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Fusing multi-source social media data and street view imagery to inform urban space quality: a study of user perceptions at Kampong Glam and Haji Lane

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Abstract

This study proposes a novel approach to urban perception studies by integrating street view imagery and multi-source social media data to infer user perceptions and preferences of urban spaces, thereby informing placemaking strategies. With advanced pre-trained Google Cloud Vision AI, this study regards street view imagery as a baseline to compare with user-generated content from social media platforms, namely, Flickr, TripAdvisor, and X (formerly Twitter), together revealing spatial elements perceived by users and diverse demands across users groups. The research evaluates urban space qualities at two spatial levels through a case study at Kampong Glam district and Haji Lane, focusing on Uniqueness, Vitality, and Liveability derived from classic urban theories. The transition in user focus from spatial and transport features in Google Street View to activities and decorations in Flickr imagery emphasizes the spatial features that contribute to Uniqueness and Vitality. In addition, textual data from Twitter and TripAdvisor differentiate residents' and tourists' perceptions of Liveability, encompassing aspects like History, Religion, Space, and Activity. The findings articulate alignments of users' perceptions from street to district levels and diverse preferences on spatial features contributing to Uniqueness, Vitality, and Liveability, offering valuable insights for user-centric placemaking and urban planning.

Keywords Urban space quality, Google Cloud Vision AI, Urban perception, Street view imagery, Social media

1 Introduction

To promote a sustainable and thriving society (UNDP, 2015), urban space quality continues to be a classic topic in both traditional research and emerging urban analytic research (Gehl, 1987; Jacobs, 1961; Ma et al., 2024; Mouratidis, 2021). Urban space quality refers to the extent to which the built environment can fulfil citizens' demands for services and impact people's mental health (Herzog, 1989; Ma et al., 2024) through spatial features

such as the building density (Trivic, 2023), sense of safety (Y. Kang et al., 2023) and urban greenery (Biljecki et al., 2023; Marchi et al., 2022). Enriching the understanding of urban space quality from users' perspectives can systematically inform the placemaking process for urban development at various spatial levels (Abdul-Rahman et al., 2021; Belkahla Driss et al., 2019), revealing urban space qualities of a district formed by spatial features of affiliated streets and users' diverse demands across the two levels. This study selects a historic district in Singapore, namely Kampong Glam, and one of its streets best known for tourism called Haji Lane for a case study on their urban space qualities.

However, limited studies have evaluated the differences in urban space qualities between subjective preferences

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from user perceptions and objective information about the built environment. To bridge this gap, this study focuses on user-perceived qualities, namely, Uniqueness, Vitality, and Liveability, and proposes a novel quantitative approach that innovatively uses Google Street View (GSV) imagery as a baseline for its consistent sight field of view and veracity (Biljecki & Ito, 2021; Guan et al., 2022) to infer user perceptions and preferences of urban spaces from Flickr, Twitter (currently called X), and TripAdvisor, with computer vision (CV) techniques from Google Cloud Vision AI. By fusing multi-source social media data and street view imagery, this structured comparative approach can capture diverse urban perceptions and sentiments of different user groups, thus contributing to the urban space quality evaluation across district and street levels.

This study prioritizes three key urban space qualities derived from classic urban theories (Gehl, 1987; Jacobs, 1961; Lynch, 1960) due to their strong connection to user-generated data and individual-level perceptions at district and street levels, namely, Uniqueness, Vitality, and Liveability. Focusing on these user-perceived qualities allows researchers to combine objective measures and subjective user perceptions for a comprehensive evaluation of urban space quality. Uniqueness, in terms of spatial identity, is the key driver that forms the image of the city (Lynch, 1960) and shapes visitors' sense of urban spaces (M. Li et al., 2021; Shekhar et al., 2019). Vitality is a feeling of urban space quality evoked by activities that make spaces become places (Gehl, 1987; Huang et al., 2020; Jacobs, 1961; Montgomery, 1998). Liveability is increasingly discussed in trending research from a human-centric perspective, motivated by the availability of user-generated social media content containing visitors' experiences and sentiments (Badland et al., 2014; Norouzian-Maleki et al., 2018).

This study applies the proposed approach in a case study evaluating the urban space quality at Kampong Glam and Haji Lane. Kampong Glam (also spelt 'Gelam') district was traditionally a residential area for Malay royalty, but now it supports both local communities and tourists (Kumar, 2020). In the southern area of Kampong Glam lies Haji Lane, which was associated with the pilgrimage undertaken by Muslims to Mecca and Medina but is now famous for its abundant shops and graffiti (URA.SG, 2024). With the integration of findings across spatial scales, district-level analysis can reveal broader infrastructural and environmental trends while providing nuanced insights into pedestrian experiences at the street level.

Computer vision (CV) methods are widely used in quantitative urban sensing research (P. Liu et al., 2023; Qiu et al., 2022; Szeliski, 2022). The rapid advancements in Artificial Intelligence (AI) and open digital tools for data-driven methodologies can significantly benefit research in sensing and modeling urban environments (P. Liu et al., 2023; Yap et al., 2022), suggesting the potential of innovative technologies from informatics fields in urban studies (Shi et al., 2022). Pre-trained AI models have become a trending tool for urban researchers (Janowicz et al., 2020; Y. Kang et al., 2023; P. Liu & Biljecki, 2022), including Google Cloud Vision AI with technology support in image labeling and object recognition tasks (Vision AI, 2024).

This study implements the proposed approach through three comparisons for a comprehensive understanding of urban space quality from users' perspectives:

i.   Using GSV imagery as a baseline and comparing it with Flickr imagery to extract spatial elements perceived by users and draw insights into the Uniqueness and Vitality of Kampong Glam and Haji Lane, respectively.
ii. Comparing social media text data generated by different user groups on Twitter and TripAdvisor to specify relevant spatial elements contributing to Liveability based on the sentiments of the user-generated content about Kampong Glam and Haji Lane, respectively.
iii. Comparing the results across district and street levels to study the differences in user perceptions and demands regarding three aspects of urban space quality—Uniqueness, Vitality, and Liveability—and to discuss the applicability of the proposed approach in various urban contexts.

The research findings justify the feasibility of the proposed approach of fusing multi-source social media data and street view imagery with pre-trained AI models to analyze diverse user groups' perceptions, reveal users' spatial preferences, and evaluate urban space quality at district and street levels. The results identify key factors contributing to the Uniqueness, Vitality, and Liveability of urban spaces, and thus inform the placemaking process and urban planning from a user-centric perspective. This approach can be applied to studies on diverse urban contexts at different levels with available street view imagery and user-generated data. Adjustments might be necessary to account for varying data availability, cultural differences, and diverse user groups unique to each urban context.

2 Theoretical framework

Urban space quality is complex in terms of the physical environment meeting citizens' functional and mental demands (Abbasi et al., 2016; J. Chen et al., 2021; Smith

et al., 1997). Despite extensive discussion in previous studies, the definition of urban space quality varies due to diverse evaluation frameworks (Ma et al., 2024; Mouratidis, 2021) and develops with the emerging data sources (Heng et al., 2020; Y. Wang et al., 2021). This study focuses on three aspects of urban space quality building upon classic urban theories, namely, Uniqueness, Vitality, and Liveability.

Classic theories into urban space quality evaluation focus on elements of the built environment within pedestrians' field of vision. Edge, one of the spatial elements according to Lynch's theory (1960), is the most visually engaged component of street perceptions (Simpson et al., 2019). As the pedestrians' field of vision is mainly horizontal, the ground floor of buildings plays a vital role in their view (Gehl, 1987), especially the continuity of the street edge and the focal endings far in the distance on streets (Jacobs, 1961). The following research quantifies objective elements of street view to study urban space quality, such as the sense of safety reflected in the broken windows (Fagan & Davies, 2000) and amenities (Zhang et al., 2021).

Existing research has revealed how activities contribute to urban space quality. Jane Jacobs defined urban vitality as the active street life expressed by the presence of pedestrians (1961). She proposed that diversity, concentration, contact opportunity and aged buildings are four generators of urban vibrancy, with two additional requirements: accessibility and border vacuums (1961). Thriving activities is a key driver of socioeconomic interactions (Montgomery, 1998). Trending research (C. Kang et al., 2021; Sulis et al., 2018) analyzes activities for quantitative measurements of urban vitality, including population concentration, activity diversity, time diversity, and space diversity.

With user-generated data, emerging sociological and urban studies have investigated citizens' experiences and satisfaction (Abbasi et al., 2016; X. P. Song et al., 2020a, 2020b) to form a user-perspective understanding of urban space quality. Owing to the advantages of the immediacy, availability and quantity (Liao et al., 2022), social media data is increasingly applied to urban space quality studies to analyze social activities and individual behaviours from a users' perspective (M. Li et al., 2021). For example, social media data have been proven reliable for the investigation of citizens' experiences (Y. Song et al., 2020a, 2020b), communications(Guo et al., 2022), and emotions (Zhu et al., 2021). Thus, citizens' perceptions can be extracted from user-generated data on social media to study users' preferences (Lee & Kang, 2021) and opinions on urban spaces (Hausmann et al., 2020; Kruse et al., 2021).

To propose a holistic user-centric evaluation framework of urban space qualities, this study selects Uniqueness, Vitality, and Liveability for incorporation of concepts from Kevin Lynch's (1960) and Jane Jacobs' theories (1961) focusing on the spatial features and activities, and contemporary research on users' experiences. Revealing how spaces are perceived, used, and preferred and specifying factors of urban space qualities can inform urban planning and placemaking strategies to meet users' demands.

The 'Uniqueness' or the 'imageability' of urban spaces is an orientation clue leading pedestrians to form the image of the city (Lynch, 1960) and perceive districts and affiliate streets. Lynch (1960) emphasizes the importance of individual perception of streets and urban spaces at the district level. Extending research on the city image further points out that the intricacy and vibrancy of activities are motivated by the street environment, including identifiable building typology and unique spatial identity (Appleyard et al., 1971; Qiu et al., 2021).

Vitality is a feeling of urban space quality formed by street activities (Huang et al., 2020). Different from Lynch's concentration on unique spatial identity, Jacobs's (1961) and Montgomery's theories (1998) in urban vitality built the classic argument of street quality studies associated with human activities (Huang et al., 2020). Jacobs (1961) defined Vitality as the active street life expressed by pedestrian activities in the built environment. Citizens perceive and use urban spaces for necessary activities, spontaneous activities, and social activities (Gehl, 1987), which activates communal spaces in cities and provokes Vitality. As optional and social activities depend considerably on the quality of urban spaces, the diversity of optional activities partly reflects urban Vitality (Montgomery, 1998).

Liveability is reflected in neighborhood satisfaction towards their individual experiences in urban spaces. Different from the observation perspective of Jacobs, Lynch, and Gehl's theories in urban spaces, the evaluation methods of recent research start to focus on citizens' perceptions and satisfaction to study the Liveability of urban spaces (Badland et al., 2014; J. Chen et al., 2021; He et al., 2024; Norouzian-Maleki et al., 2018). Although the definitions of Liveability vary from the interaction between environmental and personal characteristics (Pacione, 1990) to citizens' desires for the contentment of life (Chazal, 2010), the Australian Major Cities Unit definition proposes that liveable cities have attractive built and natural environments which can be assessed by citizens' satisfaction (Badland et al., 2014; J. Chen et al., 2021; Mouratidis et al., 2019).

In terms of data availability, Uniqueness and Vitality are reflected in the visual characteristics of the built

environment captured by GSV imagery and user-generated imagery in social media, while Liveability is best understood through user-generated content expressing individuals' experiences and sentiments. First, Uniqueness is represented by landmarks (Lynch, 1960), architectural style (Lynch, 1995), and spatial elements of the built environment (Biljecki & Ito, 2021). Google Cloud Vision AI with CV methods (e.g., semantic segmentation and object detection) is increasingly employed to quantify spatial elements beneficial to well-being, such as visual complexity (Guan et al., 2022) and physical activity (R. Wang et al., 2019). Second, the Uniqueness and Vitality perceived by visitors can be extracted from user-generated imagery in social media (J. Chen et al., 2021; Y. Liu et al., 2020a, 2020b; X. P. Song et al., 2020a, 2020b). Third, user-generated text in social media records visitors' experiences and sentiments, reflecting the Liveability of urban spaces and relevant factors. Researchers apply natural language processing techniques (e.g., topic modeling and sentiment analysis) to identify the main topic discussed by users (Hu et al., 2019; Jiang et al., 2024) and their sentiments (He et al., 2024; Plunz et al., 2019; You & Tunçer, 2016).

However, citizens' diverse preferences of spatial elements at different urban scales have not been compared to uncover key spatial elements of urban space quality. Scale effects and the incorporation of data sources should be explored in future research to enhance the precision of urban space quality studies at different spatial levels (X. P. Song et al., 2020a, 2020b). Previous research has analyzed citizens' demands and preferences based on user-generated content, such as the sentiments on transit stations (Chang et al., 2022), travel demand (Liao et al., 2022), and tourists' preferences (Lee & Kang, 2021). Further exploration of differences among user groups can enrich the understanding of various opinions and benefit equality, diversity and inclusion, especially crucial for policymaking (Quinn et al., 2021) and placemaking strategies (Burton & Mitchell, 2006; Pineo, 2022).

Given the above discussions and inspirations from existing literature, this study fuses multi-source social media data and GSV imagery to identify key spatial elements that contributed to urban space qualities (Uniqueness, Vitality, and Liveability) with imagery data and extract sentiments of different user groups from textual data. With three quantitative comparisons and qualitative discussions referring to classic theories in urban space quality (Gehl, 1987; Jacobs, 1961; Lynch, 1995; Montgomery, 1998), the findings interpret multi-user groups' perceptions and demands at both district and street scales to instruct user-centric placemaking strategies.

3 Data and methodology

This research conducts a cross-level case study at Kampong Glam and Haji Lane, using GSV imagery as a baseline and social media data for users' perceptions. The proposed approach (Fig. 1) with three creative comparisons employs a combination of image and text analysis with Google Cloud Vision AI to identify relevant spatial elements and quantitatively evaluate Uniqueness, Vitality, and Liveability at district and street levels.

3.1 Case study

Kampong Glam and Haji Lane were selected as the location of a pilot study (Fig. 2) in urban space quality assessment for their emerging development demand, cultural significance, and popularity among both locals and tourists (HAN, 2016; Kumar, 2020; URA.SG, 2024). Kampong Glam, one of Singapore's oldest urban quarters, is a mix of age-old traditions and trendy lifestyles (URA.SG, 2024). Haji Lane is a back alley filled with shops in the southwest part of Kampong Glam (HAN, 2016). This street is now a home for cafes, bars, lifestyle shops, boutiques, and graffiti walls, as well as a hangout for Instagrammers, fashionistas, artists, and troopers looking to experience a different side of Singapore (URA.SG, 2024).

3.2 Data collection

The author collected multi-source datasets by searching keywords, Kampong Glam and Haji Lane, in 2021, encompassing various digital platforms, namely, Google Street View (GSV) imagery, Flicker imagery, Twitter Tweets and TripAdvisor reviews for a broad spectrum of user perspectives and perceptions in these two urban spaces.

From March to May 2022, the author used Google Street View Image Application Programming Interface (API) to obtain street view images (Fig. 2). To form an entire representation of the streetscapes, 67 sampling points for district analysis were selected at the junctions, leading to 268 street view images. For street analysis, 12 sampling points are selected at an interval of 20 meters due to the limitation of Google Street View API, leading to 48 street view images. Coordinates of selected GSV images in Kampong Glam District can be found in supplementary material.

The social media datasets include all Flickr images about Kampong Glam and Haji Lane from 2015 to 2022 and textual data from 2012 to 2022 posted on Twitter and TripAdvisor. Flickr images with district (5052 images for #kampongglam and #kamponggelam) and street hashtags (4458 images for #hajilane) were retrieved by Flickr API in 2022. Twitter Tweets datasets were scraped using district (719 Tweets for #kampongglam and #kamponggelam) and street hashtags (1671 Tweets for
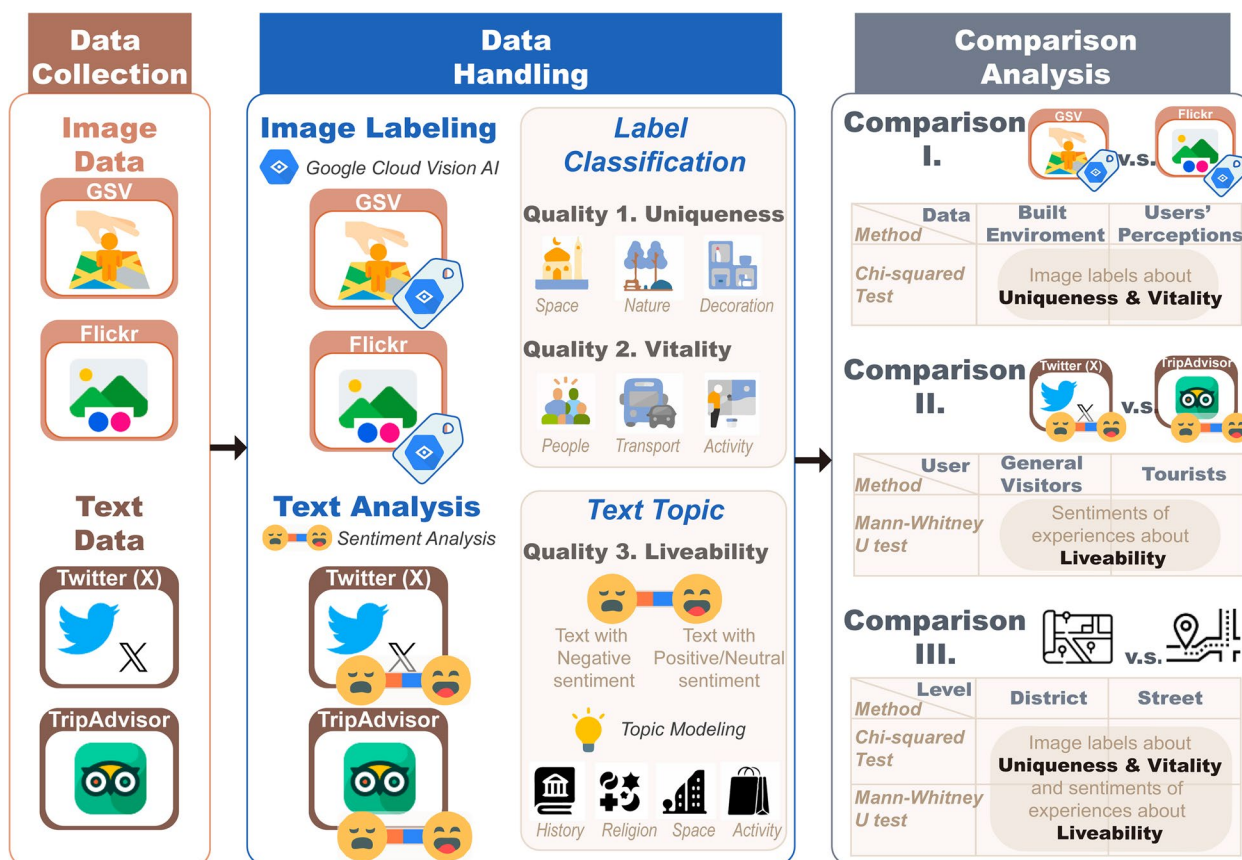
Fig. 1 The workflow of the three-comparison approach

#hajilane) in 2022. TripAdvisor reviews (319 reviews for Kampong Glam district and 706 reviews for Haji Lane) were scraped from web pages in 2022. User information and posting times were collected associated with image and text data. All the social media data were anonymized and safely stored in OneDrive for Education purposes.

3.3 Methods and AI tools

The above input data is treated in two categories: imagery and text. GSV images and Flickr images are analyzed by Google Cloud Vision AI to detect objects and get ten labels ranked by the confidence scores. These labels summarize detected objects for each image, such as sky, road, window, tree, people, etc. To represent the image content effectively for quantitative analysis, image labels are classified into six groups that reflect Uniqueness and Vitality. The three groups for Uniqueness are 'place' (indicating specific locations or structures like buildings and streets), 'nature' (related to natural elements like trees and skies), and 'decoration' (referring to decorative elements like art and architecture). For Vitality, the three groups are 'people' (identifying human presence), 'activity' (describing actions or events), and 'transport' (associated with modes

of transportation like cars and bicycles). This classification provides a general overview of the image content, revealing spatial features potentially contributing to Uniqueness and Vitality.

To quantify the statistic difference across various data sources and across district and street levels, this study applies Pearson's Chi-squared test with simulated p-value (based on 2000 replicates) to compare the diversity of image labels and the Mann–Whitney U test (also known as the Wilcoxon rank-sum test) with continuity correction to compare the distribution of sentiment scores of posts, using R package 'stats'. Chi-squared test (Plackett, 1983) is a statistical procedure for determining the difference between observed and expected data, which is suitable for identifying the potential difference between the observed label frequencies and the expected label frequencies given the six groups of image labels matching Uniqueness and Vitality respectively. This study then chooses the Mann–Whitney U test as it focuses on the differences between two groups on a single, ordinal variable with no specific distribution (Mann & Whitney, 1947), aligning with the distribution of sentiment scores of Twitter and TripAdvisor data.

Fig. 2 Site location and data collection points

3.4 Research design

This study creatively proposes a three-comparison approach integrating Google Cloud Vision AI and multi-source datasets (Fig. 1). The first comparison between GSV and Flickr imagery identifies spatial elements perceived by users relevant to the Uniqueness and Vitality at both district and street levels. The spatial elements from both sources are detected with the image label function of Google Cloud Vision AI and are compared to identify discrepancies or alignments between the physical environment (as captured by GSV imagery) and user perceptions (as captured by Flickr imagery) and thus highlight elements objectively shape the area's Uniqueness and Vitality.

The second comparison between text-based data from different social media platforms (Twitter and TripAdvisor) can uncover factors relevant to the Liveability of urban spaces from general Tweets and tourists' reviews at both district and street levels. User's Twitter Tweets provide valuable insights into the Liveability aspect of urban spaces, as they often contain subjective views and experiences of the city dwellers. By comparison, user reviews from TripAdvisor offer a tourist-oriented dimension to the study of Liveability as a complement to the Twitter data. The author conducted sentiment analysis and topic

modeling with detailed accounts of tourists' experiences in Kampong Glam to understand the themes and topics prevalent in user positive or negative discussions. Sentiments and topics from different platforms reveal the aspects most valued or criticized by different user groups and enrich the understanding of Liveability.

The third comparison contrasts the results across the district (Kampong Glam) and street (Haji Lane) levels, exploring overall differences in user perceptions and demands regarding Uniqueness, Vitality, and Liveability. The same data collection and analytic methods are conducted to understand how perceptions and demands vary at different urban scales. Unique or common elements relevant to Uniqueness, Vitality, and Liveability for both levels draw in-depth insights into future placemaking processes at Kampong Glam and Haji Lane. This approach with comparative analyses can be reproduced in different urban contexts for accordingly insights into diverse user perceptions and suggestions for placemaking processes.

4 Uniqueness and Vitality of Kampong Glam and Haji Lane

The first comparison between GSV imagery and Flickr imagery reveals spatial features specifically perceived by Flickr users over all the elements of the built environment

captured by GSV imagery. Compared with the objective information in GSV imagery, Flickr imagery with user-centric visual perceptions further indicates spatial elements preferred by users that contribute to Uniqueness and Vitality. Image labels are classified by six groups matching two urban space qualities: transport, people, and activity for Vitality, and space, nature, and decoration for Uniqueness.

4.1 Statistic differences between GSV and Flickr imagery

There are statistical differences between labels of imagery from Google Street View (GSV) and Flickr, in Kampong Glam and Haji Lane respectively (Table 1). The analysis employs Pearson's Chi-squared test to assess the independence of labeling between the two imagery datasets. For Kampong Glam, a substantial Chi-squared value of 60.934 and a p-value of 0.000 strongly suggest significant differences in the image labels between GSV and Flickr. This result is consistent across two methodologies: one including a simulated p-value based on 2000 replicates, and the standard Pearson's Chi-squared test, which justifies the role of objective information about the built environment from GSV as a baseline. Conversely, the imagery labels detected at Haji Lane showed a Chi-squared value of 9.257, with p-values of 0.065 and 0.099, respectively, indicating a less pronounced difference between GSV and Flickr images at street level. These statistical outcomes underscore the focal disparities in respective datasets collected objectively or provided by users and also reveal variability in the differences between user perceptions and the built environments when zooming in to the street level.

4.2 Uniqueness and Vitality of Kampong Glam

The comparison between GSV imagery and Flickr Imagery at Kampong Glam shows remarkable differences in image contents (Fig. 3a, b). Due to the street-level perspective of GSV, the most frequent spatial elements extracted from GSV images are 'building' and 'sky'. In addition to the commonly frequent labels, 'building' and 'plant', Flickr users captured images with a wider variety of subjects and interests with a broader diversity of labels about activity, people

and decoration, with 'facade' at 2.73%, 'event' at 2.43%, and 'art' at 2%. The group frequency chart (Fig. 3c) indicates that the 'transport' category dominates GSV images, while the 'activity' and 'people' categories appear more in Flickr images, aligning with the user-generated content's social demand.

The Uniqueness of Kampong Glam is contributed by three features, namely shops, arts, and religion. Uniqueness is reflected on labels about specific objects in local culture. For example, the label 'Font' is more frequent in Flickr images (Fig. 3a) partly because citizens tend to take photos with shop signs and item brands at Kampong Glam. Several frequent activity labels, namely 'market' and 'retail', emphasize the main function of this district with several retail streets and souvenir shops (Fig. 3b). Besides, 'visual arts', 'paint', and 'art' labels accurately capture the features of building facades with wall painting and graffiti in Kampong Glam. One label about people, 'hat' is more frequent in Flickr images because of the religious background of this district.

The Vitality of Kampong Glam is reflected in streetlights, food, and recreation (Fig. 3). Due to the constraints of label classification of Google Cloud Vision AI, only several spatial elements potentially contributing to the Vitality of Kampong Glam are detected. Among labels detected from GSV images, only 'street light' is a spatial feature of Vitality (Fig. 3a). With more labels about activities detected from Flickr images, several labels about food indicate the vibrancy of restaurants in the district, including 'recipe', 'food', and 'cuisine' (Fig. 3b). One limitation is that the labels provided by Cloud AI lack details about the food and related restaurants.

4.3 Uniqueness and Vitality of Haji Lane

The label frequency between GSV imagery and Flickr imagery at Haji Lane also presents a distinct distribution (Fig. 4a). Haji Lane's GSV images remain a concentration in label groups 'space', 'nature', and 'transport', reflecting similar physical infrastructure and environment to the district. The top frequent labels (Fig. 4a, b) detected from GSV images are 'building' and 'sky', the same as those at the district level (Fig. 3a, b). The results of Flickr images show a balance between different label groups (Fig. 4c),

Table 1 Statistical differences between Google Street View (GSV) and Flickr imagery labels in Kampong Glam and Haji Lane using Pearson's Chi-squared test
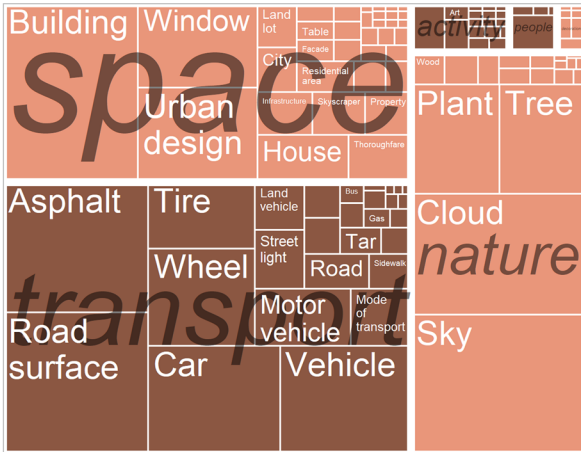
Chi-squared (X2)	*P*-value	Signif	Method	Area	Description
60.934	**0.000**	***	Pearson's Chi-squared test with simulated *p*-value (based on 2000 replicates)	**Kampong Glam**	Comparison I: GSV and Flickr images' labels
9.767	0.066	.		Haji Lane	
60.934	**0.000**	***	Pearson's Chi-squared test	**Kampong Glam**	
9.767	0.082	.		Haji Lane	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
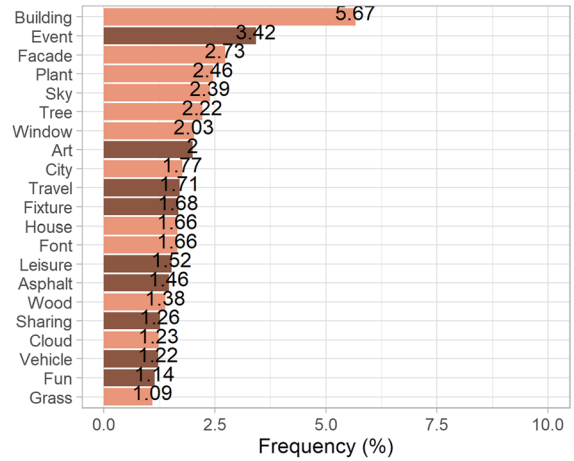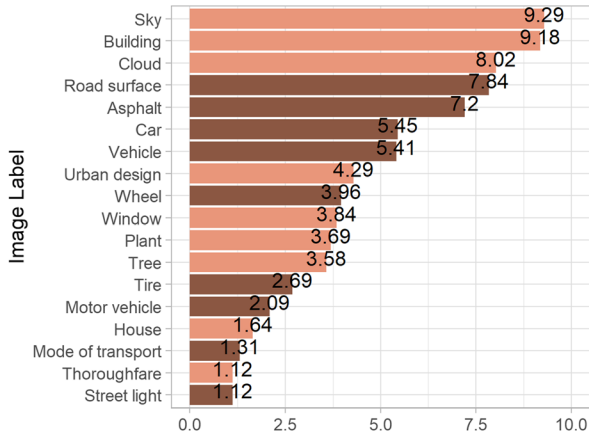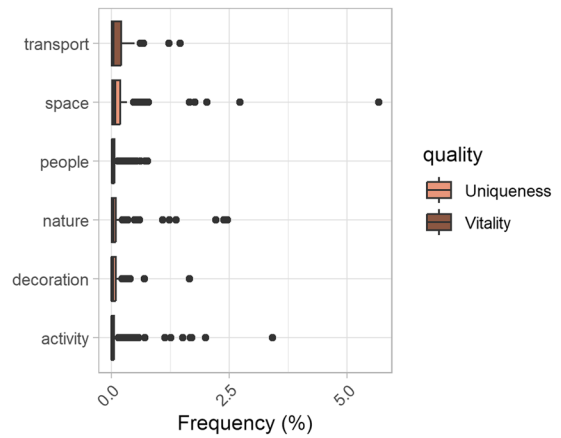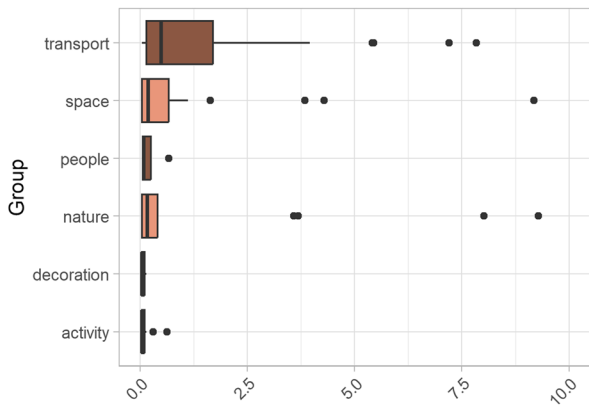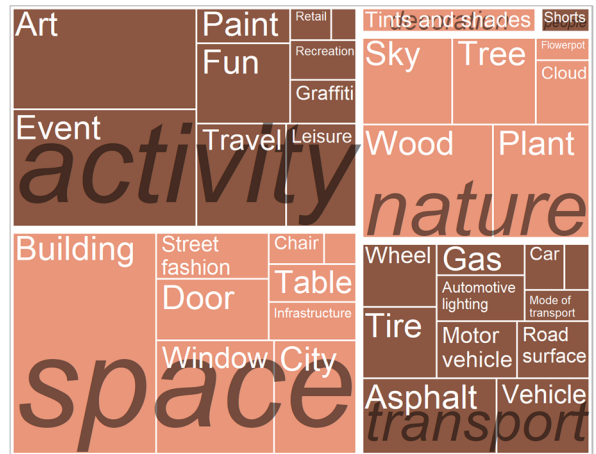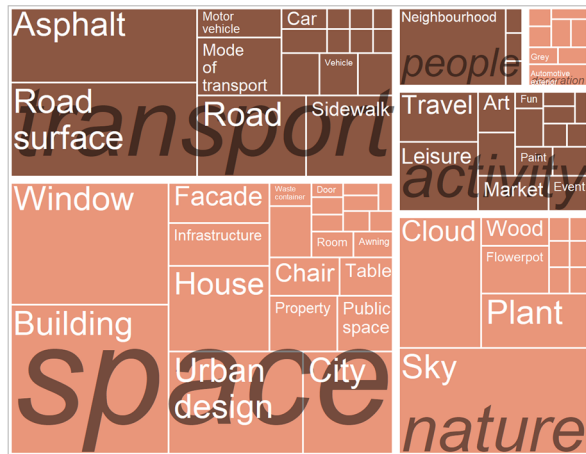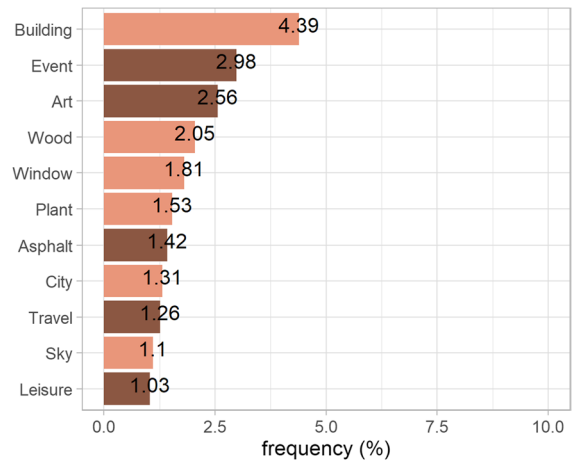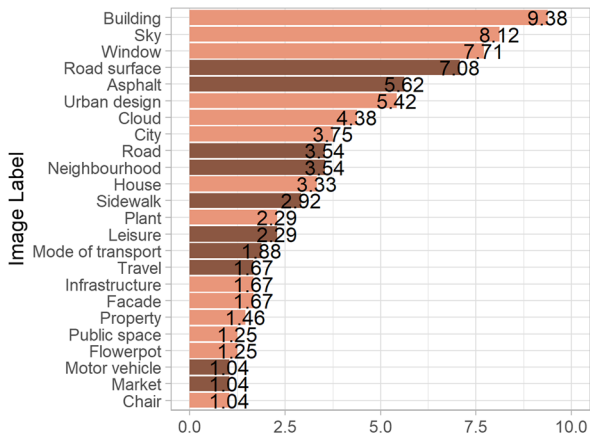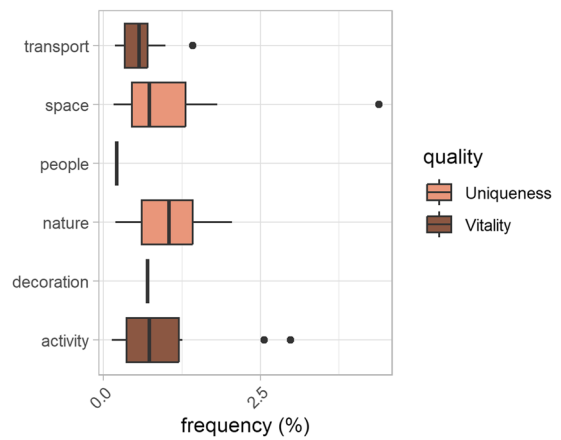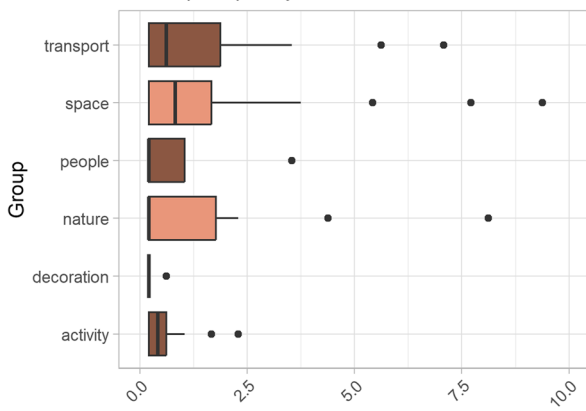
Fig. 3 Comparison I – Labels of GSV and Flickr imagery at Kampong Glam

Fig. 4 Comparison I – Labels of GSV and Flickr imagery at Haji Lane

with a larger proportion of elements about people and decoration than district-level findings (Fig. 4c).

Two spatial features of the street that reflect the Uniqueness of Haji Lane are detected, including abundant greenery and graffiti (Fig. 4c). Higher label frequencies in the 'space' and 'nature' groups of GSV image labels indicate the street's spatial dynamics, especially the vegetation and potted plants related to impressive greenery views, and street art with façade designs as a key component of its Uniqueness. Some building materials are also labeled, leaving opportunities for in-depth exploration of the building typology and colors.

The Vitality of Haji Lane is formed by diverse social and commercial activities. Street-level Flickr images show a notable presence of labels related to 'activity', 'people', and 'decoration', highlighting the social and cultural activities of the street (Fig. 4a, b). For example, the label 'event' and 'smile' indicates Haji Lane's role as a popular venue for social gatherings. The 'decoration' category (Fig. 4c) from Flickr images also suggests a thriving environment of shops and recreational activities along the Haji Lane.

5 Liveability of Kampong Glam and Haji Lane

The second comparison between Twitter Tweets and TripAdvisor reviews suggests different user groups' preferences on experiences representing Liveability. The statistical differences in sentiments of the two data sources reveal the variety in demands among user groups. By dividing user-generated content into groups with positive/neutral and negative sentiments, four main topics related to Liveability are identified: religion, history, space and activity.

5.1 Statistic differences between Twitter and TripAdvisor data

There are significant statistical differences between the sentiment scores of texts from TripAdvisor and Twitter, talking about Kampong Glam and Haji Lane respectively (Table 2), revealed by the Wilcoxon rank sum test with a continuity correction.

For Kampong Glam, a high statistic value of 22,128 and a *p*-value of 0.000 indicate a significant difference between the sentiments of TripAdvisor and Twitter content. For Haji Lane, an even more elevated statistic of 206,441.500 with a corresponding *p*-value of 0.000 further indicate that users from TripAdvisor and Twitter shared distinct sentiments as they have different experiences and demands, responding to a more diverse user group on Twitter and a remarkable focus on tourism in TripAdvisor. The results underscore the robust statistical differences between sentiments of content generated by general visitors from Twitter and tourists from Tripadvisor, suggesting the variability among the perceptions of users from different social media platforms about the Liveability of the district and the street.

5.2 Liveability of Kampong Glam

Comparative findings from sentiment scores and topic modeling between TripAdvisor and Twitter data identify factors related to the Liveability at Kampong Glam, such as cultural heritage, and reveal the differences in the feedback of two user groups, such as tourists' focus on commercial activities. The majority of Tweets about Kampong Glam are neutral to positive as the sentiments of Twitter Tweets show a bell-curve-like distribution with a skew towards positive sentiment (Fig. 5a). TripAdvisor reviews display a similar trend but with a more remarkable concentration on neutral to positive sentiments, suggesting a generally favorable scope of visitors' experiences in the district (Fig. 5a).

The frequent keywords of four topics, namely, history, religion, space and activity detected by LDA-based Topic Modeling methods are related to the Liveability of Kampong Glam (Fig. 5c, d). Topics in history and religion are emphasized in Tweets with neutral to positive sentiments (Fig. 5b). The district's rich cultural heritage not only forms a sense of identity in local communities but also provokes Liveability. The representative keywords are 'heritage', 'Malay', 'arab', and several Malay words (Fig. 5c). Specifically, the keywords 'mosque' and 'Sultan' refer to the iconic Sultan Mosque, a significant religious and cultural landmark of Kampong Glam. By comparison, the

Table 2 Statistical differences between TripAdvisor reviews and Twitter Tweets about Kampong Glam and Haji Lane using Wilcoxon rank sum test with continuity correction

Test Statistic	P_value	Signif	Method	Area	Data
22128.0	0.000	***	Wilcoxon rank sum test with continuity correction	**Kampong Glam**	Comparison II: Sentiment scores of TripAdvisor and Twitter
206441.5	0.000	***	Wilcoxon rank sum test with continuity correction	**Haji Lane**	

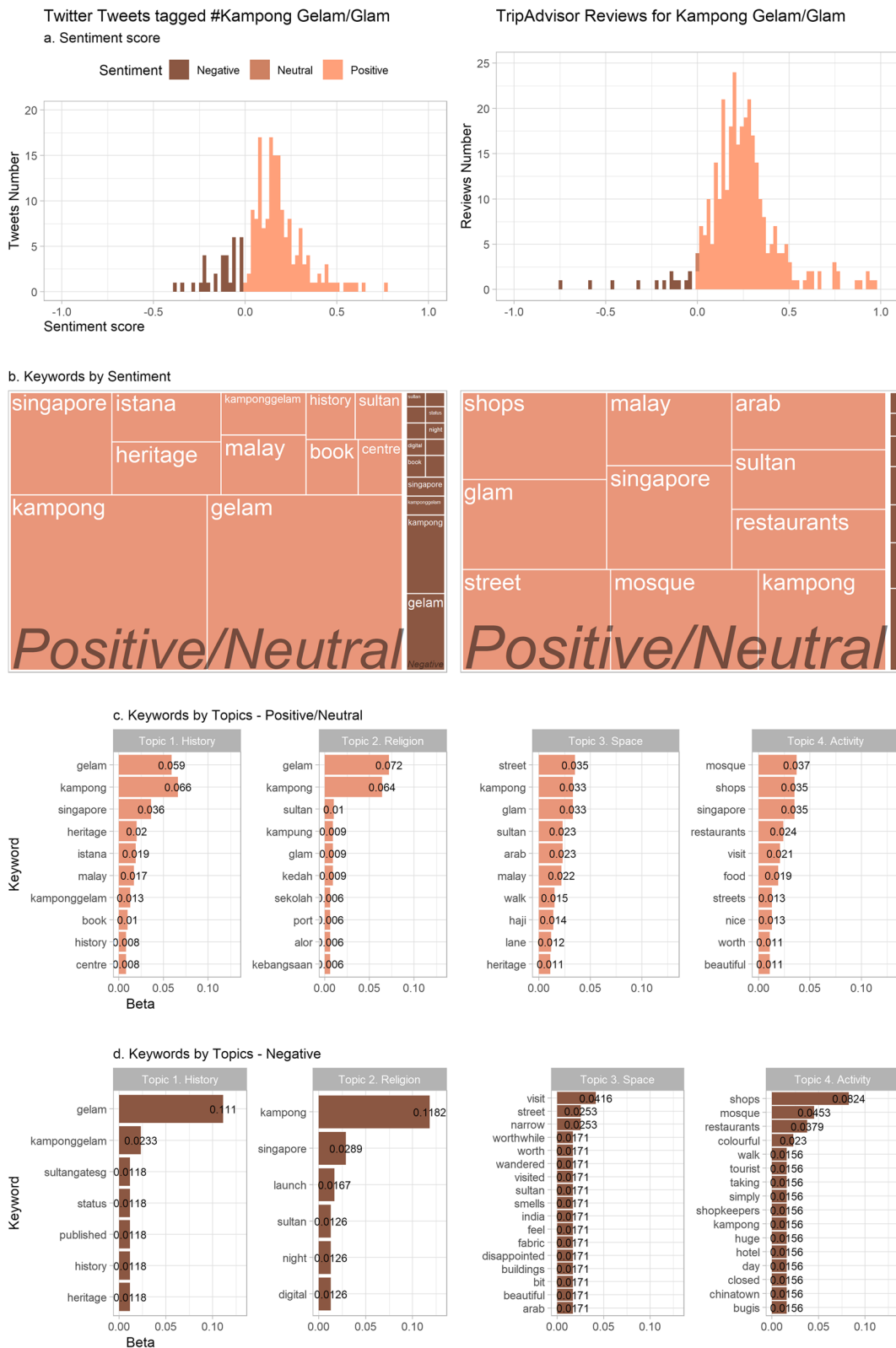Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Fig. 5 Comparison II – Twitter Tweets and TripAdvisor Reviews at Kampong Glam

topics, space and activity are more important from tourists' perspective (Fig. 5c). Dominated keywords, including 'book centre', 'shops', 'streets', and 'mosque', reflect commercial functions and attractive spaces of Kampong Glam, highlighting the relationship between its role as a historical and multicultural hub.

The proportion of negative posts on Twitter is more than that on TripAdvisor with keywords about spatial features and personal experiences (Fig. 5d). Diverse keywords about space and activities from negative TripAdvisor reviews indicate potential issues with accessibility or unmet expectations of Kampong Glam. For example, 'night' under the topic 'religion' is detected from user's negative experiences around religious spaces during evening times. Within the topic 'space', users' complaints about 'narrow streets' and 'disappointed' indicate a demand for pedestrian-friendly street spaces. Negative feedback on activities, such as 'shops', 'restaurants', and 'tourist', suggests the focus of tourists' complaints on recreational services.

While Kampong Glam is generally viewed positively, suggesting good Liveability based on its cultural, commercial, and aesthetic attributes, targeted urban planning according to tourism's demand could further enhance its Liveability. Elements that contribute to Liveability in Kampong Glam can be inferred from the positive sentiments and associated keywords. Historical and religious factors considerably enhance the Liveability for its indispensable role in forming the local identity. A vibrant commercial scene is also crucial, especially from tourists' perspective. Descriptors like 'beautiful' and 'nice' point to the aesthetic and recreational views of the district, recalling the visual arts and street facade contributed to Vitality. Negative feedback proposes an improvement in the spatial and recreational elements to enhance Liveability. Complaints about 'narrow streets' suggest a pedestrian-oriented strategy benefiting both residents and tourists. Demands on recreational experiences require additional investigations and should be considered in future policy-making processes.

5.3 Liveability of Haji Lane
Similar to the sentiment distribution of district-level data, the majority of tweets about Haji Lane are neutral to positive with a bell-curve-like distribution with a skew towards positive sentiment (Fig. 6a). TripAdvisor reviews remarkably concentrate on neutral to positive sentiments, suggesting a satisfactory scope of visitors' experiences at the street level. Keywords under four topics are discussed by two groups of sentiments and two datasets (Fig. 6b), namely, history, religion, space and activity (Fig. 6c, d). Keywords of history topic highlight Malay culture and Arab Street discussed on Twitter. TripAdvisor reviews

discuss more walking experiences and recreational activities in space and activity topics.

Findings of Twitter and TripAdvisor data suggest several spatial elements related to the Liveability at Haji Lane. The Liveability at the street level is mainly contributed by space and activity with fewer factors from history and religion topics (Fig. 6c) compared to that at the district level (Fig. 4c). More granular positive experiences are detected from TripAdvisor reviews, ranging from restaurants, cafes, shops, arts, and bars (Fig. 6c). It suggests street-level can provide more details about tourism demand and draw insights into tourism planning to enhance the Liveability. Negative sentiments (Fig. 6d) are still associated with recreational experiences which might be irrelevant to Liveability.

6 Cross-level differences in urban space quality
The third comparison is between the results of Haji Lane with the same approach and district-level findings to discuss cross-level differences in user perceptions and demands, drawing insights into placemaking strategies to enhance the Uniqueness, Vitality, and Liveability of Kampong Glam and Haji Lane.

6.1 Statistic difference between Kampong Glam and Haji Lane
Table 3 presents a detailed statistical analysis of the differences between Kampong Glam and Haji Lane among data from various platforms. For imagery data, Pearson's Chi-squared test and its variant with a simulated p-value (based on 2000 replicates) were applied to the frequency of image labels detected from GSV and Flickr images. Significant differences were noted in GSV data, with a Chi-squared value of 14.984 yielding p-values of 0.010 and 0.005, respectively, suggesting notable disparities in image labelling or content between the two spatial levels. In contrast, Flickr data showed no significant differences, with Chi-squared values of 7.402 and higher p-values of 0.192 and 0.175. Since GSV imagery is collected with a constant sight and covers the entire area, the difference between the two spatial levels justifies the reliability of using street view imagery to form an objective understanding of the built environment. For Flickr imagery, users have consistent preferences for spatial elements shared through photos, suggesting the validity of the proposed approach mining user perceptions from this platform to study their spatial preferences and evaluate urban space qualities.

For text data, the Wilcoxon rank sum test with continuity correction analyzed sentiment scores from Twitter tweets and TripAdvisor reviews. Both datasets showed high statistic values (256,310 for Twitter and 109,220 for TripAdvisor) but yielded non-significant p-values of
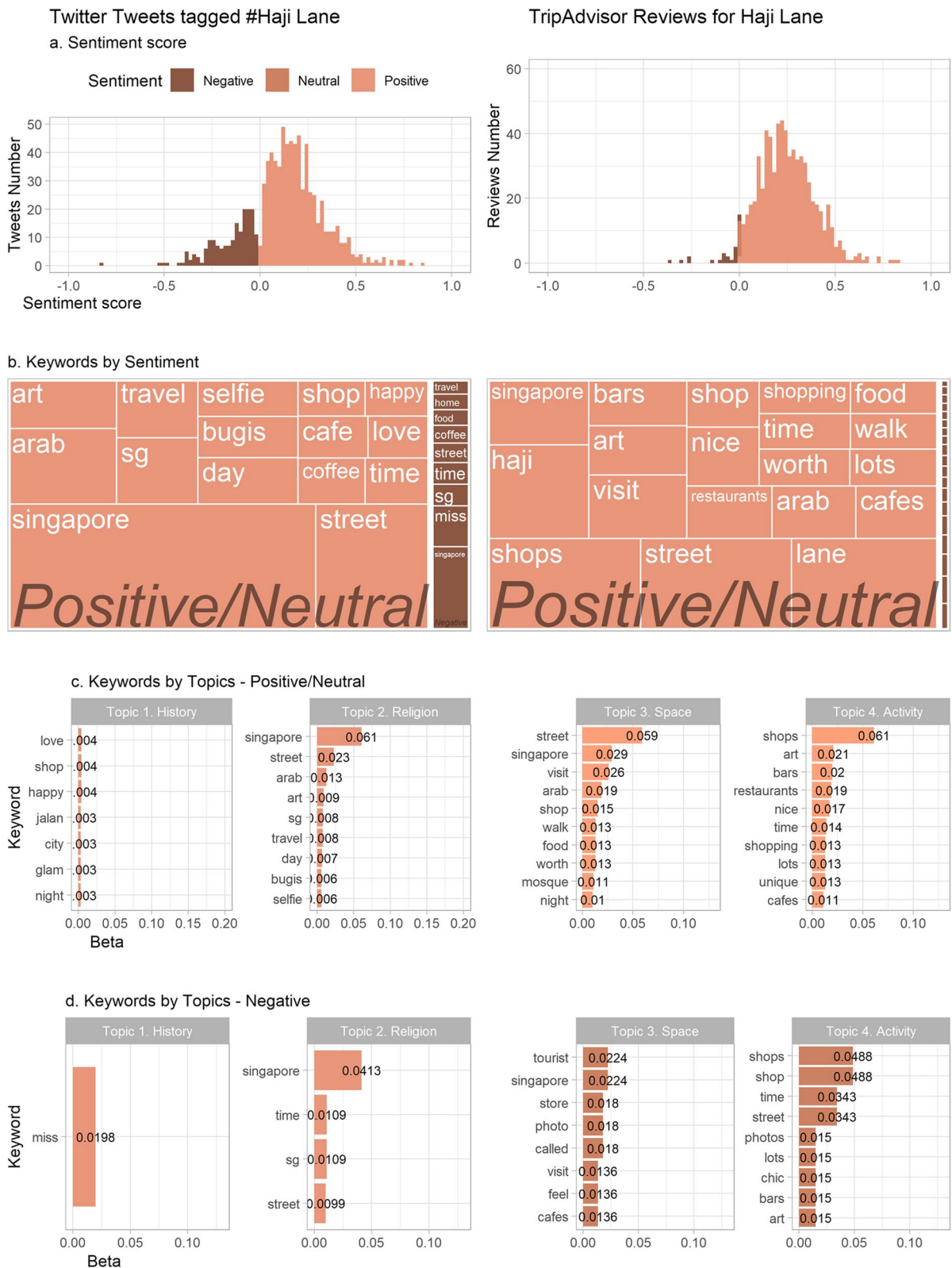
Fig. 6 Comparison II—Twitter Tweets and TripAdvisor reviews at Haji Lane

Table 3 Statistical differences in imagery labels and text sentiments between Kampong Glam and Haji Lane

a. Statistical differences in image labels of Google Street View and Flickr imagery using Pearson's Chi-squared test

Chi-squared (X2)	*P*_value	Signif	Method	Area	Description
14.984	**0.010**	**	Pearson's Chi-squared test	Comparison III: Kampong Glam and Haji Lane	**Google Street View**
7.402	0.192				Flickr
14.984	**0.005**	**	Pearson's Chi-squared test with simulated *p*-value (based on 2000 replicates)		**Google Street View**
7.402	0.175				Flickr

b. Statistical differences in sentiment scores of Twitter Tweets and TripAdvisor Reviews using Wilcoxon rank sum test with continuity correction

Statistic	*P*_value	Method	Area	Description
256310	0.836	Wilcoxon rank sum test with continuity correction	Comparison III: Kampong Glam and Haji Lane	Twitter Tweets' sentiment scores
109220	0.529	Wilcoxon rank sum test with continuity correction		TripAdvisor Reviews ' sentiment scores

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

0.836 and 0.529, respectively, indicating that there are no notable differences in sentiment between the texts regarding Kampong Glam and Haji Lane. These results further indicate the consistency of user-generated content on social media, suggesting an alignment of Liveability across district and street levels.

6.2 Relationship between Kampong Glam and Haji Lane

Although Haji Lane is part of the Kampong Glam district, users' preferences show different focuses. The Uniqueness and Vitality perceived by citizens based on their photos show a functional shift from history and religion at the district level to recreational activities at the street level. Future placemaking strategies can further emphasize the dominant elements that contributed to Uniqueness and Vitality, including diverse activities and wall painting with graffiti at Haji Lane. Experiences related to Liveability show similar focus at two levels. In Kampong Glam, keywords with high relevance to positive emotions are very diverse, encompassing a variety of aspects related to cultural background, landmarks, and activities, such as Sultan Mosque, unique streets, ethnic food, and so on. In contrast, the street-level results correspond to some of the characteristics of the district, but are more focused and prominent, relating mainly to the wall paintings, shops, and restaurants on the street. This is because the active street edges (Gehl, 1987) with wall paintings and shops enable interactions between citizens and promote online communication about popular places with photos.

Given the differences in use-generated social media text at different spatial levels, policymakers should establish different strategies when collecting specific user groups' feedback on the Liveability of the district or street. Common users from Twitter and tourists from TripAdvisor have different preferences and sharing demands in terms of Liveability. Twitter users share less information at street level compared with the amount of posts about Haji Lane. TripAdvisor users remain interested in both district and street, with considerable attention to specific places and activities.

7 Discussion

This case study at Kampong Glam and Haji Lane remarkably reveals spatial elements contributing to Uniqueness, Vitality and Liveability according to users' perceptions. The application of these insights into urban space qualities and user-centric placemaking methods extends beyond the local context. Furthermore, the results indicate the implications of this approach for urban planning and GeoAI research, underscoring the benefits of fusing street view imagery, multi-source social media data and AI tools for urban sensing. Specifically, this approach exemplifies how integrating diverse data sources can transform urban planning strategies globally, addressing challenges such as data bias caused by user groups and incomplete data coverage commonly faced in the field.

7.1 Implications of the proposed approach in broader fields

The proposed structural approach of the study can be practically applied in the preparatory phase of placemaking and urban revitalization in diverse urban contexts to form a comprehensive investigation of the built environment, users' perceptions, and users' demands on urban spaces. Identified spatial features of Uniqueness emphasize the anchor of the local culture and integrate heritage conservation with urban planning. Perceived spatial elements of Vitality specify dominant social and commercial activities in districts and streets. Variety in experiences about Liveability across different user groups indicates the necessity of inclusive placemaking strategies. The detailed investigation of the above urban space qualities can guide urban planners in the design and

implementation of public spaces that enhance community engagement and satisfaction, with insights into targeted interventions in areas facing diverse demands on residence, commerce, and tourism.

The advantages of employing advanced GeoAI techniques with street view imagery for objective information not only complement traditional investigation methods but also lead to a more granular and accurate perception of the built environment. This study justifies the applicability of using GSV as a baseline to quantify spatial elements from the built environment, building upon previous research in street view imagery (Biljecki & Ito, 2021; Y. Kang et al., 2020). This comparative approach can be implemented for urban planning as a virtual site investigation for both objective and subjective evaluation of citizens' demands. Object detection (J. Liu et al., 2020a, 2020b) and image classification(J. Kang et al., 2018; Kubany et al., 2020) have been widely used for element-level observation in the built environment with street view imagery. With a pre-trained CV model and street view imagery from an omnipresent map service, the researcher can quantify spatial elements in most urban areas with robust data sources and get valid results.

While advanced technologies provide the tools necessary for detailed urban analysis, the real insights are gleaned from the diverse data they process. The analyses of text and imagery through these technologies shed light on nuanced urban dynamics, illustrating how different types of data can reveal varied aspects of urban life perceived and preferred by citizens. This study analyses social media data in two formats, text and imagery, which play different roles in the evaluation of urban space quality from users' perspectives. In general, textual data contains more detailed and accurate descriptions of activities and spatial preferences. The richness of their expressive meanings requires information extraction with in-depth profiling and summarization (Gu & Shen, 2019). By comparison, social media imagery is usually photos recording user's experiences (Y. Li & Xie, 2020; Vaziri et al., 2020). Social media users share photos for some reasons which also reflect their sentiments when perceiving the city (Chen et al., 2017; Harvey, 2013). Elements derived from the positive or negative sentiments of tourists' reviews and social media imagery about users' experiences can be indicative of urban planning to make cities inclusive, safe, resilient and sustainable (UNDP, 2015; United Nations, 2023).

Furthermore, the fusion of multi-source data enriches the understanding of urban spaces perceived by diverse social groups and alleviates the bias of a single data source in urban sensing. Social media data as a kind of user-generated content is shared by users for communication, friendship maintenance, job seeking, or self-presentation, which is generated more spontaneously and unconsciously compared to traditional methods like surveys and interviews (Olteanu et al., 2019). As a result, social media data is believed to reflect more genuine and unfiltered user perspectives, free from the biases that might arise from the structured nature of surveys or the influence of observers. Since user groups and services vary among platforms (Harvey, 2013), a combination of data from multiple social media can provide multi-perspective information about one urban area perceived by different user groups (Heikinheimo et al., 2020; Martí et al., 2019). Social media data from Twitter contains citizen's general ideas while TripAdvisor as a tourist-oriented platform can be a convincing indicator of tourists' demands. As existing research has shed light on the different demands between residents and tourists (Chen et al., 2017; Ellard et al., 1999), such a comparison can assist policymakers in developing targeted strategies for an inclusive society.

7.2 Limitations and future work

While the insights garnered from this study are based on data from specific urban areas, the methodologies employed are designed with adaptability in mind. Urban planners in different geographical and cultural contexts might adjust the data collection method and GeoAI techniques based on local data availability and research demands. This adaptability ensures that the approach remains effective in diverse urban settings, from single public spaces such as parks, to higher spatial levels, such as cities and regions.

Constraints in data availability and pre-trained AI models lead to the limitations of this study. The selection of street view images at the junction (Fig. 2) for collection efficiency cannot cover every spatial element in the built environment. While the data fusion approach provides a comprehensive view, the reliance on social media introduces potential biases reflecting active internet users' perspectives more than populations with difficulty accessing social media platforms (Martí et al., 2019). The integration of multi-source social media data may only be suitable for research in active and popular urban spaces with large user groups for a valid analysis (Viñán-Ludeña et al., 2020). Additionally, the study's reliance on visual data may overlook non-visual aspects of urban spaces, such as smell (Henshaw, 2013) and sound (Rey Gozalo et al., 2018), that are crucial for a holistic understanding of urban space qualities, inspiring future studies to address these gaps. Besides, Geographic coordinate information of social media posts and images was not included due to the privacy restrictions of social platforms, while some social media data with crowdsourcing

services can be alternatives for geographical data (P. Liu & Biljecki, 2022; Y. Wang et al., 2021).

Google Cloud Vision AI has general limitations of pre-trained AI models (Bisong, 2019; Han et al., 2021), suggesting the potential for customized models with fine-tuning in future studies. As a pre-trained model, Google Cloud Vision AI used in this study can only extract and describe relatively rough information and object labels from images (Bisong, 2019; Omena et al., 2021), with lower accuracy for smaller objects (Nguyen et al., 2019). As a result, label detection cannot accurately quantify spatial features such as the number of windows in the GSV imagery and other important features, including street wall continuity (Jacobs, 1961), window opening density (Gehl, 1987), and building setback (Gehl, 1987). However, with the fine-tuning process and proper data, improvement in the performance of pre-trained AI models in future research will be achievable (Han et al., 2021).

Based on the above discussions on data and technique constraints, future research should focus on expanding the data sources to explore citizens' multi-facet sensory and non-visual perceptions of urban environments, such as noise (Rey Gozalo et al., 2018), smellscapes (Henshaw, 2013), and air quality (Tao et al., 2019). Additionally, longitudinal studies could assess the long-term impacts of urban planning interventions inspired by GeoAI and multi-source data insights. Furthermore, the trending multi-modal deep learning method (Qian et al., 2016; Suel et al., 2021) promotes the potential to extract users' opinions from text and imagery data with internal relationships. The correlations between textual and visual modalities and the separation of the visual-representative topics and non-visual-representative topics can level up the understanding of users' perceptions and contribute to the integration of multiple sensory data in urban sensing research. These directions would not only refine the proposed approach for user-centric urban planning but also broaden the scope of the application of data and GeoAI techniques in the field of urban informatics.

8 Conclusion

The impactful insights and the potential for future developments in urban informatics have been revealed through the integration of multi-source big data and advanced GeoAI techniques, setting a context for ongoing enhancements in how we perceive, understand and revitalize urban spaces. This section summarizes the novelty and contribution of this exploratory study and extends the implications of the research findings in urban planning, urban sensing and wider fields.

This exploratory study integrates multi-source social media data and GSV imagery with Google Cloud Vision AI to evaluate urban space quality in Kampong Glam district and one affiliate street, Haji Lane. The results identify specific physical spatial features and activities that visitors are interested in and interpret the urban space quality of the district and street from users' perspectives: Uniqueness, Vitality, and Liveability. Thus, the research findings provide suggestions for placemaking processes in Kampong Glam and Haji Lane, indicating the applicability of the proposed approach in broader urban contexts.

The variety in information from different data sources at different spatial levels is underscored through the cross-level study at Kampong Glam and Haji Lane. The cross-level comparison raises the awareness of the consistency in spatial features under same cultural background from districts to streets and emphasizes how diverse amenities, services and spaces among streets shape the overall urban perception of the district. Stakeholders such as urban planners, local businesses, and community groups can gain valuable insights from cross-level investigations into structured strategies to enhance urban space quality at different spatial levels while considering its cultural and social features.

The proposed approach employs Google Cloud Vision AI to collaboratively analyze multi-source datasets, is replicable and can address technical barriers for urban researchers. Urban designers and policymakers can apply the approach to understand the user-generated imagery of any districts or streets collected from social media (Y. Li & Xie, 2020), street view (Biljecki & Ito, 2021), etc., in combination with traditional research methods, such as observation and surveys, to improve the urban space quality and promote urban revitalization.

This study uniquely contributes to the field of urban space quality evaluation from a user-centric perspective, exploring a new approach for data-driven urban space quality analysis with multi-source data and GeoAI tools. The findings highlight the diverse perceptions of different user groups, especially the active spaces and activities that are of interest to people, and enriches the understanding of urban space qualities, including Uniqueness, Vitality, and Liveability. The evaluation approach of urban space qualities can be used to identify spaces that are currently well-developed and those that are more challenged (M. Li et al., 2021; Y. Li & Derudder, 2022). On this basis, urban planners and policymakers can propose targeted strategies towards the development needs of the site (He et al., 2024; Y. Song et al., 2020a, 2020b). The nuanced insights into user preferences and spatial demands drawn from this study can inform policymakers and contribute to future placemaking processes for more unique, vibrant and liveable urban spaces.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1007/s44212-024-00052-w.

> Supplementary Material 1

Declarations

Competing interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Abbasi, A., Alalouch, C., & Bramley, G. (2016). Open space quality in deprived urban areas: user perspective and use pattern. *Procedia - Social and Behavioral Sciences, 216*, 194–205. https://doi.org/10.1016/j.sbspro.2015.12.028

Abdul-Rahman, M., Chan, E. H. W., Wong, M. S., Irekponor, V. E., & Abdul-Rahman, M. O. (2021). A framework to simplify pre-processing location-based social media big data for sustainable urban planning and management. *Cities, 109*, 102986. https://doi.org/10.1016/j.cities.2020.102986

Appleyard, D., Lynch, K., & Myer, J. R. (1971). *The view from the road*. M.I.T. Press.

Badland, H., Whitzman, C., Lowe, M., Davern, M., Aye, L., Butterworth, I., Hes, D., & Giles-Corti, B. (2014). Urban liveability: Emerging lessons from Australia for exploring the potential for indicators to measure the social determinants of health. *Social Science & Medicine, 111*, 64–73. https://doi.org/10.1016/j.socscimed.2014.04.003

Belkahla Driss, O., Mellouli, S., & Trabelsi, Z. (2019). From citizens to government policy-makers: Social media data analysis. *Government Information Quarterly, 36*(3), 560–570. https://doi.org/10.1016/j.giq.2019.05.002

Biljecki, F., & Ito, K. (2021). Street view imagery in urban analytics and GIS: a review. *Landscape and Urban Planning, 215*, 104217. https://doi.org/10.1016/j.landurbplan.2021.104217

Biljecki, F., Zhao, T., Liang, X., & Hou, Y. (2023). Sensitivity of measuring the urban form and greenery using street-level imagery: a comparative study of approaches and visual perspectives. *International Journal of Applied Earth Observation and Geoinformation, 122*, 103385. https://doi.org/10.1016/j.jag.2023.103385

Bisong, E. (2019). An Overview of Google Cloud Platform Services. In E. Bisong (Ed.), *Building Machine Learning and Deep Learning Models on Google Cloud Platform: A Comprehensive Guide for Beginners* (pp. 7–10). Apress. https://doi.org/10.1007/978-1-4842-4470-8_2

Burton, E., & Mitchell, L. (2006). *Inclusive Urban Design: Streets For Life*. Routledge https://doi.org/10.4324/9780080456454

Chang, H., Huang, J., Yao, W., Zhao, W., & Li, L. (2022). How do new transit stations affect people's sentiment and activity? A case study based on social media data in Hong Kong. *Transport Policy, 120*, 139–155. https://doi.org/10.1016/j.tranpol.2022.03.011

de Chazal, J. (2010). A systems approach to livability and sustainability: Defining terms and mapping relationships to link desires with ecological opportunities and constraints. *Systems Research and Behavioral Science, 27*(5), 585–597. https://doi.org/10.1002/sres.1058

Chen, F.-W., Guevara Plaza, A., & Alarcón Urbistondo, P. (2017). Automatically extracting tourism-related opinion from Chinese social media. *Current Issues in Tourism, 20*(10), 1070–1087. https://doi.org/10.1080/13683500.2015.1132196

Chen, J., Konijnendijk van den Bosch, C. C., Lin, C., Liu, F., Huang, Y., Huang, Q., Wang, M., Zhou, Q., & Dong, J. (2021). Effects of personality, health and mood on satisfaction and quality perception of urban mountain parks. *Urban Forestry & Urban Greening, 63*, 127210. https://doi.org/10.1016/j.ufug.2021.127210

Ellard, A., Cheek, K., & Nickerson, N. (1999). Missoula Case Study: Direct Impact of Visitor Spending on a Local Economy. *Institute for Tourism and Recreation Research Publications*. https://scholarworks.umt.edu/itrr_pubs/120

Fagan, J., & Davies, G. (2000). Street stops and broken windows: terry, race and disorder in New York City. *Fordham Urb. l. J., 28*, 457.

Gehl, J. (1987). *Life between buildings: Using public space*. Van Nostrand Reinhold.

Gu, Y., & Shen, J. (2019). Short Text Classification Based on Keywords Extension. *Chinese Automation Congress (CAC), 2019*, 2616–2621. https://doi.org/10.1109/CAC48633.2019.8996664

Guan, F., Fang, Z., Wang, L., Zhang, X., Zhong, H., & Huang, H. (2022). Modelling people's perceived scene complexity of real-world environments using street-view panoramas and open geodata. *ISPRS Journal of Photogrammetry and Remote Sensing, 186*, 315–331. https://doi.org/10.1016/j.isprsjprs.2022.02.012

Guo, X., Yang, Y., Cheng, Z., Wu, Q., Li, C., Lo, T., & Chen, F. (2022). Spatial social interaction: an explanatory framework of urban space vitality and its preliminary verification. *Cities, 121*, 103487. https://doi.org/10.1016/j.cities.2021.103487

Han, S. J. (2016). *Effects of pedestrianisation on retail businesses: a study of a Singapore Street, Haji Lane* [Dissertation]. https://scholarbank.nus.edu.sg/handle/10635/221681

Han, X., Zhang, Z., Ding, N., Gu, Y., Liu, X., Huo, Y., Qiu, J., Yao, Y., Zhang, A., Zhang, L., Han, W., Huang, M., Jin, Q., Lan, Y., Liu, Y., Liu, Z., Lu, Z., Qiu, X., Song, R., & Zhu, J. (2021). Pre-trained models: past, present and future. *AI Open, 2*, 225–250. https://doi.org/10.1016/j.aiopen.2021.08.002

Harvey, K. (2013). *Encyclopedia of Social Media and Politics*. SAGE Publications.

Hausmann, A., Toivonen, T., Fink, C., Heikinheimo, V., Kulkarni, R., Tenkanen, H., & Di Minin, E. (2020). Understanding sentiment of national park visitors from social media data. *People and Nature, 2*(3), 750–760. https://doi.org/10.1002/pan3.10130

He, X., Zhou, Y., Yuan, X., & Zhu, M. (2024). The coordination relationship between urban development and urban life satisfaction in Chinese cities—an empirical analysis based on multi-source data. *Cities, 150*, 105016. https://doi.org/10.1016/j.cities.2024.105016

Heikinheimo, V., Tenkanen, H., Bergroth, C., Järv, O., Hiippala, T., & Toivonen, T. (2020). Understanding the use of urban green spaces from user-generated geographic information. *Landscape and Urban Planning, 201*, 103845. https://doi.org/10.1016/j.landurbplan.2020.103845

Heng, J., Liu, J., & Hui Lim, K. (2020). Urban crowdsensing using social media: an empirical study on transformer and recurrent neural networks. *IEEE International Conference on Big Data (big Data), 2020*, 5695–5697. https://doi.org/10.1109/BigData50022.2020.9377865

Henshaw, V. (2013). *Urban Smellscapes: Understanding and Designing City Smell Environments. Routledge*. https://doi.org/10.4324/9780203072776

Herzog, T. R. (1989). A cognitive analysis of preference for urban nature. *Journal of Environmental Psychology, 9*(1), 27–43. https://doi.org/10.1016/S0272-4944(89)80024-6

Hu, Y., Deng, C., & Zhou, Z. (2019). A semantic and sentiment analysis on online neighborhood reviews for understanding the perceptions of people toward their living environments. *Annals of the American Association of Geographers, 109*(4), 1052–1073. https://doi.org/10.1080/24694452.2018.1535886

Huang, B., Zhou, Y., Li, Z., Song, Y., Cai, J., & Tu, W. (2020). Evaluating and characterizing urban vibrancy using spatial big data: Shanghai as a case study. *Environment and Planning b: Urban Analytics and City Science, 47*(9), 1543–1559. https://doi.org/10.1177/2399808319828730

Jacobs, J. (1961). *The death and life of great American cities*. Random House.

Janowicz, K., Gao, S., McKenzie, G., Hu, Y., & Bhaduri, B. (2020). GeoAI: Spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. *International Journal of Geographical Information Science, 34*(4), 625–636. https://doi.org/10.1080/13658816.2019.1684500

Jiang, L., Guo, R., Wang, W., & Li, X. (2024). *Topic modelling of people's concern about the urban village unified leasing in Shenzhen*. CRC Press.

Kang, C., Fan, D., & Jiao, H. (2021). Validating activity, time, and space diversity as essential components of urban vitality. *Environment and Planning b: Urban Analytics and City Science, 48*(5), 1180–1197. https://doi.org/10.1177/2399808320919771

Kang, J., Körner, M., Wang, Y., Taubenböck, H., & Zhu, X. X. (2018). Building instance classification using street view images. *ISPRS Journal of Photogrammetry and Remote Sensing, 145*, 44–59. https://doi.org/10.1016/j.isprsjprs.2018.02.006

Kang, Y., Abraham, J., Ceccato, V., Duarte, F., Gao, S., Ljungqvist, L., Zhang, F., Näsman, P., & Ratti, C. (2023). Assessing differences in safety perceptions using GeoAI and survey across neighbourhoods in Stockholm. *Sweden. Landscape and Urban Planning, 236*, 104768. https://doi.org/10.1016/j.landurbplan.2023.104768

Kang, Y., Zhang, F., Gao, S., Lin, H., & Liu, Y. (2020). A review of urban physical environment sensing using street view imagery in public health studies. *Annals of GIS, 26*(3), 261–275. https://doi.org/10.1080/19475683.2020.1791954

Kruse, J., Kang, Y., Liu, Y.-N., Zhang, F., & Gao, S. (2021). Places for play: Understanding human perception of playability in cities using street view images and deep learning. *Computers, Environment and Urban Systems, 90*, 101693. https://doi.org/10.1016/j.compenvurbsys.2021.101693

Kubany, A., Ben Ishay, S., Ohayon, R. S., Shmilovici, A., Rokach, L., & Doitshman, T. (2020). Comparison of state-of-the-art deep learning APIs for image multi-label classification using semantic metrics. *Expert Systems with Applications, 161*, 113656. https://doi.org/10.1016/j.eswa.2020.113656

Kumar, V. (2020). When heritage meets creativity: a tale of two urban development strategies in Kampong Glam Singapore. *City & Community, 19*(2), 398–420. https://doi.org/10.1111/cico.12427

Lee, H., & Kang, Y. (2021). Mining tourists' destinations and preferences through LSTM-based text classification and spatial clustering using Flickr data. *Spatial Information Research, 29*(6), 825–839. https://doi.org/10.1007/s41324-021-00397-3

Li, M., Liu, J., Lin, Y., Xiao, L., & Zhou, J. (2021). Revitalizing historic districts: Identifying built environment predictors for street vibrancy based on urban sensor data. *Cities, 117*, 103305. https://doi.org/10.1016/j.cities.2021.103305

Li, Y., & Derudder, B. (2022). Dynamics in the polycentric development of Chinese cities, 2001–2016. *Urban Geography, 43*(2), 272–292. https://doi.org/10.1080/02723638.2020.1847938

Li, Y., & Xie, Y. (2020). Is a picture worth a thousand words? An empirical study of image content and social media engagement. *Journal of Marketing Research, 57*(1), 1–19. https://doi.org/10.1177/0022243719881113

Liao, Y., Yeh, S., & Gil, J. (2022). Feasibility of estimating travel demand using geolocations of social media data. *Transportation, 49*(1), 137–161. https://doi.org/10.1007/s11116-021-10171-x

Liu, J., Bi, H., & Wang, M. (2020a). Using multi-source data to assess livability in Hong Kong at the community-based level: a combined subjective-objective approach. *Geography and Sustainability, 1*(4), 284–294. https://doi.org/10.1016/j.geosus.2020.12.001

Liu, P., & Biljecki, F. (2022). A review of spatially-explicit GeoAI applications in urban geography. *International Journal of Applied Earth Observation and Geoinformation, 112*, 102936. https://doi.org/10.1016/j.jag.2022.102936

Liu, P., Zhao, T., Luo, J., Lei, B., Frei, M., Miller, C., & Biljecki, F. (2023). Towards human-centric digital twins: leveraging computer vision and graph models to predict outdoor comfort. *Sustainable Cities and Society, 93*, 104480. https://doi.org/10.1016/j.scs.2023.104480

Liu, Y., Yuan, Y., & Zhang, F. (2020). Mining urban perceptions from social media data. *Journal of Spatial Information Science, 20*. https://doi.org/10.5311/josis.2020.20.665

Lynch, K. (1960). *The image of the city* (33. print). M.I.T. Press.

Lynch, K. (1995). *City Sense and City Design: Writings and Projects of Kevin Lynch*. MIT Press.

Ma, S., Wang, B., Liu, W., Zhou, H., Wang, Y., & Li, S. (2024). Assessment of street space quality and subjective well-being mismatch and its impact, using multi-source big data. *Cities, 147*, 104797. https://doi.org/10.1016/j.cities.2024.104797

Mann, H. B., & Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *The Annals of Mathematical Statistics, 18*(1), 50–60.

Marchi, V., Speak, A., Ugolini, F., Sanesi, G., Carrus, G., & Salbitano, F. (2022). Attitudes towards urban green during the COVID-19 pandemic via Twitter. *Cities, 126*, 103707. https://doi.org/10.1016/j.cities.2022.103707

Martí, P., Serrano-Estrada, L., & Nolasco-Cirugeda, A. (2019). Social media data: challenges, opportunities and limitations in urban studies. *Computers, Environment and Urban Systems, 74*, 161–174. https://doi.org/10.1016/j.compenvurbsys.2018.11.001

Montgomery, J. (1998). Making a city: urbanity, vitality and urban design. *Journal of Urban Design, 3*(1), 93–116. https://doi.org/10.1080/13574809808724418

Mouratidis, K. (2021). Urban planning and quality of life: a review of pathways linking the built environment to subjective well-being. *Cities, 115*, 103229. https://doi.org/10.1016/j.cities.2021.103229

Mouratidis, K., Ettema, D., & Næss, P. (2019). Urban form, travel behavior, and travel satisfaction. *Transportation Research Part a: Policy and Practice, 129*, 306–320. https://doi.org/10.1016/j.tra.2019.09.002

Nguyen, Q. C., Khanna, S., Dwivedi, P., Huang, D., Huang, Y., Tasdizen, T., Brunisholz, K. D., Li, F., Gorman, W., Nguyen, T. T., & Jiang, C. (2019). Using google street view to examine associations between built environment characteristics and U.S. Health outcomes. *Preventive Medicine Reports, 14*, 100859. https://doi.org/10.1016/j.pmedr.2019.100859

Norouzian-Maleki, S., Bell, S., Hosseini, S.-B., Faizi, M., & Saleh-Sedghpour, B. (2018). A comparison of neighbourhood liveability as perceived by two groups of residents: Tehran, Iran and Tartu, Estonia. *Urban Forestry & Urban Greening, 35*, 8–20. https://doi.org/10.1016/j.ufug.2018.08.004

Olteanu, A., Castillo, C., Diaz, F., & Kıcıman, E. (2019). Social data: biases, methodological pitfalls, and ethical boundaries. *Frontiers in Big Data, 2*, 13. https://doi.org/10.3389/fdata.2019.00013

Omena, J. J., Elena, P., Gobbo, B., & Jason, C. (2021). The Potentials of Google Vision API-based Networks to Study Natively Digital Images. *Diseña, 19*, Article 19. https://doi.org/10.7764/disena.19.Article.1

Pacione, M. (1990). Urban liveability: a review. *Urban Geography, 11*(1), 1–30. https://doi.org/10.2747/0272-3638.11.1.1

Pineo, H. (2022). Towards healthy urbanism: Inclusive, equitable and sustainable (THRIVES) – an urban design and planning framework from theory to praxis. *Cities & Health*. https://www.tandfonline.com/doi/abs/10.1080/23748834.2020.1769527

Plackett, R. L. (1983). Karl Pearson and the Chi-Squared test. *International Statistical Review / Revue Internationale De Statistique, 51*(1), 59–72. https://doi.org/10.2307/1402731

Plunz, R. A., Zhou, Y., Carrasco Vintimilla, M. I., Mckeown, K., Yu, T., Uguccioni, L., & Sutto, M. P. (2019). Twitter sentiment in New York City parks as measure of well-being. *Landscape and Urban Planning, 189*, 235–246. https://doi.org/10.1016/j.landurbplan.2019.04.024

Qian, S., Zhang, T., Xu, C., & Shao, J. (2016). Multi-modal event topic model for social event analysis. *IEEE Transactions on Multimedia, 18*(2), 233–246. https://doi.org/10.1109/TMM.2015.2510329

Qiu, W., Li, W., Liu, X., & Huang, X. (2021). Subjectively measured streetscape perceptions to inform urban design strategies for Shanghai. *ISPRS International Journal of Geo-Information, 10*(8), 493. https://doi.org/10.3390/ijgi10080493

Qiu, W., Li, W., Liu, X., & Huang, X. (2022). Subjectively Measured Streetscape Qualities for Shanghai with Large-Scale Application of Computer Vision and Machine Learning. In P. F. Yuan, H. Chai, C. Yan, & N. Leach (Eds.), *Proceedings of the 2021 DigitalFUTURES* (pp. 242–251). Springer Singapore. https://doi.org/10.1007/978-981-16-5983-6_23

Quinn, B., Colombo, A., Lindström, K., McGillivray, D., & Smith, A. (2021). Festivals, public space and cultural inclusion: public policy insights. *Journal of Sustainable Tourism, 29*(11–12), 1875–1893. https://doi.org/10.1080/09669582.2020.1858090

Rey Gozalo, G., Barrigón Morillas, J. M., Montes González, D., & Atanasio Moraga, P. (2018). Relationships among satisfaction, noise perception,

and use of urban green spaces. *Science of the Total Environment, 624*, 438–450. https://doi.org/10.1016/j.scitotenv.2017.12.148

Shekhar, H., Schmidt, A. J., & Wehling, H.-W. (2019). Exploring wellbeing in human settlements—a spatial planning perspective. *Habitat International, 87*, 66–74. https://doi.org/10.1016/j.habitatint.2019.04.007

Shi, W., Batty, M., Goodchild, M., & Li, Q. (2022). The digital transformation of cities. *Urban Informatics, 1*(1), 1. https://doi.org/10.1007/s44212-022-00005-1

Simpson, J., Freeth, M., Simpson, K. J., & Thwaites, K. (2019). Visual engagement with urban street edges: Insights using mobile eye-tracking. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability, 12*(3), 259–278. https://doi.org/10.1080/17549175.2018.1552884

Smith, T., Nelischer, M., & Perkins, N. (1997). Quality of an urban community: a framework for understanding the relationship between quality and physical form. *Landscape and Urban Planning, 39*(2), 229–241. https://doi.org/10.1016/S0169-2046(97)00055-8

Song, X. P., Richards, D. R., & Tan, P. Y. (2020). Using social media user attributes to understand human–environment interactions at urban parks. *Scientific Reports, 10*(1), 808. https://doi.org/10.1038/s41598-020-57864-4. Article 1.

Song, Y., Fernandez, J., & Wang, T. (2020). Understanding perceived site qualities and experiences of urban public spaces: a case study of social media reviews in Bryant Park New York City. *Sustainability, 12*(19), 8036. https://doi.org/10.3390/su12198036. Article 19.

Suel, E., Bhatt, S., Brauer, M., Flaxman, S., & Ezzati, M. (2021). Multimodal deep learning from satellite and street-level imagery for measuring income, overcrowding, and environmental deprivation in urban areas. *Remote Sensing of Environment, 257*, 112339. https://doi.org/10.1016/j.rse.2021.112339

Sulis, P., Manley, E., Zhong, C., & Batty, M. (2018). Using mobility data as proxy for measuring urban vitality. *Journal of Spatial Information Science, 2018*(16), 137–162. https://doi.org/10.5311/JOSIS.2018.16.384

Szeliski, R. (2022). *Computer Vision: Algorithms and Applications* (2nd edition). Springer Nature.

Tao, Y., Zhang, F., Shi, C., & Chen, Y. (2019). Social media data-based sentiment analysis of tourists' air quality perceptions. *Sustainability, 11*(18), 5070. https://doi.org/10.3390/su11185070. Article 18.

Trivic, Z. (2023). Older adults' multi-sensory experience: an eye-tracking study of high-density residential neighbourhoods in Singapore. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability, 0*(0), 1–40. https://doi.org/10.1080/17549175.2023.2229808

UNDP. (2015). *Goal 11: Sustainable cities and communities | Sustainable Development Goals | United Nations Development Programme*. UNDP. https://www.undp.org/sustainable-development-goals/sustainable-cities-and-communities

United Nations. (2023). *The Sustainable Development Goals Report 2023: Special Edition*. https://unstats.un.org/sdgs/report/2023/?_gl=1*1ptdomb*_ga*NjQ4MzYzMjcxLjE3MDk1MTUyMTI.*_ga_TK9BQL5X7Z*MTcxMzUyNDA5MC4xLjAuMTcxMzUyNDA5MC4wLjAuMA..

URA.SG. (2024). *Kampong Glam*. https://www.ura.gov.sg/Conservation-Portal/Explore/History?bldgid=KPGL

Vaziri, F., Nanni, M., Matwin, S., & Pedreschi, D. (2020). Discovering Tourist Attractions of Cities Using Flickr and OpenStreetMap Data. In Á. Rocha, A. Abreu, J. V. de Carvalho, D. Liberato, E. A. González, & P. Liberato (Eds.), *Advances in Tourism, Technology and Smart Systems* (pp. 231–241). Springer. https://doi.org/10.1007/978-981-15-2024-2_21

Viñán-Ludeña, M. S., de Campos, L. M., Jacome-Galarza, L.-R., & Sinche-Freire, J. (2020). Social Media Influence: A Comprehensive Review in General and in Tourism Domain. In Á. Rocha, A. Abreu, J. V. de Carvalho, D. Liberato, E. A. González, & P. Liberato (Eds.), *Advances in Tourism, Technology and Smart Systems* (pp. 25–35). Springer. https://doi.org/10.1007/978-981-15-2024-2_3

Vision AI | Derive Image Insights via ML | Cloud Vision API. (2024). Google Cloud. https://cloud.google.com/vision

Wang, R., Liu, Y., Lu, Y., Yuan, Y., Zhang, J., Liu, P., & Yao, Y. (2019). The linkage between the perception of neighbourhood and physical activity in Guangzhou, China: using street view imagery with deep learning techniques. *International Journal of Health Geographics, 18*(1), 18. https://doi.org/10.1186/s12942-019-0182-z

Wang, Y., Gao, S., Li, N., & Yu, S. (2021). Crowdsourcing the perceived urban built environment via social media: the case of underutilized land. *Advanced Engineering Informatics, 50*, 101371. https://doi.org/10.1016/j.aei.2021.101371

Yap, W., Janssen, P., & Biljecki, F. (2022). Free and open source urbanism: Software for urban planning practice. *Computers, Environment and Urban Systems, 96*, 101825. https://doi.org/10.1016/j.compenvurbsys.2022.101825

You, L., & Tunçer, B. (2016). Exploring public sentiments for livable places based on a crowd-calibrated sentiment analysis mechanism. *IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), 2016*, 693–700. https://doi.org/10.1109/ASONAM.2016.7752312

Zhang, F., Fan, Z., Kang, Y., Hu, Y., & Ratti, C. (2021). "Perception bias": Deciphering a mismatch between urban crime and perception of safety. *Landscape and Urban Planning, 207*, 104003. https://doi.org/10.1016/j.landurbplan.2020.104003

Zhu, X., Gao, M., Zhang, R., & Zhang, B. (2021). Quantifying emotional differences in urban green spaces extracted from photos on social networking sites: A study of 34 parks in three cities in northern China. *Urban Forestry & Urban Greening, 62*, 127133. https://doi.org/10.1016/j.ufug.2021.127133

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