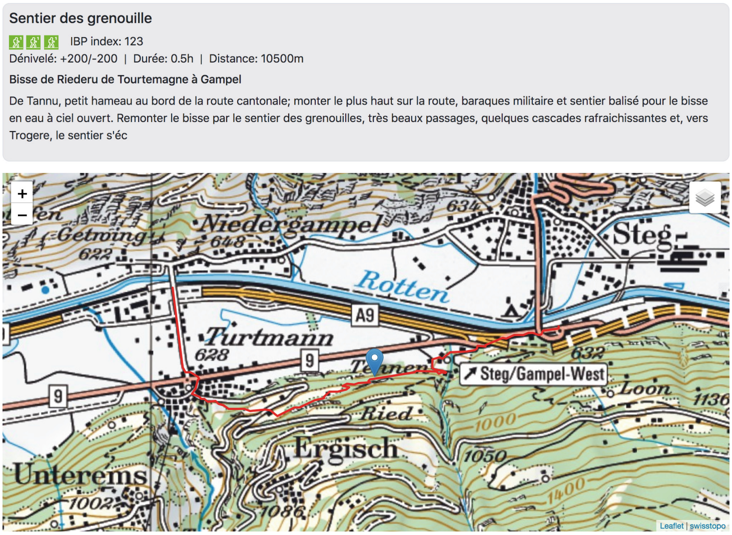


Fig. 1. Description of a hiking trail displayed on our platform, extracted from data available in a Swiss tourism office. The trail includes basic information, including distance and estimated time, but insufficient data concerning the difficulties that it may entail, including obstacles, risks, or detailed physical requirements (authors' own figure).

Clearly, these basic information items are not enough to allow people with limited physical, technical or psychological capabilities, to decide which hiking trails are better suited for them. As we have evidenced through questionnaire and workshops conducted with key stakeholders in the Swiss tourism sector [4], this type of information is highly demanded both for end users and tourism providers, with a high potential for exploitation[9]. From these previous experiences, we identify the following principles:

P1: Self-assessment. Given the difference in terms of the perception of the level of difficulty of a certain hiking track segment, enabling every potential user to provide a self-assessment of his/her physical condition is crucial, possibly through specialized questionnaires.

P2: Multi-criteria evaluation. Considering that difficulty depends on several factors, often including distinct aspects, any assessment of difficulty levels must include a combined evaluation of these criteria (e.g., combining physical or psychological difficulties).

P3: Effort assessment. The required effort for a given hiking trail is a key aspect that must be considered in the evaluation of difficulty. The physical effort can be measured in different ways (e.g., including total distance, and/or slopes).

P4: Technique assessment. The technique is another critical aspect to be considered (complementary to the effort). Although a hiking track may require a limited effort, it may demand a certain technical level to be crossed. The assessment of the technique may include evaluating the presence of obstacles, the need for specific equipment, or the use of hands for particular segments of the track.

P5: Risk assessment. Risk is often a main discriminant factor for defining the difficulty of a hiking track. Thus, it is another aspect to be considered. It should consider the track geography and geology (e.g., instability, cliffs, and void), as well as other elements increasing the occurrence of an accident (e.g., falls and slipping).

P6: Profile recommendation. A model for the difficulty in hiking trails must also include the elaboration of a profile which considers the aspects above, and which can be compared quantitatively with other profiles, so that recommendations can be based on those features. Such a model can be used as a basis for automated and personalized recommendations of hiking trails, which can be proposed to users according to their effort, technique, and risk preferences.

P7: Semantic modeling. A difficulty model should provide the necessary abstractions and concepts to describe the different features and aspects detailed in the previous points. Moreover, it should use existing standards and modeling approaches that allow this information to be reused and interlinked with other data sources, and including machine-readable representations. Linked Data and other related Semantic-Web models provide the technical foundations for creating such models, in the form of machine-interpretable ontologies.

[9] https://portal.klewel.com/watch/webcast/technoark-2018-quantified-self/talk/10/.

4 Difficulty Assessment Model

To cope with the lack of description and specification of the trials difficulty points characterizing a hiking trail, this work considers the factors mentioned above to propose a semantic model for hiking track difficulties, reusing existing concepts and notions of the hiking and leisure industry. In particular, we have adopted the classification methodology from the French Hiking Federation[10]. Such a methodology aims at providing a simple (yet comprehensive) estimation of the tracks' difficulty (for both experts and novice hikers). Concretely, it defines difficulty according to the following criteria:

– Effort: related to the difficulty associated with the physical energy required for a hiking track.
– Technique: related to the mobility/motion difficulty required for a hiking track.
– Risk: related to the psychological difficulty associated with a hiking trail.

The *effort* is directly related to the physical difficulty, and as such, it can be measured according to the energy required to cross a certain track. Several parameters can be used to estimate the effort. For example, the total distance can be an essential factor. A 2 km track will require less effort than a 4 km track, if both have similar terrain characteristics. Other factors include the slopes, altitude, descent, and slope changes (see Fig. 2). A track with steep slopes may require more energy expenditure than a flat track, even if they comprise the same distance. Although these features of the hiking tracks can be measured, it is not straightforward to come up with indicators that can be directly used for characterizing the difficulty in these terms. A promising initiative in this scope is the IBP index[11], a numerical scale for representing the human effort in hiking and biking tracks. This index is based on an algorithm that takes as input the GPS coordinates of the points that constitute a track, and calculates a numerical value considering the different slope gradients, ascending and descending distances, altitude, etc. Although this is not the only possible way of measuring effort, it is a tool that already has gained recognition from institutions such as the French Hiking Federation, and companies/applications in the field, such as Strava.

The *technical* difficulty of a hiking trail is associated with the motion/motricity required to overcome obstacles present in the track. For example, rocks can be obstacles that require specific skills to be overtaken. Small stones may require raising the feet moderately, while larger rocks may even require the use of one or both hands to overcome the obstacle. Current technologies do not provide yet a (semi)automatic way of estimating this type of difficulty, which is generally assessed by the observation of an expert. In general, an *easy* track has little if no obstacles, not requiring any particular movements or technique, other than a normal gait. More difficult hiking trails may have other types of obstacles, and there could be different ways of classifying them. For example, the

[10] Fédération Française de la Randonnée Pédestre https://www.ffrandonnee.fr.
[11] https://www.ibpindex.com.

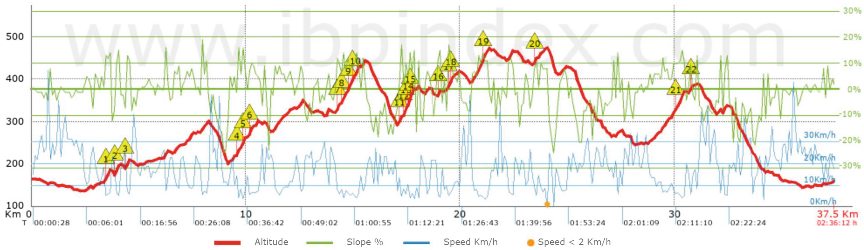


Fig. 2. Analysis of a hiking trail and its different segments, including identification of steep slopes, changes in climb and descent gradients, among other indicators that may relate to a physical difficulty. In this particular case the score is calculated according to the IBP index, although other metrics could be used (figure compiled by authors).

French Hiking Federation uses the type and height of feet movements required to cross through an obstacle, as a reference for difficulty assessment. An obstacle requiring a movement up to the height of the ankle has significantly less technical difficulty than a movement up to the height of the knee (or even more if to the height of the hip or demanding to use the hands or walking sticks).

Regarding the *risk*, it entails a psychological difficulty, related to potential accidents or situations to which the hiker is exposed. As in the previous case, it persists the difficulty to provide an assessment of risk, and in general, it is a field expert who determines it in accordance to given guidelines. As an example, urban and rural itineraries without remarkable terrain irregularities can be considered as implying low risk. Even in case of a fall, in such circumstances, the consequences would be generally benign, as opposed to other terrains (e.g., with pronounced slopes and/or very irregular and narrow paths) where a fall could even cause fractures or other more severe injuries. Moreover, in high-risk tracks, such as mountain trails, a fall could even have fatal and nearly-fatal consequences (e.g., in the presence of high cliffs and abysses).

As we have seen, in the cases of risk and technical difficulty, specific obstacles or terrain characteristics need to be clearly profiled to perform an accurate assessment. It is worth noticing that in some cases the presence of a single obstacle may be enough to change the classification of a track. For example, an otherwise entirely plain track could have a single point in which a high cliff would force it to be considered as high-risk. Hence, for hikers with limitations (e.g., fear of heights/depths) this single point of difficulty would be enough to block the entire trip.

Having described the main notions of difficulty, the model described in this paper needs to answer to the following competency questions, which represent the information requirements.

- What hiking tracks are available within a given region?
- What are the coordinates of a particular hiking track?
- What is the total distance of a given hiking track?

- What is the accumulated ascents and descents of a given track?
- Which interest points are near my current location in this track?
- Which tracks require a mild physical effort according to my capacity?
- Which tracks require advanced technical skills?
- Which segments of a given track have steep slopes?
- Which tracks have a low-risk difficulty and high effort difficulty?
- Which tracks are similar to a particular hiking trail in terms of overall difficulty?

5 Semantic Model for Difficulty Assessment

As detailed in the design principles of this model, we have chosen to follow a representation that reflects the concepts in this topic, and it is aligned with current trends in semantic data management. The chosen semantic model follows the principles of Linked Data [1], and uses the Resource Description Framework (RDF) as a basis for its technical implementation. The resulting *ontology* formalizes the domain concepts and is machine-readable. Thus, it can be fed to reasoners and other semantic data engines. Furthermore, it can be used to build a hiking knowledge graph, potentially exploited by querying and analytics tools.

The first step for this model is to represent the hiking trails. It includes name, description, geographical coordinates, places, points that are part of such an itinerary, and ratings and reviews. As shown in Fig. 3, we have followed best practices in ontology engineering, in this case, by reusing a widely used model such as schema.org[12]. This vocabulary has gained adoption in the last years, becoming one of the leading general-purpose ontologies that feed knowledge bases on the Web.

An essential portion of the information needs is already present in schema.org, including geographical emplacement and basic information about the elements that compose the track, which can be represented as a special type of *TouristTrip*. These are represented as *Places*, which could be either points, segments, or other geometries. It is possible to use the geographical information to perform spatial operations, such as calculating distance and proximity, or containment of tracks within tracks, or points of difficulty within a specific hiking trail. Using schema.org provides the additional advantage of increasing the potential compatibility with other tourism data sources published on the Web, overcoming heterogeneity issues.

Nevertheless, the data defined by schema.org for tourist trips is not enough to comply with our information needs. Figure 4 illustrates how the concept of *HikingTrack* extends from *TouristTrip*, adding a set of additional data fields, such as total distance, slope changes, ascent, descent, aggregated climb, upper and lower height. Moreover, we introduce a set of ordered places in the track itinerary, which may include both interest and difficulty points. These difficulty

[12] http://schema.org.

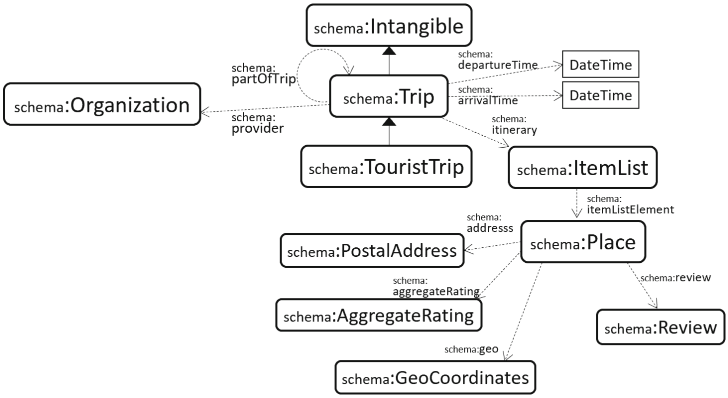


Fig. 3. Modelling a tourist trip according to schema.org. The standard trip can be used as a starting point for representing a hiking trail, as it already includes all geographical information, although it lacks specific elements such as slope information, gradient, difficulties, etc. (authors' own figure).

points represent parts of the track, for which a difficulty assessment has been performed.

The different difficulty points alongside the geographic and geometric characteristics of the track are essential components for the evaluation of the difficulty, as explained in the previous section. However, all this information would be

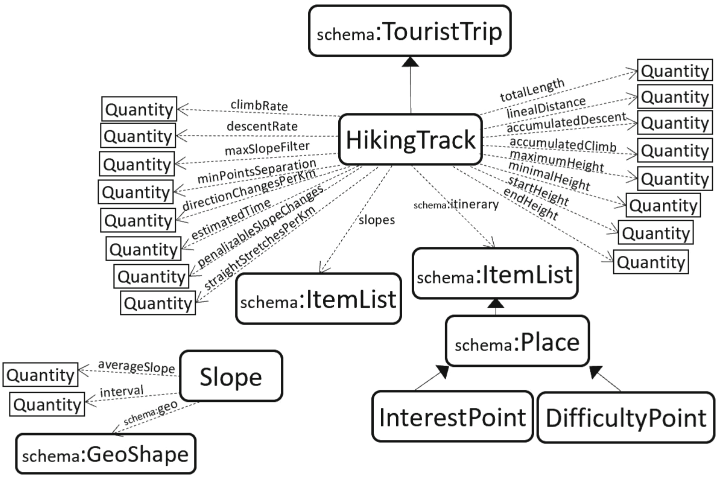


Fig. 4. Modelling of a Hiking Track, extending from schema.org. The model includes several technical information regarding the characteristics of the trail, as extracted from its geographical representation. It also includes detailed slope information and the interest and difficulty points (authors' own figure).

insufficient, as they do not provide all the necessary elements with the level of granularity (i.e., difficulty types) that is needed to perform recommendations or other analytics tasks. As we can see in Fig. 5, difficulty points include these additional data elements, including scores and evaluation, as well as the different aspects that we presented above: namely effort, technique, and risk.

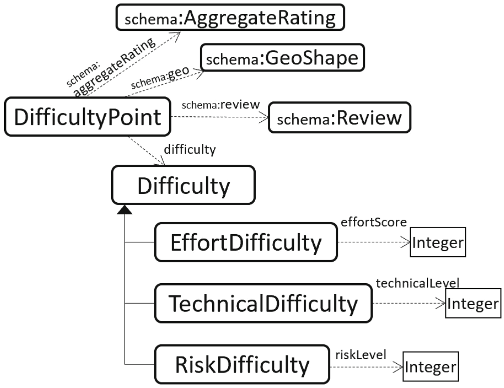


Fig. 5. Modelling Difficulty points, as extensions to a schema.org. Place the model includes the main three different types of difficulty, related to effort, risk, and technique. The model is not strongly linked to any particular type of calculation, such as the IBP index, and it could use different types of scores (authors' own figure).

By looking at the relevant parameters on the model, the addition of these information pieces enables to answer the information questions posed above. Therefore, this allows performing comparative analysis, and potentially comparing track difficulties with a given set of user preferences.

The model presented in this section, implemented as an ontology in terms of Semantic Web technologies, addresses all information requirements presented in the competency questions. In particular, it allows representing hiking trails and their parts (e.g., the necessary technical information, risks, technique, and effort levels). This also reflects the different design principles detailed earlier in this paper.

6 Discussion

This paper presents an innovative conceptual model relying on knowledge-based technologies focusing on the difficulty assessment of hiking trails. Once the model is consolidated, it will be possible to realize systems providing recommendations based on a seamless matching of the health/preferences profile of a user with the available trails. The realization of this idea lies at the intersection of disciplines that include tourism, health and well-being, and knowledge acquisition and management. Therefore, it requires a careful analysis of the needs, requirements, and perceptions of the various stakeholders involved in the subject, including regional tourist offices, local development authorities, health professionals, mountain guides, and potential hikers. The solution envisioned by this paper sets the objective of adapting the hiking offer to the physical condition and limiting factors (e.g., vertigo and lack of balance) of users. Hence, it can be an instrument of prevention for any audience: healthy people, people with reduced mobility, or people affected by chronic diseases.

The proposed model can be considered a starting point for the establishment of a trails knowledge base. To do so, each trail must be cataloged, including its different characteristics and difficulty points. The methodology to perform this task should follow the guidelines of the French Hiking Federation. To test and prepare the data acquisition phase for trail information, a series of site visits should be performed and supervised by trained guides and physiotherapist (facilitating the identification and annotation of difficulty points). For every trail, a group of people with different physical abilities and walking habits are expected to annotate the encountered difficulty points (e.g., rocks, roots on the trail, steep slopes, bridges and obstacles, vertigo points, and narrow passages). According to the model, every noted point must be associated with its geolocalization and a difficulty score.

7 Conclusions and Future Work

This paper introduced a semantic model to represent hiking trail difficulties. Its goal is to create a knowledge graph for personalized recommendations and information. The presented model, based on the principles of Semantic Web modeling and ontology engineering, complies with the elicited requirements. Moreover, it reuses concepts from the well-established schema.org vocabulary, allowing potential interoperability with other third-party systems and published data sources.

Once a sufficient amount of data using this model will be collected, a hiking trail knowledge base will be released. Such a knowledge base can enable the implementation of hiking track filtering algorithms (e.g., based on machine learning techniques). Thus, a user's profile can be classified according to other users and their preferences. This automatic matching mechanism should also establish a score or scale, facilitating decision-making for the user. A feedback mechanism is also necessary to improve the recommendations based on user satisfaction and feedback. Evolving classification algorithms will be required, as well as classification techniques based on specific profile parameters. Finally, to increase the system's efficiency, the parameters' impact on the final recommendation requires further studies.

Acknowledgements. Supported by the HES-SO RCSO ISNet grant Syris. Thanks to Joan Casares and the IBP Index team for their support, and to Michael Anthoine/ Fédération Française de la Randonnée Pédestre for the methodological assistance.

References

1. Bizer C, Heath T, Berners-Lee T (2011) Linked data: the story so far. In: Semantic services, interoperability and web applications: emerging concepts. IGI Global, pp 205–227
2. Boerger, M (2014) Hiking suggestions and planner. US Patent 8,688,374, 1 Apr 2014
3. Boller F, Hunziker M, Conedera M, Elsasser H, Krebs P (2010) Fascinating remoteness: the dilemma of hiking tourism development in peripheral mountain areas. Mt Res Dev 30(4):320–332
4. Calbimonte JP, Zappellaz N, Hébert E, Simon M, Délétroz N, Hilfiker R, Cotting A (2018) SanTour: towards personalized recommendation of hiking trails to health profiles. In: International conference on web engineering. Springer, pp 238–250
5. Delic A, Neidhardt J (2017) A comprehensive approach to group recommendations in the travel and tourism domain. In: Adjunct publication of the 25th conference on user modeling, adaptation and personalization. ACM, pp 11–16
6. Haskell WL, Lee IM, Pate RR, Powell KE, Blair SN, Franklin BA, Macera CA, Heath GW, Thompson PD, Bauman A (2007) Physical activity and public health: updated recommendation for adults from the american college of sports medicine and the American heart association. Circulation 116(9):1081
7. Heberlein TA, Fredman P, Vuorio T (2002) Current tourism patterns in the Swedish mountain region. Mt Res Dev 22(2):142–150
8. Hugo ML (1999) Energy equivalent as a measure of the difficulty rating of hiking trails. Tour Geogr 1(3):358–373
9. Jackson J, Murphy P (2002) Tourism destinations as clusters: analytical experiences from the new world. Tour Hosp Res 4(1):36–52
10. Lloyd-Jones D, Adams R, Brown T et al (2010) Health benefits of hiking. Circulation 121:e1–e170
11. Mason RC, Suner S, Williams KA (2013) An analysis of hiker preparedness: a survey of hiker habits in new hampshire. Wild Environ Med 24(3):221–227
12. Nguyen, TN, Ricci, F (2017) A chat-based group recommender system for tourism. In: Information and communication technologies in tourism 2017. Springer, pp 17–30
13. World Tourism Organization (2001) Thesaurus on tourism and leisure activities
14. Pitman A, Zanker M, Gamper J, Andritsos P (2012) Individualized hiking time estimation. In: 2012 23rd international workshop on database and expert systems applications. IEEE, pp. 101–105
15. Scarpa R, Thiene M, Tempesta T (2007) Latent class count models of total visitation demand: days out hiking in the eastern Alps. Environ Resour. Econ. 38(4):447–460
16. Thiene M, Scarpa R (2008) Hiking in the Alps: exploring substitution patterns of hiking destinations. Tour Econ 14(2):263–282

Volunteered Geographic Information for Monitoring and Exploring Cycling Activities in the Japanese Nationwide Geographical Space

Koun Sugimoto(✉)

Department of Tourism Science, Graduate School of Urban Environmental Sciences, Tokyo Metropolitan University, Hachioji, Tokyo, Japan
sugimoto@tmu.ac.jp

Abstract. This study examined the effectiveness of volunteered geographic information (VGI) for monitoring and exploring cycling activities in the nationwide geographical space in Japan. A total of 16,945 GPS trajectories of cycling activities was collected from the popular VGI website for activity mapping and sharing. Analysis is conducted through three major phases; (1) Characteristics of VGI posted by online users, (2) time series patterns and (3) spatial distribution of cycling activities at an aggregated level. In the first analysis, 1,419 users were found in the VGI, and the number of VGI posted by users whose number of posts per user was up to 100 is about 53% of the total. In the time-series analysis, the comfortable seasons for outdoor recreation in Japan such as spring and autumn produce many cycling activities, but conversely, activities are reduced in winter. In the spatial distribution of GPS trajectories, though GPS data cover the whole of Japan, the tendency to concentrate in large metropolitan areas with high populations was prominent.

Keywords: Volunteered geographic information · Cycling activity · GPS trajectory · Time-series pattern · Spatial distribution

1 Introduction

Bicycles are often used as an important mode of transportation and for cycling activities in daily life and holidays. With the increase in tourism and recreational demand, bicycle touring has become an increasingly important mode of holiday transportation [1]. In Japan, the number of bicycles owned increases continuously, and the rate of cycling activity is also on the rise [2]. The Ministry of Land, Infrastructure, Transport and Tourism formulated the "bicycle utilization promotion plan (自転車活用推進計画 in Japanese)" in 2018, which aims to promote cycle tourism and develop a cycling route and comfortable environment for cyclists. With the recent increase in the number of foreign visitors to Japan due to the inbound tourism policy, the development of an accepting environment for foreign tourists with cycling intentions has become an important issue in popular cycle tourism destinations. Given such social circumstances,

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 307–319, 2020.
https://doi.org/10.1007/978-3-030-36737-4_25

monitoring and understanding the behavior of cycle tourism will become more important for future policies and plans.

Previous studies of cycle tourism have investigated behavior through questionnaires, interviews, travel diaries, etc. [1, 3, 4]. However, people engaging in cycle tourism often take long-distance routes for their trips, and it is difficult to gather data concerning such types of movement with traditional investigation methods. Moreover, surveys are costly and usually conducted only once, so continuous monitoring is not possible.

Volunteered geographic information (VGI), obtained from social media and websites worldwide [5], can offer an alternative way to acquire data on tourist mobility more easily. VGI describes user location in both time and space, typically facilitated by GPS-enabled mobile devices, including smartphones [6]. In the tourism literature, VGI has been used to explore and monitor behavior in various space-time scales in recent years [7–13]. VGI will also be available to integrate to cycle tourism monitoring.

This study examines the effectiveness of VGI for monitoring and exploring cycling activities in the nationwide geographical space in Japan. There are some official reports on surveys conducted in several destinations, but there are none on a nationwide scale in Japan. Therefore, VGI is potentially useful for understanding the dynamics of cycling activities better and future bicycle policy-making such as road development and tourism promotion.

In the research process, three matters are examined: (1) the characteristics of online users who generate GPS trajectories and post them as VGI, (2) the temporal pattern, and (3) the spatial pattern of cycling activity derived with VGI. Activities targeted in the present study comprise trips using bicycles regardless of trip duration.

2 Related Work

Many definitions exit for cycling activity in tourism-related disciplines. Lumsdon [14] defined cycle tourism as “recreational cycling activities ranging from a day or part of the day casual outing to a long-distance touring holiday”. On the other hand, Ritchie [1] defined bicycle tourism as “any activities, whether cycling or non-cycling, that are undertaken by those who are on vacation for longer than 24 h or one night, and for whom the bicycle is an integral part of this trip”. Ritchie [1] distinguished people who engaged on such cycling activities into bicycle tourists and recreational cyclists. According to Chang and Chang [15], they have different characteristics and preferences with regard to cycle amenities; bicycle tourists are motivated mainly by a desire to enjoy attractions and engage in sightseeing, while recreational cyclists ride through areas near their homes for leisure and exercise. Thus, cycling activity is often perceived by the visitor as an integral part of an excursion or holiday [14], not including the sports like bicycle racing. In Japan, cycle tourism (サイクルツーリズム in Japanese) is a more popular word compared to other terms.

The research on cycling activity in the geospatial context includes the following. Ritchie [1] examined demands of independent bicycle tourists in terms of the characteristics, infrastructure, and travel behavior in the South Island of New Zealand through an on-site self-completion survey over three weeks. Lumsdon et al. [3]

reported the monitoring results of a long-distance cycle trail in the North East of England, which conducted mixed techniques with unit counts, intercept surveys and a travel diary. Chen and Chen [4] examined the preferences of recreational cyclists, which influences the behavior in the selection of bicycle routes, based on the data collected from a self-administered questionnaire in Taiwan. Snizek et al. [16] presented the method for the collection, mapping and analysis of cyclists' experiences using an online questionnaire built on Google Maps, and assessed the locations and elements that indicates positive or negative experiences with Copenhagen.

With the recent development of geospatial technologies, the use of advanced tracking technologies such as GPS has emerged as a novel trend in data collection and the analysis of tourist behavior [17]. Shoval and Ahas [18] noted such studies in tourism disciplines have increased substantially from 2005, and the most utilized technology is GPS tracking. Several studies have introduced GPS technology for investigations targeting visitors using bicycles. For example, Sugimoto et al. [19] and Nishimura et al. [20] investigated the movement of visitors in the context of rental bicycles and community cycle system use at local tourist destinations by using GPS receivers and questionnaires, and found that their movements can be classified into several representative patterns. Their study needed a tremendous effort in field work to acquire GPS trajectories by handing GPS receivers to participants on-site.

The use of the VGI system is regarded as an easier alternative to collect GPS trajectories. Studies on tourist behavior with VGI have been generally obtained from social media like Twitter, Instagram and Flickr, which are widely used in the world. The topics focused on the functional structures of tourist flows [7, 8], tourist attraction systems [6], and popular routes and destinations [10], not focusing on the specific type of activity.

There are a few studies applying VGI to monitor and explore tourist/recreational behavior specialized for a specific purpose such as cycling activity. Norman et al. [11, 12] and Santos et al. [13] examined the potential of VGI for park management. They used VGI to analyze the difference of spatial use among users' activity types including mountain biking, running, walking, and so on. Websites for activity mapping (e.g. MapMyFitnes, Wikiloc, and GPSies), which can post GPS trajectories and other relevant information, have been used. These previous works have applied GPS trajectories of VGI at specific destinations, although they were not used for analyzing the dynamics of cycling activities on a large scale.

3 Research Method

3.1 Data Collection

GPS trajectories of cycling activities were collected from a specific website on which users can post and share VGI. As a result of the selection process of websites, "RouteLabo" (ルートラボ in Japanese), organized by Yahoo! Japan, was selected as the platform for data collection. This is a popular VGI website for the Japanese and a lot of VGI on cycling activities is posted by online users compared to others. Anyone can post the data of GPS trajectories (GPX format, etc.) recorded during travel on the internet using PCs or mobile phones. It is also possible to create spatial line data of trajectories of past trips by using the tool implemented on the website. However, in the latter case, it is not possible to judge whether posted data is generated from real experiences of users' past trips or not, and some may include future travel plans. Therefore, in this study, only real trajectory data recorded by GPS-enabled mobile devices was collected and analyzed.

The data collection process is as follows. First, the number of posts regarding cycling activities was searched based on several tags for understanding the amount of content in each tag. Next, GPX files tagged as "自転車(Bicycle)", which had an overwhelmingly large number of posts, were downloaded. After that, we also collected GPX files with tags often used together with the "自転車(Bicycle)" tag. The number of GPX files in each tag is shown in Fig. 1.

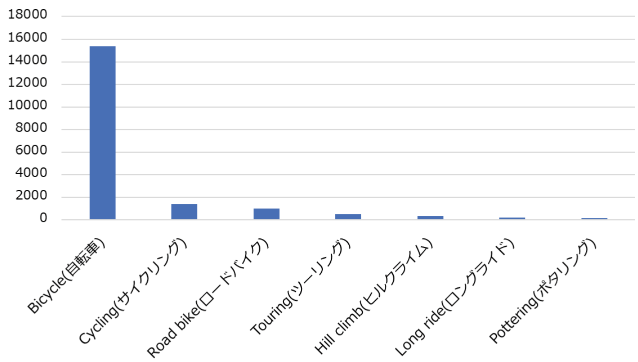


Fig. 1. Number of GPS trajectories posted by users by tag types for cycling activities. Tags are originally written in Japanese. (authors' own figure)

3.2 Data Processing

All GPX files obtained based on seven tags were converted to ESRI shape files and integrated into one file. Thereafter, data cleaning was performed. First, the data for which the unique ID was unknown or duplicated were deleted. Next, the data recorded in foreign countries but not in Japan were deleted. Lastly, the data recorded pre 2000 and post 2019 were deleted. The former included a lot of unclear information, while the latter had not yet amounted to one year's worth of data storage. In other words, GPS data from travel between 2001 and 2018 were regarded and extracted as effective samples. As a result of these processes, the number of GPS trajectories used in this study totaled 16,945.

3.3 Data Analysis

In this research, there are three major analysis phases.

(1) Characteristics of VGI posted by online users
Analyze the number of posts per user to determine the deviation of users in the whole. The basic statistic of number of posts per user is calculated, and the graph indicating frequency in the divided sections is shown. Furthermore, the actual number of posts and cumulative rate for each section are determined.
(2) Time series trend of cycling activities
Visualize the change in the number of cycling activities by year and month as a time series graph. There is a gap between the posting date and traveling date. In the time series analysis by month, only trends from 2010 to 2015 are shown because much VGI has been stored during these years, and it is more reliable than others. The traveling date acquired from GPS is used for this analysis. Here, based on the result of analysis phase 1, the data is divided into that of heavy users and others (light and medium users), and the changes in the number of posts by user group is also examined. This enables the degree of bias by user group to be checked.
(3) Spatial distribution of cycling activities
The GPS data is visualized with line shape on the map, and the spatial distribution and tendency of concentration and dispersion is analyzed. At the same time, the result of totaling in 10×10 km grid units by spatial calculation is shown. Similar to the analysis in phase 2, differences among user groups are also analyzed.

4 Results

4.1 Characteristics of VGI Posted by Online Users

A total of 1,419 online users was found in the VGI of cycling activities. The average number of posts per user is 12, the standard deviation is 39, the maximum number is 649, and the minimum number is 1. The number of users who posted only one is 605, which is the largest number of users. According to Fig. 2(a) showing the frequency for each section, as the number of posts per user increases, the number of users decreases significantly. As a result of dividing users based on the number of posts per user, the number of light users (10 or less posts per user) and medium users (11 to 100 posts per user) is 1167 (82.3%) and 212 (14.9%) respectively, accounting for about 96.2% of the total. On the other hand, there are only 40 heavy users (2.8%) who posted a large number (101 or more) of GPS trajectories. However, it is assumed that the data quantity of such heavy users has little impact on the whole. As shown in Fig. 2(b) indicating the total number of actual posts, the number of VGI posted by medium and light users is about 53% of the total. Therefore, the number of posts by the remaining heavy users is about 47%, which occupies half of the entire share.

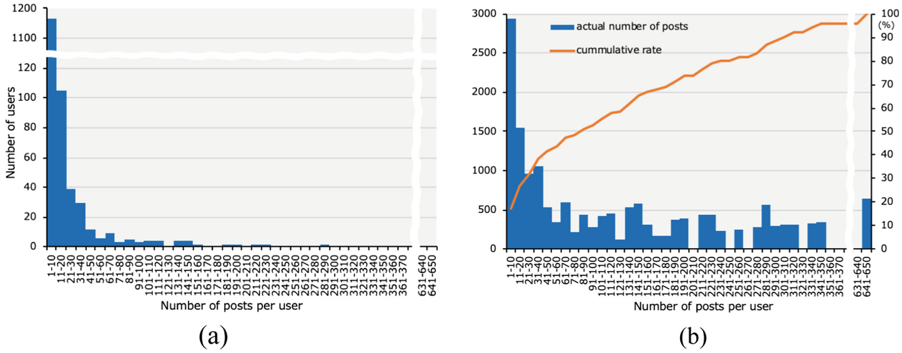


Fig. 2. Characteristics of posts of online users: the number of (a) users and (b) actual posts for the section in the number of posts per user. (authors' own figures)

4.2 Time Series Trend of Cycling Activities

We first analyze the trend in yearly changes in the number of trips and postings (Fig. 3 (a)). VGI posting began in 2009 when the web service started. The number of trips and posts dramatically increases in 2010 and reaches a peak in 2011, but after this, it decreases continuously until 2018. The time series trend is very similar, as the number of trips and posts of GPS trajectories recorded before 2009 is included in the data. However, it is found that there is a major difference by user group.

In the case of heavy users, the decrease in the number of posts and trips is small as the years go by (Fig. 3(b)). It can be considered that this type of user has used the web service continuously. On the other hand, in the case of medium and light users, the annual decrease is very large (Fig. 3(c)). In 2018, both the number of posts and trips reach about 13–14% at peak. Therefore, the impact of medium and light users may diminish, and the impact of heavy users may, conversely, grow, as the years pass. When analyzing the time series trend of cycling activities from VGI, it is necessary to consider the share of each type of user in the whole and the period of data recorded.

Next, we analyze the monthly change in the number of cycling activities in Fig. 4. To easily compare each year, the ratio of the number of trips divided by the total number for each year is shown. Overall, the data increased in the spring in April and May and in autumn in September and October, for most years from 2010 to 2015. In contrast, there are many cases of the number of data being extremely low in winter, i.e., in February. In other words, cycling activities are a seasonal trend. In Japan, the spring and autumn seasons are generally considered to be comfortable; therefore, cycling activities follow them.

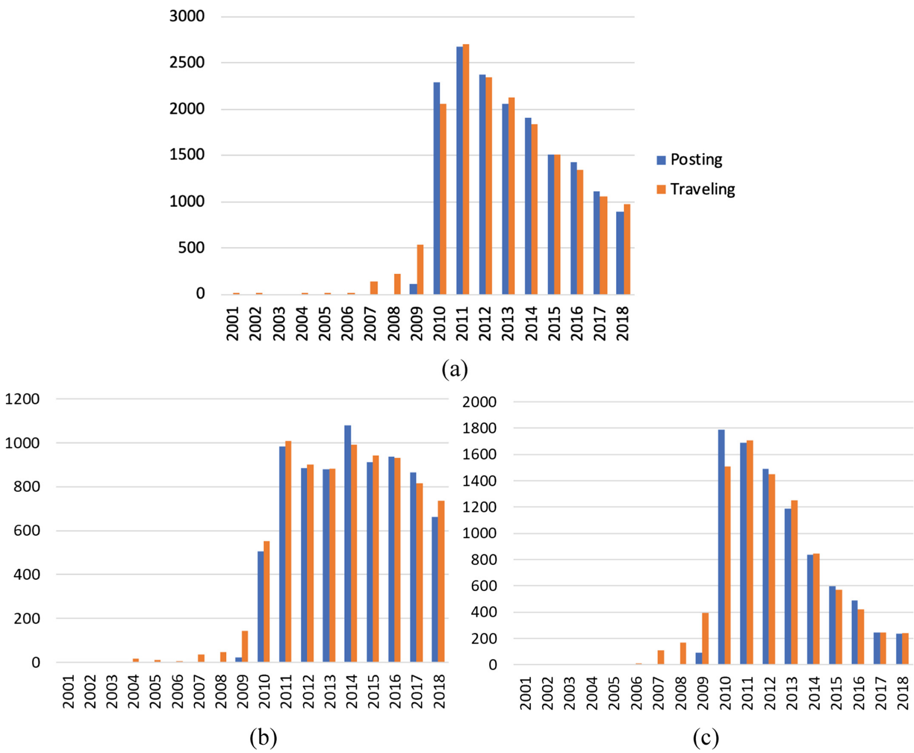


Fig. 3. Changes in the number of cycling activities by year in terms of posting and traveling: (a) all users, (b) heavy users, and (c) medium and light users. (authors' own figures)

In the case of heavy users, the three-year period of 2013–2015 is consistent with the overall data trend. However, although there are few common points in winter in the three years from 2010 to 2012, the number of trips did not change significantly from spring to autumn or peak from autumn to winter. For the medium and light users, the time-series trend by month is found to be almost in line with that of all the data in any year. Cycling activities are therefore actively conducted in spring or autumn.

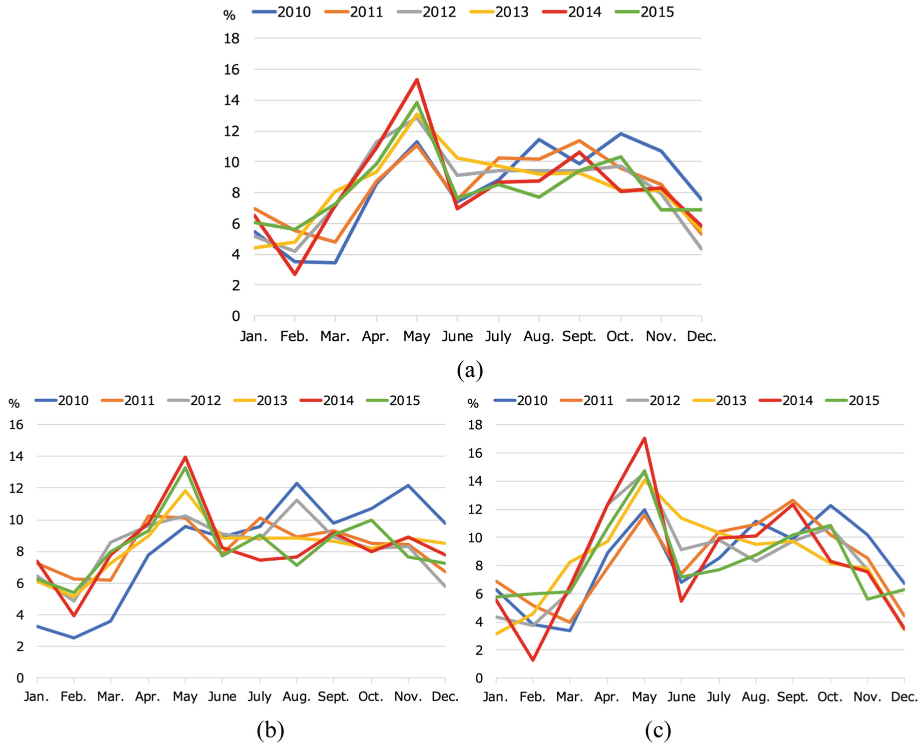


Fig. 4. Changes in the ratio of the number of cycling activities derived from GPS data by month: (a) all users, (b) heavy users, and (c) medium and light users. (authors' own figures)

4.3 Spatial Distribution of Cycling Activities

In this section, spatial use of cycling activities is explored from the distribution of GPS data. Figure 5(a) shows GPS trajectories of all online users, visualized as line shape data of cyclists' movement on the map of Japan. Since GPS trajectories cover the whole of Japan, it is understood that cycling activities are conducted nationwide.

Figure 5(b) illustrates the distribution of spatial use more clearly, with spatial line data aggregated into 10 × 10 km grid units. The accumulation of activity is particularly high in the Tokyo and Keihanshin metropolitan areas. It is surmised that many users of VGI websites are located in large cities with high populations and carry out many short trips for cycling activity in a city and its surrounding area.

Next, differences between two types of online users are examined. Heavy users are similar to the tendency of all users; they are concentrated in the Tokyo and Keihanshin metropolitan areas (Fig. 6(a)). This is probably because many heavy users live in metropolitan areas and post many records of casual cycling activity conducted around their residence area. Referring to Fig. 7, the activity spaces of five heavy users with 300 or more posts are actually concentrated in specific areas. On the other hand, the activity space of medium and light users is relatively widely distributed and dispersed

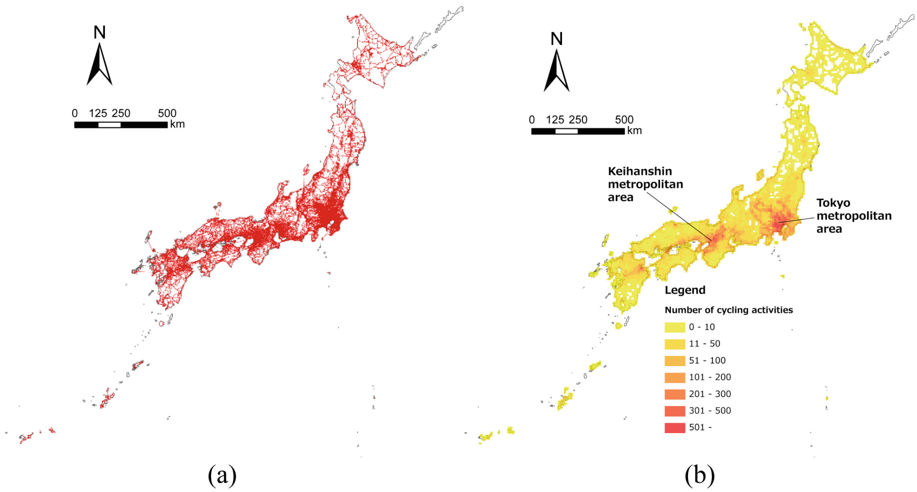


Fig. 5. Spatial distribution of GPS trajectories of all users' cycling activities in Japan: (a) spatial line features and (b) aggregated results into 10 × 10 km grid units. (authors' own figures)

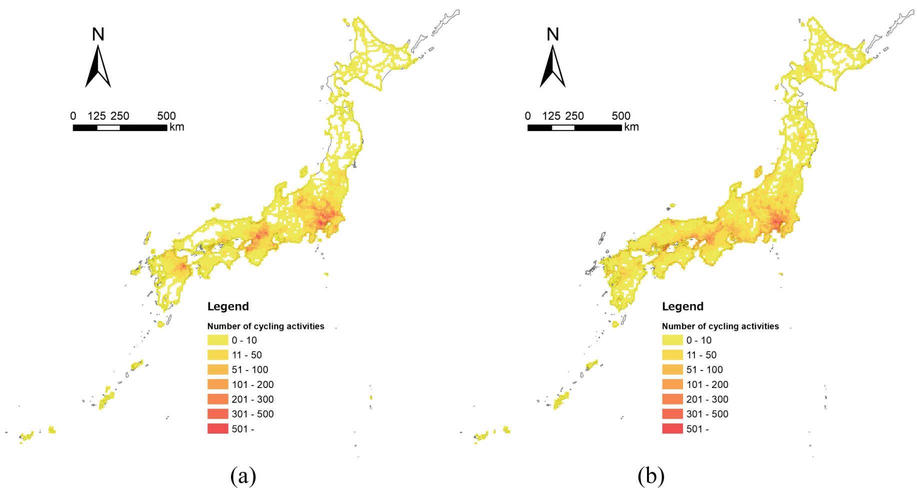


Fig. 6. Comparison of spatial use by user type: (a) heavy users, (b) medium and light users. (authors' own figures)

compared to the case of heavy users (Fig. 6(b)). The reason for this is considered to be because the number of medium and light users is large, their homes are located in various areas in Japan, and records of cycle tourism in regions far from home were singly posted.

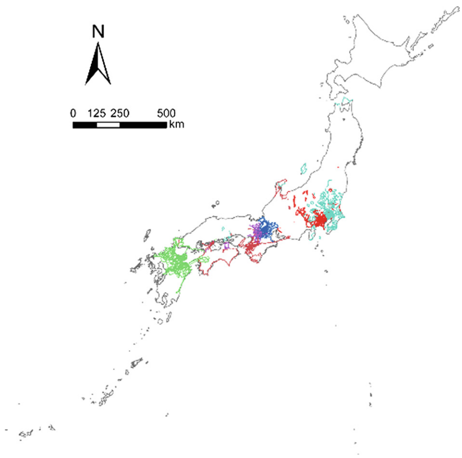


Fig. 7. Distribution of GPS trajectories of users who posted over 300 VGI per user. (authors' own figure)

5 Discussion and Conclusion

This study examined whether VGI is effective for monitoring and exploring cycling activities in the nationwide geographical space in Japan. Analysis was conducted through three major phases: Characteristics of VGI posted by online users, time series patterns, and spatial distribution at an aggregated level. These revealed specific patterns and biases in terms of users, time, and space during cycling activities.

5.1 Validity of VGI

An advantage of VGI is that it makes it possible to understand, continuously and broadly, tourist/recreational behavior that is specialized for a specific purpose such as cycling activity. In the time-series analysis, the comfortable seasons for outdoor recreation in Japan such as spring and autumn produce many cycling activities, but conversely, activities are reduced in winter. The number of tourists in domestic accommodation travel in Japan displays a pattern that peaks in the summer vacation between July and August (Oi, 2016), but the pattern of cycling activity is different. This is considered a reasonable result of the characteristics of Japan's seasonality and outdoor environment. Adding a comparison of other survey results may be necessary to ensure the strong validity of VGI as monitoring data, but there are no official sources to check the number of people who perform cycling activities nationwide per month. There is room to consider using a web service for the survey of cycling activities of a large number of people.

In the analysis of the spatial distribution of GPS trajectories, the tendency to concentrate in large metropolitan areas with high populations was prominent. It can be considered that heavy users live in metropolitan areas and that there is a relatively large number of posts associated with short-term travels conducted in places around such metropolitan areas. To derive a tendency closer to the average, it may be effective to perform the weighting according to the number of posts by users in the space aggregation. Normalization, for example by the number of people living, may be useful in deriving more general spatial patterns of cycling activities.

The spatial distribution of long-distance trips with a small number of posts has been hidden in the result of spatial aggregation, although it is important to determine the spatial pattern of long-distance travels for understanding the actual conditions of cycling activity throughout Japan. It is necessary to perform spatial aggregation after dividing the GPS trajectories by long or short travel distances and to visualize the differences in spatial patterns between short and long-distances. However, in the case of VGI for long-distance travel, many individual GPS data were divided by day and posted separately. Developing automatic processing to find and join separated GPS trajectories indicating one long-distance journey is needed.

5.2 Limitation

The use of the VGI platform is influenced by trends. Obtaining sufficient data to capture cycling activities across a wide area depends on the period. In the case of this study, the data from 2010 to 2015 is large compared to other years, and the trend in the number of cycling activities by month is relatively stable, indicating typical seasonal trends. This led to the discovery of the seasonal pattern of cycling activity. However, in years with small data quantity or the early stages of service start-up, the collected data were unstable and insufficient for monitoring, because the data of a small number of users with a large number of posts is likely to strongly reflect the whole, and the number of posts is affected by events unrelated to tourism phenomena such as topicality of web service. Therefore, it is desirable to use the data at a relatively stable time which has many data and is used by various users for analysis in monitoring and exploring VGI on cycling activity.

A total of 1,419 users may not be enough as a sample for monitoring the whole space of Japan, though reasonable spatial and temporal trends were found through the analysis. Moreover, the VGI used in this study was derived from domestic users in Japan, and does not reflect the ones posted by foreign visitors. Previous research reported that each VGI platform has different user characteristics [11]. Collecting larger samples and mixing different user types with multiple VGI platforms will overcome these limitations.

5.3 Future Work

The analysis in this study focused on patterns of aggregated data such as the transition of number of posts and travel by year and month and the visualization of space use in grid units. In the field of tourist/recreationist spatial behavior, analysis in non-aggregate units such as personal travel orientation and individual movement patterns is also important for a deep understanding of phenomena and practical applications. To clarify the actual situation of cycle tourism in more detail and verify the utility of non-aggregate analysis of VGI is a topic of future work.

In addition, determining users' activity types is another challenge. This study has not been able to address this limitation because of the large size and complexity of the data. As mentioned in the Related Works section, Ritchie [1] distinguished people who engage in cycling activities into bicycle tourists and recreational cyclists. Nishimra et al. [21] reported that most of the cycling VGI in Hokkaido prefecture, a famous region for bicycle tourism, can be determined as activities of cycle tourists. However, in metropolitan areas, there is a possibility that daily cycling activities such as commuting to work are included. Segmentation based on activity types will contribute to the generalizability of the data.

Acknowledgements. This work was supported by JSPS KAKENHI Grant Number 19K20572.

References

1. Ritchie BW (1998) Bicycle tourism in the South Island of New Zealand: planning and management issues. Tour Manag 19(6):567–582
2. Hokkaido Regional Development Bureau, the Ministry of Land, Infrastructure, Transport and Tourism: Environment surrounding cycle tourism and the scope of review by the committee (in Japanese). https://www.hkd.mlit.go.jp/ky/kn/dou_kei/splaat000000i6wl-att/splaat000000i6z2.pdf. Accessed 22 July 2019
3. Lumsdon L, Downward P, Cope A (2004) Monitoring of cycle tourism on long distance trails: the north sea cycle route. J Transp Geogr 12(1):13–22
4. Chen CF, Chen PC (2013) Estimating recreational cyclists' preferences for bicycle routes: evidence from Taiwan. Transp Policy 26:23–30
5. Goodchild MF (2007) Citizens as sensors: the world of volunteered geography. GeoJournal 69(4):211–221
6. Stienmetz JL, Fesenmaier DR (2016) Validating volunteered geographic information: can we reliably trace visitors' digital footprints? Travel and tourism research association: advancing tourism research globally, vol 24
7. Vu HQ, Li G, Law R, Ye BH (2015) Exploring the travel behaviors of inbound tourists to Hong Kong using geotagged photos. Tour Manag 46:222–232
8. Vu HQ, Li G, Law R, Zhang Y (2017) Tourist activity analysis by leveraging mobile social media data. J Travel Res 57(7):883–898
9. Stinmetz JL (2018) Fesenmaier DR (2018) Destination value systems: modeling visitor flow structure and economic impact. J Travel Res 58:1249–1261
10. Maeda T, Yoshida M, Toriumi F, Ohashi H (2018) Extraction of tourist destinations and comparative analysis of preferences between foreign tourists and domestic tourists on the basis of geotagged social media data. ISPRS Int J Geo-Inform 7(3):99
11. Norman P, Pickering CM (2017) Using volunteered geographic information to assess park visitation: comparing three on-line platforms. Appl Geogr 89c:163–172
12. Norman P, Pickering C, Castly G (2019) What can volunteered geographic information tell us about the different ways mountain bikers, runners and walkers use urban reserves? Landsc Urban Plann 185:180–190
13. Santos T, Nogueira Mendes R, Vasco A (2016) Recreational activities in urban parks: spatial interactions among users. J Outdoor Recreat Tour 15:1–9
14. Lumsdon L (2000) Transport and tourism: cycle tourism–a model for sustainable development? J Sustain Tour 8(5):361–377

15. Chang HL, Chang HW (2009) Exploring recreational cyclists' environmental preferences and satisfaction: experimental study in Hsinchu technopolis. Environ Plann B: Plann Design 36(2):319–335
16. Snizek B, Nielsen TAS, Skov-Petersen H (2013) Mapping bicyclists' experiences in Copenhagen. J Transp Geogr 30:227–233
17. Sugimoto K, Ota K, Suzuki S (2019) Visitor mobility and spatial structure in a local urban tourism destination: GPS tracking and network analysis. Sustainability 11(3):919
18. Shoval N, Ahas R (2016) The use of tracking technologies in tourism research: the first decade. Tour Geogr 18:587–606
19. Sugimoto K, Okano Y, Kikuchi T (2013) Patterns of tourists' behavior in the context of rental bicycle use: investigation and data-analysis using GPS and GIS in Azumino, Nagano, Japan. Tour Stud 24(2):15–27 (in Japanese with English abstract)
20. Nishimura K, Sugimoto K, Kikuchi T (2018) Visitor movement patterns in the context of community cycle system for holiday use: a case study in Kawagoe city, Saitama prefecture. Tour Stud 29(2):29–42 (in Japanese with English abstract)
21. Nishimura K, Sugimoto K, Kikuchi T (2020) Analysis of inter-destination cycle tourist movement in Hokkaido prefecture, Japan using volunteered geographic information. Theory and Application of GIS (2020, in press). (in Japanese with English abstract)

Correction to: Exploring the Use of Chatbots in Hotels: Technology Providers' Perspective

Dimitrios Buhalis and Emily Siaw Yen Cheng

Correction to: Chapter "Exploring the Use of Chatbots in Hotels: Technology Providers' Perspective" in: J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, https://doi.org/10.1007/978-3-030-36737-4_19

In the original version of the chapter, the following belated correction has been incorporated: The author name "Emily Cheng Siaw Yen" has been changed to "Emily Siaw Yen Cheng".

The updated version of this chapter can be found at
https://doi.org/10.1007/978-3-030-36737-4_19

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, p. C1, 2020.
https://doi.org/10.1007/978-3-030-36737-4_26

Author Index

J. Neidhardt and W. Wörndl (Eds.): *Information and Communication Technologies in Tourism 2020*, pp. 321–322, 2020.
https://doi.org/10.1007/978-3-030-36737-4