Electronic Markets (2022) 32:297–338
https://doi.org/10.1007/s12525-022-00537-z

RESEARCH PAPER

Artificial intelligence in E-Commerce: a bibliometric study and literature review

Ransome Epie Bawack[1] · Samuel Fosso Wamba[2] · Kevin Daniel André Carillo[2] · Shahriar Akter[3]

Received: 11 September 2021 / Accepted: 22 February 2022 / Published online: 18 March 2022

Abstract
This paper synthesises research on artificial intelligence (AI) in e-commerce and proposes guidelines on how information systems (IS) research could contribute to this research stream. To this end, the innovative approach of combining bibliometric analysis with an extensive literature review was used. Bibliometric data from 4335 documents were analysed, and 229 articles published in leading IS journals were reviewed. The bibliometric analysis revealed that research on AI in e-commerce focuses primarily on recommender systems. Sentiment analysis, trust, personalisation, and optimisation were identified as the core research themes. It also places China-based institutions as leaders in this researcher area. Also, most research papers on AI in e-commerce were published in computer science, AI, business, and management outlets. The literature review reveals the main research topics, styles and themes that have been of interest to IS scholars. Proposals for future research are made based on these findings. This paper presents the first study that attempts to synthesise research on AI in e-commerce. For researchers, it contributes ideas to the way forward in this research area. To practitioners, it provides an organised source of information on how AI can support their e-commerce endeavours.

Keywords Artificial intelligence · e-commerce · Literature review · Bibliometrics

JEL classification O3

Introduction

Electronic commerce (e-commerce) can be defined as activities or services related to buying and selling products or services over the internet (Holsapple & Singh, 2000; Kalakota & Whinston, 1997). Firms increasingly indulge in e-commerce because of customers' rising demand for online services and its ability to create a competitive advantage (Gielens & Steenkamp, 2019; Hamad et al., 2018; Tan et al., 2019). However, firms struggle with this e-business practice due to its integration with rapidly evolving, easily adopted, and highly affordable information technology (IT). This forces firms to constantly adapt their business models to changing customer needs (Gielens & Steenkamp, 2019; Klaus & Changchit, 2019; Tan et al., 2007). Artificial intelligence (AI) is the latest of such technologies. It is transforming e-commerce through its ability to "correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019. p. 15). Depending on the context, AI could be a system, a tool, a technique, or an algorithm (Akter et al., 2021; Bawack et al., 2021; Benbya et al., 2021). It creates opportunities for firms to gain a competitive advantage by using big data to uniquely meet their customers' needs through personalised services (Deng et al., 2019; Kumar, Rajan, et al., 2019; Kumar, Venugopal, et al., 2019).

AI in e-commerce can be defined as using AI techniques, systems, tools, or algorithms to support activities related to buying and selling products or services over the internet.

Responsible Editor: Jianwei Hou

✉ Ransome Epie Bawack
ransome.bawack@icn-artem.com

Samuel Fosso Wamba
s.fosso-wamba@tbs-education.fr

Kevin Daniel André Carillo
k.carillo@tbs-education.fr

Shahriar Akter
sakter@uow.edu.au

1 ICN Business School, CEREFIGE - Université de Lorraine, 86 rue du Sergent Blandan, 54003 Nancy, France

2 TBS Business School, 6 Place Alfonse Jourdain, 31000 Toulouse, France

3 School of Management and Marketing, University of Wollongong, Wollongong, NSW 2522, Australia

Research on AI in e-commerce has been going on for the past three decades. About 4000 academic research articles have been published on the topic across multiple disciplines, both at the consumer (de Bellis & Venkataramani Johar, 2020; Sohn & Kwon, 2020) and organisational levels (Campbell et al., 2020; Kietzmann et al., 2018; Vanneschi et al., 2018). However, knowledge on the topic has not been synthesised despite its rapid growth and dispersion. This lack of synthesis makes it difficult for researchers to determine how much the extant literature covers concepts of interest or addresses relevant research gaps. Synthesising research on AI in e-commerce is an essential condition for advancing knowledge by providing the background needed to describe, understand, or explain phenomena, to develop/test new theories, and to develop teaching orientations in this research area (Cram et al., 2020; Paré et al., 2015). Thus, this study aims to synthesise research on AI in e-commerce and propose directions for future research in the IS discipline. The innovative approach of combining bibliometric analysis with an extensive literature review is used to answer two specific research questions: (i) what is the current state of research on AI in e-commerce? (ii) what research should be done next on AI in e-commence in general, and within information systems (IS) research in particular?

This study's findings show that AI in e-commerce primarily focuses on recommender systems and the main research themes are sentiment analysis, optimisation, trust, and personalisation. This study makes timely contributions to ongoing debates on the connections between business strategy and the use of AI technologies (Borges et al., 2020; Dwivedi et al., 2019, 2020). It also contributes to research on how firms can address challenges regarding the use of AI-related benefits and opportunities for new product or service developments and productivity improvements (Makridakis, 2017). Furthermore, no study currently synthesises AI in e-commerce research despite its rapid evolution in the last decade triggered by big data, advanced machine learning (ML) algorithms, and cloud computing. Using well-established e-commerce classification frameworks (Ngai & Wat, 2002; Wareham et al., 2005), this study classifies information systems (IS) literature on AI in e-commerce. These classifications make it easier for researchers and managers to identify relevant literature based on the topic area, research style, and research theme. A future research agenda is proposed based on the gaps revealed during the classification to guide researchers on making meaningful contributions to AI knowledge in e-commerce.

Research method

Bibliometric analysis

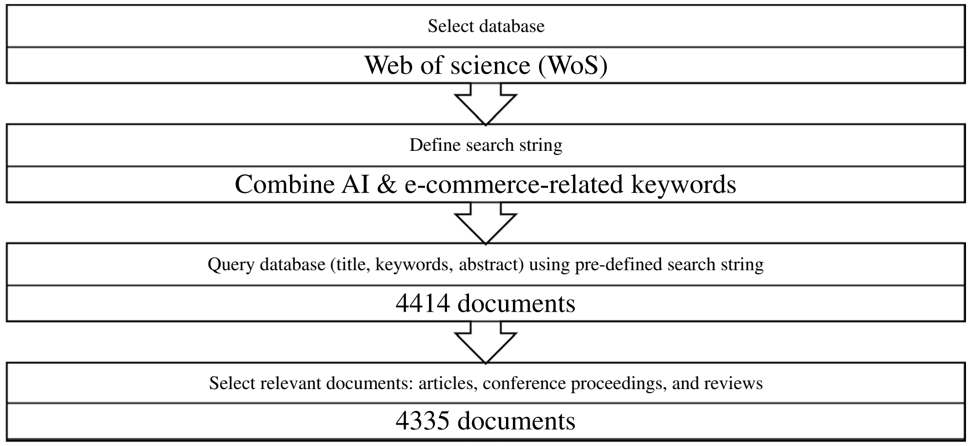
Bibliometric analysis has been increasingly used in academic research in general and in IS research to evaluate the quality, impact, and influence of authors, journals, and institutions in a specific research area (Hassan & Loebbecke, 2017; Lowry et al., 2004, 2013). It has also been used extensively to understand AI research on specific fields or topics (Hinojo-Lucena et al., 2019; Tran et al., 2019; Zhao, Dai, et al., 2020; Zhao, Lou, et al., 2020). In this study, a bibliometric analysis was conducted to understand research on AI in e-commerce using the approach Aria and Cuccurullo (2017) proposed. This methodology involves three main phases: data collection, data analysis, and data visualisation & reporting. The data collection phase involves querying, selecting, and exporting data from selected databases. This study's data sample was obtained by querying the Web of Science (WoS) core databases for publications from 1975 to 2020. This database was chosen over others like Google Scholar or Scopus because WoS provides better quality bibliometric information due to its lower rate of duplicate records (Aria et al., 2020) and greater coverage of high-impact journals (Aghaei Chadegani et al., 2013). The following search string was used to query the title, keywords, and abstracts of all documents in the WoS collection:

(''Electronic Commerce'' OR ''Electronic business'' OR ''Internet Commerce'' OR “e-business” OR “ebusiness” OR "e-commerce" OR “ecommerce” OR “online shopping” OR “online purchase” OR “internet shopping” OR “e-purchase” OR “online store” OR “electronic shopping”).
AND (“Artificial intelligence” OR “Artificial neural network” OR “case-based reasoning” OR “cognitive computing” OR “cognitive science” OR “computer vision” OR “data mining” OR “data science” OR “deep learning” OR “expert system” OR “fuzzy linguistic modelling” OR “fuzzy logic” OR “genetic algorithm” OR “image recognition” OR “k-means” OR “knowledge-based system” OR “logic programming” OR “machine learning” OR “machine vision” OR “natural language processing” OR “neural network” OR “pattern recognition” OR “recommendation system” OR “recommender system” OR “semantic network” OR “speech recognition” OR “support vector machine” OR “SVM” OR “text mining”).

This search string led to 4414 documents that made up the initial dataset of this study. For quality reasons, only document types tagged as articles, reviews, and proceeding papers were selected for this study because they are most likely to have undergone a rigorous peer-review process before publication (Milian et al., 2019). Thus, editorial material, letters, news items, meeting abstracts, and retracted publications were removed from the dataset, leaving 4335 documents that made up the final dataset used for bibliometric analysis. Figure 1 summarises the data collection phase.

Table 1 summarises the main information about the dataset regarding the timespan, document sources, document

Fig. 1 Summary of the data collection phase



types, document contents, authors, and author collaborations. The dataset consists of documents from 2599 sources, published by 8663 authors and 84,474 references.

Bibliometrix[1] is the R package used to conduct bibliometric analysis (Aria & Cuccurullo, 2017). This package has been extensively used to conduct bibliometric studies published in top-tier journals. It incorporates the most renowned bibliometric tools for citation analysis (Esfahani et al., 2019; Fosso Wamba, 2020; Pourkhani et al., 2019). It was specifically used to analyse the sources, documents, conceptual, and intellectual structure of AI in e-commerce research. Publication sources and their source impacts were analysed based on their h-index quality factors (Hirsch, 2010). The most significant, impactful, prestigious, influential, and quality publication sources, affiliations, and countries regarding research on AI in e-commerce were identified. This contributed to the identification of the most relevant disciplines in this area of research. Documents were analysed using total citations to identify the most cited documents in the dataset. Through content analysis, the most relevant topics/concepts, AI technologies/techniques, research methods, and application domains were identified.

Furthermore, citation analysis and reference publication year spectroscopy (RPYS) were used to identify research contributions that form the foundations of research on AI in e-commerce (Marx et al., 2014; Rhaiem & Bornmann, 2018). These techniques were also used to identify the most significant changes in the research area. Co-word network analysis on author-provided keywords using the Louvain clustering algorithm was used to understand the research area's conceptual structure. This algorithm is a greedy optimisation method used to identify communities in large networks by comparing the density of links inside communities with links between communities (Blondel et al., 2008). This study used it to identify key research themes by analysing author-provided keywords.

[1] Download the bibliometrix R package and read more here: https://www.bibliometrix.org/index.html

Table 1 Main information about the dataset

Description	Results
Timespan	1991:2020
Sources (journals, books, etc.)	2599
Documents	4335
Average years from publication	7.43
Average citations per document	8.645
Average citations per year per doc	1.026
References	84,474
Document types	
Article	1524
Article; proceedings paper	150
Proceedings paper	2550
Review	111
Document contents	
Keywords plus (id)	1978
Author's keywords (de)	8668
Authors	
Authors	8663
Author appearances	13,141
Authors of single-authored documents	408
Authors of multi-authored documents	8255
Authors collaboration	
Single-authored documents	462
Documents per author	0.5
Authors per document	2
Co-authors per documents	3.03
Collaboration index	2.13

Co-citation network analysis using the Louvain clustering algorithm was also used to analyse publication sources through which journals communities were identified. It further contributed to identifying the most relevant disciplines in this research area by revealing journal clusters.

The bibliometric analysis results were reported from functionalist, normative, and interpretive perspectives (Hassan & Loebbecke, 2017). The functionalist perspective presents the results of the key concepts and topics investigated in this research area. The normative perspective focuses on the foundations and norms of the research area. The interpretive perspective emphasises the main themes that drive AI in e-commerce research.

Literature review

An extensive review and classification of IS literature on AI in e-commerce complemented the bibliometric analysis. It provides more details on how research in this area is conducted in the IS discipline. The review was delimited to the most impactful and influential management information systems (MIS) journals identified during the bibliometric analysis and completed by other well-established MIS journals known for their contributions to e-commerce research (Ngai & Wat, 2002; Wareham et al., 2005). Thus, 20 journals were selected for this review: *Decision sciences, Decision support systems, Electronic commerce research and applications, Electronic markets, E-service journal, European journal of information systems, Information and management, Information sciences, Information systems research, International journal of electronic commerce, International journal of information management, Journal of information systems, Journal of information technology, Journal of management information systems, Journal of organisational computing and electronic commerce, Journal of strategic information systems, Journal of the association for information systems, Knowledge-based systems, Management science, MIS Quarterly*.

The literature review was conducted in three stages (Templier & Paré, 2015; Webster & Watson, 2002): (i) identify and analyse all relevant articles from the targeted journals found in the bibliometric dataset (ii) use the keyword string to search for other relevant articles found on the official publication platforms of the targeted journals, and (iii) identify relevant articles from the references of the articles identified in stages one and two found within the target journals. All articles with content that did not focus on AI in e-commerce were eliminated. This process led to a final dataset of 229 research articles on AI in e-commerce. The articles were classified into three main categories: by topic area (Ngai & Wat, 2002), by research style (Wareham et al., 2005), and by research themes (from bibliometric analysis).

Classification by topic area involved classifying relevant literature into four broad categories: (i) applications, (ii) technological issues, (iii) support and implementation, and (iv) others. *Applications* refer to the specific domain in which the research was conducted (marketing, advertising, retailing…). *Technological issues* contain e-commerce research by AI technologies, systems, algorithms, or methodologies that support or enhance e-commerce applications. *Support and Implementation* include articles that discuss how AI supports public policy and corporate strategy. *Others* contain all other studies that do not fall into any of the above categories. It includes articles on foundational concepts, adoption, and usage. Classification by research style involved organizing the relevant literature by type of AI studied, the research approach, and the research method used in the studies. The research themes identified in the bibliometric analysis stage were used to classify the relevant IS literature by research theme.

Findings

Results of the bibliometric analysis

Scientific publications on AI in e-commerce began in 1991 with an annual publication growth rate of 10.45%. Figure 2 presents the number of publications per year. Observe the steady increase in the number of publications since 2013.

Institutions in Asia, especially China, are leading this research area. The leading institution is Beijing University of Posts and Telecommunications, with 88 articles, followed by Hong Kong Polytechnic University with 84 articles. Table 2 presents the top 20 institutions publishing on AI in e-commerce.

As expected, China-based affiliations appear most frequently in publications (4261 times). They have over 2.5 times as many appearances as US-based affiliations (1481 times). Interestingly, publications with US-based affiliations attract more citations than those in China. Table 3 presents the number of times authors from a given country feature in publications and the corresponding total number of citations.

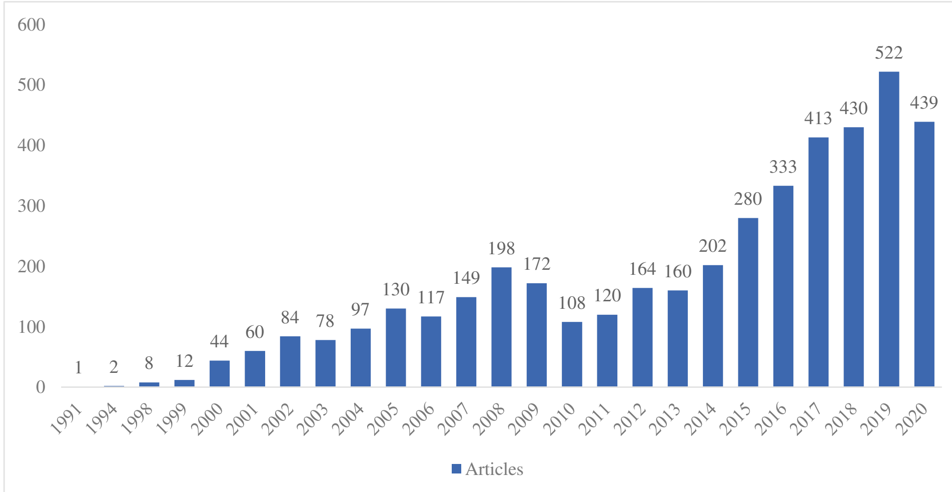


Fig. 2 Number of publications on AI in e-commerce per year

Table 2 Top 20 institutions publishing on AI in e-commerce

Affiliations	Articles
Beijing University of Posts and Telecommunications	88
Hong Kong Polytechnic University	84
Northeastern University	73
Wuhan University	72
Tsinghua University	63
Zhejiang University	63
Beijing Jiaotong University	56
Beihang University	52
University of Technology Sydney	51
National Chiao Tung University	47
Islamic Azad University	43
Wuhan University of Technology	43
Xi'an Jiaotong University	43
Universiti Teknologi Malaysia	39
Indian Institute of Technology	38
Zhejiang Business Technology Institute	38
Huazhong University of Science and Technology	37
Nanyang Technological University	37
University of Electronic Science and Technology of China	37
Hefei University of Technology	34

Table 3 Top 20 countries contributing to research on AI in e-commerce

Country	Appearance frequency	Total citations
China	4261	8407
USA	1481	9859
India	1397	2328
South Korea	379	1827
UK	308	1421
Japan	297	466
Australia	268	1368
Spain	256	1847
Germany	246	2378
Iran	223	534
Italy	199	507
Canada	189	1327
Malaysia	158	647
Turkey	145	597
Brazil	135	166
Greece	124	260
France	116	158
Pakistan	109	192
Poland	104	199
Indonesia	100	35

Functional perspective

Analysing the most globally cited documents[2] in the dataset (those with 100 citations) reveals that recommender systems are the main topic of interest in this research area (Appendix Table 10). Recommender systems are software agents that make recommendations for consumers by implicitly or explicitly evoking their interests or preferences (Bo et al., 2007). The topic has been investigated in many flavours, including hybrid recommender systems (Burke, 2002), personalised recommender systems (Cho et al., 2002), collaborative recommender systems (Lin et al., 2002) and social recommender systems (Li et al., 2013). The central concept of interest is personalisation, specifically leveraging recommender systems to offer more personalised product/service

[2] Global citation refers to the total number of times the document has been cited in other documents in general and local citations refer to the total number of times a document has been cited by other documents in our dataset.

Table 4 Main research themes for AI in e-commerce

Cluster: Research theme	Corresponding keywords
Cluster 1: Sentiment analysis	Machine learning, natural language processing, text mining, sentiment analysis, opinion mining
Cluster 2: Trust and personalisation	Collaborative filtering, clustering algorithms, case-based reasoning, ontology, recommender systems, recommendation, trust, personalised recommendation, personalisation, electronic commerce system
Cluster 3: Optimisation	Optimisation, electronic commerce, genetic algorithm
Cluster 4: AI concepts and related technologies	Neural networks, machine learning, deep learning, artificial intelligence, data mining, random forest, fuzzy logic, classification, web mining, web usage mining, data analysis, cloud computing, business intelligence, big data, internet, e-commerce, e-business, online shopping

recommendations to customers using e-commerce platforms. Thus, designing recommender systems that surpass existing ones is the leading orientation of AI in e-commerce research. Researchers have mostly adopted experimental rather than theory-driven research designs to meet this overarching research objective. Research efforts focus more on improving the performance of recommendations using advanced AI algorithms than on understanding and modelling the interests and preferences of individual consumers. Nevertheless, the advanced AI algorithms developed are trained primarily using customer product reviews.

Interpretive perspective

Four themes characterise research on AI in e-commerce: sentiment analysis, trust & personalisation, optimisation, AI concepts, and related technologies. The keyword clusters that led to the identification of these themes are presented in Table 4. The *sentiment analysis* theme represents the stream of research focused on interpreting and classifying emotions and opinions within text data in e-commerce using AI techniques like ML and natural language processing (NLP). The *trust and personalisation* theme represents research that focuses on establishing trust and making personalised recommendations for consumers in e-commerce using AI techniques like collaborative filtering, case-based reasoning, and clustering algorithms. The *optimisation* theme represents research that focuses on using AI algorithms like genetic algorithms to solve optimisation problems in e-commerce. Finally, the *AI concepts and related technologies* theme represent research that focuses on using different techniques and concepts used in the research area.

Normative perspective

Research on AI in e-commerce is published in two main journal subject areas: computer science & AI and business & management. This result confirms the multidisciplinary nature of this research area, which has both business and technical orientations. Table 5 presents the most active publication outlets in each subject area. The outlets listed in the table could help researchers from different disciplines to select the proper outlet for their research results. It could also help researchers identify the outlets wherein they are most likely to find relevant information for their research on AI in e-commerce.

However, some disciplines set the foundations and standards of research on AI in e-commerce through the impact of their contributions to its body of knowledge. Analysing document references shows that the most cited contributions come from journals in the IS, computer science, AI, management science, and operations research disciplines (Table 6). It shows the importance of these disciplines to AI's foundations and standards in e-commerce research and their major publication outlets.

The IS discipline is a significant contributor to AI in e-commerce research, given that 24 out of the 40 top publications in the area can be assimilated to IS sources. Table 7 also shows that 7 out of the top 10 most impactful publication sources are assimilated to the IS discipline. The leading paper from the IS field reviews approaches to automatic schema matching (Rahm & Bernstein, 2001) and it is the second most globally cited paper in the research area. Meanwhile, the leading paper from the MIS subfield reviews recommender system application developments (Lu et al., 2015).

Collaborative filtering, recommender systems, social information filtering, latent Dirichlet allocation, and matrix factoring techniques are the foundational topics in research on AI in e-commerce (Table 8). They were identified by analysing the most cited references in the dataset. These references were mostly literature reviews and documents that discussed the basic ideas and concepts behind specific technologies or techniques used in recommender systems.

Furthermore, the specific documents that set the foundations of research on AI in e-commerce and present the most significant historical contributions and turning points in the field were identified using RPYS (Appendix Table 11).

Table 5 Publication structure of research on AI in e-commerce

Subject area 1: computer science and AI	Subject area 2: business and management
Journal of machine learning research	Marketing science
IEEE transactions on pattern analysis and machine intelligence	Electronic commerce research and applications
Advances in neural information processing systems	Management science
ACM transactions on information systems	MIS quarterly
Information processing and management	Journal of business research
IEEE data mining	Journal of the academy of marketing science
Lecture notes in artificial intelligence	Journal of marketing
Expert systems with applications	Journal of marketing research
IEEE transactions on knowledge and data engineering	Computers in human behaviour
Machine learning	Decision support systems
Knowledge-based systems	Journal of retailing
User modelling and user-adapted interaction	International journal of electronic commerce
Computer	European journal of operational research
Recommender systems handbook	International journal of production economics
Proceedings of the 10th international conference on the world wide web	Harvard business review
Lecture notes in computer science	Journal of interactive marketing
Procedia computer science	Information and management
Neurocomputing	Internet research
Artificial intelligence review	Journal of consumer research
ACM computing surveys	Industrial management & data systems
IEEE internet computing	Information systems research
IEEE intelligent systems	International journal of information management
Applied soft computing	Journal of management information systems
Communications of the ACM	
Data mining and knowledge discovery	
Information sciences	

Table 6 Most local cited sources on AI in e-commerce

Subject area	Sources	Articles
Information systems	Decision support systems	1392
	MIS quarterly	736
	Information sciences	705
Computer science & artificial intelligence	Expert systems with applications	2924
	Lecture notes in computer science	1314
	Communications of the ACM	1255
	IEEE transactions on knowledge and data engineering	995
	Knowledge-based systems	837
	Lecture notes in artificial intelligence	608
Management science & operations research	European journal of operational research	744
	Management science	609

2001, 2005, 2007, 2011, and 2015 are the years with the highest number of documents referenced by the documents in the sample. The most cited studies published in 2001 focused on recommendation algorithms, especially item-based collaborative filtering, random forest, gradient boosting machine, and data mining. The main concept of interest was how to personalise product recommendations. In 2005, the most referenced documents focused on enhancing recommendation systems using hybrid collaborative filtering, advanced machine learning tools and techniques, and topic diversification. That year also contributed a solid foundation for research on trust in recommender systems.

Table 7 Publication source impact by h-index

Source	Subject area	H—index	TC	NP	PY start
Expert systems with applications	IS, AI, CSA	40	4704	142	1999
Decision support systems	IS, MIS	22	1995	44	2000
Knowledge-based systems	IS, KM, CSA	13	940	24	2005
Electronic commerce research and applications	MIS, MKT	11	551	31	2005
Information sciences	IS, AI, CSA	10	430	15	2004
Applied soft computing	CS	9	325	16	2004
International journal of information management	IS, MIS, MKT	9	291	10	2006
Artificial intelligence review	AI	8	704	13	2002
IEEE transactions on knowledge and data engineering	IS, CSA	8	666	10	2003
Computers in human behavior	IS, CSA	8	360	9	2007

TC: total citations; NP: number of publications; PY: publication year.
See Appendix Table 10 for full meanings of abbreviations.

Table 8 Foundational studies on AI in e-commerce

Topic of interest	Author(s), date	(Short) title
Collaborative filtering	(Linden et al., 2003)	Amazon. Com recommendations: item-to-item collaborative filtering
	(Sarwar et al., 2001)	Item-based collaborative filtering recommendation algorithms
	(Herlocker et al., 2004)	Evaluating collaborative filtering recommender systems
	(Goldberg et al., 1992)	Using collaborative filtering to weave an information tapestry
	(Balabanović & Shoham, 1997)	Fab: content-based, collaborative recommendation
	(Konstan et al., 1997)	GroupLens: applying collaborative filtering to USENET news
	(Resnick et al., 1994)	GroupLens: an open architecture for collaborative filtering of netnews
	(Su & Khoshgoftaar, 2009)	A survey of collaborative filtering techniques
Latent Dirichlet allocation	(Blei et al., 2002)	Latent Dirichlet allocation
Matrix factoring techniques	(Koren et al., 2009)	Matrix factorization techniques for recommender systems
Recommender systems	(Adomavicius & Tuzhilin, 2005)	Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions
	(Resnick & Varian, 1997)	Recommender systems
	(Burke, 2002)	Hybrid recommender systems: survey and experiments
	(Bobadilla et al., 2013)scop	Recommender systems survey
	(Ricci et al., 2011)	Introduction to recommender systems handbook
Social information filtering	(Shardanand & Maes, 1995)	Social information filtering: algorithms for automating "word of mouth"
	(Agrawal et al., 1993)	Mining association rules between sets of items in large databases

In 2007, significant contributions continued on enhanced collaborative filtering techniques for recommender systems. Meanwhile, Bo & Benbasat (2007) set the basis for research on recommender systems' characteristics, use, and impact, shifting from traditional studies focused on underlying algorithms towards a more consumer-centric approach. In 2011, major contributions were made to enhance recommender systems, like developing a new library for support vector machines (Chang & Lin, 2011) and the Scikit-learn package for machine learning in Python (Pedregosa et al., 2011). In 2015, the most critical contributions primarily focused on deep learning algorithms, especially with an essential contribution to using them in recommender systems (Wang et al., 2015).

Results of the literature review study

Classification by topic area

Most articles on AI in e-commerce focus on technological issues (107 articles, 47%), followed by applications (87

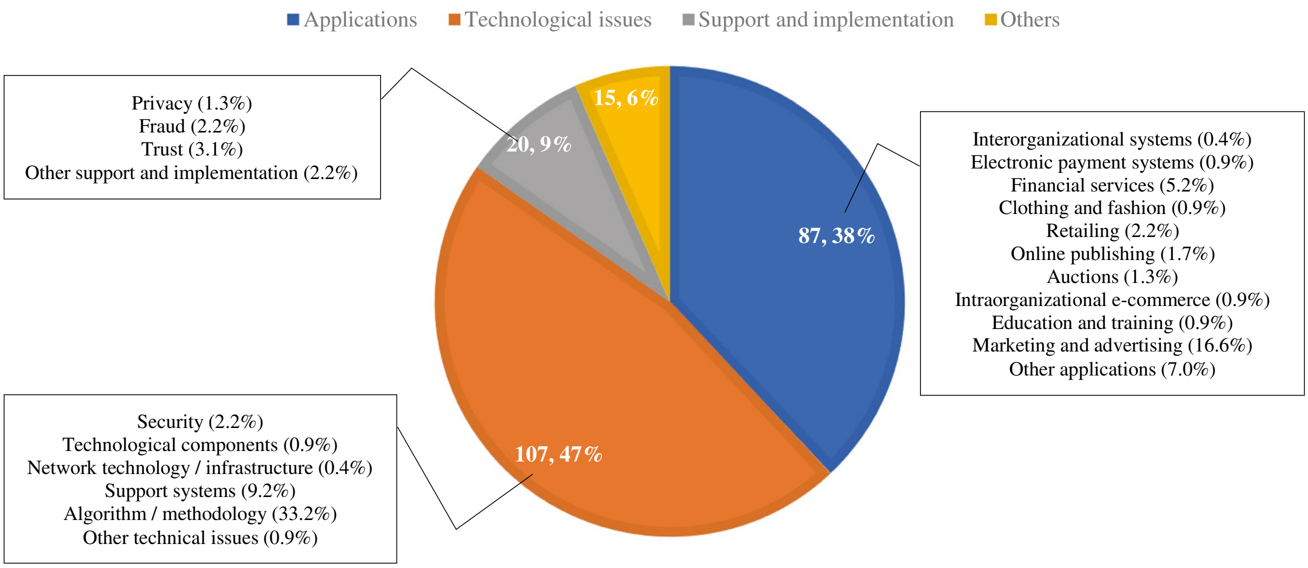


Fig. 3 Classification of MIS literature on AI in e-commerce by topic area

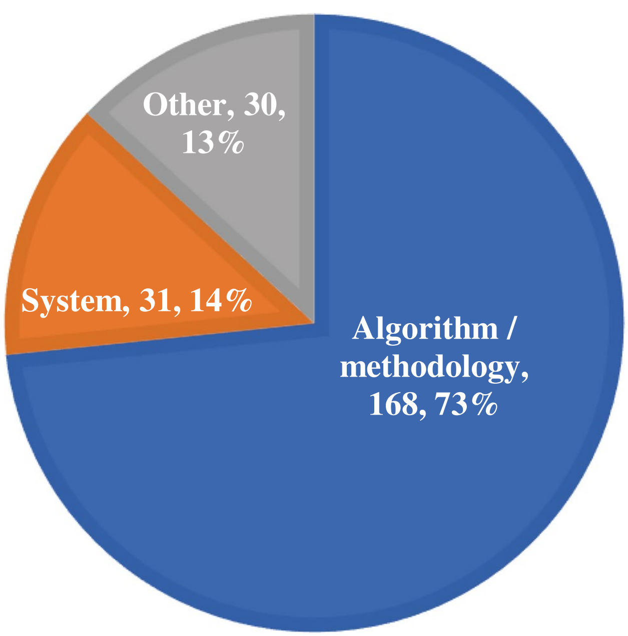


Fig. 4 Classification of MIS literature on AI in e-commerce by type of AI

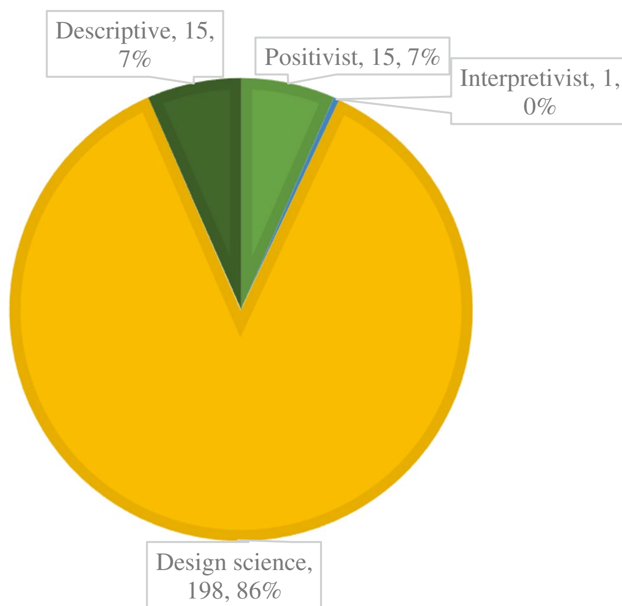


Fig. 5 Classification of MIS literature on AI in e-commerce by research approach

articles, 38%), support and implementation (20 articles, 9%), then others (15 articles, 6%). Specifically, most articles focus on AI algorithms, models, and methodologies that support or improve e-commerce applications (76 articles, 33.2%) or emphasise the applications of AI in marketing, advertising, and sales-related issues (38 articles, 16.6%). Figure 3 presents the distribution of articles, while Appendix Table 12 presents the articles in each topic area.

Classification by research style

Most authors discuss AI algorithms, models, computational approaches, or methodologies (168 articles, 73%).

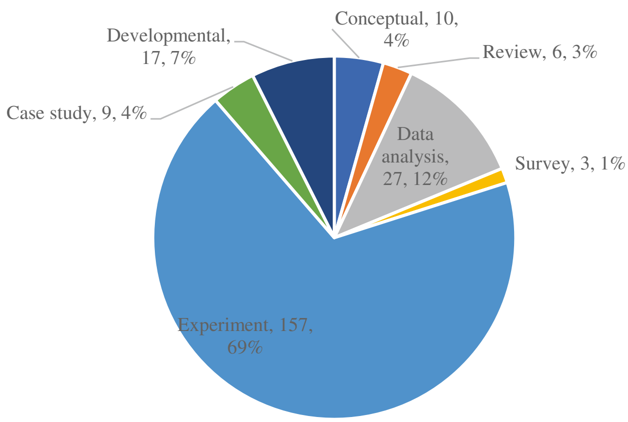


Fig. 6 Classification of MIS literature on AI in e-commerce by research method

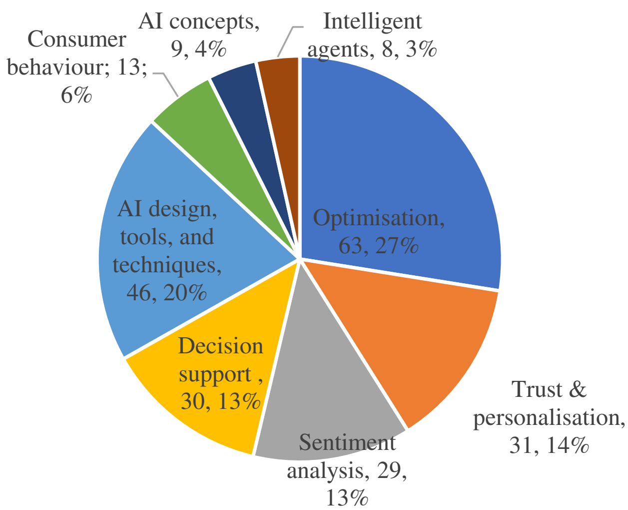


Fig. 7 Classification of MIS literature on AI in e-commerce by current research themes

Specifically, current research focuses on how AI algorithms like ML, deep learning (DL), NLP, and related techniques could be used to model and understand phenomena in the e-commerce environment. It also focuses on studies that involve designing intelligent agent algorithms that support learning processes in e-commerce systems. Many studies also focus on AI as systems (31 articles, 14%), especially on recommender systems and expert systems that leverage AI algorithms in the back end. The "others" category harboured all articles that did not clearly refer to AI as either an algorithm or as a system (30 articles, 13%) (see Fig. 4 and Appendix Table 13).

Furthermore, most publications use the design science research approach (198 articles, 86%). Researchers prefer this approach because it allows them to develop their algorithms and models or improve existing ones, thereby creating a new IS artefact (see Fig. 5 and Appendix Table 14).

Also, authors adopt experimental methods in their papers (157 articles, 69%), especially those who adopted a design science research approach. They mostly use experiments to test their algorithms or prove their concepts (see Fig. 6 and Appendix Table 15).

Classification by research theme

Based on the main research themes on AI in e-commerce identified during the bibliometric analysis, most authors published on optimisation (63 articles, 27%). They mostly focused on optimising recommender accuracy (25 articles), prediction accuracy (29 articles), and other optimisation aspects (9 articles) like storage optimisation. This trend was followed by publications on trust & personalisation (31 articles, 14%), wherein more articles were published on personalisation (17 articles) than on trust (14 articles). Twenty-nine articles focused on sentiment analysis (13%). The rest of the papers focus on AI design, tools and techniques (46 articles), decision support (30 articles), customer behaviour (13 articles), AI concepts (9 articles), and intelligent agents (8 articles) (see Fig. 7 and Appendix Table 16).

Discussion

This study's overall objective was to synthesise research on AI in e-commerce and propose avenues for future research. Thus, it sought to answer two research questions: (i) what is the current state of research on AI in e-commerce? (ii) what research should be done next on AI in e-commerce in general and within IS research in particular? This section summarises the findings of the bibliometric analysis and literature review. It highlights some key insights from the results, starting with the leading role of China and the USA in this research area. This highlight is followed by discussions on the focus of current research on recommender systems, the extensive use of design science and experiments in this research area, and a limited focus on modelling consumer behaviour. This section also discusses the little research found on some research themes and the limited number of publications from some research areas. Implications for research and practice are discussed at the end of this section.

Need for more research from other countries

Research on AI in e-commerce has been rising steadily since 2013. Overall, these results indicate a growing interest in the applications of AI in e-commerce. China-based institutions lead this research area, although US-based affiliations attract more citations. Tables 2 and 3 indicate that China is in the leading position regarding research on AI in e-commerce. Observe that Amazon Inc. (USA), JD.com (China), Alibaba Group Holding Ltd. (China), Suning.com (China), Meituan (China), Wayfair (USA), eBay (USA), and Groupon (USA) are referenced among the largest e-commerce companies in the world (in terms of market capitalisation, revenue, and the number of employees).[3] These companies are primarily from China and the USA. These findings correlate with Table 3, which could indicate that China and the USA are investing more in the research and development of AI applications in e-commerce (especially China, based on Table 2) because of the positions they occupy in the industry. This logic would imply that companies seeking to penetrate the e-commerce industry and remain competitive should also consider investing more in the research and development of AI applications in the area. The list of universities provided could become partner universities for countries with institutions that have less experience in the research area. Especially with the COVID-19 pandemic, e-commerce has become a global practice. Thus, other countries need to contribute more research on the realities of e-commerce in their respective contexts to develop more globally acceptable AI solutions in e-commerce practices. It is essential because different countries approach e-commerce differently. For example, although Amazon's marketplace is well-developed in continents like Europe, Asia, and North America, it has difficulty penetrating Africa because the context is very different (culturally and infrastructurally). While mobile wallet payment systems are fully developed on the African continent, Amazon's marketplace does not accommodate this payment method. Therefore, it would be impossible for many Africans to use Amazon's *Alexa* to purchase products online. What does this mean for research on digital inclusion? Are there any other cross-cultural differences between countries that affect the adoption and use of AI in e-commerce? Are there any legal boundaries that affect the implementation and internationalisation of AI in e-commerce? Such questions highlight the need for more country-specific research on AI in e-commerce to ensure more inclusion.

[3] https://axiomq.com/blog/8-largest-e-commerce-companies-in-the-world/

Focus on recommender systems

AI in e-commerce research is essentially focused on recommender systems in the past years. The results indicate that in the last 20 years, AI in e-commerce research has primarily focused on using AI algorithms to enhance recommender systems. This trend is understandable because recommender systems have become an integral part of almost every e-commerce platform nowadays (Dokyun Lee & Hosanagar, 2021; Stöckli & Khobzi, 2021). As years go by, observe how novel AI algorithms have been proposed, the most recent being deep learning (Chaudhuri et al., 2021; Liu et al., 2020; Xiong et al., 2021; Zhang et al., 2021). Thus, researchers are increasingly interested in how advanced AI algorithms can enable recommender systems in e-commerce platforms to correctly interpret external data, learn from such data, and use those learnings to improve the quality of user recommendations through flexible adaptation. With the advent of AI-powered chatbots and voice assistants, firms increasingly include these technologies in their e-commerce platforms (Ngai et al., 2021). Thus, researchers are increasingly interested in conversational recommender systems (De Carolis et al., 2017; Jannach et al., 2021; Viswanathan et al., 2020). These systems can play the role of recommender systems and interact with the user through natural language (Iovine et al., 2020). Thus, conversational recommender systems is an up-and-coming research area for AI-powered recommender systems, especially given the ubiquitous presence of voice assistants in society today. Therefore, researchers may want to investigate how conversational recommender systems can be designed effectively and the factors that influence their adoption.

Limited research themes

The main research themes in AI in e-commerce are sentiment analysis, trust, personalisation, and optimisation. Researchers have focused on these themes to provide more personalised recommendations to recommendation system users. Personalising recommendations based on users' sentiment and trust circle has been significantly researched. Extensive research has also been conducted on how to optimise the algorithmic performance of recommender systems. ML, DL, NLP are the leading AI algorithms and techniques currently researched in this area. The foundational topics for applying these algorithms include collaborative filtering, latent Dirichlet allocation, matrix factoring techniques, and social information filtering.

Current research shows how using AI for personalisation would enable firms to deliver high-quality customer experiences through precise personalisation based on real-time information (Huang & Rust, 2018, 2020). It is highly effective in data-rich environments and can help firms to significantly improve customer satisfaction, acquisition, and retention rates, thereby ideal for service personalisation (Huang & Rust, 2018). AI could enable firms to personalise products based on preferences, personalise prices based on willingness to pay, personalise frontline interactions, and personalise promotional content in real-time (Huang & Rust, 2021).

Research also shows how AI could help firms optimise product prices by channel and customer (Huang & Rust, 2021; Huang & Rust, 2020) and develop accurate and personalised recommendations for customers. It is beneficial when the firm lacks initial data on customers that it can use to make recommendations (cold start problem) (Guan et al., 2019; Wang, Feng, et al., 2018; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Lu, et al., 2018). It also gives firms the ability to automatically estimate optimal prices for their products/services and define dynamic pricing strategies that increase profits and revenue (Bauer & Jannach, 2018; Greenstein-Messica & Rokach, 2018). It also gives firms the ability to predict consumer behaviours like customer churn (Bose & Chen, 2009), preferences based on their personalities (Buettner, 2017), engagement (Ayvaz et al., 2021; Sung et al., 2021; Yim et al., 2021), and customer payment default (Vanneschi et al., 2018). AI also gives firms the ability to predict product, service, or feature demand and sales (Cardoso & Gomide, 2007; Castillo et al., 2017; Ryoba et al., 2021), thereby giving firms the ability to anticipate and dynamically adjust their advertising and sales strategies (Chen et al., 2014; Greenstein-Messica & Rokach, 2020). Even further, it gives firms the ability to predict the success or failure of these strategies (Chen & Chung, 2015).

Researchers have shown that using AI to build trust-based recommender systems can help e-commerce firms increase user acceptance of the recommendations made by e-commerce platforms (Bedi & Vashisth, 2014). This trust is created by accurately measuring the level of trust customers have in the recommendations made by the firm's e-commerce platforms (Fang et al., 2018) or by making recommendations based on the recommendations of people the customers' trust in their social sphere (Guo et al., 2014; Zhang et al., 2017).

Sentiment analytics using AI could give e-commerce firms the ability to provide accurate and personalised recommendations to customers by assessing their opinions expressed online such as through customer reviews (Al-Natour & Turetken, 2020; Qiu et al., 2018). It has also proven effective in helping brands better understand their customers over time and predict their behaviours (Das & Chen, 2007; Ghiassi et al., 2016; Pengnate & Riggins, 2020). For example, it helps firms better understand customer requirements for product improvements (Ou et al., 2018; Qi et al., 2016) and predict product sales based on customer sentiments (Li, Wang, et al., 2019; Li, Wu, et al., 2019; Li, Zhang, et al., 2019). Thus, firms can accurately guide their customers towards discovering desirable products (Liang & Wang, 2019) and predict the prices they would be willing to pay for products based on their sentiments (Tseng et al., 2018). Thus, firms that use AI-powered sentiment analytics would have the ability to constantly adapt their product development, sales, and pricing strategies while improving the quality of their e-commerce services and personalised recommendations for their customers.

While the current research themes are exciting and remain relevant in today's context, it highlights the need for researchers to explore other research themes. For example, privacy, explainable, and ethical AI are trendy research themes in AI research nowadays. These themes are relevant to research on AI in e-commerce as well. Thus, developing these research themes would make significant contributions to research on AI in e-commerce. In the IS discipline, marketing & advertising is where AI applications in e-commerce have been researched the most. This finding complements Davenport et al. (2020)'s argument, suggesting that marketing functions have the most to gain from AI. Most publications focus on technological issues like algorithms, support systems, and security. Very few studies investigated privacy, and none was found on topics like ethical, explainable, or sustainable AI. Therefore, future research should pay more attention to other relevant application domains like education & training, auctions, electronic payment systems, inter-organisational e-commerce, travel, hospitality, and leisure (Blöcher & Alt, 2021; Manthiou et al., 2021; Neuhofer et al., 2021). To this end, questions that may interest researchers include, what are the privacy challenges caused by using AI in e-commerce? How can AI improve e-commerce services in education and training? How can AI improve e-commerce services in healthcare? How can AI bring about sustainable e-commerce practices?

Furthermore, research on AI in e-commerce is published in two main journal categories: computer science & AI and business & management. Most citations come from the information systems, computer science, artificial intelligence, management science, and operations research disciplines. Thus, researchers interested in research on AI in e-commerce are most likely to find relevant information in such journals (see Tables 5 and 6). Researchers seeking to publish their research on AI in e-commerce can also target such journals. However, researchers are encouraged to publish their work in other equally important journal categories. For example, law and government-oriented journals would greatly benefit from research on AI in e-commerce. International laws and government policies could affect how AI is used in e-commerce. For example, due to the General Data Protection Regulation (GDPR), how firms use AI algorithms and applications to analyse user data in Europe may differ from how they would in the US. Such factors may have profound performance implications given that AI systems are as good as the volume and quality of data they can access for analysis. Thus, future research in categories other than those currently researched would benefit the research community.

More experiment than theory-driven research

Most of the research done on AI in e-commerce have adopted experimental approaches. Very few adopted theory-driven designs. This trend is also observed in IS research, where 69% of the studies used experimental research methods and 86% adopted a design science research approach instead of the positivist research approach often adopted in general e-commerce research (Wareham et al., 2005). However, this study's findings complement a recent review that shows that laboratory experiments and secondary data analysis were becoming increasingly popular in e-commerce research. Given that recommender systems support customer decision-making, this study also complements recent studies that show the rising use of design science research methods in decision support systems research (Arnott & Pervan, 2014) and in IS research in general (Jeyaraj & Zadeh, 2020). This finding could be explained by the fact that researchers primarily focused on enhancing the performance of AI algorithms used in recommender systems. Therefore, to test the performance of their algorithms in the real world, the researchers have to build a prototype and test it in real-life contexts. Using performance accuracy scores, the researchers would then tell the extent to which their proposed algorithm is performant. However, ML has been highlighted as a powerful tool that can help advance theory in behavioural IS research (Abdel-Karim et al., 2021). Therefore, key research questions on AI in e-commerce could be approached using ML as a tool for theory testing in behavioural studies. Researchers could consider going beyond using AI algorithms for optimising recommender systems to understand its users' behaviour. In Fig. 4, observe that 73% of IS researcher papers reviewed approached AI as an algorithm or methodology to solve problems in e-commerce. Only 14% approached AI as a system. Researchers can adopt both approaches in the same study in the sense that they can leverage ML algorithms to understand human interactions with AI systems, not just for optimisation. This approach could provide users with insights by answering questions regarding the adoption and use of AI systems.

Furthermore, only 6% of the studies focus on consumer behaviour. Thus, most researchers on AI in e-commerce this far have focused more on algorithm performance than on modelling the behaviour of consumers who use AI systems. It is also clear that behavioural aspects of using recommender systems are often overlooked (Adomavicius et al., 2013). There is relatively limited research on the adoption, use, characteristics, and impact of AI algorithms or systems on its users. This issue was raised as a fundamental problem in this research area (Bo et al., 2007) and seems to remain the case today. However, understanding consumer behaviour could help improve the accuracy of AI algorithms. Thus, behavioural science researchers need to conduct more research on modelling consumer behaviours regarding consumers' acceptance, adoption, use, and post-adoption behaviours targeted by AI applications in e-commerce. As AI algorithms, systems, and use cases multiply in e-commerce, studies explaining their unique characteristics, adoption, use, and impact at different levels (individual, organisational, and societal) should also increase. It implies adopting a more theory-driven approach to research on AI in e-commerce. Therefore, behavioural science researchers should be looking into questions on the behavioural factors that affect the adoption of AI in e-commerce.

Implications for research

This study contributes to research by innovatively synthesising the literature on AI in e-commerce. Despite the recent evolution of AI and the steady rise of research on how it could affect e-commerce environments, no review has been conducted to understand this research area's state and evolution. Yet, a recent study shows that e-commerce and AI are currently key research topics and themes in the IS discipline (Jeyaraj & Zadeh, 2020). This paper has attempted to fill this research gap by providing researchers with a global view of AI research in e-commerce. It offers a multidimensional view of the knowledge structure and citation behaviour in this research area by presenting the study's findings from functional, normative, and interpretive perspectives. Specifically, it reveals the most relevant topics, concepts, and themes on AI in e-commerce from a multidisciplinary perspective.

This contribution could help researchers evaluate the value and contributions of their research topics in the research area with respect to other disciplines and choose the best publication outlets for their research projects. This study also reveals the importance of AI in designing recommender systems and shows the foundational literature on which this research area is built. Thus, researchers could use this study to design the content of AI or e-commerce courses in universities and higher education institutions. Its content provides future researchers and practitioners with the foundational knowledge required to build quality recommender systems. Researchers could also use this study to inform their fields on the relevance of their research topics and the specific gaps to fill therein. For example, this study reveals the extent to which the IS discipline has appropriated research on AI in e-commerce. It also shows contributions of the IS discipline to the current research themes, making it easier for IS researchers to identify research gaps as well as gaps between IS theory and practice.

Implications for practice

This study shows that AI in e-commerce primarily focuses on recommender systems. It highlights sentiment analysis, optimisation, trust, and personalisation as the core themes in the research area. Thus, managers could tap into these resources to improve the quality of their recommender systems. Specifically, it could help them understand how to develop optimised, personalised, trust-based and sentiment-based analytics supported by uniquely designed AI algorithms. This knowledge would make imitating or replicating the quality of recommendations rendered through e-commerce platforms practically impossible for competitors. Firms willing to use AI in e-commerce would need unique access and ownership of customer data, AI algorithms, and expertise in analytics (De Smedt et al., 2021; Kandula et al., 2021; Shi et al., 2020). The competition cannot imitate these resources because they are unique to the firm, especially if patented (Pantano & Pizzi, 2020). Also, this research paper classifies IS literature on AI in e-commerce by topic area, research style, and research theme. Thus, IS practitioners interested in implementing AI in e-commerce platforms would easily find the research papers that best meet their needs. It saves them the time to search for articles themselves, which may not always be relevant and reliable.

Limitations

This study has some limitations. It was challenging to select a category for each article in the sample dataset. Most of those articles could be rightfully placed in several categories of the classification frameworks. However, assigning articles to a single category in each framework simplifies the research area's conceptualisation and understanding (Wareham et al., 2005). Thus, categories were assigned to each article based on the most apparent orientation from the papers' titles, keywords, and abstracts. Another challenge was whether or not to include a research paper in the review. For example, although some studies on recommender systems featured in the keyword search results, the authors did not specify if the system's underlying algorithms were AI algorithms. Consequently, such articles were not classified to ensure that those included in this review certainly had an AI orientation. Despite our efforts, we humbly acknowledge that this study may have missed some publications, and others may have been published since this paper started the review process. Thus, in no way does this study claim to be exhaustive but rather extensive. Nonetheless, the findings from our rigorous literature review process strongly match the bibliometric analysis findings and those from similar studies we referenced. Therefore, we believe our contributions to IS research on AI in e-commerce remain relevant.

Future research

In addition to recommendations for future research discussed in the previous sections, the findings of this study are critically analysed through the lens of recent AI research published in leading IS journals. The aim is to identify other potential gaps for future research on AI in e-commerce that could interest the IS community.

One of the fundamental issues with AI research in IS today is understanding the AI concept (Ågerfalk, 2020). Our findings show that researchers have mostly considered algorithms and techniques like ML, DL, and NLP AI in their e-commerce research. Are these algorithms and techniques AI? Does the fact that an algorithm helps to analyse data and make predictions about e-commerce activities mean that the algorithm is AI? It is crucial for researchers to clearly explain what they mean by AI and differentiate between different types of AI used in their studies to avoid ambiguity. This explanation would help prevent confusion between AI and business intelligence & analytics in e-commerce. It would also help distinguish between AI as a social actor and AI as a technology with the computational capability to perform cognitive functions.

A second fundamental issue with AI research in IS is context (Ågerfalk, 2020). Using the same data, an AI system would/should be able to interpret the message communicated or sought by the user based on

Table 9 Future research questions for AI in e-commerce research

Title	Research agenda description	Sample future research questions
Research boundaries	Need for more research from other countries	• Are there any cross-cultural differences between countries that affect the adoption and use of AI in e-commerce? • Are there any legal boundaries that affect the implementation and internationalisation of AI in e-commerce
Research focus	Strong focus on recommender systems	• How can conversational recommender systems be designed effectively? • What are the factors that influence the adoption of conversational recommender systems?
Research themes & topics	Limited research themes	• What are the privacy challenges faced by AI in e-commerce? • How can AI improve e-commerce services in education and training? • How can AI improve e-commerce services in healthcare? • How can AI bring about sustainable e-commerce practices?
Theorisation	More experiment than theory-driven research	• What are the behavioural factors that affect the adoption of AI in e-commerce? • How can AI algorithms be used for theory development in the e-commerce context?
Conceptualisation	Limited understanding of the AI concept	• What does AI mean in different e-commerce contexts? • What are the types of AI that are used in e-commerce?
Contextualisation	Lack of IS context	• What type of AI best suits which e-commerce context?
Ethics	Ethical choices and challenges	• What ethical choices do e-commerce firms need to make when implementing AI solutions? • What are the ethical challenges e-commerce firms face when implementing AI solutions?
Future of work	Controversy on the role of AI in the workplace	• How is the emergent digital/human work configuration driven by AI affecting e-commerce firms?
Decision support	Role of AI in transforming decision making	• How is AI affecting managerial mindsets and actions in e-commerce? • How is AI affecting the rationality of consumers using e-commerce platforms?
Voice assistants	Limited research on AI-powered voice assistants	• What factors affect the adoption and use of voice assistants in e-commerce? • What is the impact of voice assistants on consumers and e-commerce firms?

context. Context gives meaning to the data, making the AI system's output relevant in the real world. Research on AI in e-commerce did not show much importance to context. Many authors used existing datasets to test their algorithms without connecting them to a social context. Thus, it is difficult to assess whether the performance of the proposed algorithms is relevant in every social context. Future research should consider using AI algorithms to analyse behavioural data alongside 'hard' data (facts) to identify patterns and draw conclusions in specific contexts. It implies answering the crucial question, what type of AI best suits which e-commerce context? Thus, researchers would need to collaborate with practitioners to better understand and delineate contexts (Ågerfalk, 2020) of investigation rather than make general claims on fraud detection or product prices, for example.

The IS community is also interested in understanding ethical choices and challenges organisations face when adopting AI systems and algorithms. What ethical decisions do e-commerce firms need to make when implementing AI solutions? What are the ethical challenges e-commerce firms face when implementing AI solutions? Following a sociotechnical approach, firms seeking to implement AI systems need to make ethical choices. These include transparent vs black-boxed algorithms, slow & careful vs expedited & timely designs, passive vs active implementation approach, obscure vs open system implementation, compliance vs risk-taking, and contextualised vs standardised use of AI systems (Marabelli et al., 2021). Thus, future research on AI in e-commerce should investigate how e-commerce firms address these ethical choices when implementing their AI solutions and the challenges they face in the process.

AI and the future of work is another primary source of controversy in the IS community (Huysman, 2020; Willcocks, 2020a, b). Several researchers are investigating how AI is transforming the work configurations of organisations. Workplace technology platforms are increasingly observed to integrate office applications, social media features and AI-driven self-learning capabilities (Baptista et al., 2020; Grønsund & Aanestad, 2020; Lyytinen et al., 2020). Is this emergent digital/human work configuration also happening in e-commerce firms? How is this changing the future of work in the e-commerce industry?

IS researchers have increasingly called for research on how AI transforms decision making. For example, they are interested in understanding how AI could help augment mental processing, change managerial mindsets and actions, and affect the rationality of economic agents (Brynjolfsson et al., 2021). A recent study also makes several research propositions for IS researchers regarding conceptual and theoretical development, AI-human interaction, and AI implementation in the context of decision making (Duan et al., 2019). This study shows that decision-making is not a fundamental research theme as it accounts for only 13% of the research papers reviewed. Thus, future research on AI in e-commerce should contribute to developing this AI research theme in the e-commerce context. It involves proposing answers to questions like how AI affects managerial mindsets and actions in e-commerce? How is AI affecting the rationality of consumers who use e-commerce platforms?

This study shows that relatively few research papers on AI in e-commerce are theory-driven. Most adopted experimental research methods and design science research approaches wherein they use AI algorithms to explain phenomena. The IS community is increasingly interested in developing theories using AI algorithms (Abdel-Karim et al., 2021). Contrary to traditional theory development approaches, such theories developed based on AI algorithms like ML are called to be focused, context-specific, and as transparent as possible (Chiarini Tremblay et al., 2021). Thus, rather than altogether abandoning the algorithm-oriented approach used for AI in e-commerce research, researchers who master it should develop skills to use it as a basis for theorising.

Last but not least, more research is needed on the role of AI-powered voice-based AI in e-commerce. It is becoming common for consumers to use intelligent personal assistants like Google's Google Assistant, Amazon's Alexa, and Apple's Siri for shopping activities since many retail organisations are making them an integral part of their e-commerce platforms (de Barcelos Silva et al., 2020). Given the rising adoption of smart speakers by consumers, research on voice commerce should become a priority for researchers on AI in e-commerce. Yet, this study shows that researchers are still mostly focused on web-based, social networking (social commerce), and mobile (m-commerce) platforms. Therefore, research on the factors that affect the adoption and use of voice assistants in e-commerce and the impact on consumers and e-commerce firms would make valuable contributions to e-commerce research. Table 9 summarises the main research directions recommended in this paper.

Conclusions

AI has emerged as a technology that can differentiate between two competing firms in e-commerce environments. This study presents the state of research of AI in e-commerce based on bibliometric analysis and a literature review of IS research. The bibliometric analysis highlights China and the USA as leaders in this research area. Recommender systems are the most investigated technology. The main research themes in this area of research are optimisation, trust & personalisation, sentiment analysis, and AI concepts & related technologies. Most research papers on AI in e-commerce are published in computer science, AI, business, and management outlets. Researchers in the IS discipline has focused on AI applications and technology-related issues like algorithm performance. Their focus has been more on AI algorithms and methodologies than AI systems. Also, most studies have adopted a design science research approach and experiment-style research methods. In addition to the core research themes of the area, IS researchers have also focused their research on AI design, tools and techniques, decision support, consumer behaviour, AI concepts, and intelligent agents. The paper discusses opportunities for future research revealed directly by analysing the results of this study. It also discusses future research directions based on current debates on AI research in the IS community. Thus, we hope that this paper will help inform future research on AI in e-commerce.

Appendix

Table 10 Most cited documents on AI in e-commerce (by total citations)

Author(s), year	Source	(short) title / topic	Concept of interest	Research methodology	AI technology, technique, or tool	Subject area	Total Citations	Local Citations
(Burke, 2002)	User modeling and user-adapted interaction	Hybrid recommender systems	Product/service recommendation	Survey and experiment	Recommender systems	HCI, CSA	1501	107
(Rahm & Bernstein, 2001)	VLDB journal	A survey of approaches to automatic schema matching	Schema matching	Review	Machine learning	IS	1488	3
(Patcha & Park, 2007)	Computer networks	An overview of anomaly detection techniques	Anomaly detection	Review	Machine learning, data mining	CNC	555	4
(Knorr et al., 2000)	VLDB journal	Distance-based outliers	Outliers in multidimensional datasets	Experiment	Data mining	IS	541	5
(Sabater & Sierra, 2005)	Artificial intelligence review	Computational trust and reputation models	Computational trust and reputation	Review	Intelligent or autonomous agents and multi-agent systems (MAS)	AI	455	7
(Bolton & Hand, 2002)	Statistical science	Statistical fraud detection	Fraud	Review	Machine learning	STAT	417	18
(Ghose & Ipeirotis, 2011)	IEEE transactions on knowledge and data engineering	Helpfulness and economic impact of product reviews	Sales prediction, perceived usefulness	Econometric analysis	Random forest	IS, CSA	415	28
(Schafer et al., 2001)	Data mining and knowledge discovery	E-commerce recommendation applications	Product/service recommendation	Review	Recommender systems	IS, CNC, CSA	403	59
(Lu et al., 2015)	Decision support systems	Recommender system application developments	Product/service recommendation	Review	Recommender systems	IS, MIS	362	29
(Ravi & Ravi, 2015)	Knowledge-based systems	Opinion mining and sentiment analysis	Opinion mining, sentiment analysis	Review	Machine learning, natural language processing	IS, KM	342	11
(Nikolay et al., 2011)	Management science	Deriving the pricing power of product features	Consumer choice, consumer reviews	Econometric analysis	Text mining, sentiment analysis, opinion mining	MS, OR	294	17
(Cho et al., 2002)	Expert systems with applications	Personalized recommender system	Product/service recommendation	Experiment	Recommender systems	IS, AI, CSA	226	41

Table 10 (continued)

Author(s), year	Source	(short) title / topic	Concept of interest	Research methodology	AI technology, technique, or tool	Subject area	Total Citations	Local Citations
(Chen et al., 2002)	Proceedings international conference on dependable systems and networks	Problem determination in large, dynamic internet services	Problem determination	Experiment	Data mining	CNC	225	0
(Song et al., 2005)	IEEE internet computing	Trusted p2p transactions with fuzzy reputation aggregation	Computational trust and reputation	Experiment	Fuzzy logic	CNC	216	0
(Guttman et al., 1998)	Knowledge engineering review	Agent-mediated electronic commerce	Consumer buying behaviours	Review	Software agents	AI	211	18
(Kohavi et al., 2009)	Data mining and knowledge discovery	Controlled experiments on the web	Controlled experiments on the web	Review	Data mining	IS, CNC, CSA	210	5
(Büyüközkan et al., 2008)	International journal of production economics	Selection of the strategic alliance partner in logistics value chain	Decision support for the selection of e-logistics partners	Multi-criteria decision-making (MCDM) approach	Fuzzy logic	MS, OR, POM	203	0
(Zhang, Du, et al., 2018; Zhang, Yang, et al., 2018)	Information fusion	A survey on deep learning for big data	Big data	Review	Deep learning	IS	199	0
(Hanani et al., 2001)	User modeling and user-adapted interaction	Information filtering	Information filtering	Review	N/a	HCI, CSA	198	15
(Lin et al., 2002)	Data mining and knowledge discovery	Efficient association rule mining for recommender systems	Product/service recommendation	Mathematical	Collaborative Recommender systems	IS, CNC, CSA	192	13
(Hansen & Hasan, 2015)	IEEE signal processing magazine	Speaker recognition by machines and humans	Voice recognition	Review	Speech recognition, Feature extraction	SP	175	0
(Zaïane, 2002)	International conference on computers in education	Building a recommender agent for e-learning systems	Product/service recommendation	N/a	Recommender systems, web mining	CSA	147	0
(Cheung et al., 2003)	Decision support systems	Mining customer product ratings for personalized marketing	Personalized marketing, customer product ratings	Mathematical	Recommender systems, support vector machines	IS, MIS	145	24
(Wei et al., 2017)	Expert systems with applications	Collaborative filtering and deep learning-based recommendation system	Product/service recommendation	Experiment, mathematical	Recommender systems, deep learning	IS, AI, CSA	144	15

Table 10 (continued)

Author(s), year	Source	(short) title / topic	Concept of interest	Research methodology	AI technology, technique, or tool	Subject area	Total Citations	Local Citations
(Law et al., 2009)	Journal of travel & tourism marketing	IT applications in hospitality and tourism	N/a	Review	N/a	MKT, TLH	137	0
(Decker & Trusov, 2010)	International journal of research in marketing	Estimating aggregate consumer preferences from online product reviews	Consumer preferences, consumer behavior	Econometric analysis	Natural language processing	MKT	135	8
(Kim & Ahn, 2008)	Expert systems with applications	A recommender system in an online shopping market	Product/service recommendation	Experiment, mathematical	Recommender systems, genetic algorithms, K-means	IS, AI, CSA	132	11
(Cao & Li, 2007)	Expert systems with applications	An intelligent fuzzy-based recommendation system for consumer electronic products	Product/service recommendation	Experiment	Recommender systems	IS, AI, CSA	130	28
(Hong et al., 2004)	Journal of management information systems	The effects of information format and shopping task on consumers' online shopping behavior	Consumer online shopping behavior	Experiment	N/A	MIS	129	1
(Chang et al., 2014)	Decision support systems	Understanding the paradigm shift to computational social science in the presence of big data	Computational social science, big data	Conceptual	Data mining	IS, MIS	126	3
(Akter & Wamba, 2016)	Electronic markets	Big data in e-commerce	Big data analytics	Review	N/a	MIS, MKT	118	9
(Dongwen Zhang et al., 2015)	Expert systems with applications	Chinese comments sentiment classification	Sentiment analysis	Experiment	Machine learning (Word2vec, SVM^{perf}	IS, AI, CSA	117	3
(Lee et al., 2010)	Information sciences	Implicit ratings for mobile music recommendations	Product/service recommendation	Experiment	Recommender systems, mobile Web usage mining	IS, AI, CSA	117	9
(A. Y.-L. Chong, 2013a, b)	Expert systems with applications	Understanding and predicting the determinants of m-commerce adoption	M-commerce adoption	Quantitative (SEM-neural network)	Neural networks	IS, AI, CSA	116	14

Table 10 (continued)

Author(s), year	Source	(short) title / topic	Concept of interest	Research methodology	AI technology, technique, or tool	Subject area	Total Citations	Local Citations
(Gokmen & Vlasov, 2016)	Frontiers in neuroscience	Acceleration of deep neural network training with resistive cross-point devices	Deep neural networks	Conceptual	Deep neural networks	NSC	111	0
(Kim, Song, et al., 2005; Kim, Yum, et al., 2005)	Decision support systems	A multidimensional trust formation model in b-to-c e-commerce	Trust	Conceptual	N/a	IS, MIS	111	3
(Tan & Kumar, 2002)	Data mining and knowledge discovery	Discovery of web robot sessions	Web robot detection	Experiment	Web usage mining, web robots (software agents), data mining	IS, CNC, CSA	111	3
(A. Y. L. Chong, 2013a, b)	Expert systems with applications	Predicting m-commerce adoption determinants	M-commerce adoption	Quantitative	Neural networks	IS, AI, CSA	110	16
(Datta et al., 2006)	IEEE internet computing	Distributed data mining in peer-to-peer networks	N/a	Review	Data mining	CNC	110	1
(Li et al., 2013)	Decision support systems	A social recommender mechanism for e-commerce	Product/service recommendation, similarity, trust, relationships	Experiment	Social recommender systems	IS, MIS	102	14

Legend: HCI: Human computer interactions; CSA: Computer science applications; IS: Information systems; CNC: Computer networks and communications; AI: Artificial intelligence; STAT: Statistics; MIS: Management information systems; KM: Knowledge management; MS: Management science; OR: Operations research; POM: Production and operations management; SP: Signal processing; MKT: Marketing; TLH: Tourism, leisure, and hospitality; NSC: Neuroscience.

Subject area categories come from SCIMAGOJR classification standards (https://www.scimagojr.com/).

Table 11 Significant contributions and turning points in research on AI in e-commerce

Authors, date	(Short) title	Source
2001		
(Sarwar et al., 2001)	Item-based collaborative filtering recommendation algorithms	WWW '01: Proceedings of the 10th international conference on World Wide Web
(Breiman, 2001)	Random Forests	Machine Learning
(Schafer et al., 2001)	E-Commerce Recommendation Applications	Data Mining and Knowledge Discovery
(Goldberg et al., 2001)	Eigentaste: A constant time collaborative filtering algorithm	Information retrieval
(Friedman, 2001)	Greedy function approximation: A gradient boosting machine	Annals of statistics
(Jiawei H. et al., 2001)	Data mining: concepts and technologies	Book
(Lawrence et al., 2001)	Personalization of Supermarket Product Recommendations	Data Mining and Knowledge Discovery
(Lee et al., 2001)	Visualization and Analysis of Clickstream Data of Online Stores for Understanding Web Merchandising	Data Mining and Knowledge Discovery
2005		
(Adomavicius & Tuzhilin, 2005)	Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions	IEEE Transactions on Knowledge and Data Engineering
(Witten et al., 2016)	Data Mining: Practical Machine Learning Tools and Techniques	Book
(Yu Li et al., 2005)	A hybrid collaborative filtering method for multiple-interests and multiple-content recommendation in E-Commerce	Expert systems with applications
(Adomavicius et al., 2005)	Incorporating contextual information in recommender systems using a multi-dimensional approach	ACM Transactions on Information Systems
(Kim, Song, et al., 2005; Kim, Yum, et al., 2005)	Development of a recommender system based on navigational and behavioral patterns of customers in e-commerce sites	Expert systems with applications
(O'Donovan & Smyth, 2005)	Trust in recommender systems	IUI '05: Proceedings of the 10th international conference on Intelligent user interfaces
(Ziegler et al., 2005)	Improving recommendation lists through topic diversification	WWW '05: Proceedings of the 14th international conference on World Wide Web
(Xue et al., 2005)	Scalable collaborative filtering using cluster-based smoothing	Proceedings of the 28th annual international ACM SIGIR conference on Research and development in information retrieval
(Liu et al., 2005)	Opinion observer: analyzing and comparing opinions on the Web	WWW '05: Proceedings of the 14th international conference on World Wide Web
(Shani et al., 2005)	An MDP-Based Recommender System	Journal of Machine Learning Research
2007		
(Brusilovski et al., 2007)	The adaptive web: methods and strategies of web personalization	Book
(Bo et al., 2007)	E-commerce product recommendation agents: use, characteristics, and impact	MIS Quarterly
(Cao & Li, 2007)	An intelligent fuzzy-based recommendation system for consumer electronic products	Expert systems with applications
(Jøsang et al., 2007)	A survey of trust and reputation systems for online service provision	Decision support systems

Table 11 (continued)

Authors, date	(Short) title	Source
(Salakhutdinov et al., 2007)	Restricted Boltzmann machines for collaborative filtering	ICML '07: Proceedings of the 24th international conference on Machine learning
(Huang et al., 2007)	A Comparison of Collaborative-Filtering Recommendation Algorithms for E-commerce	IEEE Intelligent Systems
(Vozalis & Margaritis, 2007)	Using SVD and demographic data for the enhancement of generalized Collaborative Filtering	Information Sciences
2011		
(Ricci et al., 2011)	Introduction to Recommender Systems Handbook	Book
(Ghose & Ipeirotis, 2011)	Estimating the Helpfulness and Economic Impact of Product Reviews: Mining Text and Reviewer Characteristics	IEEE Transactions on Knowledge and Data Engineering
(Chang & Lin, 2011)	LIBSVM: A library for support vector machines	ACM Transactions on Intelligent Systems and Technology
(Pedregosa et al., 2011)	Scikit-learn: Machine learning in Python	Journal of Machine Learning Research
(Cacheda et al., 2011)	Comparison of collaborative filtering algorithms: Limitations of current techniques and proposals for scalable, high-performance recommender systems	ACM Transactions on the Web
2015		
(McAuley et al., 2015)	Image-Based Recommendations on Styles and Substitutes	SIGIR '15: Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval
(LeCun et al., 2015)	Deep learning	Nature
(Lu et al., 2015)	Recommender system application developments: A survey	Decision support systems
(Wang et al., 2015)	Collaborative deep learning for recommender systems	KDD '15: Proceedings of the 21st ACM SIGKDD International Conference on Knowledge Discovery and Data Mining
(Szegedy et al., 2015)	Going deeper with convolutions	2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)
(Schmidhuber, 2015)	Deep learning in neural networks: An overview	Neural Networks
(Chen et al., 2015)	Recommender systems based on user reviews: the state of the art	User Modeling and User-Adapted Interaction
(Isinkaye et al., 2015)	Recommendation systems: Principles, methods, and evaluation	Egyptian Informatics Journal

Table 12 Classification of MIS literature on AI in e-commerce by topic area

Category	Subcategory	Articles
Applications	Interorganizational systems	(Lin et al., 2003)
	Electronic payment systems	(Fiore et al., 2019; Xinwei Zhang, Du, et al., 2019; Zhang, Han, et al., 2019)
	Financial services	(Chen, 2012; Das & Chen, 2007; Hill & Ready-Campbell, 2011; Ma et al., 2018; Manahov & Zhang, 2019; Maqsood et al., 2020; Pengnate & Riggins, 2020; Sul et al., 2017; Sun et al., 2020; Wang et al., 2012; Ye et al., 2018; Weiguo Zhang, Wang, et al., 2020; Zhang, Liu, et al., 2020)
	Clothing and fashion	(Dong et al., 2020; Liu et al., 2017)
	Retailing	(Chang & Jang, 2009; R. Chen et al., 2018; Greenstein-Messica & Rokach, 2020; D. Lee et al., 2020; Luo et al., 2019; Park & Park, 2003)
	Online publishing	(Cardoso & Gomide, 2007; Castillo et al., 2017; Liu et al., 2018; Ma et al., 2011)
	Auctions	(Bandyopadhyay et al., 2008; Chang & Chang, 2012; Chen & Chung, 2015)
	Intra organizational e-commerce	(Guo, Qiu, et al., 2017; Guo, Wei, et al., 2017; Guo, Zhang, et al., 2017; Stoeckli et al., 2020)
	Education and training	(Aher & Lobo, 2013; Núñez-Valdez et al., 2018)
	Marketing and advertising	(Al-Natour & Turetken, 2020; Bassano et al., 2017; Bauer & Jannach, 2018; Beladev et al., 2016; Bose & Chen, 2009; Chang, 2011; Chen et al., 2014, 2017; Chu et al., 2007; Cui et al., 2006; Ghiassi et al., 2016; Gong et al., 2018; Gunnec & Raghavan, 2017; Guo et al., 2015; He et al., 2018; Kagan & Bekkerman, 2018; Kazienko & Adamski, 2007; Ketter et al., 2012; Khopkar & Nikolaev, 2017; Kim et al., 2001; Kühl et al., 2020; Kuo et al., 2004; Lessmann et al., 2019; Li et al., 2014, 2019; Li, Wang, et al., 2019; Li, Wang, et al., 2019; Li, Wu, et al., 2019; Li, Wu, et al., 2019; Li, Zhang, et al., 2019; Miralles-Pechuán et al., 2018; Nassiri-Mofakham et al., 2009; Nikolay et al., 2011; Padmanabhan & Tuzhilin, 2003; Qi et al., 2016; Rao et al., 2016; Takeuchi et al., 2009; Wang, 2008; Wang & Doong, 2010; Wenxuan Ding et al., 2015; Wu & Chou, 2011; Yan et al., 2020)
	Other applications	(Abbasi et al., 2010; Bai et al., 2020; Brazier et al., 2002; Bukhari & Kim, 2012; Cao & Schniederjans, 2006; Guan et al., 2014; Hogenboom et al., 2015; Jeong et al., 2003; Kiekintveld et al., 2009; Leloup, 2003; Liebman et al., 2019; Martens & Provost, 2014; Mo et al., 2018; Motiwalla & Nunamaker, 1992; Nilashi et al., 2015; Pfeiffer et al., 2020; Praet & Martens, 2020; Wei et al., 2002; Zhao, Dai, et al., 2020; Zhao, Lou, et al., 2020)

Table 12 (continued)

Category	Subcategory	Articles
Technological issues	Security	(Ariyaluran Habeeb et al., 2019; Cai & Zhang, 2019; Laorden et al., 2012; Yang Cai, & Guan, 2016; Yang, Cai, et al., 2016; Yang, Xu, et al., 2016; Yang, Xu, et al., 2016)
	Technological components	(Dastani et al., 2005; Keegan et al., 2008)
	Network technology / infrastructure	(Manvi & Venkataram, 2005)
	Support systems	(Adomavicius et al., 2013; Barzegar Nozari & Koohi, 2020; Bobadilla et al., 2013; Chow et al., 2007; Chung, 2014; Da'u et al., 2020; Ghavipour & Meybodi, 2016; Gupta & Kant, 2020; Ito et al., 2002; Julià et al., 2009; Kaiser et al., 2011; Khare & Chougule, 2012; Lau, 2007; Pontelli & Son, 2003; Saleh et al., 2015; Tan & Thoen, 2000; Villegas et al., 2018; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Watson & Rasmussen, 2008; Xiaofeng Zhang, Wang, et al., 2020; Zhang, Liu, et al., 2020; Zheng et al., 2013)
	Algorithm / methodology	(Aguwa et al., 2017; Al-Shamri, 2016; Bag et al., 2019; Bedi & Vashisth, 2014; Jesús Bobadilla et al., 2012; Carbó et al., 2007; Chen & Wang, 2013; Chen, 2013; Chen et al., 2013; Esmeli et al., 2021; Fang et al., 2018; Fang et al., 2013; Fasli & Kovalchuk, 2011; Feng et al., 2019; Geng et al., 2020; Greenstein-Messica & Rokach, 2018; Gu et al., 2017; S.-U. Guan et al., 2005; Guan et al., 2019; Guo, Qiu, et al., 2017; Guo, Zhang, et al., 2017; Guo, Wei, et al., 2017; Ha & Lee, 2009; Han et al., 2019; He et al., 2019; Herce-Zelaya et al., 2020; Hernando et al., 2017; Himabindu et al., 2018; Hirt et al., 2019; Hu, 2014; Iwański et al., 2018; Ji & Shen, 2015; Jiang et al., 2014; Jiang et al., 2005; Kim et al., 2017; Kim et al., 2002; Kumar et al., 2018; Kumar, Venugopal, et al., 2019; Kumar, Rajan, et al., 2019; Kuo et al., 2005; Lee et al., 2019; S. Lee & Kim, 2017; Lee et al., 2012; Liu et al., 2019; Liu & Shen, 2020; Liu et al., 2013; Mao et al., 2019; Martinez-Cruz et al., 2015; Nishimura et al., 2018; Oliver, 1996; Ortega et al., 2013, 2016; Ou et al., 2018; Pang et al., 2019; Park Kim, & Yu, 2019; Park, Kim, et al., 2020; Park, Song, et al., 2020; Park et al., 2020; Park, Song, et al., 2020; Patra et al., 2015; Pendharkar, 2006; Pourgholamali et al., 2020; Pröllochs et al., 2020; Pujahari & Sisodia, 2019; Qiu et al., 2018; Ranjbar Kermany & Alizadeh, 2017; Saumya et al., 2018; Si et al., 2017; Singh & Tucker, 2017; Tang et al., 2020; Tian et al., 2016; Varshney et al., 2017; Vizine Pereira & Hruschka, 2015; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Wang Jhou, & Tsai, 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Wu, Ye, et al., 2019; Wu, Huang, et al., 2019; Xia et al., 2021; Xie et al., 2014; Yan et al., 2015; Wen Zhang, Yang, et al., 2018; Zhang, Du, et al., 2018; Zhang, Du, et al., 2019; Zhang, Han, et al., 2019; Zheng & Padmanabhan, 2006; Zoghbi et al., 2016)
	Other technical issues	(Chou & Seng, 2009; Yang Li, Zhang, et al., 2019; Li, Wu, et al., 2019; Li, Wang, et al., 2019)
Support and implementation	Privacy	(Preibusch et al., 2016; Viejo et al., 2012; Zhao et al., 2019)
	Fraud	(Chang & Chang, 2014; Juan Ji et al., 2020; Lin et al., 2016; Suchacka & Iwański, 2020; Dongsong Zhang et al., 2014)
	Trust	(Azadjalal et al., 2017; Guo et al., 2014; Guo, Qiu, et al., 2017; Guo, Wei, et al., 2017; Guo, Zhang, et al., 2017; Li et al., 2017; Parvin et al., 2019; Pranata & Susilo, 2016; Pu & Chen, 2007; Thiebes et al., 2021)
	Other support and implementation	(Griggs & Wild, 2003; Hopkins et al., 2019; Kauffman et al., 2017; Li et al., 2006; Xu et al., 2019)
Others		(Al-Natour et al., 2006, 2011; Alt et al., 2019; Bondielli & Marcelloni, 2019; Buettner, 2017; Chen et al., 2019; Ferrara et al., 2014; Galitsky, 2006; Kwon et al., 2006; Mokryn et al., 2019; Moussawi et al., 2020; O'Neil et al., 2016; Ravi & Ravi, 2015; Wang, Feng, et al., 2018; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Lu, et al., 2018; Wu, Huang, et al., 2019; Wu, Ye, et al., 2019)

Table 13 Classification of MIS literature on AI in e-commerce by type of AI

Category	Articles
Algorithm / methodology	(Aguwa et al., 2017; Aher & Lobo, 2013; Al-Shamri, 2016; Azadjalal et al., 2017; Bag et al., 2019; Bandyopadhyay et al., 2008; Bauer & Jannach, 2018; Beladev et al., 2016; Jesús Bobadilla et al., 2012; Bose & Chen, 2009; Bukhari & Kim, 2012; Cai & Zhang, 2019; Cardoso & Gomide, 2007; Castillo et al., 2017; Chang & Chang, 2014; Chang & Jang, 2009; Chang & Chang, 2012; Chang, 2011; Chen & Chung, 2015; Chen et al., 2017; Chen & Wang, 2013; Chen, 2013; Chen et al., 2018, 2019; Chen, 2012; Chen et al., 2013, 2014; Chou & Seng, 2009; Chu et al., 2007; Cui et al., 2006; Das & Chen, 2007; Dastani et al., 2005; Esmeli et al., 2021; Fang et al., 2018; Fang et al., 2013; Fasli & Kovalchuk, 2011; Feng et al., 2019; Fiore et al., 2019; Geng et al., 2020; Ghiassi et al., 2016; Gong et al., 2018; Greenstein-Messica & Rokach, 2020; Gu et al., 2017; Guan et al., 2014; Guan et al., 2005; Guan et al., 2019; Gunnec & Raghavan, 2017; Guo et al., 2014; Guo, Qiu, et al., 2017; Guo, Zhang, et al., 2017; Guo, Wei, et al., 2017; Guo et al., 2017; Guo, Zhang, et al., 2017; Guo, Wei, et al., 2017; Guo et al., 2017; Guo et al., 2017; Guo, Wei, et al., 2017; Ha & Lee, 2009; Han et al., 2019; He et al., 2019, 2018; Herce-Zelaya et al., 2020; Hernando et al., 2017; Hill & Ready-Campbell, 2011; Himabindu et al., 2018; Hirt et al., 2019; Hogenboom et al., 2015; Hu, 2014; Iwański et al., 2018; Jeong et al., 2003; Ji & Shen, 2015; Juan Ji et al., 2020; Jiang et al., 2014; Julià et al., 2009; Khopkar & Nikolaev, 2017; Kiekintveld et al., 2009; Kim et al., 2017; Kim et al., 2001; Kim et al., 2002; Kühl et al., 2020; Kumar et al., 2018; Kumar, Venugopal, et al., 2019; Kumar, Rajan, et al., 2019; Kuo et al., 2004, 2005; Laorden et al., 2012; Lee et al., 2019; Lee & Kim, 2017; Lee et al., 2012; Leloup, 2003; Lessmann et al., 2019; Li et al., 2017; Li, Zhang, et al., 2019; Li, Wu, et al., 2019; Li, Wang, et al., 2019; Li et al., 2019; Li, Wu, et al., 2019; Li, Wang, et al., 2019; Yang Li et al., 2019; Li Wu, & Mai, 2019; Li, Wang, et al., 2019; Liebman et al., 2019; Lin et al., 2003; Lin et al., 2016; Liu et al., 2018; Liu et al., 2019; Liu et al., 2017; Liu & Shen, 2020; Liu et al., 2013; Ma et al., 2018; Ma et al., 2011; Manahov & Zhang, 2019; Manvi & Venkataram, 2005; Mao et al., 2019; Maqsood et al., 2020; Martens & Provost, 2014; Martinez-Cruz et al., 2015; Miralles-Pechuán et al., 2018; Mo et al., 2018; Mokryn et al., 2019; Nassiri-Mofakham et al., 2009; Nilashi et al., 2015; Nishimura et al., 2018; O'Neil et al., 2016; Oliver, 1996; Ortega et al., 2013, 2016; Ou et al., 2018; Pang et al., 2019; C. Park Kim, & Yu, 2019; Park, Kim, et al., 2020; Park, Song, et al., 2020; Park et al., 2020; Park, Song, et al., 2020; Park & Park, 2003; Parvin et al., 2019; Patra et al., 2015; Pendharkar, 2006; Pfeiffer et al., 2020; Pourgholamali et al., 2020; Praet & Martens, 2020; Pranata & Susilo, 2016; Preibusch et al., 2016; Pröllochs et al., 2020; Pujahari & Sisodia, 2019; Qi et al., 2016; Qiu et al., 2018; Ranjbar Kermany & Alizadeh, 2017; Rao et al., 2016; Saumya et al., 2018; Si et al., 2017; Singh & Tucker, 2017; Suchacka & Iwański, 2020; Takeuchi et al., 2009; Tang et al., 2020; Tian et al., 2016; Varshney et al., 2017; Viejo et al., 2012; Vizine Pereira & Hruschka, 2015; Wang, 2008; Wang et al., 2012; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Wang Jhou, & Tsai, 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Wang Jhou, & Tsai, 2018; Wang Li, & Singh, 2018b; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Wei et al., 2002; Wenxuan Ding et al., 2015; Wu, Ye, et al., 2019; Wu, Huang, et al., 2019; Wu & Chou, 2011; Xie et al., 2014; Xu et al., 2019; Yan et al., 2015; Yan et al., 2020; Yang, Cai, et al., 2016; Yang, Xu, et al., 2016; Ye et al., 2018; Dongsong Zhang et al., 2014; Weiguo Zhang, Wang, et al., 2020; Zhang, Liu, et al., 2020; Wen Zhang, Yang, et al., 2018; Zhang, Du, et al., 2018; Zhang, Du, et al., 2019; Zhang, Han, et al., 2019; Xiaofeng Zhang et al., 2020; Zhang, Liu, et al., 2020; Xinwei Zhang, Du, et al., 2019; Zhang, Han, et al., 2019; Zhao, Lou, et al., 2020; Zhao, Dai, et al., 2020; Zhao et al., 2019; Zheng & Padmanabhan, 2006; Zoghbi et al., 2016)
System	(Abbasi et al., 2010; Barzegar Nozari & Koohi, 2020; Bedi & Vashisth, 2014; Brazier et al., 2002; Carbó et al., 2007; Chow et al., 2007; Da'u et al., 2020; Dong et al., 2020; Ghavipour & Meybodi, 2016; Greenstein-Messica & Rokach, 2018; Gupta & Kant, 2020; Ito et al., 2002; Kaiser et al., 2011; Kazienko & Adamski, 2007; Keegan et al., 2008; Ketter et al., 2012; Khare & Chougule, 2012; Kwon et al., 2006; Lau, 2007; D. Lee et al., 2020; Li et al., 2014; Motiwalla & Nunamaker, 1992; Núñez-Valdez et al., 2018; Pu & Chen, 2007; Saleh et al., 2015; Stoeckli et al., 2020; Tan & Thoen, 2000; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Wang & Doong, 2010; Watson & Rasmussen, 2008; Xia et al., 2021; Yang, Cai, et al., 2016; Yang, Xu, et al., 2016; Zheng et al., 2013)
Other	(Adomavicius et al., 2013; Al-Natour & Turetken, 2020; Al-Natour et al., 2006, 2011; Alt et al., 2019; Ariyaluran Habeeb et al., 2019; Bai et al., 2020; Bassano et al., 2017; Bobadilla et al., 2013; Bondielli & Marcelloni, 2019; Buettner, 2017; Cao & Schniederjans, 2006; Chung, 2014; Ferrara et al., 2014; Galitsky, 2006; Griggs & Wild, 2003; Guo et al., 2015; Hopkins et al., 2019; Jiang et al., 2005; Kagan & Bekkerman, 2018; Kauffman et al., 2017; Li et al., 2006; Luo et al., 2019; Moussawi et al., 2020; Padmanabhan & Tuzhilin, 2003; Pontelli & Son, 2003; Ravi & Ravi, 2015; Sul et al., 2017; Sun et al., 2020; Thiebes et al., 2021; Villegas et al., 2018; Wu, Huang, et al., 2019; Wu, Ye, et al., 2019)

Table 14 Classification of MIS literature on AI in e-commerce by research approach

Approach	Articles
Positivist	(Adomavicius et al., 2013; Al-Natour et al., 2006, 2011; Al-Shamri, 2016; Chen et al., 2017; Guo et al., 2015; Jiang et al., 2005; Li, Wang, et al., 2019; Li, Wu, et al., 2019; Li, Zhang, et al., 2019; Luo et al., 2019; Moussawi et al., 2020; Park, Kim, et al., 2020; Park, Song, et al., 2020; Sul et al., 2017; Sun et al., 2020; Wang & Doong, 2010; Wu, Huang, et al., 2019; Wu, Ye, et al., 2019)
Interpretivist	(Stoeckli et al., 2020)
Design science	(Abbasi et al., 2010; Aguwa et al., 2017; Aher & Lobo, 2013; Al-Natour & Turetken, 2020; Azadjalal et al., 2017; Bag et al., 2019; Bandyopadhyay et al., 2008; Barzegar Nozari & Koohi, 2020; Bauer & Jannach, 2018; Bedi & Vashisth, 2014; Beladev et al., 2016; Jesús Bobadilla et al., 2012; Bose & Chen, 2009; Brazier et al., 2002; Buettner, 2017; Bukhari & Kim, 2012; Cai & Zhang, 2019; Q. Cao & Schniederjans, 2006; Carbó et al., 2007; Cardoso & Gomide, 2007; Castillo et al., 2017; Chang & Chang, 2014; Chang & Jang, 2009; Chang & Chang, 2012; Chang, 2011; Chen & Chung, 2015; Chen & Wang, 2013; Chen, 2013; Chen et al., 2018, 2019; Chen, 2012; Chen et al., 2013, 2014; Chou & Seng, 2009; Chow et al., 2007; Chu et al., 2007; Chung, 2014; Cui et al., 2006; Da'u et al., 2020; Das & Chen, 2007; Dastani et al., 2005; Dong et al., 2020; Esmeli et al., 2021; Fang et al., 2018; Fang et al., 2013; Fasli & Kovalchuk, 2011; Feng et al., 2019; Fiore et al., 2019; Geng et al., 2020; Ghavipour & Meybodi, 2016; Ghiassi et al., 2016; Gong et al., 2018; Greenstein-Messica & Rokach, 2018, 2020; Gu et al., 2017; Guan et al., 2014; Guan et al., 2005; Guan et al., 2019; Gunnec & Raghavan, 2017; Guo et al., 2014; Guo, Qiu, et al., 2017; Guo, Zhang, et al., 2017; Guo, Wei, et al., 2017; Guo et al., 2017; Guo, Zhang, et al., 2017; Guo, Wei, et al., 2017; Guo et al., 2017; Guo et al., 2017; Guo, Wei, et al., 2017; Gupta & Kant, 2020; Ha & Lee, 2009; Han et al., 2019; He et al., 2019, 2018; Herce-Zelaya et al., 2020; Hernando et al., 2017; Hill & Ready-Campbell, 2011; Himabindu et al., 2018; Hirt et al., 2019; Hogenboom et al., 2015; Hopkins et al., 2019; Hu, 2014; Iwański et al., 2018; Jeong et al., 2003; K. Ji & Shen, 2015; S. juan Ji et al., 2020; G. Jiang et al., 2014; Julià et al., 2009; Kagan & Bekkerman, 2018; Kaiser et al., 2011; Kazienko & Adamski, 2007; Keegan et al., 2008; Ketter et al., 2012; Khare & Chougule, 2012; Khopkar & Nikolaev, 2017; Kiekintveld et al., 2009; Kim et al., 2017; Kim et al., 2001; Kim et al., 2002; Kühl et al., 2020; Kumar et al., 2018; Kumar, Venugopal, et al., 2019; Kumar, Rajan, et al., 2019; Kuo et al., 2004, 2005; Kwon et al., 2006; Laorden et al., 2012; Lau, 2007; Lee et al., 2020; Lee et al., 2019; Lee & Kim, 2017; Lee et al., 2012; Leloup, 2003; Lessmann et al., 2019; Li et al., 2017; Li, Zhang, et al., 2019; Li, Wu, et al., 2019; Li, Wang, et al., 2019; Li et al., 2014; Yang Li et al., 2019; Li, Wu, et al., 2019; Li, Wang, et al., 2019; Liebman et al., 2019; Lin et al., 2003; Lin et al., 2016; Liu et al., 2018; Liu et al., 2019; Liu et al., 2017; Liu & Shen, 2020; Liu et al., 2013; Ma et al., 2018; Ma et al., 2011; Manahov & Zhang, 2019; Manvi & Venkataram, 2005; Mao et al., 2019; Maqsood et al., 2020; Martens & Provost, 2014; Martinez-Cruz et al., 2015; Miralles-Pechuán et al., 2018; Mo et al., 2018; Mokryn et al., 2019; Nassiri-Mofakham et al., 2009; Nikolay et al., 2011; Nilashi et al., 2015; Nishimura et al., 2018; Núñez-Valdez et al., 2018; O'Neil et al., 2016; Oliver, 1996; Ortega et al., 2013, 2016; Ou et al., 2018; Pang et al., 2019; Park et al., 2019; Park, Kim, et al., 2020; Park, Song, et al., 2020; Park & Park, 2003; Parvin et al., 2019; Patra et al., 2015; Pendharkar, 2006; Pfeiffer et al., 2020; Pontelli & Son, 2003; Pourgholamali et al., 2020; Praet & Martens, 2020; Pranata & Susilo, 2016; Preibusch et al., 2016; Pröllochs et al., 2020; Pu & Chen, 2007; Pujahari & Sisodia, 2019; Qi et al., 2016; Qiu et al., 2018; Ranjbar Kermany & Alizadeh, 2017; Rao et al., 2016; Saleh et al., 2015; Saumya et al., 2018; Si et al., 2017; Singh & Tucker, 2017; Suchacka & Iwański, 2020; Takeuchi et al., 2009; Tang et al., 2020; Tian et al., 2016; Varshney et al., 2017; Viejo et al., 2012; Vizine Pereira & Hruschka, 2015; Wang, 2008; Wang et al., 2012; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Wang Jhou, & Tsai, 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Wang Jhou, & Tsai, 2018; Wang Li, & Singh, 2018b; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Wang Jhou, & Tsai, 2018; Wang Li, & Singh, 2018b; Wang Feng, & Dai, 2018; Wang, Lu, et al., 2018; Watson & Rasmussen, 2008; Wei et al., 2002; Wenxuan Ding et al., 2015; Wu, Ye, et al., 2019; Wu, Huang, et al., 2019; Wu & Chou, 2011; Xia et al., 2021; Xie et al., 2014; Xu et al., 2019; Yan et al., 2015; Yan et al., 2020; Yang, Cai, et al., 2016; Yang, Xu, et al., 2016; Yang Cai, & Guan, 2016; Yang, Xu, et al., 2016; Ye et al., 2018; Dongsong Zhang et al., 2014; Weiguo Zhang, Wang, et al., 2020; Zhang, Liu, et al., 2020; Wen Zhang, Yang, et al., 2018; Zhang, Du, et al., 2018; Zhang, Du, et al., 2019; Zhang, Han, et al., 2019; Xiaofeng Zhang et al., 2020; Zhang, Liu, et al., 2020; Xinwei Zhang, Du, et al., 2019; Zhang, Han, et al., 2019; G. Zhao, Lou, et al., 2020; Zhao, Dai, et al., 2020; Zhao et al., 2019; Zheng et al., 2013; Zheng & Padmanabhan, 2006; Zoghbi et al., 2016)
Descriptive	(Alt et al., 2019; Ariyaluran Habeeb et al., 2019; Bai et al., 2020; Bassano et al., 2017; Bobadilla et al., 2013; Bondielli & Marcelloni, 2019; Galitsky, 2006; Griggs & Wild, 2003; Ito et al., 2002; Kauffman et al., 2017; Li et al., 2006; Motiwalla & Nunamaker, 1992; Padmanabhan & Tuzhilin, 2003; Ravi & Ravi, 2015; Tan & Thoen, 2000; Thiebes et al., 2021; Villegas et al., 2018)

Table 15 Classification of MIS literature on AI in e-commerce by research method

Method	Articles
Conceptual	(Aguwa et al., 2017; Alt et al., 2019; Bassano et al., 2017; Griggs & Wild, 2003; Li et al., 2006; Lin et al., 2003; Motiwalla & Nunamaker, 1992; Padmanabhan & Tuzhilin, 2003; Tan & Thoen, 2000; Thiebes et al., 2021; Zhao et al., 2019)
Review	(Ariyaluran Habeeb et al., 2019; Bobadilla et al., 2013; Bondielli & Marcelloni, 2019; Ferrara et al., 2014; Ravi & Ravi, 2015; Villegas et al., 2018)
Data analysis	(Bai et al., 2020; Chen et al., 2014; Fang et al., 2013; Guan et al., 2014; Guo et al., 2015; He et al., 2019, 2018; Hill & Ready-Campbell, 2011; Khopkar & Nikolaev, 2017; Kumar et al., 2018; Laorden et al., 2012; Lee et al., 2012; Li, Zhang, et al., 2019; Li, Wu, et al., 2019; Li, Wang, et al., 2019; Liu et al., 2013; Ma et al., 2018; Ma et al., 2011; Mo et al., 2018; Mokryn et al., 2019; Nikolay et al., 2011; Park & Park, 2003; Singh & Tucker, 2017; Stoeckli et al., 2020; Sul et al., 2017; Sun et al., 2020; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Wang Jhou, & Tsai, 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Dongsong Zhang et al., 2014; Weiguo Zhang, Wang, et al., 2020; Zhang, Liu, et al., 2020)
Survey	(Cao & Schniederjans, 2006; Moussawi et al., 2020; Wu, Huang, et al., 2019; Wu, Ye, et al., 2019)
Experiment	(Abbasi et al., 2010; Adomavicius et al., 2013; Al-Natour et al., 2006, 2011; Al-Natour & Turetken, 2020; Al-Shamri, 2016; Azadjalal et al., 2017; Bag et al., 2019; Bandyopadhyay et al., 2008; Barzegar Nozari & Koohi, 2020; Bauer & Jannach, 2018; Bedi & Vashisth, 2014; Beladev et al., 2016; Jesús Bobadilla et al., 2012; Bose & Chen, 2009; Brazier et al., 2002; Buettner, 2017; Bukhari & Kim, 2012; Cai & Zhang, 2019; Carbó et al., 2007; Cardoso & Gomide, 2007; Castillo et al., 2017; Chang & Chang, 2014; Chang & Jang, 2009; Chang & Chang, 2012; Chang, 2011; Chen & Chung, 2015; Chen et al., 2017; Chen & Wang, 2013; Chen, 2013; Chen et al., 2018, 2019; Chen, 2012; Chen et al., 2013; Chu et al., 2007; Cui et al., 2006; Da'u et al., 2020; Das & Chen, 2007; Dong et al., 2020; Esmeli et al., 2021; Fang et al., 2018; Fasli & Kovalchuk, 2011; Feng et al., 2019; Fiore et al., 2019; Geng et al., 2020; Ghavipour & Meybodi, 2016; Ghiassi et al., 2016; Gong et al., 2018; Greenstein-Messica & Rokach, 2020; Gu et al., 2017; Guan et al., 2005; Guan et al., 2019; Gunnec & Raghavan, 2017; Guo et al., 2014; Guo, Qiu, et al., 2017; Guo, Zhang, et al., 2017; Guo, Wei, et al., 2017; Guo et al., 2017; Guo, Zhang, et al., 2017; Guo, Wei, et al., 2017; Guo et al., 2017; Guo et al., 2017; Guo, Wei, et al., 2017; Gupta & Kant, 2020; Ha & Lee, 2009; Han et al., 2019; Herce-Zelaya et al., 2020; Hernando et al., 2017; Himabindu et al., 2018; Hirt et al., 2019; Hopkins et al., 2019; Hu, 2014; Ito et al., 2002; Iwański et al., 2018; Jeong et al., 2003; Ji & Shen, 2015; Juan Ji et al., 2020; Jiang et al., 2014; Jiang et al., 2005; Julià et al., 2009; Kagan & Bekkerman, 2018; Kauffman et al., 2017; Kiekintveld et al., 2009; Kim et al., 2017; Kim et al., 2001; Kumar, Venugopal, et al., 2019; Kumar, Rajan, et al., 2019; Kuo et al., 2004, 2005; Lau, 2007; Lee et al., 2020; Lee et al., 2019; Lee & Kim, 2017; Leloup, 2003; Lessmann et al., 2019; Li et al., 2017; Li et al., 2014; Yang Li, Zhang, et al., 2019; Li, Wu, et al., 2019; Li, Wang, et al., 2019; Liebman et al., 2019; Lin et al., 2016; Liu et al., 2018; Liu et al., 2019; Liu & Shen, 2020; Luo et al., 2019; Manahov & Zhang, 2019; Manvi & Venkataram, 2005; Mao et al., 2019; Maqsood et al., 2020; Martinez-Cruz et al., 2015; Miralles-Pechuán et al., 2018; Nassiri-Mofakham et al., 2009; Nilashi et al., 2015; Nishimura et al., 2018; Núñez-Valdez et al., 2018; O'Neil et al., 2016; Oliver, 1996; Ortega et al., 2013, 2016; Ou et al., 2018; Pang et al., 2019; Park Kim, & Yu, 2019; Park, Kim, et al., 2020; Park, Song, et al., 2020; Park et al., 2020; Park, Song, et al., 2020; Parvin et al., 2019; Pendharkar, 2006; Pfeiffer et al., 2020; Pourgholamali et al., 2020; Praet & Martens, 2020; Preibusch et al., 2016; Pu & Chen, 2007; Pujahari & Sisodia, 2019; Qiu et al., 2018; Ranjbar Kermany & Alizadeh, 2017; Rao et al., 2016; Saleh et al., 2015; Saumya et al., 2018; Si et al., 2017; Suchacka & Iwański, 2020; Takeuchi et al., 2009; Tang et al., 2020; Tian et al., 2016; Varshney et al., 2017; Vizine Pereira & Hruschka, 2015; Wang, 2008; Wang et al., 2012; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Wang & Doong, 2010; Wei et al., 2002; Wenxuan Ding et al., 2015; Wu, Ye, et al., 2019; Wu, Huang, et al., 2019; Wu & Chou, 2011; Xia et al., 2021; Xie et al., 2014; Xu et al., 2019; S. R. Yan et al., 2015; Yan et al., 2020; Yang, Cai, et al., 2016; Yang, Xu, et al., 2016; Yang Cai, & Guan, 2016; Yang, Xu, et al., 2016; Ye et al., 2018; Wen Zhang, Yang, et al., 2018; Zhang, Du, et al., 2018; Zhang, Du, et al., 2019; Zhang, Han, et al., 2019; Xiaofeng Zhang, Wang, et al., 2020; Zhang, Liu, et al., 2020; Xinwei Zhang, Du, et al., 2019; Zhang, Han, et al., 2019; Zhao, Lou, et al., 2020; Zhao, Dai, et al., 2020; Zheng et al., 2013; Zheng & Padmanabhan, 2006; Zoghbi et al., 2016)
Case study	(Chou & Seng, 2009; Ketter et al., 2012; Kühl et al., 2020; Li, Wang, et al., 2019; Li, Wu, et al., 2019; Li, Zhang, et al., 2019; Martens & Provost, 2014; Pranata & Susilo, 2016; Pröllochs et al., 2020; Qi et al., 2016; Wang, Feng, et al., 2018; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Lu, et al., 2018)
Developmental	(Aher & Lobo, 2013; Chow et al., 2007; Chung, 2014; Dastani et al., 2005; Galitsky, 2006; Greenstein-Messica & Rokach, 2018; Hogenboom et al., 2015; Kaiser et al., 2011; Kazienko & Adamski, 2007; Keegan et al., 2008; Khare & Chougule, 2012; Kim et al., 2002; Kwon et al., 2006; Patra et al., 2015; Pontelli & Son, 2003; Viejo et al., 2012; Watson & Rasmussen, 2008)

Table 16 Classification of MIS literature on AI in e-commerce by current research themes

Category	Subcategory	Article
Sentiment analysis		(Al-Natour & Turetken, 2020; Chen & Wang, 2013; Chen et al., 2014, 2017; Da'u et al., 2020; Das & Chen, 2007; Ghiassi et al., 2016; He et al., 2018; Hill & Ready-Campbell, 2011; Hirt et al., 2019; Kaiser et al., 2011; Kühl et al., 2020; Lee & Kim, 2017; Li, Wang, et al., 2019; Li, Wu, et al., 2019; Li, Zhang, et al., 2019; Liu & Shen, 2020; Maqsood et al., 2020; Nikolay et al., 2011; Ou et al., 2018; Park, Kim, et al., 2020; Park, Song, et al., 2020; Pröllochs et al., 2020; Qi et al., 2016; Qiu et al., 2018; Rao et al., 2016; Ravi & Ravi, 2015; Sul et al., 2017; Sun et al., 2020; Tian et al., 2016; Wu, Huang, et al., 2019; Wu, Ye, et al., 2019; Zhao, Dai, et al., 2020; Zhao, Lou, et al., 2020)
Trust & personalisation	Trust	(Azadjalal et al., 2017; Barzegar Nozari & Koohi, 2020; Bedi & Vashisth, 2014; Carbó et al., 2007; Fang et al., 2018; Guo et al., 2014; Guo, Qiu, et al., 2017; Guo, Wei, et al., 2017; Guo, Zhang, et al., 2017; Li et al., 2017; Liu et al., 2013; Martinez-Cruz et al., 2015; Parvin et al., 2019; Pranata & Susilo, 2016; Pu & Chen, 2007; Thiebes et al., 2021; Yan et al., 2015)
	Personalisation	(Beladev et al., 2016; Buettner, 2017; Bukhari & Kim, 2012; Dong et al., 2020; Greenstein-Messica & Rokach, 2018; Guan et al., 2019; Ha & Lee, 2009; Hu, 2014; Kazienko & Adamski, 2007; Kim et al., 2001, 2002; Liebman et al., 2019; Mao et al., 2019; Ortega et al., 2016; Wang, Feng, et al., 2018; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Lu, et al., 2018; Watson & Rasmussen, 2008; Wu, Huang, et al., 2019; Wu, Ye, et al., 2019)
Optimisation	Recommendation accuracy	(Aher & Lobo, 2013; Bag et al., 2019; Jesús Bobadilla et al., 2012; Chang, 2011; Feng et al., 2019; Ghavipour & Meybodi, 2016; He et al., 2019; Jiang et al., 2005; Lee et al., 2012; Li et al., 2014; Liu et al., 2018; Liu et al., 2019; Luo et al., 2019; Miralles-Pechuán et al., 2018; Nilashi et al., 2015; Núñez-Valdez et al., 2018; Ortega et al., 2013; Padmanabhan & Tuzhilin, 2003; Pang et al., 2019; Saleh et al., 2015; Si et al., 2017; Wenxuan Ding et al., 2015; Xia et al., 2021; Xie et al., 2014; Wen Zhang, Yang, et al., 2018; Zhang, Du, et al., 2018; Zhang, Du, et al., 2019; Zhang, Han, et al., 2019)
	Prediction accuracy	(Bauer & Jannach, 2018; Castillo et al., 2017; Chen & Chung, 2015; Chen, 2013; Chen et al., 2018; Chen, 2012; Chu et al., 2007; Cui et al., 2006; Esmeli et al., 2021; Fang et al., 2013; Greenstein-Messica & Rokach, 2020; Guan et al., 2014; Himabindu et al., 2018; Ji & Shen, 2015; Julià et al., 2009; Kagan & Bekkerman, 2018; Ketter et al., 2012; Khopkar & Nikolaev, 2017; Kiekintveld et al., 2009; D. Kim et al., 2017; Lee et al., 2019; Li, Zhang, et al., 2019; Li, Wu, et al., 2019; Li, Wang, et al., 2019; Liu et al., 2017; Mo et al., 2018; Nishimura et al., 2018; Park Kim, & Yu, 2019; Park, Kim, et al., 2020; Park, Song, et al., 2020; Pfeiffer et al., 2020; Praet & Martens, 2020; Ranjbar Kermany & Alizadeh, 2017; Varshney et al., 2017; Vizine Pereira & Hruschka, 2015)

Table 16 (continued)

Category	Subcategory	Article
	Other	(Cai & Zhang, 2019; Chang & Chang, 2012; Fiore et al., 2019; Juan Ji et al., 2020; Kumar, Venugopal, et al., 2019; Kumar, Rajan, et al., 2019; Yang Li, Zhang, et al., 2019; Li, Wu, et al., 2019; Li, Wang, et al., 2019; Yang, Cai, et al., 2016; Yang, Xu, et al., 2016; Yang Cai, & Guan, 2016; Yang, Xu, et al., 2016; Dongsong Zhang et al., 2014)
AI concepts and related technologies		(Bobadilla et al., 2013; Bondielli & Marcelloni, 2019; Dastani et al., 2005; Gupta & Kant, 2020; J. Han et al., 2019; Suchacka & Iwański, 2020; Villegas et al., 2018)
Decision support (online reputation, dynamic pricing, promotions, product/service management, customer segmentation, loan & credit risk evaluations		(Aguwa et al., 2017; Bai et al., 2020; Bandyopadhyay et al., 2008; Cao & Schniederjans, 2006; Chen et al., 2019; Chen et al., 2013; Fasli & Kovalchuk, 2011; Geng et al., 2020; Gunnec & Raghavan, 2017; Guo, Qiu, et al., 2017; Guo, Zhang, et al., 2017; Guo, Wei, et al., 2017; Hogenboom et al., 2015; Kauffman et al., 2017; Khare & Chougule, 2012; Kuo et al., 2004; Lel-oup, 2003; Lessmann et al., 2019; Nassiri-Mofakham et al., 2009; O'Neil et al., 2016; Park & Park, 2003; Wang, 2008; Wei et al., 2002; Wu & Chou, 2011; Yan et al., 2020; Ye et al., 2018; Weiguo Zhang, Wang, et al., 2020; Zhang, Liu, et al., 2020; Zheng et al., 2013; Zheng & Padmanabhan, 2006)
AI design, tools and techniques (modelling, ranking, mining, forecasting, anomaly detection)		(Abbasi et al., 2010; Al-Natour et al., 2006; Ariyaluran Habeeb et al., 2019; Brazier et al., 2002; Chang & Chang, 2014; Chou & Seng, 2009; Chow et al., 2007; Chung, 2014; Gong et al., 2018; Griggs & Wild, 2003; Gu et al., 2017; Guo et al., 2015; Herce-Zelaya et al., 2020; Hernando et al., 2017; Hopkins et al., 2019; Ito et al., 2002; Iwański et al., 2018; Kumar et al., 2018; Kuo et al., 2005; Kwon et al., 2006; Laorden et al., 2012; Lau, 2007; Lin et al., 2003; Lin et al., 2016; Ma et al., 2018; Ma et al., 2011; Manahov & Zhang, 2019; Patra et al., 2015; Pendharkar, 2006; Pourgholamali et al., 2020; Preibusch et al., 2016; Pujahari & Sisodia, 2019; Saumya et al., 2018; Singh & Tucker, 2017; Tang et al., 2020; Viejo et al., 2012; Wang et al., 2012; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Wang Jhou, & Tsai, 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Xu et al., 2019; Xinwei Zhang, Du, et al., 2019; Zhang, Han, et al., 2019; Zoghbi et al., 2016)
Customer behaviour (satisfaction, adoption, attitudes, preferences		(Adomavicius et al., 2013; Al-Natour et al., 2006; Al-Shamri, 2016; Bassano et al., 2017; Bose & Chen, 2009; S. E. Chang & Jang, 2009; Galitsky, 2006; Lee et al., 2020; Mokryn et al., 2019; Moussawi et al., 2020; Takeuchi et al., 2009; Wang, Jhou, et al., 2018; Wang, Li, et al., 2018; Wang, Feng, et al., 2018; Wang, Lu, et al., 2018; Xiaofeng Zhang, Wang, et al., 2020; Zhang, Liu, et al., 2020)
AI concepts (knowledge sharing, data/information extraction, automation		(Alt et al., 2019; Ferrara et al., 2014; Guo, Qiu, et al., 2017; Guo, Wei, et al., 2017; Guo, Zhang, et al., 2017; Jiang et al., 2014; Li et al., 2006; Manvi & Venkataram, 2005; Martens & Provost, 2014; Oliver, 1996; Zhao et al., 2019)
Intelligent agents		(Guan et al., 2005; Jeong et al., 2003; Keegan et al., 2008; Motiwalla & Nunamaker, 1992; Pontelli & Son, 2003; Stoeckli et al., 2020; Tan & Thoen, 2000; Wang & Doong, 2010)

References

Abbasi, A., Zhang, Z., Zimbra, D., Chen, H., & Nunamaker, J. F. (2010). Detecting fake websites: The contribution of statistical learning theory. *MIS Quarterly, 34*(3), 435–461. https://doi.org/10.2307/25750686

Abdel-Karim, B. M., Pfeuffer, N., & Hinz, O. (2021). Machine learning in information systems - a bibliographic review and open research issues. *Electronic Markets, 31*(3), 643–670. https://doi.org/10.1007/s12525-021-00459-2

Adomavicius, G., Bockstedt, J. C., Curley, S. P., & Zhang, J. (2013). Do Recommender Systems Manipulate Consumer Preferences? A Study of Anchoring Effects. *Information Systems Research, 24*(4), 956–975. https://doi.org/10.1057/isre.2013.0497

Adomavicius, G., Sankaranarayanan, R., Sen, S., & Tuzhilin, A. (2005). Incorporating contextual information in recommender systems using a multidimensional approach. *ACM Transactions on Information Systems, 23*(1), 103–145. https://doi.org/10.1145/1055709.1055714

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering, 17*(6), 734–749. https://doi.org/10.1109/TKDE.2005.99

Ågerfalk, P. J. (2020). Artificial intelligence as digital agency. *European Journal of Information Systems, 29*(1), 1–8. https://doi.org/10.1080/0960085X.2020.1721947

Aghaei Chadegani, A., Salehi, H., Md Yunus, M. M., Farhadi, H., Fooladi, M., Farhadi, M., & Ale Ebrahim, N. (2013). A comparison between two main academic literature collections: Web of science and scopus databases. *Asian Social Science, 9*(5), 18–26. https://doi.org/10.5539/ass.v9n5p18

Agrawal, R., Imieliński, T., & Swami, A. (1993). Mining Association Rules Between Sets of Items in Large Databases. *ACM SIGMOD Record, 22*(2), 207–216. https://doi.org/10.1145/170036.170072

Aguwa, C., Olya, M. H., & Monplaisir, L. (2017). Modeling of fuzzy-based voice of customer for business decision analytics. *Knowledge-Based Systems, 125*, 136–145. https://doi.org/10.1016/j.knosys.2017.03.019

Aher, S. B., & Lobo, L. M. R. J. (2013). Combination of machine learning algorithms for recommendation of courses in E-Learning System based on historical data. *Knowledge-Based Systems, 51*, 1–14. https://doi.org/10.1016/j.knosys.2013.04.015

Akter, S., & Wamba, S. F. (2016). Big data analytics in E-commerce: A systematic review and agenda for future research. *Electronic Markets, 26*(2), 173–194. https://doi.org/10.1007/s12525-016-0219-0

Akter, S., Wamba, S. F., Mariani, M., & Hani, U. (2021). How to Build an AI Climate-Driven Service Analytics Capability for Innovation and Performance in Industrial Markets? *Industrial Marketing Management, 97*, 258–273. https://doi.org/10.1016/j.indmarman.2021.07.014

Al-Natour, S., Benbasat, I., & Cenfetelli, R. (2011). The adoption of online shopping assistants: Perceived similarity as an antecedent to evaluative beliefs. *Journal of the Association for Information Systems, 12*(5), 347–374. https://doi.org/10.17705/1jais.00267

Al-Natour, S., Benbasat, I., & Cenfetelli, R. T. (2006). The role of design characteristics in shaping perceptions of similarity: The case of online shopping assistants. *Journal of the Association for Information Systems, 7*(12), 821–861.

Al-Natour, S., & Turetken, O. (2020). A comparative assessment of sentiment analysis and star ratings for consumer reviews. *International Journal of Information Management, 54*, 102132. https://doi.org/10.1016/j.ijinfomgt.2020.102132

Al-Shamri, M. Y. H. (2016). User profiling approaches for demographic recommender systems. *Knowledge-Based Systems, 100*, 175–187. https://doi.org/10.1016/j.knosys.2016.03.006

Alt, R., Ehmke, J. F., Haux, R., Henke, T., Mattfeld, D. C., Oberweis, A., Paech, B., & Winter, A. (2019). Towards customer-induced service orchestration - requirements for the next step of customer orientation. *Electronic Markets, 29*(1), 79–91. https://doi.org/10.1007/s12525-019-00340-3

Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics, 11*(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

Aria, M., Misuraca, M., & Spano, M. (2020). Mapping the Evolution of Social Research and Data Science on 30 Years of Social Indicators Research. *Social Indicators Research, 149*(3), 803–831. https://doi.org/10.1007/s11205-020-02281-3

Ariyaluran Habeeb, R. A., Nasaruddin, F., Gani, A., Targio Hashem, I. A., Ahmed, E., & Imran, M. (2019). Real-time big data processing for anomaly detection: A Survey. *International Journal of Information Management, 45*, 289–307. https://doi.org/10.1016/j.ijinfomgt.2018.08.006

Arnott, D., & Pervan, G. (2014). A critical analysis of decision support systems research revisited: The rise of design science. *Journal of Information Technology, 29*(4), 269–293. https://doi.org/10.1057/jit.2014.16

Ayvaz, D., Aydoğan, R., Akçura, M. T., & Şensoy, M. (2021). Campaign participation prediction with deep learning. *Electronic Commerce Research and Applications, 48*, 101058. https://doi.org/10.1016/j.elerap.2021.101058

Azadjalal, M. M., Moradi, P., Abdollahpouri, A., & Jalili, M. (2017). A trust-aware recommendation method based on Pareto dominance and confidence concepts. *Knowledge-Based Systems, 116*, 130–143. https://doi.org/10.1016/j.knosys.2016.10.025

Bag, S., Kumar, S. K., & Tiwari, M. K. (2019). An efficient recommendation generation using relevant Jaccard similarity. *Information Sciences, 483*, 53–64. https://doi.org/10.1016/j.ins.2019.01.023

Bai, X., Marsden, J. R., Ross, W. T., & Wang, G. (2020). A note on the impact of daily deals on local retailers' online reputation: Mediation effects of the consumer experience. *Information Systems Research, 31*(4), 1132–1143. https://doi.org/10.1287/isre.2020.0935

Balabanović, M., & Shoham, Y. (1997). Content-Based, Collaborative Recommendation. *Communications of the ACM, 40*(3), 66–72. https://doi.org/10.1145/245108.245124

Bandyopadhyay, S., Rees, J., & Barron, J. M. (2008). Reverse auctions with multiple reinforcement learning agents. *Decision Sciences, 39*(1), 33–63. https://doi.org/10.1111/j.1540-5915.2008.00181.x

Baptista, J., Stein, M.-K., Klein, S., Watson-Manheim, M. B., & Lee, J. (2020). Digital work and organisational transformation: Emergent Digital/Human work configurations in modern organisations. *The Journal of Strategic Information Systems, 29*(2), 101618. https://doi.org/10.1016/j.jsis.2020.101618

Barzegar Nozari, R., & Koohi, H. (2020). A novel group recommender system based on members' influence and leader impact. *Knowledge-Based Systems, 205*, 106296. https://doi.org/10.1016/j.knosys.2020.106296

Bassano, C., Gaeta, M., Piciocchi, P., & Spohrer, J. C. (2017). Learning the Models of Customer Behavior: From Television Advertising to Online Marketing. *International Journal of Electronic Commerce, 21*(4), 572–604. https://doi.org/10.1080/10864415.2016.1355654

Bauer, J., & Jannach, D. (2018). Optimal pricing in e-commerce based on sparse and noisy data. *Decision Support Systems, 106*, 53–63. https://doi.org/10.1016/j.dss.2017.12.002

Bawack, R. E., Wamba, S. F., & Carillo, K. (2021). A framework for understanding artificial intelligence research: insights from practice. *Journal of Enterprise Information Management, 34*(2), 645–678. https://doi.org/10.1108/JEIM-07-2020-0284

Bedi, P., & Vashisth, P. (2014). Empowering recommender systems using trust and argumentation. *Information Sciences, 279*, 569–586. https://doi.org/10.1016/j.ins.2014.04.012

Beladev, M., Rokach, L., & Shapira, B. (2016). Recommender systems for product bundling. *Knowledge-Based Systems, 111*, 193–206. https://doi.org/10.1016/j.knosys.2016.08.013

Benbya, H., Pachidi, S., & Jarvenpaa, S. L. (2021). Special issue editorial: Artificial intelligence in organizations: Implications for information systems research. *Journal of the Association for Information Systems, 22*(2), 281–303. https://doi.org/10.17705/1jais.00662

Blei, D. M., Ng, A. Y., & Jordan, M. T. (2002). Latent dirichlet allocation. *Advances in Neural Information Processing Systems, 3*(Jan), 993–1022.

Blöcher, K., & Alt, R. (2021). AI and robotics in the European restaurant sector: Assessing potentials for process innovation in a high-contact service industry. *Electronic Markets, 31*(3), 529–551. https://doi.org/10.1007/s12525-020-00443-2

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment, 2008*(10), P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008

Bo, X., Benbasat, I., Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly, 31*(1), 137–209. https://doi.org/10.2307/25148784

Bobadilla, J., Ortega, F., Hernando, A., & Gutiérrez, A. (2013). Recommender systems survey. *Knowledge-Based Systems, 46*, 109–132. https://doi.org/10.1016/j.knosys.2013.03.012

Bobadilla, J., Ortega, F., Hernando, A., & Bernal, J. (2012). A collaborative filtering approach to mitigate the new user cold start problem. *Knowledge-Based Systems, 26*, 225–238. https://doi.org/10.1016/j.knosys.2011.07.021

Bolton, R. J., & Hand, D. J. (2002). Statistical fraud detection: A review. *Statistical Science, 17*(3), 235–255. https://doi.org/10.1214/ss/1042727940

Bondielli, A., & Marcelloni, F. (2019). A survey on fake news and rumour detection techniques. *Information Sciences, 497*, 38–55. https://doi.org/10.1016/j.ins.2019.05.035

Borges, A. F. S., Laurindo, F. J. B., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2020). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*, 102225. https://doi.org/10.1016/j.ijinfomgt.2020.102225

Bose, I., & Chen, X. (2009). Hybrid models using unsupervised clustering for prediction of customer churn. *Journal of Organizational Computing and Electronic Commerce, 19*(2), 133–151. https://doi.org/10.1080/10919390902821291

Brazier, F. M. T., Cornelissen, F., Gustavsson, R., Jonker, C. M., Lindeberg, O., Polak, B., & Treur, J. (2002). A multi-agent system performing one-to-many negotiation for load balancing of electricity use. *Electronic Commerce Research and Applications, 1*(2), 208–224. https://doi.org/10.1016/S1567-4223(02)00013-3

Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Brusilovski, P., Kobsa, A., & Nejdl, W. (2007). *The Adaptive Web Methods and Strategies of Web Personalization. In Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol 4321 LNCS*. Springer Science & Business Media.

Brynjolfsson, E., Wang, C., & Zhang, X. (2021). The economics of IT and digitization: Eight questions for research. *MIS Quarterly, 45*(1), 473–477.

Buettner, R. (2017). Predicting user behavior in electronic markets based on personality-mining in large online social networks: A personality-based product recommender framework. *Electronic Markets, 27*(3), 247–265. https://doi.org/10.1007/s12525-016-0228-z

Bukhari, A. C., & Kim, Y.-G. (2012). Integration of a secure type-2 fuzzy ontology with a multi-agent platform: A proposal to automate the personalized flight ticket booking domain. *Information Sciences, 198*, 24–47. https://doi.org/10.1016/j.ins.2012.02.036

Burke, R. (2002). Hybrid Recommender Systems: Survey and Experiments. *User Modeling and User-Adapted Interaction, 12*(4), 331–370. https://doi.org/10.1023/A:1021240730564

Büyüközkan, G., Feyzioğlu, O., & Nebol, E. (2008). Selection of the strategic alliance partner in logistics value chain. *International Journal of Production Economics, 113*(1), 148–158. https://doi.org/10.1016/j.ijpe.2007.01.016

Cacheda, F., Carneiro, V., Fernández, D., & Formoso, V. (2011). Comparison of collaborative filtering algorithms: Limitations of current techniques and proposals for scalable, high-performance recommender systems. *ACM Transactions on the Web*, *5*(1). https://doi.org/10.1145/1921591.1921593

Cai, H., & Zhang, F. (2019). Detecting shilling attacks in recommender systems based on analysis of user rating behavior. *Knowledge-Based Systems, 177*, 22–43. https://doi.org/10.1016/j.knosys.2019.04.001

Campbell, C., Sands, S., Ferraro, C., Tsao (Jody), H.-Y., & Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. *Business Horizons, 63*(2), 227–243. https://doi.org/10.1016/j.bushor.2019.12.002

Cao, Q., & Schniederjans, M. J. (2006). Agent-mediated architecture for reputation-based electronic tourism systems: A neural network approach. *Information and Management, 43*(5), 598–606. https://doi.org/10.1016/j.im.2006.03.001

Cao, Y., & Li, Y. (2007). An intelligent fuzzy-based recommendation system for consumer electronic products. *Expert Systems with Applications, 33*(1), 230–240. https://doi.org/10.1016/j.eswa.2006.04.012

Carbó, J., Molina, J. M., & Dávila, J. (2007). Avoiding malicious agents in E-commerce using fuzzy recommendations. *Journal of Organizational Computing and Electronic Commerce, 17*(2), 101–117. https://doi.org/10.1080/10919390701293972

Cardoso, G., & Gomide, F. (2007). Newspaper demand prediction and replacement model based on fuzzy clustering and rules. *Information Sciences, 177*(21), 4799–4809. https://doi.org/10.1016/j.ins.2007.05.009

Castillo, P. A., Mora, A. M., Faris, H., Merelo, J. J., García-Sánchez, P., Fernández-Ares, A. J., De las Cuevas, P., & García-Arenas, M. I. (2017). Applying computational intelligence methods for predicting the sales of newly published books in a real editorial business management environment. *Knowledge-Based Systems, 115*, 133–151. https://doi.org/10.1016/j.knosys.2016.10.019

Chang, C. C., & Lin, C. J. (2011). LIBSVM: A Library for support vector machines. *ACM Transactions on Intelligent Systems and Technology*, *2*(3). https://doi.org/10.1145/1961189.1961199

Chang, J.-S., & Chang, W.-H. (2014). Analysis of fraudulent behavior strategies in online auctions for detecting latent fraudsters. *Electronic Commerce Research and Applications, 13*(2), 79–97. https://doi.org/10.1016/j.elerap.2013.10.004

Chang, R. M., Kauffman, R. J., & Kwon, Y. (2014). Understanding the paradigm shift to computational social science in the presence of big data. *Decision Support Systems, 63*, 67–80. https://doi.org/10.1016/j.dss.2013.08.008

Chang, S. E., & Jang, Y. T. (2009). Assessing customer satisfaction in a V-commerce environment. *Journal of Organizational Computing and Electronic Commerce, 19*(1), 30–49. https://doi.org/10.1080/10919390802605083

Chang, W.-H., & Chang, J.-S. (2012). An effective early fraud detection method for online auctions. *Electronic Commerce Research and Applications, 11*(4), 346–360. https://doi.org/10.1016/j.elerap.2012.02.005

Chang, W.-L. (2011). iValue: A knowledge-based system for estimating customer prospect value. *Knowledge-Based Systems, 24*(8), 1181–1186. https://doi.org/10.1016/j.knosys.2011.05.004

Chaudhuri, N., Gupta, G., Vamsi, V., & Bose, I. (2021). On the platform but will they buy? Predicting customers' purchase behavior using deep learning. *Decision Support Systems, 149*, 113622. https://doi.org/10.1016/j.dss.2021.113622

Chen, C. C., & Chung, M.-C. (2015). Predicting the success of group buying auctions via classification. *Knowledge-Based Systems, 89*, 627–640. https://doi.org/10.1016/j.knosys.2015.09.009

Chen, K., Luo, P., & Wang, H. (2017). An influence framework on product word-of-mouth (WoM) measurement. *Information and Management, 54*(2), 228–240. https://doi.org/10.1016/j.im.2016.06.010

Chen, L., Chen, G., & Wang, F. (2015). Recommender systems based on user reviews: The state of the art. *User Modeling and User-Adapted Interaction, 25*(2), 99–154. https://doi.org/10.1007/s11257-015-9155-5

Chen, L., & Wang, F. (2013). Preference-based clustering reviews for augmenting e-commerce recommendation. *Knowledge-Based Systems, 50*, 44–59. https://doi.org/10.1016/j.knosys.2013.05.006

Chen, M.-Y. (2013). A hybrid ANFIS model for business failure prediction utilizing particle swarm optimization and subtractive clustering. *Information Sciences, 220*, 180–195. https://doi.org/10.1016/j.ins.2011.09.013

Chen, M. Y., Kiciman, E., Fratkin, E., Fox, A., & Brewer, E. (2002). Pinpoint: Problem determination in large, dynamic internet services. *Proceedings of the 2002 International Conference on Dependable Systems and Networks*, 595–604. https://doi.org/10.1109/DSN.2002.1029005

Chen, R., Wang, Q., & Xu, W. (2019). Mining user requirements to facilitate mobile app quality upgrades with big data. *Electronic Commerce Research and Applications, 38*, 100889. https://doi.org/10.1016/j.elerap.2019.100889

Chen, R., Zheng, Y., Xu, W., Liu, M., & Wang, J. (2018). Secondhand seller reputation in online markets: A text analytics framework. *Decision Support Systems, 108*, 96–106. https://doi.org/10.1016/j.dss.2018.02.008

Chen, Y.-S. (2012). Classifying credit ratings for Asian banks using integrating feature selection and the CPDA-based rough sets approach. *Knowledge-Based Systems, 26*, 259–270. https://doi.org/10.1016/j.knosys.2011.08.021

Chen, Y. L., Cheng, L. C., & Hsu, W. Y. (2013). A new approach to the group ranking problem: Finding consensus ordered segments from users' preference data. *Decision Sciences, 44*(6), 1091–1119. https://doi.org/10.1111/deci.12048

Chen, Y. L., Tang, K., Wu, C. C., & Jheng, R. Y. (2014). Predicting the influence of users' posted information for eWOM advertising in social networks. *Electronic Commerce Research and Applications, 13*(6), 431–439. https://doi.org/10.1016/j.elerap.2014.10.001

Cheung, K. W., Kwok, J. T., Law, M. H., & Tsui, K. C. (2003). Mining customer product ratings for personalized marketing. *Decision Support Systems, 35*(2), 231–243. https://doi.org/10.1016/S0167-9236(02)00108-2

Chiarini Tremblay, M., Kohli, R., & Forsgren, N. (2021). Theories in Flux: Reimagining Theory Building in the Age of Machine Learning. *MIS Quarterly, 45*(1), 455–459.

Cho, Y. H., Kim, J. K., & Kim, S. H. (2002). A personalized recommender system based on web usage mining and decision tree induction. *Expert Systems with Applications, 23*(3), 329–342. https://doi.org/10.1016/S0957-4174(02)00052-0

Chong, A.Y.-L. (2013a). A two-staged SEM-neural network approach for understanding and predicting the determinants of m-commerce adoption. *Expert Systems with Applications, 40*(4), 1240–1247. https://doi.org/10.1016/j.eswa.2012.08.067

Chong, A. Y. L. (2013b). Predicting m-commerce adoption determinants: A neural network approach. *Expert Systems with Applications, 40*(2), 523–530. https://doi.org/10.1016/j.eswa.2012.07.068

Chou, T. H., & Seng, J. L. (2009). An intelligent multi-agent e-services method-An international telecommunication example. *Information and Management, 46*(6), 342–350. https://doi.org/10.1016/j.im.2009.05.006

Chow, H. K. H., Choy, K. L., & Lee, W. B. (2007). A dynamic logistics process knowledge-based system - An RFID multi-agent approach. *Knowledge-Based Systems, 20*(4), 357–372. https://doi.org/10.1016/j.knosys.2006.08.004

Chu, B.-H., Tsai, M.-S., & Ho, C.-S. (2007). Toward a hybrid data mining model for customer retention. *Knowledge-Based Systems, 20*(8), 703–718. https://doi.org/10.1016/j.knosys.2006.10.003

Chung, W. (2014). BizPro: Extracting and categorizing business intelligence factors from textual news articles. *International Journal of Information Management, 34*(2), 272–284. https://doi.org/10.1016/j.ijinfomgt.2014.01.001

Cram, W. A., Templier, M., & Paré, G. (2020). (Re)considering the concept of literature review reproducibility. *Journal of the Association for Information Systems, 21*(5), 1103–1114. https://doi.org/10.17705/1jais.00630

Cui, G., Wong, M. L., & Lui, H. K. (2006). Machine learning for direct marketing response models: Bayesian networks with evolutionary programming. *Management Science, 52*(4), 597–612. https://doi.org/10.1287/mnsc.1060.0514

Da'u, A., Salim, N., Rabiu, I., & Osman, A. (2020). Recommendation system exploiting aspect-based opinion mining with deep learning method. *Information Sciences, 512*, 1279–1292. https://doi.org/10.1016/j.ins.2019.10.038

Das, S. R., & Chen, M. Y. (2007). Yahoo! for amazon: Sentiment extraction from small talk on the Web. *Management Science, 53*(9), 1375–1388. https://doi.org/10.1287/mnsc.1070.0704

Dastani, M., Jacobs, N., Jonker, C. M., & Treur, J. (2005). Modelling user preferences and mediating agents in electronic commerce. *Knowledge-Based Systems, 18*(7), 335–352. https://doi.org/10.1016/j.knosys.2005.05.001

Datta, S., Bhaduri, K., Giannella, C., Wolff, R., & Kargupta, H. (2006). Distributed Data Mining in Peer-to-Peer Networks. *IEEE Internet Computing, 10*(4), 18–26. https://doi.org/10.1109/MIC.2006.74

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24–42. https://doi.org/10.1007/s11747-019-00696-0

de Barcelos Silva, A., Gomes, M. M., da Costa, C. A., da Rosa Righi, R., Barbosa, J. L. V., Pessin, G., De Doncker, G., & Federizzi, G. (2020). Intelligent personal assistants: A systematic literature review. *Expert Systems with Applications, 147*, 113193. https://doi.org/10.1016/j.eswa.2020.113193

de Bellis, E., & Venkataramani Johar, G. (2020). Autonomous Shopping Systems: Identifying and Overcoming Barriers to Consumer Adoption. *Journal of Retailing, 96*(1), 74–87. https://doi.org/10.1016/j.jretai.2019.12.004

De Carolis, B., de Gemmis, M., Lops, P., & Palestra, G. (2017). Recognizing users feedback from non-verbal communicative acts in conversational recommender systems. *Pattern Recognition Letters, 99*, 87–95.

De Smedt, J., Lacka, E., Nita, S., Kohls, H. H., & Paton, R. (2021). Session stitching using sequence fingerprinting for web page visits. *Decision Support Systems, 150*, 113579. https://doi.org/10.1016/j.dss.2021.113579

Decker, R., & Trusov, M. (2010). Estimating aggregate consumer preferences from online product reviews. *International Journal of Research in Marketing, 27*(4), 293–307. https://doi.org/10.1016/j.ijresmar.2010.09.001

Deng, S., Tan, C. W., Wang, W., & Pan, Y. (2019). Smart Generation System of Personalized Advertising Copy and Its Application to Advertising Practice and Research. *Journal of Advertising, 48*(4), 356–365. https://doi.org/10.1080/00913367.2019.1652121

Dong, M., Zeng, X., Koehl, L., & Zhang, J. (2020). An interactive knowledge-based recommender system for fashion product design in the big data environment. *Information Sciences, 540*, 469–488. https://doi.org/10.1016/j.ins.2020.05.094

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, Medaglia, R., Le Meunier-FitzHugh, K., Le Meunier-FitzHugh, L. C., Misra, S., Mogaji, E., Sharma, S. K., Bahadur Singh, J., Raghavan, V., Raman, R., P. Rana, N., Samothrakis, S., Spencer, J., Tamilmani, K., Tubadji, A. Walton, P., & Williams, M. D. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., Kumar, V., Rahman, M. M., Raman, R., Rauschnabel, P. A., Rowley, J., Salo, J., Tran, G. A., & Wang, Y. (2020). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, 102168. https://doi.org/10.1016/j.ijinfomgt.2020.102168

Esfahani, H. J., Tavasoli, K., & Jabbarzadeh, A. (2019). Big data and social media: A scientometrics analysis. *International Journal of Data and Network Science, 3*(3), 145–164. https://doi.org/10.5267/j.ijdns.2019.2.007

Esmeli, R., Bader-El-Den, M., & Abdullahi, H. (2021). Towards early purchase intention prediction in online session based retailing systems. *Electronic Markets, 31*(3). https://doi.org/10.1007/s12525-020-00448-x

Fang, H., Zhang, J., & Şensoy, M. (2018). A generalized stereotype learning approach and its instantiation in trust modeling. *Electronic Commerce Research and Applications, 30*, 149–158. https://doi.org/10.1016/j.elerap.2018.06.004

Fang, X., Hu, P. J. H., Li, Z. L., & Tsai, W. (2013). Predicting adoption probabilities in social networks. *Information Systems Research, 24*(1), 128–145. https://doi.org/10.1287/isre.1120.0461

Fasli, M., & Kovalchuk, Y. (2011). Learning approaches for developing successful seller strategies in dynamic supply chain management. *Information Sciences, 181*(16), 3411–3426. https://doi.org/10.1016/j.ins.2011.04.014

Feng, S., Zhang, H., Wang, L., Liu, L., & Xu, Y. (2019). Detecting the latent associations hidden in multi-source information for better group recommendation. *Knowledge-Based Systems, 171*, 56–68. https://doi.org/10.1016/j.knosys.2019.02.002

Ferrara, E., De Meo, P., Fiumara, G., & Baumgartner, R. (2014). Web data extraction, applications and techniques: A survey. *Knowledge-Based Systems, 70*, 301–323. https://doi.org/10.1016/j.knosys.2014.07.007

Fiore, U., De Santis, A., Perla, F., Zanetti, P., & Palmieri, F. (2019). Using generative adversarial networks for improving classification effectiveness in credit card fraud detection. *Information Sciences, 479*, 448–455. https://doi.org/10.1016/j.ins.2017.12.030

Fosso Wamba, S. (2020). Humanitarian supply chain: a bibliometric analysis and future research directions. *Annals of Operations Research*, 1–27. https://doi.org/10.1007/s10479-020-03594-9

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics, 29*(5), 1189–1232. https://doi.org/10.1214/aos/1013203451

Galitsky, B. (2006). Reasoning about attitudes of complaining customers. *Knowledge-Based Systems, 19*(7), 592–615. https://doi.org/10.1016/j.knosys.2006.03.006

Geng, Q., Deng, S., Jia, D., & Jin, J. (2020). Cross-domain ontology construction and alignment from online customer product reviews. *Information Sciences, 531*, 47–67. https://doi.org/10.1016/j.ins.2020.03.058

Ghavipour, M., & Meybodi, M. R. (2016). An adaptive fuzzy recommender system based on learning automata. *Electronic Commerce Research and Applications, 20*, 105–115. https://doi.org/10.1016/j.elerap.2016.10.002

Ghiassi, M., Zimbra, D., & Lee, S. (2016). Targeted Twitter Sentiment Analysis for Brands Using Supervised Feature Engineering and the Dynamic Architecture for Artificial Neural Networks. *Journal of Management Information Systems, 33*(4), 1034–1058. https://doi.org/10.1080/07421222.2016.1267526

Ghose, A., & Ipeirotis, P. G. (2011). Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics. *IEEE Transactions on Knowledge and Data Engineering, 23*(10), 1498–1512. https://doi.org/10.1109/TKDE.2010.188

Gielens, K., & Steenkamp, J.-B.E.M. (2019). Branding in the era of digital (dis)intermediation. *International Journal of Research in Marketing, 36*(3), 367–384. https://doi.org/10.1016/j.ijresmar.2019.01.005

Gokmen, T., & Vlasov, Y. (2016). Acceleration of Deep Neural Network Training with Resistive Cross-Point Devices: Design Considerations. *Frontiers in Neuroscience, 10*, 333. https://doi.org/10.3389/fnins.2016.00333

Goldberg, D., Nichols, D., Oki, B. M., & Terry, D. (1992). Using collaborative filtering to Weave an Information tapestry. *Communications of the ACM, 35*(12), 61–70. https://doi.org/10.1145/138859.138867

Goldberg, K., Roeder, T., Gupta, D., & Perkins, C. (2001). Eigentaste: A Constant Time Collaborative Filtering Algorithm. *Information Retrieval, 4*(2), 133–151. https://doi.org/10.1023/A:1011419012209

Gong, J., Abhishek, V., & Li, B. (2018). Examining the impact of keyword ambiguity on search advertising performance: A topic model approach. *MIS Quarterly, 42*(3), 805–829. https://doi.org/10.25300/MISQ/2018/14042

Greenstein-Messica, A., & Rokach, L. (2018). Personal price aware multi-seller recommender system: Evidence from eBay. *Knowledge-Based Systems, 150*, 14–26. https://doi.org/10.1016/j.knosys.2018.02.026

Greenstein-Messica, A., & Rokach, L. (2020). Machine learning and operation research based method for promotion optimization of products with no price elasticity history. *Electronic Commerce Research and Applications, 40*, 100914. https://doi.org/10.1016/j.elerap.2019.100914

Griggs, K., & Wild, R. (2003). Intelligent support for sophisticated e-commerce services: An agent-based auction framework modeled after the New York stock exchange specialist system. *E-Service Journal, 2*(2), 87–104. https://doi.org/10.2979/esj.2003.2.2.87

Grønsund, T., & Aanestad, M. (2020). Augmenting the algorithm: Emerging human-in-the-loop work configurations. *Journal of*

Strategic Information Systems, *29*(2). https://doi.org/10.1016/j.jsis.2020.101614
Gu, X., Wu, S., Peng, P., Shou, L., Chen, K., & Chen, G. (2017). CSIR4G: An effective and efficient cross-scenario image retrieval model for glasses. *Information Sciences, 417*, 310–327. https://doi.org/10.1016/j.ins.2017.07.027
Guan, J., Shi, D., Zurada, J. M., & Levitan, A. S. (2014). Analyzing Massive Data Sets: An Adaptive Fuzzy Neural Approach for Prediction, with a Real Estate Illustration. *Journal of Organizational Computing and Electronic Commerce, 24*(1), 94–112. https://doi.org/10.1080/10919392.2014.866505
Guan, S.-U., Chan, T. K., & Zhu, F. (2005). Evolutionary intelligent agents for e-commerce: Generic preference detection with feature analysis. *Electronic Commerce Research and Applications, 4*(4), 377–394. https://doi.org/10.1016/j.elerap.2005.07.002
Guan, Y., Wei, Q., & Chen, G. (2019). Deep learning based personalized recommendation with multi-view information integration. *Decision Support Systems, 118*, 58–69. https://doi.org/10.1016/j.dss.2019.01.003
Gunnec, D., & Raghavan, S. (2017). Integrating Social Network Effects in the Share-Of-Choice Problem. *Decision Sciences, 48*(6), 1098–1131. https://doi.org/10.1111/deci.12246
Guo, G., Qiu, H., Tan, Z., Liu, Y., Ma, J., & Wang, X. (2017a). Resolving data sparsity by multi-type auxiliary implicit feedback for recommender systems. *Knowledge-Based Systems, 138*, 202–207. https://doi.org/10.1016/j.knosys.2017.10.005
Guo, G., Zhang, J., & Thalmann, D. (2014). Merging trust in collaborative filtering to alleviate data sparsity and cold start. *Knowledge-Based Systems, 57*, 57–68. https://doi.org/10.1016/j.knosys.2013.12.007
Guo, G., Zhang, J., Zhu, F., & Wang, X. (2017b). Factored similarity models with social trust for top-N item recommendation. *Knowledge-Based Systems, 122*, 17–25. https://doi.org/10.1016/j.knosys.2017.01.027
Guo, H., Pathak, P., & Cheng, H. K. (2015). Estimating Social Influences from Social Networking Sites-Articulated Friendships versus Communication Interactions. *Decision Sciences, 46*(1), 135–163. https://doi.org/10.1111/deci.12118
Guo, X., Wei, Q., Chen, G., Zhang, J., & Qiao, D. (2017). Extracting representative information on intra-organizational blogging platforms. *MIS Quarterly, 41*(4), 1105–1127. https://doi.org/10.25300/MISQ/2017/41.4.05
Gupta, S., & Kant, V. (2020). Credibility score based multi-criteria recommender system. *Knowledge-Based Systems, 196*, 105756. https://doi.org/10.1016/j.knosys.2020.105756
Guttman, R. H., Moukas, A. G., & Maes, P. (1998). Agent-mediated electronic commerce: A survey. *Knowledge Engineering Review, 13*(2), 147–159. https://doi.org/10.1017/S0269888998002082
Ha, S. H., & Lee, J. H. (2009). Dynamic dissemination of personalized content on the web. *Journal of Organizational Computing and Electronic Commerce, 19*(2), 96–111. https://doi.org/10.1080/10919390902821218
Hamad, H., Elbeltagi, I., & El-Gohary, H. (2018). An empirical investigation of business-to-business e-commerce adoption and its impact on SMEs competitive advantage: The case of Egyptian manufacturing SMEs. *Strategic Change, 27*(3), 209–229. https://doi.org/10.1002/jsc.2196
Han, J., Zheng, L., Huang, H., Xu, Y., Yu, P. S., & Zuo, W. (2019). Deep Latent Factor Model with Hierarchical Similarity Measure for recommender systems. *Information Sciences, 503*, 521–532. https://doi.org/10.1016/j.ins.2019.07.024
Han, J., Kamber, M., & Pei, J. (2001). Data mining: Concepts and technologies. *Data Mining Concepts Models Methods & Algorithms, 5*(4), 1–18.
Hanani, U., Shapira, B., & Shoval, P. (2001). Information filtering: Overview of issues, research and systems. *User Modeling and User-Adapted Interaction, 11*(3), 203–259. https://doi.org/10.1023/A:1011196000674
Hansen, J. H. L., & Hasan, T. (2015). Speaker recognition by machines and humans: A tutorial review. *IEEE Signal Processing Magazine, 32*(6), 74–99. https://doi.org/10.1109/MSP.2015.2462851
Hassan, N. R., & Loebbecke, C. (2017). Engaging scientometrics in information systems. *Journal of Information Technology, 32*(1), 85–109.
He, J., Fang, X., Liu, H., & Li, X. (2019). Mobile app recommendation: An involvement-enhanced approach. *MIS Quarterly, 43*(3), 827–850. https://doi.org/10.25300/MISQ/2019/15049
He, W., Zhang, Z., & Akula, V. (2018). Comparing consumer-produced product reviews across multiple websites with sentiment classification. *Journal of Organizational Computing and Electronic Commerce, 28*(2), 142–156. https://doi.org/10.1080/10919392.2018.1444350
Herce-Zelaya, J., Porcel, C., Bernabé-Moreno, J., Tejeda-Lorente, A., & Herrera-Viedma, E. (2020). New technique to alleviate the cold start problem in recommender systems using information from social media and random decision forests. *Information Sciences, 536*, 156–170. https://doi.org/10.1016/j.ins.2020.05.071
Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems, 22*(1), 5–53. https://doi.org/10.1145/963770.963772
Hernando, A., Bobadilla, J., Ortega, F., & Gutiérrez, A. (2017). A probabilistic model for recommending to new cold-start non-registered users. *Information Sciences, 376*, 216–232. https://doi.org/10.1016/j.ins.2016.10.009
Hill, S., & Ready-Campbell, N. (2011). Expert Stock Picker: The Wisdom of (Experts in) Crowds. *International Journal of Electronic Commerce, 15*(3), 73–102. https://doi.org/10.1093/JEC1086-4415150304
Himabindu, T. V. R., Padmanabhan, V., & Pujari, A. K. (2018). Conformal matrix factorization based recommender system. *Information Sciences, 467*, 685–707. https://doi.org/10.1016/j.ins.2018.04.004
Hinojo-Lucena, F. J., Aznar-Díaz, I., Cáceres-Reche, M. P., & Romero-Rodríguez, J. M. (2019). Artificial intelligence in higher education: A bibliometric study on its impact in the scientific literature. *Education Sciences, 9*(1), 51. https://doi.org/10.3390/educsci9010051
Hirsch, J. E. (2010). An index to quantify an individual's scientific research output that takes into account the effect of multiple coauthorship. *Scientometrics, 85*(3), 741–754. https://doi.org/10.1007/s11192-010-0193-9
Hirt, R., Kühl, N., & Satzger, G. (2019). Cognitive computing for customer profiling: Meta classification for gender prediction. *Electronic Markets, 29*(1), 93–106. https://doi.org/10.1007/s12525-019-00336-z
Hogenboom, A., Ketter, W., van Dalen, J., Kaymak, U., Collins, J., & Gupta, A. (2015). Adaptive Tactical Pricing in Multi-Agent Supply Chain Markets Using Economic Regimes. *Decision Sciences, 46*(4), 791–818. https://doi.org/10.1111/deci.12146
Holsapple, C. W., & Singh, M. (2000). Electronic commerce: From a definitional taxonomy toward a knowledge-management view. *Journal of Organizational Computing and Electronic Commerce, 10*(3), 149–170. https://doi.org/10.1207/S15327744JOCE1003_01
Hong, W., Thong, J. Y. L., & Tam, K. Y. (2004). The effects of information format and shopping task on consumers' online shopping behavior: A cognitive fit perspective. *Journal of Management Information Systems, 21*(3), 149–184. https://doi.org/10.1080/07421222.2004.11045812

Hopkins, J., Kafali, Ö., Alrayes, B., & Stathis, K. (2019). Pirasa: Strategic protocol selection for e-commerce agents. *Electronic Markets, 29*(2), 239–252. https://doi.org/10.1007/s12525-018-0307-4

Hu, Y.-C. (2014). Recommendation using neighborhood methods with preference-relation-based similarity. *Information Sciences, 284*, 18–30. https://doi.org/10.1016/j.ins.2014.06.043

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50. https://doi.org/10.3239/s11747-020-00749-9

Huang, M. H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research, 21*(2), 155–172. https://doi.org/10.1177/1094670517752459

Huang, M. H., & Rust, R. T. (2020). Engaged to a robot? The role of AI in service. *Journal of Service Research*, 24(1), 30–41. https://doi.org/10.1177/1094670520902266

Huang, Z., Zeng, D., & Chen, H. (2007). A comparison of collaborative-filtering algorithms for ecommerce. *IEEE Intelligent Systems, 22*(5), 68–78. https://doi.org/10.1109/MIS.2007.4338497

Huysman, M. (2020). Information systems research on artificial intelligence and work: A commentary on "Robo-Apocalypse cancelled? Reframing the automation and future of work debate." *Journal of Information Technology, 35*(4), 307–309. https://doi.org/10.1177/0268396220926511

Iovine, A., Narducci, F., & Semeraro, G. (2020). Conversational Recommender Systems and natural language: A study through the ConveRSE framework. *Decision Support Systems, 131*, 113250. https://doi.org/10.1016/j.dss.2020.113250

Isinkaye, F. O., Folajimi, Y. O., & Ojokoh, B. A. (2015). Recommendation systems: Principles, methods and evaluation. *Egyptian Informatics Journal, 16*(3), 261–273. https://doi.org/10.1016/j.eij.2015.06.005

Ito, T., Hattori, H., & Shintani, T. (2002). A cooperative exchanging mechanism among seller agents for group-based sales. *Electronic Commerce Research and Applications, 1*(2), 138–149. https://doi.org/10.1016/S1567-4223(02)00010-8

Iwański, J., Suchacka, G., & Chodak, G. (2018). Application of the Information Bottleneck method to discover user profiles in a Web store. *Journal of Organizational Computing and Electronic Commerce, 28*(2), 98–121. https://doi.org/10.1080/10919392.2018.1444340

Jannach, D., Manzoor, A., Cai, W., & Chen, L. (2021). A Survey on Conversational Recommender Systems. *ACM Computing Surveys (CSUR), 54*(5), 1–36.

Jeong, W. S., Han, S. G., & Jo, G. S. (2003). Intelligent Cyber Logistics Using Reverse Auction in Electronic Commerce. *Journal of Organizational Computing and Electronic Commerce, 13*(3–4), 191–209. https://doi.org/10.1207/s15327744joce133&4_03

Jeyaraj, A., & Zadeh, A. H. (2020). Evolution of information systems research: Insights from topic modeling. *Information & Management, 57*(4), 103207. https://doi.org/10.1016/j.im.2019.103207

Ji, K., & Shen, H. (2015). Addressing cold-start: Scalable recommendation with tags and keywords. *Knowledge-Based Systems, 83*, 42–50. https://doi.org/10.1016/j.knosys.2015.03.008

Ji, S., & juan, Zhang, Q., Li, J., Chiu, D. K. W., Xu, S., Yi, L., & Gong, M. (2020). A burst-based unsupervised method for detecting review spammer groups. *Information Sciences, 536*, 454–469. https://doi.org/10.1016/j.ins.2020.05.084

Jiang, G., Ma, F., Shang, J., & Chau, P. Y. K. (2014). Evolution of knowledge sharing behavior in social commerce: An agent-based computational approach. *Information Sciences, 278*, 250–266. https://doi.org/10.1016/j.ins.2014.03.051

Jiang, Z., Mookerjee, V. S., & Sarkar, S. (2005). Lying on the web: Implications for expert systems redesign. *Information Systems Research, 16*(2), 131–148. https://doi.org/10.1287/isre.1050.0046

Jøsang, A., Ismail, R., & Boyd, C. (2007). A survey of trust and reputation systems for online service provision. *Decision Support Systems, 43*(2), 618–644. https://doi.org/10.1016/j.dss.2005.05.019

Julià, C., Sappa, A. D., Lumbreras, F., Serrat, J., & López, A. (2009). Predicting Missing Ratings in Recommender Systems: Adapted Factorization Approach. *International Journal of Electronic Commerce, 14*(2), 89–108. https://doi.org/10.1093/JEC1086-4415140203

Kagan, S., & Bekkerman, R. (2018). Predicting Purchase Behavior of Website Audiences. *International Journal of Electronic Commerce, 22*(4), 510–539. https://doi.org/10.0456/10864415.2018.1485084

Kaiser, C., Schlick, S., & Bodendorf, F. (2011). Warning system for online market research - Identifying critical situations in online opinion formation. *Knowledge-Based Systems, 24*(6), 824–836. https://doi.org/10.1016/j.knosys.2011.03.004

Kalakota, R., & Whinston, A. B. (1997). *Electronic commerce: a manager's guide*. Addison-Wesley Professional.

Kandula, S., Krishnamoorthy, S., & Roy, D. (2021). A prescriptive analytics framework for efficient E-commerce order delivery. *Decision Support Systems, 147*, 113584. https://doi.org/10.1016/j.dss.2021.113584

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Kauffman, R. J., Kim, K., Lee, S.-Y.T., Hoang, A.-P., & Ren, J. (2017). Combining machine-based and econometrics methods for policy analytics insights. *Electronic Commerce Research and Applications, 25*, 115–140. https://doi.org/10.1016/j.elerap.2017.04.004

Kazienko, P., & Adamski, M. (2007). AdROSA-Adaptive personalization of web advertising. *Information Sciences, 177*(11), 2269–2295. https://doi.org/10.1016/j.ins.2007.01.002

Keegan, S., O'Hare, G. M. P., & O'Grady, M. J. (2008). Easishop: Ambient intelligence assists everyday shopping. *Information Sciences, 178*(3), 588–611. https://doi.org/10.1016/j.ins.2007.08.027

Ketter, W., Collins, J., Gini, M., Gupta, A., & Schrater, P. (2012). Real-Time tactical and strategic sales management for intelligent agents guided by economic regimes. *Information Systems Research, 23*(4), 1263–1283. https://doi.org/10.1287/isre.1110.0415

Khare, V. R., & Chougule, R. (2012). Decision support for improved service effectiveness using domain aware text mining. *Knowledge-Based Systems, 33*, 29–40. https://doi.org/10.1016/j.knosys.2012.03.005

Khopkar, S. S., & Nikolaev, A. G. (2017). Predicting long-term product ratings based on few early ratings and user base analysis. *Electronic Commerce Research and Applications, 21*, 38–49. https://doi.org/10.1016/j.elerap.2016.12.002

Kiekintveld, C., Miller, J., Jordan, P. R., Callender, L. F., & Wellman, M. P. (2009). Forecasting market prices in a supply chain game. *Electronic Commerce Research and Applications, 8*(2), 63–77. https://doi.org/10.1016/j.elerap.2008.11.005

Kietzmann, J., Paschen, J., & Treen, E. (2018). Artificial intelligence in advertising: How marketers can leverage artificial intelligence along the consumer journey. *Journal of Advertising Research, 58*(3), 263–267. https://doi.org/10.2501/JAR-2018-035

Kim, D. J., Song, Y. I., Braynov, S. B., & Rao, H. R. (2005a). A multidimensional trust formation model in B-to-C e-commerce: A conceptual framework and content analyses of academia/practitioner perspectives. *Decision Support Systems, 40*(2), 143–165. https://doi.org/10.1016/j.dss.2004.01.006

Kim, D., Park, C., Oh, J., & Yu, H. (2017). Deep hybrid recommender systems via exploiting document context and statistics of items.

Information Sciences, 417, 72–87. https://doi.org/10.1016/j.ins.2017.06.026
Kim, J. W., Lee, B. H., Shaw, M. J., Chang, H. L., & Nelson, M. (2001). Application of decision-tree induction techniques to personalized advertisements on internet storefronts. *International Journal of Electronic Commerce, 5*(3), 45–62. https://doi.org/10.1080/10864415.2001.11044215
Kim, K., & Ahn, H. (2008). A recommender system using GA K-means clustering in an online shopping market. *Expert Systems with Applications, 34*(2), 1200–1209. https://doi.org/10.1016/j.eswa.2006.12.025
Kim, W., Kerschberg, L., & Scime, A. (2002). Learning for automatic personalization in a semantic taxonomy-based meta-search agent. *Electronic Commerce Research and Applications, 1*(2), 150–173. https://doi.org/10.1016/S1567-4223(02)00011-X
Kim, Y. S., Yum, B. J., Song, J., & Kim, S. M. (2005b). Development of a recommender system based on navigational and behavioral patterns of customers in e-commerce sites. *Expert Systems with Applications, 28*(2), 381–393. https://doi.org/10.1016/j.eswa.2004.10.017
Klaus, T., & Changchit, C. (2019). Toward an Understanding of Consumer Attitudes on Online Review Usage. *Journal of Computer Information Systems, 59*(3), 277–286. https://doi.org/10.1080/08874417.2017.1348916
Knorr, E. M., Ng, R. T., & Tucakov, V. (2000). Distance-based outliers: Algorithms and applications. *The VLDB Journal, 8*(3), 237–253. https://doi.org/10.1007/s007780050006
Kohavi, R., Longbotham, R., Sommerfield, D., & Henne, R. M. (2009). Controlled experiments on the web: Survey and practical guide. *Data Mining and Knowledge Discovery, 18*(1), 140–181. https://doi.org/10.1007/s10618-008-0114-1
Konstan, J. A., Miller, B. N., Maltz, D., Herlocker, J. L., Gordon, L. R., & Riedl, J. (1997). Applying Collaborative Filtering to Usenet News. *Communications of the ACM, 40*(3), 77–87. https://doi.org/10.1145/245108.245126
Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix Factorization Techniques for Recommender Systems. *Computer, 42*(8), 30–37. https://doi.org/10.1109/MC.2009.263
Kühl, N., Mühlthaler, M., & Goutier, M. (2020). Supporting customer-oriented marketing with artificial intelligence: Automatically quantifying customer needs from social media. *Electronic Markets, 30*(2), 351–367. https://doi.org/10.1007/s12525-019-00351-0
Kumar, N., Venugopal, D., Qiu, L., & Kumar, S. (2018). Detecting Review Manipulation on Online Platforms with Hierarchical Supervised Learning. *Journal of Management Information Systems, 35*(1), 350–380. https://doi.org/10.1080/07421222.2018.1440758
Kumar, N., Venugopal, D., Qiu, L., & Kumar, S. (2019a). Detecting Anomalous Online Reviewers: An Unsupervised Approach Using Mixture Models. *Journal of Management Information Systems, 36*(4), 1313–1346. https://doi.org/10.1080/07421222.2019.1661089
Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019b). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review, 61*(4), 135–155. https://doi.org/10.1177/0008125619859317
Kuo, R. J., Chang, K., & Chien, S. Y. (2004). Integration of Self-Organizing Feature Maps and Genetic-Algorithm-Based Clustering Method for Market Segmentation. *Journal of Organizational Computing and Electronic Commerce, 14*(1), 43–60. https://doi.org/10.1207/s15327744joce1401_3
Kuo, R. J., Liao, J. L., & Tu, C. (2005). Integration of ART2 neural network and genetic K-means algorithm for analyzing Web browsing paths in electronic commerce. *Decision Support Systems, 40*(2), 355–374. https://doi.org/10.1016/j.dss.2004.04.010
Kwon, O., Yoo, K., & Suh, E. (2006). ubiES: Applying ubiquitous computing technologies to an expert system for context-aware proactive services. *Electronic Commerce Research and Applications, 5*(3), 209–219. https://doi.org/10.1016/j.elerap.2005.10.011
Laorden, C., Santos, I., Sanz, B., Alvarez, G., & Bringas, P. G. (2012). Word sense disambiguation for spam filtering. *Electronic Commerce Research and Applications, 11*(3), 290–298. https://doi.org/10.1016/j.elerap.2011.11.004
Lau, R. Y. K. (2007). Towards a web services and intelligent agents-based negotiation system for B2B eCommerce. *Electronic Commerce Research and Applications, 6*(3), 260–273. https://doi.org/10.1016/j.elerap.2006.06.007
Law, R., Leung, R., & Buhalis, D. (2009). Information technology applications in hospitality and tourism: A review of publications from 2005 to 2007. *Journal of Travel and Tourism Marketing, 26*(5–6), 599–623. https://doi.org/10.1080/10548400903163160
Lawrence, R. D., Almasi, G. S., Kotlyar, V., Viveros, M. S., & Duri, S. S. (2001). Personalization of supermarket product recommendations. In *Data Mining and Knowledge Discovery* (Vol. 5, Issues 1–2, pp. 11–32). Springer. https://doi.org/10.1023/A:1009835726774
LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444.
Lee, D., & Hosanagar, K. (2021). How do product attributes and reviews moderate the impact of recommender systems through purchase stages? *Management Science, 67*(1), 524–546. https://doi.org/10.1287/mnsc.2019.3546
Lee, D., Gopal, A., & Park, S. H. (2020). Different but equal? a field experiment on the impact of recommendation systems on mobile and personal computer channels in retail. *Information Systems Research, 31*(3), 892–912. https://doi.org/10.1287/ISRE.2020.0922
Lee, H.-C., Rim, H.-C., & Lee, D.-G. (2019). Learning to rank products based on online product reviews using a hierarchical deep neural network. *Electronic Commerce Research and Applications, 36*, 100874. https://doi.org/10.1016/j.elerap.2019.100874
Lee, J., Podlaseck, M., Schonberg, E., & Hoch, R. (2001). Visualization and analysis of clickstream data of online stores for understanding web merchandising. *Data Mining and Knowledge Discovery, 5*(1–2), 59–84. https://doi.org/10.1023/A:1009843912662
Lee, S. K., Cho, Y. H., & Kim, S. H. (2010). Collaborative filtering with ordinal scale-based implicit ratings for mobile music recommendations. *Information Sciences, 180*(11), 2142–2155. https://doi.org/10.1016/j.ins.2010.02.004
Lee, S., & Kim, W. (2017). Sentiment labeling for extending initial labeled data to improve semi-supervised sentiment classification. *Electronic Commerce Research and Applications, 26*, 35–49. https://doi.org/10.1016/j.elerap.2017.09.006
Lee, Y. H., Hu, P. J. H., Cheng, T. H., & Hsieh, Y. F. (2012). A cost-sensitive technique for positive-example learning supporting content-based product recommendations in B-to-C e-commerce. *Decision Support Systems, 53*(1), 245–256. https://doi.org/10.1016/j.dss.2012.01.018
Leloup, B. (2003). Pricing with local interactions on agent-based electronic marketplaces. *Electronic Commerce Research and Applications, 2*(2), 187–198. https://doi.org/10.1016/S1567-4223(03)00023-1
Lessmann, S., Haupt, J., Coussement, K., & De Bock, K. W. (2019). Targeting customers for profit: An ensemble learning framework to support marketing decision-making. *Information Sciences*. https://doi.org/10.1016/j.ins.2019.05.027
Li, H., Su, S. Y. W., & Lam, H. (2006). On automated e-business negotiations: Goal, policy, strategy, and plans of decision and action. *Journal of Organizational Computing and Electronic Commerce, 16*(1), 1–29. https://doi.org/10.1080/10919390609540288

Li, J., Chen, C., Chen, H., & Tong, C. (2017). Towards Context-aware Social Recommendation via Individual Trust. *Knowledge-Based Systems, 127*, 58–66. https://doi.org/10.1016/j.knosys.2017.02.032

Li, S., Zhang, Y., Yu, Z., Zhang, F., & Lu, H. (2019a). Predicting the influence of viral message for VM campaign on Weibo. *Electronic Commerce Research and Applications, 36*, 100875. https://doi.org/10.1016/j.elerap.2019.100875

Li, X., Wu, C., & Mai, F. (2019b). The effect of online reviews on product sales: A joint sentiment-topic analysis. *Information & Management, 56*(2), 172–184. https://doi.org/10.1016/j.im.2018.04.007

Li, Y.-M., Chou, C.-L., & Lin, L.-F. (2014). A social recommender mechanism for location-based group commerce. *Information Sciences, 274*, 125–142. https://doi.org/10.1016/j.ins.2014.02.079

Li, Y. M., Wu, C. T., & Lai, C. Y. (2013). A social recommender mechanism for e-commerce: Combining similarity, trust, and relationship. *Decision Support Systems, 55*(3), 740–752. https://doi.org/10.1016/j.dss.2013.02.009

Li, Y., Wang, S., Pan, Q., Peng, H., Yang, T., & Cambria, E. (2019c). Learning binary codes with neural collaborative filtering for efficient recommendation systems. *Knowledge-Based Systems, 172*, 64–75. https://doi.org/10.1016/j.knosys.2019.02.012

Li, Yu., Lu, L., & Xuefeng, L. (2005). A hybrid collaborative filtering method for multiple-interests and multiple-content recommendation in E-Commerce. *Expert Systems with Applications, 28*(1), 67–77. https://doi.org/10.1016/j.eswa.2004.08.013

Liang, R., Wang, J., & qiang. (2019). A Linguistic Intuitionistic Cloud Decision Support Model with Sentiment Analysis for Product Selection in E-commerce. *International Journal of Fuzzy Systems, 21*(3), 963–977. https://doi.org/10.1007/s40815-019-00606-0

Liebman, E., Saar-Tsechansky, M., & Stone, P. (2019). The right music at the right time: Adaptive personalized playlists based on sequence modeling. *MIS Quarterly, 43*(3), 765–786. https://doi.org/10.25300/MISQ/2019/14750

Lin, Q.-Y., Chen, Y.-L., Chen, J.-S., & Chen, Y.-C. (2003). Mining inter-organizational retailing knowledge for an alliance formed by competitive firms. *Information & Management, 40*(5), 431–442. https://doi.org/10.1016/S0378-7206(02)00062-9

Lin, W., Alvarez, S. A., & Ruiz, C. (2002). Efficient Adaptive-Support Association Rule Mining for Recommender Systems. *Data Mining and Knowledge Discovery, 6*(1), 83–105. https://doi.org/10.1023/A:1013284820704

Lin, W. H., Wang, P., & Tsai, C. F. (2016). Face recognition using support vector model classifier for user authentication. *Electronic Commerce Research and Applications, 18*, 71–82. https://doi.org/10.1016/j.elerap.2016.01.005

Linden, G., Smith, B., & York, J. (2003). Amazon.com recommendations: item-to-item collaborative filtering. *IEEE Internet Computing, 7*(1), 76–80. https://doi.org/10.1109/MIC.2003.1167344

Liu, B., Hu, M., & Cheng, J. (2005). Opinion observer. *Proceedings of the 14th International Conference on World Wide Web*, 342. https://doi.org/10.1145/1060745.1060797

Liu, D.-R., Chen, K.-Y., Chou, Y.-C., & Lee, J.-H. (2018). Online recommendations based on dynamic adjustment of recommendation lists. *Knowledge-Based Systems, 161*, 375–389. https://doi.org/10.1016/j.knosys.2018.07.038

Liu, H., Jiang, Z., Song, Y., Zhang, T., & Wu, Z. (2019). User preference modeling based on meta paths and diversity regularization in heterogeneous information networks. *Knowledge-Based Systems, 181*, 104784. https://doi.org/10.1016/j.knosys.2019.05.027

Liu, K., Zeng, X., Bruniaux, P., Wang, J., Kamalha, E., & Tao, X. (2017). Fit evaluation of virtual garment try-on by learning from digital pressure data. *Knowledge-Based Systems, 133*, 174–182. https://doi.org/10.1016/j.knosys.2017.07.007

Liu, N., & Shen, B. (2020). Aspect-based sentiment analysis with gated alternate neural network. *Knowledge-Based Systems, 188*, 105010. https://doi.org/10.1016/j.knosys.2019.105010

Liu, R., Mai, F., Shan, Z., & Wu, Y. (2020). Predicting shareholder litigation on insider trading from financial text: An interpretable deep learning approach. *Information & Management, 57*(8), 103387. https://doi.org/10.1016/j.im.2020.103387

Liu, X., Datta, A., & Rzadca, K. (2013). Trust beyond reputation: A computational trust model based on stereotypes. *Electronic Commerce Research and Applications, 12*(1), 24–39. https://doi.org/10.1016/j.elerap.2012.07.001

Lowry, P. B., Moody, G. D., Gaskin, J., Galletta, D. F., Humpherys, S. L., Barlow, J. B., & Wilson, D. W. (2013). Evaluating journal quality and the association for information systems senior scholars' journal basket via bibliometric measures: Do expert journal assessments add value? *MIS Quarterly, 37*(4), 993–1012. https://doi.org/10.25300/MISQ/2013/37.4.01

Lowry, P., Romans, D., & Curtis, A. (2004). Global Journal Prestige and Supporting Disciplines: A Scientometric Study of Information Systems Journals. *Journal of the Association for Information Systems, 5*(2), 29–77. https://doi.org/10.17705/1jais.00045

Lu, J., Wu, D., Mao, M., Wang, W., & Zhang, G. (2015). Recommender system application developments: A survey. *Decision Support Systems, 74*, 12–32. https://doi.org/10.1016/j.dss.2015.03.008

Luo, X., Lu, X., & Li, J. (2019). When and How to Leverage E-commerce Cart Targeting: The relative and moderated effects of scarcity and price incentives with a two-stage field experiment and causal forest optimization. *Information Systems Research, 30*(4), 1203–1227. https://doi.org/10.1287/isre.2019.0859

Lyytinen, K., Nickerson, J. V, & King, J. L. (2020). Metahuman systems = humans + machines that learn. *Journal of Information Technology, 36*(4), 427–445. https://doi.org/10.1177/0268396220915917

Ma, X., Sha, J., Wang, D., Yu, Y., Yang, Q., & Niu, X. (2018). Study on a prediction of P2P network loan default based on the machine learning LightGBM and XGboost algorithms according to different high dimensional data cleaning. *Electronic Commerce Research and Applications, 31*, 24–39. https://doi.org/10.1016/j.elerap.2018.08.002

Ma, Z., Pant, G., & Sheng, O. R. L. (2011). Mining competitor relationships from online news: A network-based approach. *Electronic Commerce Research and Applications, 10*(4), 418–427. https://doi.org/10.1016/j.elerap.2010.11.006

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures, 90*, 46–60. https://doi.org/10.1016/j.futures.2017.03.006

Manahov, V., & Zhang, H. (2019). Forecasting Financial Markets Using High-Frequency Trading Data: Examination with Strongly Typed Genetic Programming. *International Journal of Electronic Commerce, 23*(1), 12–32. https://doi.org/10.1080/10864415.2018.1512271

Manthiou, A., Klaus, P., Kuppelwieser, V. G., & Reeves, W. (2021). Man vs machine: Examining the three themes of service robotics in tourism and hospitality. *Electronic Markets, 31*(3), 511–527. https://doi.org/10.1007/s12525-020-00434-3

Manvi, S. S., & Venkataram, P. (2005). An intelligent product-information presentation in E-commerce. *Electronic Commerce Research and Applications, 4*(3), 220–239. https://doi.org/10.1016/j.elerap.2005.01.001

Mao, M., Lu, J., Han, J., & Zhang, G. (2019). Multiobjective e-commerce recommendations based on hypergraph ranking. *Information Sciences, 471*, 269–287. https://doi.org/10.1016/j.ins.2018.07.029

Maqsood, H., Mehmood, I., Maqsood, M., Yasir, M., Afzal, S., Aadil, F., Selim, M. M., & Muhammad, K. (2020). A local and global event sentiment based efficient stock exchange forecasting using deep learning. *International Journal of Information Management, 50*, 432–451. https://doi.org/10.1016/j.ijinfomgt.2019.07.011

Marabelli, M., Newell, S., & Handunge, V. (2021). The lifecycle of algorithmic decision-making systems: Organizational choices and ethical challenges. *The Journal of Strategic Information Systems, 30*(3), 101683. https://doi.org/10.1016/j.jsis.2021.101683

Martens, D., & Provost, F. (2014). Explaining data-driven document classifications. *MIS Quarterly, 38*(1), 73–99. https://doi.org/10.25300/MISQ/2014/38.1.04

Martinez-Cruz, C., Porcel, C., Bernabé-Moreno, J., & Herrera-Viedma, E. (2015). A model to represent users trust in recommender systems using ontologies and fuzzy linguistic modeling. *Information Sciences, 311*, 102–118. https://doi.org/10.1016/j.ins.2015.03.013

Marx, W., Bornmann, L., Barth, A., & Leydesdorff, L. (2014). Detecting the historical roots of research fields by reference publication year spectroscopy (RPYS). *Journal of the Association for Information Science and Technology, 65*(4), 751–764. https://doi.org/10.1002/asi.23089

McAuley, J., Targett, C., Shi, Q., & Van Den Hengel, A. (2015). Image-based recommendations on styles and substitutes. *SIGIR 2015 - Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 43–52. https://doi.org/10.1145/2766462.2767755

Milian, E. Z., de Spinola, M., & M., & Carvalho, M. M. d. (2019). Fintechs: A literature review and research agenda. *Electronic Commerce Research and Applications, 34*, 100833. https://doi.org/10.1016/j.elerap.2019.100833

Miralles-Pechuán, L., Ponce, H., & Martínez-Villaseñor, L. (2018). A novel methodology for optimizing display advertising campaigns using genetic algorithms. *Electronic Commerce Research and Applications, 27*, 39–51. https://doi.org/10.1016/j.elerap.2017.11.004

Mo, J., Sarkar, S., & Menon, S. (2018). Know when to run: Recommendations in crowdsourcing contests. *MIS Quarterly, 42*(3), 919–943. https://doi.org/10.25300/MISQ/2018/14103

Mokryn, O., Bogina, V., & Kuflik, T. (2019). Will this session end with a purchase? Inferring current purchase intent of anonymous visitors. *Electronic Commerce Research and Applications, 34*, 100836. https://doi.org/10.1016/j.elerap.2019.100836

Motiwalla, L. F., & Nunamaker, J. F. (1992). Mail-man: A knowledge-based mail assistant for managers. *Journal of Organizational Computing, 2*(2), 131–154. https://doi.org/10.1080/10919399209540179

Moussawi, S., Koufaris, M., & Benbunan-Fich, R. (2020). How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents. *Electronic Markets*. https://doi.org/10.1007/s12525-020-00411-w

Nassiri-Mofakham, F., Nematbakhsh, M. A., Baraani-Dastjerdi, A., & Ghasem-Aghaee, N. (2009). Electronic promotion to new customers using mkNN learning. *Information Sciences, 179*(3), 248–266. https://doi.org/10.1016/j.ins.2008.09.019

Neuhofer, B., Magnus, B., & Celuch, K. (2021). The impact of artificial intelligence on event experiences: A scenario technique approach. *Electronic Markets, 31*(3), 601–617. https://doi.org/10.1007/s12525-020-00433-4

Ngai, E. W. T., & Wat, F. K. T. (2002). A literature review and classification of electronic commerce research. *Information and Management, 39*(5), 415–429. https://doi.org/10.1016/S0378-7206(01)00107-0

Ngai, E. W. T., Lee, M. C. M., Luo, M., Chan, P. S. L., & Liang, T. (2021). An intelligent knowledge-based chatbot for customer service. *Electronic Commerce Research and Applications, 50*, 101098. https://doi.org/10.1016/j.elerap.2021.101098

Nikolay, A., Anindya, G., & Panagiotis, G. I. (2011). Deriving the pricing power of product features by mining consumer reviews. *Management Science, 57*(8), 1485–1509. https://doi.org/10.1287/mnsc.1110.1370

Nilashi, M., & bin Ibrahim, O., Ithnin, N., & Sarmin, N. H. (2015). A multi-criteria collaborative filtering recommender system for the tourism domain using Expectation Maximization (EM) and PCA–ANFIS. *Electronic Commerce Research and Applications, 14*(6), 542–562. https://doi.org/10.1016/j.elerap.2015.08.004

Nishimura, N., Sukegawa, N., Takano, Y., & Iwanaga, J. (2018). A latent-class model for estimating product-choice probabilities from clickstream data. *Information Sciences, 429*, 406–420. https://doi.org/10.1016/j.ins.2017.11.014

Núñez-Valdez, E. R., Quintana, D., González Crespo, R., Isasi, P., & Herrera-Viedma, E. (2018). A recommender system based on implicit feedback for selective dissemination of ebooks. *Information Sciences, 467*, 87–98. https://doi.org/10.1016/j.ins.2018.07.068

O'Donovan, J., & Smyth, B. (2005). Trust in recommender systems. *International Conference on Intelligent User Interfaces, Proceedings IUI*, 167–174. https://doi.org/10.1145/1040830.1040870

O'Neil, S., Zhao, X., Sun, D., & Wei, J. C. (2016). Newsvendor Problems with Demand Shocks and Unknown Demand Distributions. *Decision Sciences, 47*(1), 125–156. https://doi.org/10.1111/deci.12187

Oliver, J. R. (1996). A Machine-Learning Approach to Automated Negotiation and Prospects for Electronic Commerce. *Journal of Management Information Systems, 13*(3), 83–112. https://doi.org/10.1080/07421222.1996.11518135

Ortega, F., Hernando, A., Bobadilla, J., & Kang, J. H. (2016). Recommending items to group of users using Matrix Factorization based Collaborative Filtering. *Information Sciences, 345*, 313–324. https://doi.org/10.1016/j.ins.2016.01.083

Ortega, F., Sánchez, J. L., Bobadilla, J., & Gutiérrez, A. (2013). Improving collaborative filtering-based recommender systems results using Pareto dominance. *Information Sciences, 239*, 50–61. https://doi.org/10.1016/j.ins.2013.03.011

Ou, W., Huynh, V.-N., & Sriboonchitta, S. (2018). Training attractive attribute classifiers based on opinion features extracted from review data. *Electronic Commerce Research and Applications, 32*, 13–22. https://doi.org/10.1016/j.elerap.2018.10.003

Padmanabhan, B., & Tuzhilin, A. (2003). On the use of optimization for data mining: Theoretical interactions and eCRM opportunities. *Management Science, 49*(10), 1327–1343. https://doi.org/10.1287/mnsc.49.10.1327.17310

Pang, G., Wang, X., Hao, F., Xie, J., Wang, X., Lin, Y., & Qin, X. (2019). ACNN-FM: A novel recommender with attention-based convolutional neural network and factorization machines. *Knowledge-Based Systems, 181*, 104786. https://doi.org/10.1016/j.knosys.2019.05.029

Pantano, E., & Pizzi, G. (2020). Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis. *Journal of Retailing and Consumer Services, 55*, 102096. https://doi.org/10.1016/j.jretconser.2020.102096

Paré, G., Trudel, M. C., Jaana, M., & Kitsiou, S. (2015). Synthesizing information systems knowledge: A typology of literature reviews. *Information and Management, 52*(2), 183–199. https://doi.org/10.1016/j.im.2014.08.008

Park, C., Kim, D., Yang, M. C., Lee, J. T., & Yu, H. (2020a). Click-aware purchase prediction with push at the top. *Information Sciences, 521*, 350–364. https://doi.org/10.1016/j.ins.2020.02.062

Park, C., Kim, D., & Yu, H. (2019). An encoder–decoder switch network for purchase prediction. *Knowledge-Based Systems, 185*, 104932. https://doi.org/10.1016/j.knosys.2019.104932

Park, H., Song, M., & Shin, K.-S. (2020b). Deep learning models and datasets for aspect term sentiment classification: Implementing holistic recurrent attention on target-dependent memories. *Knowledge-Based Systems, 187*, 104825. https://doi.org/10.1016/j.knosys.2019.06.033

Park, J. H., & Park, S. C. (2003). Agent-based merchandise management in business-to-business electronic commerce. *Decision Support Systems, 35*(3), 311–333. https://doi.org/10.1016/S0167-9236(02)00111-2

Parvin, H., Moradi, P., Esmaeili, S., & Qader, N. N. (2019). A scalable and robust trust-based nonnegative matrix factorization recommender using the alternating direction method. *Knowledge-Based Systems, 166*, 92–107. https://doi.org/10.1016/j.knosys.2018.12.016

Patcha, A., & Park, J.-M. (2007). An overview of anomaly detection techniques: Existing solutions and latest technological trends. *Computer Networks, 51*(12), 3448–3470. https://doi.org/10.1016/j.comnet.2007.02.001

Patra, B. K., Launonen, R., Ollikainen, V., & Nandi, S. (2015). A new similarity measure using Bhattacharyya coefficient for collaborative filtering in sparse data. *Knowledge-Based Systems, 82*, 163–177. https://doi.org/10.1016/j.knosys.2015.03.001

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research, 12*, 2825–2830.

Pendharkar, P. C. (2006). Inductive Regression Tree and Genetic Programming Techniques for Learning User Web Search Preferences. *Journal of Organizational Computing and Electronic Commerce, 16*(3–4), 223–245. https://doi.org/10.1080/10919392.2006.9681201

Pengnate (Fone), S., & Riggins, F. J. (2020). The role of emotion in P2P microfinance funding: A sentiment analysis approach. *International Journal of Information Management, 54*, 102138. https://doi.org/10.1016/j.ijinfomgt.2020.102138

Pfeiffer, J., Pfeiffer, T., Meißner, M., & Weiß, E. (2020). Eye-tracking-based classification of information search behavior using machine learning: Evidence from experiments in physical shops and virtual reality shopping environments. *Information Systems Research, 31*(3), 675–691. https://doi.org/10.1287/ISRE.2019.0907

Pontelli, E., & Son, T. C. (2003). Designing intelligent agents to support universal accessibility of E-commerce services. *Electronic Commerce Research and Applications, 2*(2), 147–161. https://doi.org/10.1016/S1567-4223(03)00012-7

Pourgholamali, F., Kahani, M., & Bagheri, E. (2020). A neural graph embedding approach for selecting review sentences. *Electronic Commerce Research and Applications, 40*, 100917. https://doi.org/10.1016/j.elerap.2019.100917

Pourkhani, A., Abdipour, K., Baher, B., & Moslehpour, M. (2019). The impact of social media in business growth and performance: A scientometrics analysis. *International Journal of Data and Network Science, 3*(3), 223–244. https://doi.org/10.5267/j.ijdns.2019.2.003

Praet, S., & Martens, D. (2020). Efficient Parcel Delivery by Predicting Customers' Locations*. *Decision Sciences, 51*(5), 1202–1231. https://doi.org/10.1111/deci.12376

Pranata, I., & Susilo, W. (2016). Are the most popular users always trustworthy? The case of Yelp. *Electronic Commerce Research and Applications, 20*, 30–41. https://doi.org/10.1016/j.elerap.2016.09.005

Preibusch, S., Peetz, T., Acar, G., & Berendt, B. (2016). Shopping for privacy: Purchase details leaked to PayPal. *Electronic Commerce Research and Applications, 15*, 52–64. https://doi.org/10.1016/j.elerap.2015.11.004

Pröllochs, N., Feuerriegel, S., Lutz, B., & Neumann, D. (2020). Negation scope detection for sentiment analysis: A reinforcement learning framework for replicating human interpretations. *Information Sciences, 536*, 205–221. https://doi.org/10.1016/j.ins.2020.05.022

Pu, P., & Chen, L. (2007). Trust-inspiring explanation interfaces for recommender systems. *Knowledge-Based Systems, 20*(6), 542–556. https://doi.org/10.1016/j.knosys.2007.04.004

Pujahari, A., & Sisodia, D. S. (2019). Modeling Side Information in Preference Relation based Restricted Boltzmann Machine for recommender systems. *Information Sciences, 490*, 126–145. https://doi.org/10.1016/j.ins.2019.03.064

Qi, J., Zhang, Z., Jeon, S., & Zhou, Y. (2016). Mining customer requirements from online reviews: A product improvement perspective. *Information and Management, 53*(8), 951–963. https://doi.org/10.1016/j.im.2016.06.002

Qiu, J., Liu, C., Li, Y., & Lin, Z. (2018). Leveraging sentiment analysis at the aspects level to predict ratings of reviews. *Information Sciences, 451–452*, 295–309. https://doi.org/10.1016/j.ins.2018.04.009

Rahm, E., & Bernstein, P. A. (2001). A survey of approaches to automatic schema matching. *VLDB Journal, 10*(4), 334–350. https://doi.org/10.1007/s007780100057

Ranjbar Kermany, N., & Alizadeh, S. H. (2017). A hybrid multi-criteria recommender system using ontology and neuro-fuzzy techniques. *Electronic Commerce Research and Applications, 21*, 50–64. https://doi.org/10.1016/j.elerap.2016.12.005

Rao, Y., Xie, H., Li, J., Jin, F., Wang, F. L., & Li, Q. (2016). Social emotion classification of short text via topic-level maximum entropy model. *Information and Management, 53*(8), 978–986. https://doi.org/10.1016/j.im.2016.04.005

Ravi, K., & Ravi, V. (2015). A survey on opinion mining and sentiment analysis: Tasks, approaches and applications. *Knowledge-Based Systems, 89*, 14–46. https://doi.org/10.1016/j.knosys.2015.06.015

Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., & Riedl, J. (1994). GroupLens: An open architecture for collaborative filtering of netnews. *Proceedings of the 1994 ACM Conference on Computer Supported Cooperative Work, CSCW 1994*, 175–186. https://doi.org/10.1145/192844.192905

Resnick, P., & Varian, H. R. (1997). Recommender Systems. *Communications of the ACM, 40*(3), 56–58. https://doi.org/10.1145/245108.245121

Rhaiem, M., & Bornmann, L. (2018). Reference Publication Year Spectroscopy (RPYS) with publications in the area of academic efficiency studies: What are the historical roots of this research topic? *Applied Economics, 50*(13), 1442–1453. https://doi.org/10.1080/00036846.2017.1363865

Ricci, F., Rokach, L., & Shapira, B. (2011). *Introduction to recommender systems handbook. In Recommender systems handbook* (pp. 1–35). Springer.

Ryoba, M. J., Qu, S., & Zhou, Y. (2021). Feature subset selection for predicting the success of crowdfunding project campaigns. *Electronic Markets, 31*(3), 671–684. https://doi.org/10.1007/s12525-020-00398-4

Sabater, J., & Sierra, C. (2005). Review on computational trust and reputation models. *Artificial Intelligence Review, 24*(1), 33–60. https://doi.org/10.1007/s10462-004-0041-5

Salakhutdinov, R., Mnih, A., & Hinton, G. (2007). Restricted Boltzmann machines for collaborative filtering. *ACM International Conference Proceeding Series, 227*, 791–798. https://doi.org/10.1145/1273496.1273596

Saleh, A. I., El Desouky, A. I., & Ali, S. H. (2015). Promoting the performance of vertical recommendation systems by applying new classification techniques. *Knowledge-Based Systems, 75*, 192–223. https://doi.org/10.1016/j.knosys.2014.12.002

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001). Item-based collaborative filtering recommendation algorithms. *Proceedings of the 10th International Conference on World Wide Web, WWW 2001*, 285–295. https://doi.org/10.1145/371920.372071

Saumya, S., Singh, J. P., Baabdullah, A. M., Rana, N. P., & Dwivedi, Y. K. (2018). Ranking online consumer reviews. *Electronic Commerce Research and Applications, 29*, 78–89. https://doi.org/10.1016/j.elerap.2018.03.008

Schafer, J. B., Konstan, J. A., & Riedl, J. (2001). E-Commerce Recommendation Applications. *Data Mining and Knowledge Discovery, 5*(1), 115–153. https://doi.org/10.1023/A:1009804230409

Schmidhuber, J. (2015). Deep Learning in neural networks: An overview. *Neural Networks, 61*, 85–117. https://doi.org/10.1016/j.neunet.2014.09.003

Shani, G., Heckerman, D., & Brafman, R. I. (2005). An MDP-based recommender system. *Journal of Machine Learning Research, 6*(Sep), 1265–1295.

Shardanand, U., & Maes, P. (1995). Social information filtering. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 210–217. https://doi.org/10.1145/223904.223931

Shi, Y., Wang, T., & Alwan, L. C. (2020). Analytics for Cross-Border E-Commerce: Inventory Risk Management of an Online Fashion Retailer. *Decision Sciences, 51*(6), 1347–1376. https://doi.org/10.1111/deci.12429

Si, Y., Zhang, F., & Liu, W. (2017). CTF-ARA: An adaptive method for POI recommendation based on check-in and temporal features. *Knowledge-Based Systems, 128*, 59–70. https://doi.org/10.1016/j.knosys.2017.04.013

Singh, A., & Tucker, C. S. (2017). A machine learning approach to product review disambiguation based on function, form and behavior classification. *Decision Support Systems, 97*, 81–91. https://doi.org/10.1016/j.dss.2017.03.007

Sohn, K., & Kwon, O. (2020). Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products. *Telematics and Informatics, 47*, 101324. https://doi.org/10.1016/j.tele.2019.101324

Song, S., Hwang, K., Zhou, R., & Kwok, Y. K. (2005). Trusted P2P transactions with fuzzy reputation aggregation. *IEEE Internet Computing, 9*(6), 24–34. https://doi.org/10.1109/MIC.2005.136

Stöckli, D. R., & Khobzi, H. (2021). Recommendation systems and convergence of online reviews: The type of product network matters! *Decision Support Systems, 142*, 113475. https://doi.org/10.1016/j.dss.2020.113475

Stoeckli, E., Dremel, C., Uebernickel, F., & Brenner, W. (2020). How affordances of chatbots cross the chasm between social and traditional enterprise systems. *Electronic Markets, 30*(2), 369–403. https://doi.org/10.1007/s12525-019-00359-6

Su, X., & Khoshgoftaar, T. M. (2009). A Survey of Collaborative Filtering Techniques. *Advances in Artificial Intelligence, 2009*, 1–19. https://doi.org/10.1155/2009/421425

Suchacka, G., & Iwański, J. (2020). Identifying legitimate Web users and bots with different traffic profiles — an Information Bottleneck approach. *Knowledge-Based Systems, 197*, 105875. https://doi.org/10.1016/j.knosys.2020.105875

Sul, H. K., Dennis, A. R., & Yuan, L. I. (2017). Trading on Twitter: Using Social Media Sentiment to Predict Stock Returns. *Decision Sciences, 48*(3), 454–488. https://doi.org/10.1111/deci.12229

Sun, Y., Liu, X., Chen, G., Hao, Y., & Zhang (Justin), Z. (2020). How mood affects the stock market: Empirical evidence from microblogs. *Information & Management, 57*(5), 103181. https://doi.org/10.1016/j.im.2019.103181

Sung (Christine), E., Bae, S., Han, D.-I.D., & Kwon, O. (2021). Consumer engagement via interactive artificial intelligence and mixed reality. *International Journal of Information Management, 60*, 102382. https://doi.org/10.1016/j.ijinfomgt.2021.102382

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2015). Going deeper with convolutions. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015*, 1–9. https://doi.org/10.1109/CVPR.2015.7298594

Takeuchi, H., Subramaniam, L. V., Nasukawa, T., & Roy, S. (2009). Getting insights from the voices of customers: Conversation mining at a contact center. *Information Sciences, 179*(11), 1584–1591. https://doi.org/10.1016/j.ins.2008.11.026

Tan, F. T. C., Pan, S. L., & Zuo, M. (2019). Realising platform operational agility through information technology–enabled capabilities: A resource-interdependence perspective. *Information Systems Journal, 29*(3), 582–608. https://doi.org/10.0487/isj.12221

Tan, J., Tyler, K., & Manica, A. (2007). Business-to-business adoption of eCommerce in China. *Information & Management, 44*(3), 332–351. https://doi.org/10.1016/j.im.2007.04.001

Tan, P.-N., & Kumar, V. (2002). Discovery of Web Robot Sessions Based on their Navigational Patterns. *Data Mining and Knowledge Discovery, 6*(1), 9–35. https://doi.org/10.1023/A:1013228602957

Tan, Y.-H., & Thoen, W. (2000). INCAS: A legal expert system for contract terms in electronic commerce. *Decision Support Systems, 29*(4), 389–411. https://doi.org/10.1016/S0167-9236(00)00085-3

Tang, P., Qiu, W., Huang, Z., Chen, S., Yan, M., Lian, H., & Li, Z. (2020). Anomaly detection in electronic invoice systems based on machine learning. *Information Sciences, 535*, 172–186. https://doi.org/10.1016/j.ins.2020.03.089

Templier, M., & Paré, G. (2015). A framework for guiding and evaluating literature reviews. *Communications of the Association for Information Systems, 37*(1), 112–137. https://doi.org/10.17705/1CAIS.03706

Thiebes, S., Lins, S., & Sunyaev, A. (2021). Trustworthy artificial intelligence. *Electronic Markets, 31*(2). https://doi.org/10.1007/s12525-020-00441-4

Tian, F., Wu, F., Chao, K. M., Zheng, Q., Shah, N., Lan, T., & Yue, J. (2016). A topic sentence-based instance transfer method for imbalanced sentiment classification of Chinese product reviews. *Electronic Commerce Research and Applications, 16*, 66–76. https://doi.org/10.1016/j.elerap.2015.10.003

Tran, B., Vu, G., Ha, G., Vuong, Q.-H., Ho, M.-T., Vuong, T.-T., La, V.-P., Ho, M.-T., Nghiem, K.-C., Nguyen, H., Latkin, C., Tam, W., Cheung, N.-M., Nguyen, H.-K., Ho, C., & Ho, R. (2019). Global Evolution of Research in Artificial Intelligence in Health and Medicine: A Bibliometric Study. *Journal of Clinical Medicine, 8*(3), 360. https://doi.org/10.3390/jcm8030360

Tseng, K.-K., Lin, R.F.-Y., Zhou, H., Kurniajaya, K. J., & Li, Q. (2018). Price prediction of e-commerce products through Internet sentiment analysis. *Electronic Commerce Research, 18*(1), 65–88. https://doi.org/10.1007/s10660-017-9272-9

Vanneschi, L., Horn, D. M., Castelli, M., & Popovič, A. (2018). An artificial intelligence system for predicting customer default in e-commerce. *Expert Systems with Applications, 104*, 1–21. https://doi.org/10.1016/j.eswa.2018.03.025

Varshney, D., Kumar, S., & Gupta, V. (2017). Predicting information diffusion probabilities in social networks: A Bayesian networks based approach. *Knowledge-Based Systems, 133*, 66–76. https://doi.org/10.1016/j.knosys.2017.07.003

Viejo, A., Sánchez, D., & Castellà-Roca, J. (2012). Preventing automatic user profiling in Web 2.0 applications. *Knowledge-Based Systems, 36*, 191–205. https://doi.org/10.1016/j.knosys.2012.07.001

Villegas, N. M., Sánchez, C., Díaz-Cely, J., & Tamura, G. (2018). Characterizing context-aware recommender systems: A systematic literature review. *Knowledge-Based Systems, 140*, 173–200. https://doi.org/10.1016/j.knosys.2017.11.003

Viswanathan, S., Guillot, F., & Grasso, A. M. (2020). What is natural?: Challenges and opportunities for conversational recommender systems. *ACM International Conference Proceeding Series*, 1–4. https://doi.org/10.1145/3405755.3406174

Vizine Pereira, A. L., & Hruschka, E. R. (2015). Simultaneous co-clustering and learning to address the cold start problem in recommender systems. *Knowledge-Based Systems, 82*, 11–19. https://doi.org/10.1016/j.knosys.2015.02.016

Vozalis, M. G., & Margaritis, K. G. (2007). Using SVD and demographic data for the enhancement of generalized Collaborative Filtering. *Information Sciences, 177*(15), 3017–3037. https://doi.org/10.1016/j.ins.2007.02.036

Wang, F.-H. (2008). On discovery of soft associations with "most" fuzzy quantifier for item promotion applications. *Information Sciences, 178*(7), 1848–1876. https://doi.org/10.1016/j.ins.2007.11.018

Wang, G., Ma, J., Huang, L., & Xu, K. (2012). Two credit scoring models based on dual strategy ensemble trees. *Knowledge-Based Systems, 26*, 61–68. https://doi.org/10.1016/j.knosys.2011.06.020

Wang, H.-C., Jhou, H.-T., & Tsai, Y.-S. (2018a). Adapting topic map and social influence to the personalized hybrid recommender system. *Information Sciences*. https://doi.org/10.1016/j.ins.2018.04.015

Wang, H. C., & Doong, H. S. (2010). Argument form and spokesperson type: The recommendation strategy of virtual salespersons. *International Journal of Information Management, 30*(6), 493–501. https://doi.org/10.1016/j.ijinfomgt.2010.03.006

Wang, H., Wang, N., & Yeung, D. Y. (2015). Collaborative deep learning for recommender systems. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, *2015-Augus*, 1235–1244. https://doi.org/10.1145/2783258.2783273

Wang, Q., Li, B., & Singh, P. V. (2018). Copycats vs. original mobile apps: A machine learning copycat-detection method and empirical analysis. *Information Systems Research, 29*(2), 273–291. https://doi.org/10.1287/isre.2017.0735

Wang, W., Feng, Y., & Dai, W. (2018c). Topic analysis of online reviews for two competitive products using latent Dirichlet allocation. *Electronic Commerce Research and Applications, 29*, 142–156. https://doi.org/10.1016/j.elerap.2018.04.003

Wang, Y., Lu, X., & Tan, Y. (2018d). Impact of product attributes on customer satisfaction: An analysis of online reviews for washing machines. *Electronic Commerce Research and Applications, 29*, 1–11. https://doi.org/10.1016/j.elerap.2018.03.003

Wareham, J., Zheng, J. G., & Straub, D. (2005). Critical themes in electronic commerce research: A meta-analysis. *Journal of Information Technology, 20*(1), 1–19. https://doi.org/10.1057/palgrave.jit.2000034

Watson, G. R., & Rasmussen, C. E. (2008). An integrated environment for the development of parallel applications. *Proceedings of the 2nd International Workshop on Parallel Tools for High Performance Computing*, *11*(2), 19–34. https://doi.org/10.1007/978-3-540-68564-7

Webster, J., & Watson, R. T. (2002). Analyzing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly*, *26*(2), xiii–xxiii. 10.1.1.104.6570

Wei, C. P., Hu, P. J., & Dong, Y. X. (2002). Managing document categories in e-commerce environments: An evolution-based approach. *European Journal of Information Systems, 11*(3), 208–222. https://doi.org/10.1057/palgrave.ejis.3000429

Wei, J., He, J., Chen, K., Zhou, Y., & Tang, Z. (2017). Collaborative filtering and deep learning based recommendation system for cold start items. *Expert Systems with Applications, 69*, 29–39. https://doi.org/10.1016/j.eswa.2016.09.040

Wenxuan Ding, A., Li, S., & Chatterjee, P. (2015). Learning User Real-Time Intent for Optimal Dynamic Web Page Transformation. *Information Systems Research, 26*(2), 339–359. https://doi.org/10.1057/isre.2015.0568

Willcocks, L. (2020a). Robo-Apocalypse cancelled? Reframing the automation and future of work debate. *Journal of Information Technology, 35*(4), 286–302. https://doi.org/10.1177/0268396220925830

Willcocks, L. (2020b). Robo-Apocalypse? Response and outlook on the post-COVID-19 future of work. *Journal of Information Technology, 36*(2), 188–194. https://doi.org/10.1177/0268396220978660

Witten, I. H., Frank, E., Hall, M. A., & Pal, C. J. (2016). Data Mining: Practical Machine Learning Tools and Techniques. In *Data Mining: Practical Machine Learning Tools and Techniques*. Morgan Kaufmann. https://doi.org/10.1016/c2009-0-19715-5

Wu, B., Ye, Y., & Chen, Y. (2019). Visual appearance or functional complementarity: Which aspect affects your decision making? *Information Sciences, 476*, 19–37. https://doi.org/10.1016/j.ins.2018.10.011

Wu, J., Huang, L., & Zhao, J. L. (2019). Operationalizing regulatory focus in the digital age: Evidence from an e-commerce context. *MIS Quarterly, 43*(3), 745–764. https://doi.org/10.25300/MISQ/2019/14420

Wu, R. S., & Chou, P. H. (2011). Customer segmentation of multiple category data in e-commerce using a soft-clustering approach. *Electronic Commerce Research and Applications, 10*(3), 331–341. https://doi.org/10.1016/j.elerap.2010.11.002

Xia, H., Wei, X., An, W., Zhang, Z. J., & Sun, Z. (2021). Design of electronic-commerce recommendation systems based on outlier mining. *Electronic Markets, 31*(2). https://doi.org/10.1007/s12525-020-00435-2

Xie, F., Chen, Z., Shang, J., & Fox, G. C. (2014). Grey Forecast model for accurate recommendation in presence of data sparsity and correlation. *Knowledge-Based Systems, 69*(1), 179–190. https://doi.org/10.1016/j.knosys.2014.04.011

Xiong, J., Yu, L., Zhang, D., & Leng, Y. (2021). DNCP: An attention-based deep learning approach enhanced with attractiveness and timeliness of News for online news click prediction. *Information and Management, 58*(2), 103428. https://doi.org/10.1016/j.im.2021.103428

Xu, Y., Yang, Y., Han, J., Wang, E., Ming, J., & Xiong, H. (2019). Slanderous user detection with modified recurrent neural networks in recommender system. *Information Sciences, 505*, 265–281. https://doi.org/10.1016/j.ins.2019.07.081

Xue, G. R., Lin, C., Yang, Q., Xi, W., Zeng, H. J., Yu, Y., & Chen, Z. (2005). Scalable collaborative filtering using cluster-based smoothing. *SIGIR 2005 - Proceedings of the 28th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, 114–121. https://doi.org/10.1145/1076034.1076056

Yan, S. R., Zheng, X. L., Wang, Y., Song, W. W., & Zhang, W. Y. (2015). A graph-based comprehensive reputation model: Exploiting the social context of opinions to enhance trust in social commerce. *Information Sciences, 318*, 51–72. https://doi.org/10.1016/j.ins.2014.09.036

Yan, Y., Huang, C., Wang, Q., & Hu, B. (2020). Data mining of customer choice behavior in internet of things within relationship network. *International Journal of Information Management, 50*, 566–574. https://doi.org/10.1016/j.ijinfomgt.2018.11.013

Yang, Z., Cai, Z., & Guan, X. (2016a). Estimating user behavior toward detecting anomalous ratings in rating systems. *Knowledge-Based Systems, 111*, 144–158. https://doi.org/10.1016/j.knosys.2016.08.011

Yang, Z., Xu, L., Cai, Z., & Xu, Z. (2016b). Re-scale AdaBoost for attack detection in collaborative filtering recommender systems. *Knowledge-Based Systems, 100*, 74–88. https://doi.org/10.1016/j.knosys.2016.02.008

Ye, X., Dong, L., & Ma, D. (2018). Loan evaluation in P2P lending based on Random Forest optimized by genetic algorithm with profit score. *Electronic Commerce Research and Applications, 32*, 23–36. https://doi.org/10.1016/j.elerap.2018.10.004

Yim, D., Malefyt, T., & Khuntia, J. (2021). Is a picture worth a thousand views? Measuring the effects of travel photos on user engagement using deep learning algorithms. *Electronic Markets, 31*(3), 619–637. https://doi.org/10.1007/s12525-021-00472-5

Zaïane, O. R. (2002). Building a recommender agent for e-learning systems. *Proceedings - International Conference on Computers in Education, ICCE, 2002*, 55–59. https://doi.org/10.1109/CIE.2002.1185862

Zhang, D., Yan, Z., Jiang, H., & Kim, T. (2014). A domain-feature enhanced classification model for the detection of Chinese phishing e-Business websites. *Information and Management, 51*(7), 845–853. https://doi.org/10.1016/j.im.2014.08.003

Zhang, D., Xu, H., Su, Z., & Xu, Y. (2015). Chinese comments sentiment classification based on word2vec and SVMperf. *Expert Systems with Applications, 42*(4), 1857–1863. https://doi.org/10.1016/j.eswa.2014.09.011

Zhang, Q., Yang, L. T., Chen, Z., & Li, P. (2018a). A survey on deep learning for big data. *Information Fusion, 42*, 146–157. https://doi.org/10.1016/j.inffus.2017.10.006

Zhang, W., Wang, C., Zhang, Y., & Wang, J. (2020a). Credit risk evaluation model with textual features from loan descriptions for P2P lending. *Electronic Commerce Research and Applications, 42*, 100989. https://doi.org/10.1016/j.elerap.2020.100989

Zhang, W., Du, Y., Yang, Y., & Yoshida, T. (2018b). DeRec: A data-driven approach to accurate recommendation with deep learning and weighted loss function. *Electronic Commerce Research and Applications, 31*, 12–23. https://doi.org/10.1016/j.elerap.2018.08.001

Zhang, W., Du, Y., Yoshida, T., & Yang, Y. (2019a). DeepRec: A deep neural network approach to recommendation with item embedding and weighted loss function. *Information Sciences, 470*, 121–140. https://doi.org/10.1016/j.ins.2018.08.039

Zhang, X., Liu, H., Chen, X., Zhong, J., & Wang, D. (2020b). A novel hybrid deep recommendation system to differentiate user's preference and item's attractiveness. *Information Sciences, 519*, 306–316. https://doi.org/10.1016/j.ins.2020.01.044

Zhang, X., Han, Y., Xu, W., & Wang, Q. (2019b). HOBA: A novel feature engineering methodology for credit card fraud detection with a deep learning architecture. *Information Sciences*. https://doi.org/10.1016/j.ins.2019.05.023

Zhang, Y., Chen, H., Lu, J., & Zhang, G. (2017). Detecting and predicting the topic change of knowledge-based systems: A topic-based bibliometric analysis from 1991 to 2016. *Knowledge-Based Systems, 133*, 255–268. https://doi.org/10.1016/j.knosys.2017.07.011

Zhang, Z., Wei, X., Zheng, X., & Zeng, D. D. (2021). Predicting product adoption intentions: An integrated behavioral model-inspired multiview learning approach. *Information & Management, 58*(7), 103484. https://doi.org/10.1016/j.im.2021.103484

Zhao, G., Lou, P., Qian, X., & Hou, X. (2020a). Personalized location recommendation by fusing sentimental and spatial context. *Knowledge-Based Systems, 196*, 105849. https://doi.org/10.1016/j.knosys.2020.105849

Zhao, L., Dai, T., Qiao, Z., Sun, P., Hao, J., & Yang, Y. (2020b). Application of artificial intelligence to wastewater treatment: A bibliometric analysis and systematic review of technology, economy, management, and wastewater reuse. *Process Safety and Environmental Protection, 133*, 169–182. https://doi.org/10.1016/j.psep.2019.11.014

Zhao, Y., Yu, Y., Li, Y., Han, G., & Du, X. (2019). Machine learning based privacy-preserving fair data trading in big data market. *Information Sciences, 478*, 449–460. https://doi.org/10.1016/j.ins.2018.11.028

Zheng, X., Zhu, S., & Lin, Z. (2013). Capturing the essence of word-of-mouth for social commerce: Assessing the quality of online e-commerce reviews by a semi-supervised approach. *Decision Support Systems, 56*, 211–222. https://doi.org/10.1016/j.dss.2013.06.002

Zheng, Z., & Padmanabhan, B. (2006). Selectively acquiring customer information: A new data acquisition problem and an active learning-based solution. *Management Science, 52*(5), 697–712. https://doi.org/10.1287/mnsc.1050.0488

Ziegler, C.-N., McNee, S. M., Konstan, J. A., & Lausen, G. (2005). Improving recommendation lists through topic diversification. *Proceedings of the 14th International Conference on World Wide Web*, 22. https://doi.org/10.1145/1060745.1060754

Zoghbi, S., Vulić, I., & Moens, M. F. (2016). Latent Dirichlet allocation for linking user-generated content and e-commerce data. *Information Sciences, 367–368*, 573–599. https://doi.org/10.1016/j.ins.2016.05.047