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Service chatbot: Co-citation and big data analysis toward a review and research agenda

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ABSTRACT

This study identified the research trends and intellectual structure of chatbots, through chatbot-related articles to suggest a future research agenda. Systematic literature reviews were performed on 386 articles from the Web of Science database. The intellectual structure investigated major articles and research topics, wherein the research gap and agenda were identified by analyzing keywords. Research on chatbots has been rapidly increasing since 2021, and is being conducted based on the theory of technology adoption. Althrough the bias of chatbots as well as issues related to ethics and security were treated as important topics in newspaper articles, studies were found to be insufficient. As a research variable, there have been many studies verifying the effect of chatbot humanness. However, studies on individual factors and strategies that influence the adoption and proliferation of chatbots are insufficient.

1. Introduction

Robots, which are used for industrial automation, are being actively researched and developed to assist humans in daily life as well as provide services with the development of technologies, such as big data, machine learning, and artificial intelligence (AI). In November 2019, Whole Foods Market introduced the AI-loaded barista robot, “Briggo,” to provide coffee, while CaliBurger, a US burger chain, introduced the burger-grilling robot “Flippy.” As such, companies are rushing to introduce various service robots, upon which consumers are gradually adjusting to Chatbots, one of the most actively introduced technologies in the service field. Chatbot, is a compound word of "chatting" and "robot," which is an intelligent conversational process, system, or service that operates in the language that people use in daily life (natural language) (Radziwill and Benton, 2017). The global chatbot market is expected to grow 23.5 % annually from $2.9 billion in 2020 to $10.5 billion by 2026 (GlobeNewswire, 2023).

Over recent years, chatbot has been attracting much attention from both scholars and practitioners in the business and consumer study domain. As the use of chatbots accelerated due to the COVID-19 pandemic (Davis, 2020), various studies on chatbots have been conducted. Research on chatbots can be more broadly divided into studies related to its development and performance improvement as well as consumer reactions to the technology, the latter of which has been conducted in various fields such as psychotherapy, linguistics, and consumer studies. Specifically, social science researchers have been engaged in analyzing the social acceptance of chatbots. Therefore, at this point in time, it will be beneficial to examine the type of research that has been conducted and including the academic and intellectual structure which it followed. According to Khatoon and Rehman (2021) and Lai (2020), a complete and systematic review of a particular topic can help other researchers better understand important research trends, identify research gaps, and suggest future research topics in the field. Recently, a number of review papers have been published, mostly based on a systematic literature review (SLR) or other qualitative approaches that examine the research state on chatbots (Luo et al., 2022; Nagarhalli et al., 2020; Rapp et al., 2021). In particular, despite the ongoing, intense endeavors in both academia and industry, the current body of knowledge on chatbots is still far from maturity. While SLRs reduce bias with advantages such as improved transparency and reliability compared to narrative reviews, they are still influenced by self-reporting bias and subjectivity that make the obtained results less reproducible (O'Brien and Mc Guckin, 2016; Khorram Niaki and Nonino, 2017). Moreover, the published reviews in this domain rely upon academic

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research as the only source of information. However, a large portion of the accumulated knowledge is represented in gray literature including news articles, blogs, and white papers. This is particularly the case with emerging technologies such as chatbots, where applied research and development activities have mainly taken place outside academia. Today, chatbot-related topics are discussed in academic papers, reports on leading business technologies, as well as news around the world. The development trends of chatbots, opinions of professionals and practitioners, commercial chatbot solutions and use cases, and reports in the media can provide original, timely information that academic research content cannot. Technology is moving rapidly, and the media can react to its unrelenting progress much faster than the academic literature (Jones, 2018). More importantly, news content comes from the practitioner standpoint and reflects on the expertise and experience in business as well as industrial settings (Garousi et al., 2019). Particularly within the technology domain, these characteristics make news content a rich and informative source for academic research (Canito et al., 2018; Lim and Maglio, 2018).

In this study, co-citation analysis was performed focusing on article citations to understand the academic structure and characteristics of chatbot-related research. Additionally, by examining issues that appear in chatbot-related news, this study analyzed whether there is a difference between academic research, issues that people and the media consider important. Thus, in light of the fact that service chatbots are an important area in consumer research, this study proposes a highly plausible research agenda on the basis of an examination of the intellectual structure and research gaps in service chatbots.

RQ1. What intellectual base and theoretical foundation support retail service chatbots?

RQ2. What are the key themes of news articles on chatbots?

RQ3. Compared with newspaper articles, what are the gaps and limitations in extant literature that needs to be addressed?

RQ4. What are the avenues of future research?

2. Theoretical background

2.1. Review of service robots-chatbots

Intelligent service robots are one of the research fields in robotics with the highest potential for practical use after cleaning, educational, and entertainment robots. Among various intelligent service robots, companies are adopting online conversational agents such as chatbots to aggregate and analyze large scale human data for exploring and understanding consumer behavior patterns in order to effectively manage the decision-making process (Leonardi and Treem, 2012).

Traditionally, chatbots have been used for customer service tasks that require simple, generic answers, such as making a reservation or providing more detailed product information (Joshi, 2018). Since these types of chatbots are designed to be keyword-based, reacting only to specific words, this makes them vulnerable to typos, which in turn increase the risk of incorrect answers and create a disappointing customer experience (Sadekov, 2020). In contrast, AI chatbots provide human-like responses to questions (Libai et al., 2020) since these use natural language processing (NLP) technology to understand the intent of a question and solve a consumer's problem without human assistance (Sadekov, 2020). Several studies on chatbots in the field of consumer studies have investigated the perception of their humanity and the effect of these characteristics on user acceptance and satisfaction. Nguyen and Sidorova (2018) pointed out that the humanness of chatbots influences positive consumer experiences. The perceived humanity of chatbots is accomplished through visual cues such as human figures and human-associated names as wekk as conversational cues like human language imitation, message interactivity, and perceived usefulness (Araujo, 2018; Go and Sundar, 2019; Van den Broeck et al., 2019). Meanwhile, the theoretical basis for humanizing chatbots is based on anthropomorphism literature. In studies related to chatbots, anthropomorphism can appear as a difference in the conversational style (speaking style), an aspect which Thomas et al. (2018) found to have a significant impact on consumers regarding their impression of chatbots. In addition, many previous studies have verified that a human-like chatbot identity affects purchase intentions and positive evaluations of specific products (Kuberkar and Singhal, 2020; Roy and Naidoo, 2021; Sheehan et al., 2020), and identifies factors affecting the acceptance of chatbots using a technology acceptance model (Pillai and Sivathanu, 2020; Rodríguez Cardona et al., 2019).

A review of literature on service robots has shown that primarily two aspects of analysis have been attempted: content analysis and meta-analysis. Krippendorff (2004) defined content analysis as, “A research technique for making replicable and valid inferences from text (or other meaningful matter) to the contexts of their use.” According to Weber (1985), “Content analysis is a research methodology that utilizes a set of procedures to make valid inferences from the text.” In other words, it can be conceptualized as a series of procedures that lead to reasonable inferences about the content contained in the medium of data. In a quantitative content analysis study on service robots, Bavaresco et al. (2020) asserted the need for conversational agents in the business domain, such that future research directions and machine learning methods were suggested. Meanwhile, Van Pinxteren et al. (2020) performed a qualitative content analysis on chatbots in service studies and identified potentially effective communicative behaviors for optimizing encounters between chatbots and customers. As quantitative content analysis is a simple method of counting word frequency, it is difficult to analyze potential meanings because it only deals with superficial content, while qualitative content analysis has some disadvantages that are somewhat abstract and not systematic.

Glass (1976) formally defined meta-analysis as the statistical analysis of a large collection of analysis results from individual studies to comprehensively integrate findings. In other words, meta-analysis is a research method used to draw objective and reliable conclusions by synthesizing research results of individual studies. Blut et al. (2021) analyzed chatbots, robots, and other AI by meta-analysis of service provision anthropomorphism, wherein consumer intentions and future agendas for robot use were also presented. In addition, Abd-Alrazaq et al. (2020) performed a meta-analysis on chatbots to improve mental health; however, as there were extremely few studies (8), it was not possible to derive sufficient results for effectiveness and safety. Thus, meta-analysis can only be used when there are more than adequate previous studies as research results may be oversimplified and research quality may be synthesized without distinguishing it (Glass et al., 1981). As the aforementioned content analysis and meta-analysis studies do not consider the superficial contents of service robot research or simplify the research results, these therefore do not examine the academic structure of such research, which in turn mandates its need to be investigated.

2.2. Co-citation analysis

Content analysis has been mainly used to grasp the flow of research, such as research topics and methods, over a long period of time in a specific academic field (Yale and Gilly, 1988). However, as content analysis studies provide descriptive data using methods such as frequency analysis and cross-analysis, the limitation of being unable to identify the discipline arises (Doh, 2018). As a result, co-citation analysis is a new research approach to comprehensively understand research flow. Co-citation, a bibliometrics analysis, is widely used to examine knowledge structures in specific disciplines or subject areas. This approach categorizes co-cited documents within the reference list of literature and links cited papers together after publication. This is based on the premise that documents with high citation frequencies contain core concepts or methods in the field (Garfield, 1979). Co-citation analysis is a combination of author co-citation analysis (ACA) and document co-citation analysis (DCA). ACA is a built author network, which is a useful method for identifying subtopics by clustering authors in specific subject areas (White and Griffith, 1981). Meanwhile, DCA is a built document network that models the knowledge structure of the relevant field by including the relationship between important concepts in the research field (Small, 1973).

Based on citation data from various academic fields, co-citation analysis is useful for grasping research trends and intellectual structure. Hence, research in this study was conducted using this analysis type. In particular, research using co-citation analysis has been published in marketing, communication, and advertising. Yoo et al. (2013) conducted a co-citation analysis to examine how research on customer value progressed in the marketing industry as well as its future direction. Moreover, Huang et al. (2021) identified the intellectual base, research front, and potential research avenues through a multiple-perspective DCA on consumer innovation resistance. In addition, Xu et al. (2018) examined the evolution of supply chain finance and suggested additional insights along with future research directions through clusters. Also, Doh (2018) explored the intellectual structure of new media research in public relations and provided implications for its developmental direction and future research in advertising.

2.3. Topic modeling

Delen and Crossland (2008) proposed text mining as a viable method for finding knowledge in an expansive volume of literature to overcome the shortcomings associated with manual reviews. Specifically, topic modeling has been used to explore large collections of scholarly publications, analyze research developments, and explore new directions in a number of fields (Jeyaraj and Zadeh, 2020; Sharma et al., 2021). In addition to extracting knowledge, it is also being used extensively to highlight trends in academic research on emerging technologies, such as business intelligence (Moro et al., 2015) and AI (Mustak et al., 2021). Topic modeling has also been recognized as an effective method of extracting and categorizing knowledge from large volumes of unstructured textual data. This includes text available through news aggregators such as LexisNexis (Ardia et al., 2019) as well as social media platforms like Reddit (Jeong et al., 2019). Alagheband et al. (2020) used topic modeling to compare cybersecurity-related content in news media and academia over time. Using news articles and literature data, Sangari and Mashatan (2022) have also created a data-driven insight into blockchain-enabled supply chain management.

3. Methodology

In this study, a simultaneous literature citation analysis was performed to understand the knowledge structure of service chatbots, chatbot-related agenda, and relevant keywords that appeared in various newspaper articles, using text analysis. Considering rapidly changing technologies such as chatbots, media such as news, technical reports, and professional magazines can respond more quickly to developments than academic literature. News media in particular is a rich, informative source for scholarly research as it reflects expert and practitioner opinions, current use cases in business and industry settings, as well as original and timely issues. Therefore, understanding what is covered in the news media helps identify topics that require academic attention and thereby guide the research direction.

3.1. Data collection

The literature data was collected by chatbot-related research from Web of Science (WoS), the world's largest citation database. To increase the understanding of research analyses related to service chatbots among various studies on the topic, consumer-related and English language journals were included. The study used documents indexed in the WoS database (Vanhala et al., 2020), which offers a wide coverage of scientific publications and high-impact journals, as well as a reference index with more than one billion cited references. As a result of keyword searches in WoS with “chatbot,” “chatterbot,” “talkbot,” “conversational agent,” and “intelligent service robot,” were found 3,807 studies until February 2023. Afterwards, in order to narrow it down to consumer-related topics, it was limited to articles only, and the category of WoS was determined through consultation between researchers. The category of WoS were behavioral sciences (1); ethics (5); family studies (3); operations research management science (16); business (98); communication (41); hospitality leisure sport tourism (14); humanities multidisciplinary (5); psychology (applied (17), developmental (4), experimental (42), multidisciplinary (77), social (7)); computer science interdisciplinary applications (80); cultural studies (1); management (61); economics (3); social issue (4); social sciences interdisciplinary (18); sociology (4); multidisciplinary sciences (19); telecommunications (66); women's studies (1). The filtered result output 497 studies. All data including references were exported as plain files.

To identify valid articles, Moher et al. (2009) selected the final articles, “Preferred reporting items for systematic reviews and meta-analyses (PRISMA)”. First, due to language limitation, only papers published in English language journals were included in the analysis. Second, 486 studies including chatbot algorithm studies and development of technology to improve chatbot performance studies that did not include consumer perception, were excluded from chatbot-related studies by two researchers who reviewed titles and abstracts. Third, if the two researchers were unable to arrive at a consensus, the study was identified by reviewing the full article, and 11 studies were added after discussion with a third researcher. Fourth, 386 studies were selected, including seven papers that were considered suitable after the full article and references were examined (Fig. 1).

In addition, for this study, news articles on the Google News Initiative were collected from January 1, 2018 to February 28, 2023 using keywords such as “chatbots” and “chatterbots” for text analysis. Online newspapers and articles provided through Google News describe the latest developments in a country and provide insights into companies in a particular region at an unprecedented speed. Thus, the systematic screening of online newspapers can reveal significant additional insights. Google News has been used as a flexible and powerful platform for news data collection in a range of studies (Canito et al., 2018; Chu et al., 2020). It aggregates original, rich news content from thousands of recognized news publishers and websites. Moreover, it applies different quality criteria, policies, and algorithms for publisher assessment based on transparency, accountability, and accuracy (Google, 2021; Stvilia, 2021). It also applies ranking to ensure reliability, originality, and consistency of the content based on factors such as the source authoritativeness. These, along with the comprehensiveness of coverage, make Google News the appropriate choice to collect news articles (Lim and Maglio, 2018).

For analysis, 4,840 newspaper articles by 649 worldwide news sources including The New York Times, Reuters, USA Today, Wall Street Journal, Washington Post, The Economist, Forbes, BBC, The Guardian, The Telegraph, Telegraph India, The Times of India, Indian Express, Hindustan Times, China Daily, and South China Morning Post, were finally used.

3.1.1. Co-citation analysis

In this study, the DCA was applied, rather than the ACA to structure the service chatbot knowledge. Due to the delayed citation of ACA, it was difficult to grasp the latest research trends. In addition, because of its repetitive citation tendency, it is difficult to grasp the research trends of currently active researchers by habitually citing prestigious researchers even if they have already died or retired (Zhao and Strotmann, 2008). Furthermore, the accuracy of ACA may be reduced due to its faulty processing of persons with the same name, inaccurate transcripts of authors' names, and omission of multiple authors other than the first author (Persson, 2001). On the other hand, DCA can be used as an

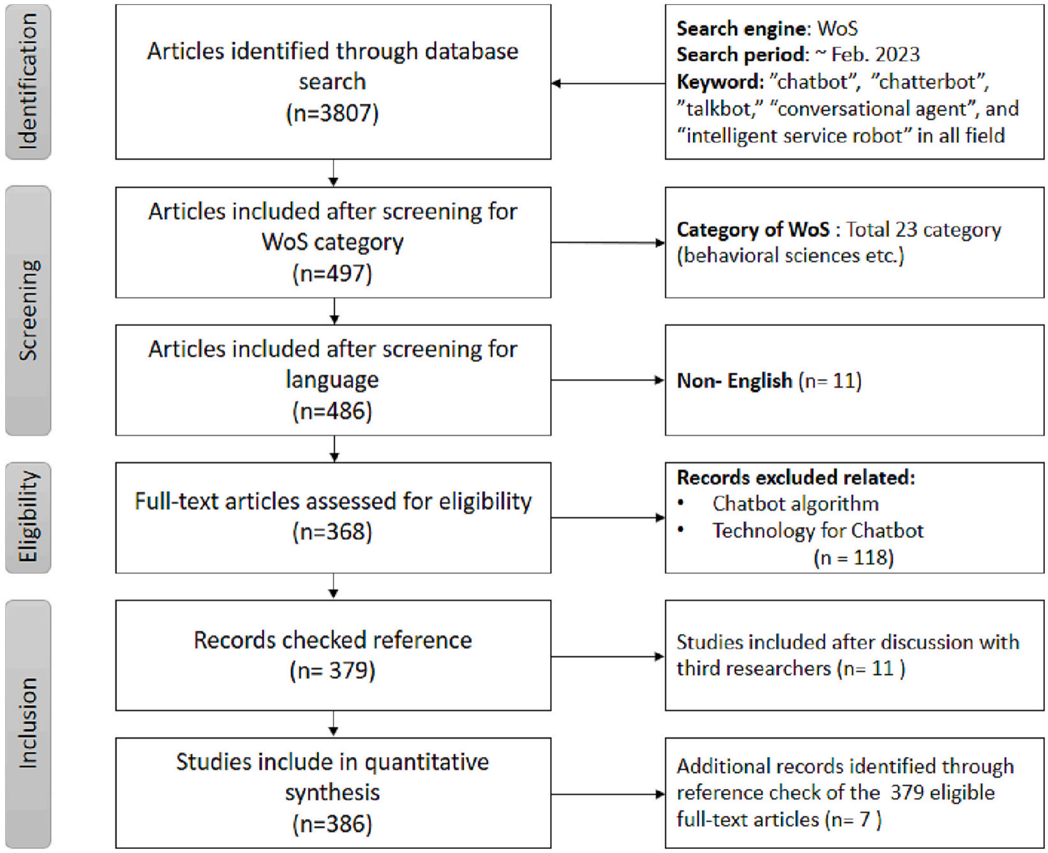

Fig. 1. Flow of literature identification through the meta-analyses (PRISMA) procedure.

objective tool to identify the intellectual structure by representing concepts or subjects' relationships with a discipline (Small, 1973; Small and Griffith, 1974; Small and Griffith, 1974). DCA has been studied and proven useful by many researchers since Small's proposal with its advantage of being able to effectively grasp the development process of changing and disappearing subject files over time as well as and creating new topics.

CiteSpace was used to extract cited and co-cited document pairs. The DCA of CiteSpace counts cases where there is a connectivity of cited documents and represents the knowledge domain through the standardization process wherein its basic premise is the co-citation cluster represents the intellectual structure (Chen, 2004, 2006, 2017; Chen et al., 2010a, 2010b). In addition, based on the co-cited papers, the meanings of nodes and links are identified, from which the generated cluster subject is analyzed. The automatically labeled clusters allow the identification of the co-citation cluster research front characteristics wherein key references and major clusters are revealed as intellectual structures for service chatbot research development (Chen and Song, 2019; Synnestvedt et al., 2005). The research data was exported in plain text format from WoS, and analysis was attempted using CiteSapce 6.2. R1.[2] Since the WoS service chatbot research started in 2004, the time slice was set to 20 so that it could be viewed as visualization. The node type was set to "reference" while the term source was "title," "abstract," and "keyword" (Chen, 2016).

3.1.2. Text analysis

In the age of information overload, where large amounts of data are collected daily, the need for a more robust analyzation has arisen. In particular, using data mining techniques to analyze news in which countless amounts of data are generated in real-time, is a promising approach to solving these challenges (Handfield et al., 2020). According to some, text mining methods, especially those that analyze news data, are simply extensions of classical data mining methods. However, Hearst (1999) defines text mining as, "The discovery of new facts and trends about the world using large online text collections."

To begin text mining, a structured dataset must be extracted. Therefore, to obtain the study empirical dataset, a global online newspaper database that was independent and unbiased, which allowed searching by particular keywords and dates, was needed. Google News (news.google.com) aggregates rich news content from thousands of popular news publishers and websites, using a variety of quality criteria, policies, and algorithms to evaluate publishers for transparency, accountability, and accuracy. This makes it an appropriate choice for aggregating independent and unbiased news articles in the study data collection. For the study, research focused on newspapers in the English language in order to compare content and use text mining techniques without having to rely on potentially poor translations.

Furthermore, in this study, objectivity is ensured, as general newspapers are not pre-selected by personal preference but by popularity, while the sentiment analysis was performed using a pre-made sentiment lexicon. For the frequency analysis, no validation is needed since no models are used and only words are counted. Repeatability is ensured as the chosen approach is clearly documented. This makes the research reliable because simultaneously collecting the dataset ensures the same answers can be obtained. However, as the Google News feed has the limitation that once news articles of the past X days are collected, selecting the exact same dataset is difficult, if done at a later stage. Therefore, to measure the reliability of this research, the code was run one month later on March 28, 2023 while the same main trends, patterns, and topics remained (Meyer et al., 2021). Of course, findings are dependent on article content which by nature vary on events that will

[2] Download: citespace.podia.com

happen in the future. If the search date could be specified, the results could be repeated in the exact same manner.

Text analysis is the extraction and analysis of meaningful information from text based on NLP techniques, such as text mining and document mining. In text analysis, the most important phase is data preprocessing. For this study, special characters, numbers, and punctuation were removed using regular expressions so that only English was analyzed. Also, keyword analysis was conducted to find words or phrases that compress important issues in chatbot-related news. It is the most fundamental method of text analysis that extracts keywords and analyzes the frequency of word appearances in the text. Next, sentiment analysis was conducted. It is a field of text mining analysis that performs vocabulary-level emotional analysis through emotional vocabulary lists classified as positive, negative, and neutral. This study performed sentiment analysis using a dictionary created by Big Liu. Latent Dirichlet Allocation (LDA) analysis assumes that a document is a random mixture of various latent topics, which can be specified by a probability distribution of words (Blei et al., 2003). To perform LDA, it is first necessary to specify the total number of topics (K) to which documents are to be allocated. An optimal K is determined by the perplexity score (Blei et al., 2003; Cao et al., 2009; Puschmann and Scheffler, 2016); topic coherence (Maier et al., 2018; Newman et al., 2011) has also been discussed. However, for social science, it may be more important to set the number of interpretability topics that cause information loss only within an acceptable range as several previous studies also set the K value according to researcher judgment (Chang et al., 2009; Hollibaugh, 2019). In this study, while changing the K value from 2 to 10, it was first examined whether the top 20 keywords for each topic were properly categorized before the K value was finally set to five. Word cleaning and morpheme analysis were performed using nltk, and a document-word matrix was generated using the Sklearn Package (ver. 0.22.2) TD-IDF vectorizer.

4. Results

4.1. Landmark reference of service chatbot

From 386 main articles, it is evident that articles about service chatbots first appeared in 2004, and rapidly increased from 2019 (Fig. 2). Although the data collection unit of February 2023 is limited to only 24, it can be expected that a large number of articles will appear in the future.

In the DCA using CiteSpace, 17,592 valid references appeared in core articles with a validation rate of 99.12 %. The network used in the DCA consisted of 311 nodes and 19,970 links. As shown in Table 1, each node is the main article cited in the 386 studies, which indicates the "first author" and publication data, listed in order of size according to the

Table 1
Top 20 landmark references (with high citations and betweenness centrality, see Appendix A).

Count	Centrality	Author	Year	Clustering
93	0.03	Araujo	2018	1
72	0.03	Nass & Moon	2000	0
66	0.02	Chung et al.	2020	1
62	0.02	Go & Sundar	2019	3
51	0.03	Hill et al.	2015	1
47	0.02	Luo al.	2019	1
45	0.02	Fornell & Larcker	1981	1
42	0.02	Reeves & Nass	1996	0
39	0.02	Weizenbaum	1966	0
36	0.01	Wirtz et al.	2018	2
36	0.01	Ho et al.	2018	0
35	0.02	Ciechanowski et al.	2019	1
33	0.02	Epley et al.	2007	0
33	0.01	Sheehan et al.	2020	2
32	0.01	Huang & Rust	2018	2
31	0.02	Zarouali et al.	2018	1
31	0.01	Van den Broek et al.	2019	1
30	0.01	Adam et al.	2021	2
30	0.01	Davis et al.	1989	2
29	0.01	van Doorn et al.	2017	2

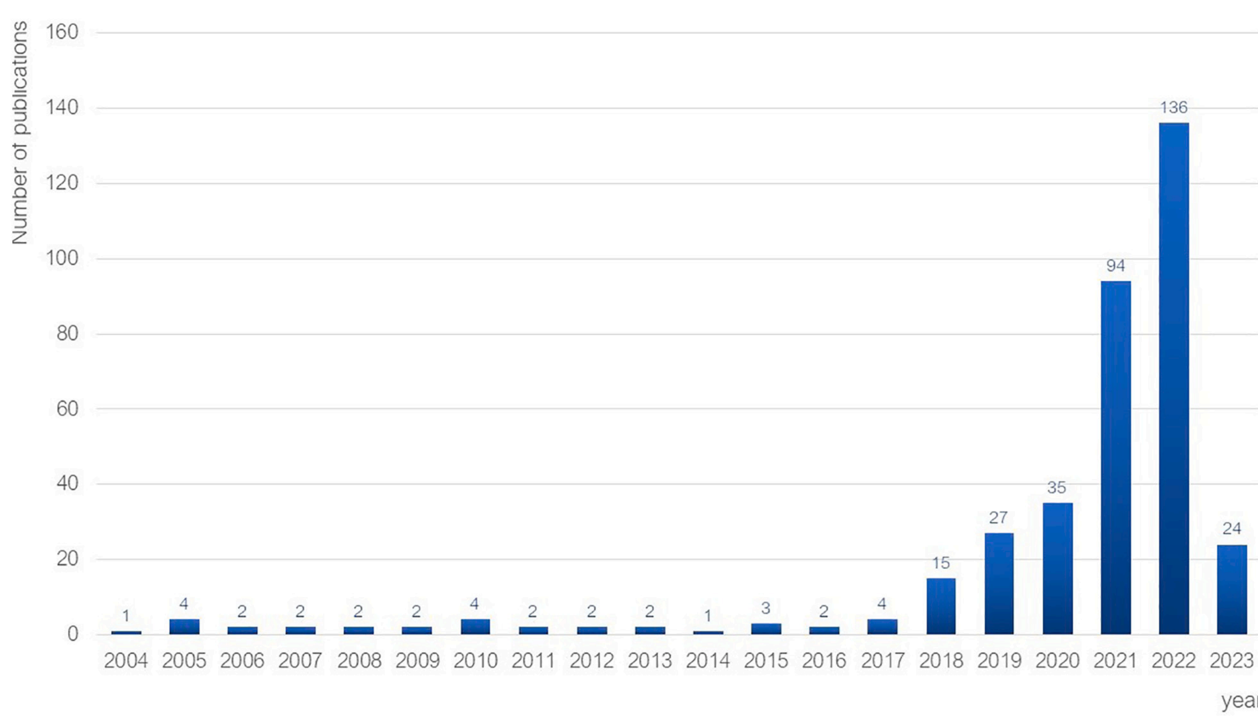

Fig. 2. Distribution of the 386 Articles (2004–2023 February).

number of citations. References from landmark and high betweenness centrality are intellectual-based indicators in consumer chatbot research.

To establish an intellectual basis through the landmark 20 references, the study examined independent and dependent variables as well as theory. The main landmark service chatbot reference is the study by Araujo (2018) who used embodied theory to expand the chatbot with social reaction using social presence and anthropomorphism. Business (31.0 %) was cited in related studies such as satisfaction, intention to continue using, and adoption in the context of providing customer service (Adam et al., 2021; De Keyser et al., 2019; Pelau et al., 2021). In management (15.7 %), it was cited in a study to successfully implement chatbots in business (e.g., Kaushal and Yadav, 2023). It was cited in conversational design, atmosphere visualization studies in computer science cybernetics(13.7 %) (e.g., Pujiarti et al., 2022; Silva and Canedo, 2022).

Based on media equivalency and computers as social actors (CASA) framework, Reeves and Nass (1996) examined the politeness of people according to media type. It was cited as a basis for various chatbot research such as communication (40.6 %), computer science cybernetics (28.1 %), ergonomics (21.9 %) (e.g., Mick and Fournier, 1998). Subsequently, Nass and Moon (2000) investigated social responses to the influence of gender stereotypes. It was cited in psychology multidisciplinary (23 %), psychology experimental (16.5 %), and computer science cybernetics (14 %), in particular, it was cited as a basis for Araujo (2018). Chung et al. (2020) looked at the e-service properties of chatbots, and business (51.1 %) and management (16.1 %) were cited in studies related to customer satisfaction, adoption, and m-commerce (Omar et al., 2021; Rese 2020). In computer science information systems (11.8 %), it has been cited in research such as scenario and context (Behera et al., 2021; Calvaresi et al., 2021).

Furthermore, research has been conducted based on the various technical characteristics of chatbots (Ciechanowski et al., 2019; Go and Sundar, 2019), which appeared as a landmark reference. In particular, Ciechanowski et al. (2019) as well as Go and Sundar (2019) were frequently cited in consumer-related studies in the areas of business, psychology multidisciplinary, and computer science cybernetics. Moreover, it was found to be cited in Araujo (2018) and Adam et al. (2021), which are the key papers referenced by this study. The study by Hill et al. (2015) is the first applied science article that appeared in WoS regarding chatbots as it explored the comparison between human-human and human-chatbot conversations. There are also landmark references for motivation in business (14.1 %) (e.g., Rese et al., 2020). Meanwhile, Ho et al. (2018) and Luo et al. (2019) examined people's responses according to the self-disclosure type between human and chatbot. These studies were widely cited in business, management, and psychology multidisciplinary, especially in the design of follow-up studies on disclosure (e.g., Cheng et al., 2021; Park et al., 2022). Weizenbaum (1966), however, was the first to study computer programs (ELIZA) and has since been widely cited regarding in the theoretical background of AI and chatbots. More than 90 % were mainly cited in the field of computer science, with some being cited in psychology (5.65 %), education (4.09 %), and communication (2.23 %). Wirtz et al. (2018) proposed a research agenda for chatbot service as the study especially examined ethical issues at the individual, market, and societal levels. It was used in business (42.1 %) and management (32.0 %), as well as frequently cited in studies on negative issues like service failure, service recovery, and barriers (e.g., Cardinali et al., 2023; Cheng, 2023; Shi et al., 2023). Also, in business (24.8 %), various studies on consumer anthropomorphism have been cited (e.g., Roy and Naidoo, 2021; Sheehan et al., 2020). Epley et al. (2007) studied various theories of anthropomorphism. In particular, it was used as a basic background for Adam et al. (2021) and Sheehan et al. (2020). Meanwhile, in the studies of psychology multidisciplinary (15.8 %) and psychology experimental (9.3 %), it was cited in research on the emotional aspect (e.g., Huaman-Ramirez et al., 2022; Xie et al., 2022). For situations of miscommunication, Sheehan et al. (2020) looked at reduced anthropomorphism and adoption. This study was frequently cited in business (44.6 %) and used as a basis for research on consumer loyalty, service failure, and service recovery (e.g., Chen et al., 2023; Hsu and Lin, 2023; Huang and Dootson, 2022). Huang and Rust (2018) conducted research with various intelligence on service chatbots, which was an early study that revealed the importance of empathetic and intuitive intelligence. Therefore, the study was mainly used in business (46.7 %) and management (30 %) as well as cited in numerous chatbot-related studies such as co-creation, consumer experience and sentiment (e.g., Bonetti et al., 2022; Moore et al., 2022; Schiavone et al., 2022; Tran et al., 2021). Zarouali et al. (2018) and Van den Broeck et al. (2019) conducted consumer research on Facebook chatbots such as advertisements and brands in other business fields. Both papers have been likewise cited in business and management. Moreover, Zarouali et al. (2018) was cited in the study on chatbots in advertising and communication (12.5 %) (e.g., Van Noort et al., 2020; Wen et al., 2022), while Van den Broeck et al. (2019) was cited in psychology multidisciplinary (14.6 %) and communication (12.5 %) for communication style and experimental research (e.g., Yang et al., 2022; Xu et al., 2022).

In addition, Adam et al. (2021) explored anthropomorphism and social presence of chatbots based on the commitment-consistency theory. The area of business (42.7 %) cited research on chatbots in customer service, especially in empathy or service failure (e.g., Liu-Thompkins et al., 2022; Sands et al., 2022; Song et al., 2022). In management (24.7 %), it was cited in studies for application in various industries (e.g., Blöcher and Alt, 2021; Pillai and Sivathanu, 2020). Meanwhile, in computer science information systems (13.5 %), it was cited in a study on the evolution and types of chatbots (e.g., Wang et al., 2023; Nguyen et al., 2022). Van Doorn et al. (2017) was an early study on automated social presence that investigated the relationship between social presence and psychological ownership. As such, this was used as a basis for various presence studies in business (49.0 %) and management (29.9 %) as well as cited in various research on psychological anthropomorphism for the tourism and service industry (e.g., Pelau et al., 2021; Ruiz-Equihua et al., 2023).

With regard to studies on technology adoption, the work by Davis et al. (1989) is the most cited followed by media equivalency, embodied theory, uses and gratifications, as well as cognitive fit theory (Appendix). Furthermore, Fornell and Larcker (1981) were the most frequently used statistical structural equation modeling(SEM) references.

4.2. Structure of the intellectual bases

To understand the structure of intellectual bases, this study analyzed the cited references cluster in CiteSpace. The four clusters listed in Table 2 were labeled with the title term based on the log-likelihood ratio by combining the title, keyword and abstract. There were 98 articles assigned to the # 0 cluster, 92 articles to the # 1 cluster, 77 articles to the #2 cluster, and 44 articles to the # 3 cluster.

Chen et al. (2010a, 2010b) asserted that the term extracted from citations in a cluster has the characteristics of research fronts. Therefore, the research fronts in the service chatbot appeared as four cluster titles: social exclusion (# 0), emotion word (# 1), service failure (# 2), and customer satisfaction (# 3). These were all related to consumer service. Given the characteristics of service chatbots, the main factors are related to the service aspect. In addition, various factors for understanding the intellectual structure of service chatbot research can be identified through title, keywords, or abstracts by clustering. Observing the title, keywords, and abstracts that appeared in social exclusion (# 0), these produced "transaction conversion," "CASA," and "social presence." Nass and Moon (2000), Reeves and Nass (1996), along with Weizenbaum (1966) were cited the most in #0 as these studies conducted research on the necessary requirements according to conditions for conversation agent skill and interaction. The main title, keywords, and abstracts in the emotional word (#1) contained "technology acceptance," "brand

Table 2
Knowledge cluster and label terms.

Cluster	Silhouette	Size	Publication year mean	Most cited article	Title	Keyword	Abstract
#0 Social exclusion	0.61	98	2006	Nass and Moon (2000)	social exclusion; social chatbot; human user; emerging theory; transaction conversion	human-machine communication; social presence; self-disclosure; CASA; loyalty	social exclusion; social chatbot; human user; transaction conversion; control condition
#1 Emotional word	0.544	92	2010	Araujo (2018)	emotion word; initial trust; brand attachment; privacy concern; customer satisfaction	chatbot services; technology acceptance; brand communication; conversational agents; ai chatbot	initial trust; brand attachment; fintech chatbot; privacy concern; emotion word
#2 Service failure	0.685	77	2014	Wirtz (2018)	service failure; social-oriented communication style; boundary condition; service robot; kindchenschema chatbot strategy	service recovery; level of robot intelligence; warmth perception; artificial intelligence; user engagement	service failure; social-oriented communication style; boundary condition; kindchenschema chatbot strategy; chatbots consumer
#3 Customer satisfaction	0.717	44	2015	Go (2019)	customer satisfaction; service failure; service robot; privacy concern; chatbot anthropomorphism	natural language processing; mhealth; user experience; human-machine communication; disclosure	customer satisfaction; service failure; chatbot anthropomorphism; service robot; artificial intelligence

attachment," and "initial trust." Araujo (2018), Chung et al. (2020), and Hill et al. (2015) were the most cited in #1 as studies on the attributes and e-service adoption of chatbots in business. When examining title, keywords, and abstracts that appeared in service failure (#2), there were "service recovery," "social oriented communication style," and "user engagement." Wirts et al. (2018), Sheehan et al. (2020) as well as Huang and Rust (2018) were cited the most in #2 as studies for anthropomorphism, including ethical and psychological issues with a bot. The main title, keywords, and abstracts in customer satisfaction (#3) were "user experience," "anthropomorphism," and "privacy concern." Go and Sundar (2019) as well as Brandtzaeg and Følstad (2017) were cited the most in #3 as studies for consumer expectations and effects, including collaboration with a bot.

In addition, "emotion word," as an emotional factor, appeared in the abstracts, upon which Huang and Rust (2018) conducted a study using empathetic and intuitive intelligence as variables. Meanwhile, "user perception" appeared in the cognitive aspect, upon which Nass and Moon (2000) conducted a gender stereotypes study. As an outcome, many different aspects were explored by the approaches, such as user engagement, customer expectations, and working alliances. This can be found in “willingness to collaborate with a bot” (Ciechanowski et al., 2019). However, factors related to environmental aspects did not appear in DCA clustering results (Fig. 3).

Fig. 3. DCA clusters of service chatbots.

4.3. Keywords and sentiment analysis

First, words that frequently appeared in newspaper articles related to chatbots were “service,” “customer,” “user,” “business,” “artificial_intelligence,” “assistant,” “help,” “answer,” “brand,” and “marketing.” Thus, it is evident that chatbots are being widely used as service robots in the business field. In addition, through words such as “student,” “patient,” “health,” “covid,” “marketing,” and “banking,” it was found that chatbot development and introduction are actively taking place in finance, healthcare, marketing, and education. Words such as “chat GPT,” which have recently attracted attention, were also noticed, while others such as “conversational” and “natural_language” appeared frequently in news articles. Through this, it can be seen that the chatbot, which only gave fixed answers in the early stages of development, has recently been developed into a “conversational” chatbot that induces emotions through more sophisticated and detailed conversations with the development of “natural language” processing technology.

Next, it was found that chatbots have developed significantly given the use of positive words such as “intelligence,” “smart,” “advanced,” “effective,” “improve,” “better,” “best,” “personalized,” “available,” “lead,” “important,” “enhance,” and “sophisticated” that appeared in chatbot-related newspaper articles. In addition, it was found that chatbots are in charge of resolving user inconvenience and providing help when given the words “support” and “help.” By contrast, however, words such as “free,” “rapid,” “seamless,” “easy,” and “fun,” made it possible to identify the advantages of chatbots such as quick response, easy use, pleasure, and financial benefits. In addition, through the word “protection” it was found that companies and chatbot developers are making various efforts, such as introducing blockchain technology, to solve security-related issues in protecting chatbot user's privacy and ensuring the stability of payments processed through chatbots (Fig. 4).

The problems that chatbots are solving and the problems that chatbots have can be confirmed concurrently through the negative words appearing in newspaper articles related to chatbots. First, chatbots are the victims of “abuse” at home and work from those who suffer from “depression,” “loneliness,” and “anxiety,” as well as those who have decided to commit “suicide,” including those who have experienced “loss,” such as the death of a loved one. Moreover, the word “harassment” has appeared in news articles related to the development of chatbots that can report or receive various types of harassment in peer groups, at work, or online. When chatbots collect cases related to harassment, victims can easily and conveniently report it without fear of retaliation; so “harassment” is a negative word, but rather a word related to the positive role of chatbots in resolving such issues. It is expected that many social problems can be addressed if research related to the

Fig. 4. Word cloud visualization of the sentiment keywords extracted from the news articles on chatbot.

development and use of customized chatbots in the mental healthcare field is more actively conducted. In contrast, it was found that AI chatbots based on machine learning and deep learning can be developed in the wrong direction or provide an answer depending on the training data type and quality through words of "bias," "racist," and "discrimination." Meanwhile, words such as "fake" and "scams" also appeared. Recently, however, fake chatbots, which are made similar to legitimate use chatbots have been developed to conduct activities such as delivering fake news. Additionally, through words such as "complex," "difficult," "confused," "failure," "lack," "limit," "mistake," "inappropriate," and "unsettling," it can be seen that the chatbot function is not yet complete. Moreover, words such as "furious," "rigid," "static," "bad," and "hate" indicate that if a company introduces a chatbot that does not present proper services, it may upset consumers. Also, through words like "hype," the capabilities, functions, and advantages of chatbots are being emphasized excessively. In addition, the "job loss problem" of people who are engaged in jobs that have been automated or replaced by machines due to the Fourth Industrial Revolution should also be considered.

4.4. LDA topic modeling

In this study, by considering the top keywords and the contents of document comprehensively, topic names were determined in the order of document weight and word weight as: "Basic role of chatbots," "Expanded role of chatbots," "Chatbot development trend and market analysis," "Main development fields," and "Problems to be solved" (Table 3).

First, the basic functions of chatbots are 24-h customer response and service provision. Many companies have improved customer satisfaction using chatbots. In particular, as an increasing number of consumers seek immediate answers and non-face-to-face services, chatbots are being used in various fields from light conversations to product orders, product consultations, service inquiries, and shopping. In addition to the basic functions of "business automation" and "customer service," chatbots have recently played multiple roles in various fields. In particular, in the hiring process, AI chatbots can answer applicant questions, perform simple screening tests, and guide interview schedules for candidates who have passed the document screening process. AI chatbots used in customer service have also evolved, allowing customers to receive services in multiple languages not only through text but also with voice. The "Chatbot development trend and market analysis" is also a topic heavily covered in the news. Recently, there was a news article about how effective chatbots are as a marketing tool to stabilize society (Q&A on vaccines and COVID-19) and increase sales of businesses. Meanwhile, starting with Facebook opening its messenger to developers in 2016, various messenger apps, such as WhatsApp, Facebook Messenger, and WeChat are emerging as new chatbot platforms. If this type of chatbot spreads rapidly in the future, the existing mobile ecosystem centered on applications will be absorbed into the chatbot platform, and major changes will take place in the manner of how companies provide products and services. The last topic related to chatbots that is discussed in newspaper articles is "Problems that chatbots need to solve." In October 2020, the Chief Information Office of technology-specialized media operated by International Data Group, the world's largest technology media, data, and marketing service company, cited Microsoft's chatbot "Tay," as one of the worst AI accidents in the past decade (Olavsrud, 2020). "Tay" was developed based on "neural network AI" technology that can "learn" by inputting data into a computer and allowing it to identify patterns on its own. Even if these chatbots start from the same basic algorithm, their responses can vary enormously depending on what data is input and "trained." After "Tay" went online, some Twitter users immediately began teaching "Tay" to make racist and misogynistic remarks. As a result, "Tay" quickly learned these inappropriate tweets and started creating racist, misogynistic, and anti-Semitic tweets.

Table 3
Topic modeling analysis of chatbot-related news.

Topic	Words
Basic role of chatbots	Chatbot, **AI**, help, customer, fact, use, launch, provide, **bank, online, question, service,** HR, **answer,** large, artificial, tool, new, **support, automate**
Expanded role of chatbots	Washington, insurance, **AirAsia,** chatbot, Australia, post, usage, **recruiters,** site, local, model, introduce, **Ava,** claim, **multilingual, assistant,** excite, virtual, **voice,** union
Chatbot development trend, market analysis	Chatbot, **market, growth,** AI, **global, software, message, enterprise,** industry, **key, social, China,** use, customer, **WhatsApp,** product, artificial, **analysis, share,** study
Major development fields	Chatbot, AI, **healthcare, health, startup,** service, fund, join, student, technology, raise, patients, based, Spanish, use, Babylon, university, develop, customer, million
Problems to be solved	Chatbot, recruit, commerce, president, Vodafone, Tata, version, **Microsoft,** Smith, AI, https, fun, **sue, Tay,** Taylor, corporation, try, **service, fail, racist**

5. Discussion and agenda for future research

This study was conducted to suggest a research gap and a direction for future research by analyzing articles and newspapers related to chatbots, which have been increasingly accepted socially and researched in recent years, through CiteSapce and big data analysis. On the research front, many technical parts appeared, while individual and environmental elements appeared as other factors. Chatbots became prevalent in various fields, such as communication, psychotherapy, and business, where most studies used in research implemented SEM (Fig. 5). Based on results from the previous analysis, such as DCA and big data analysis, this section aims to enhance the understanding of service chatbot research.

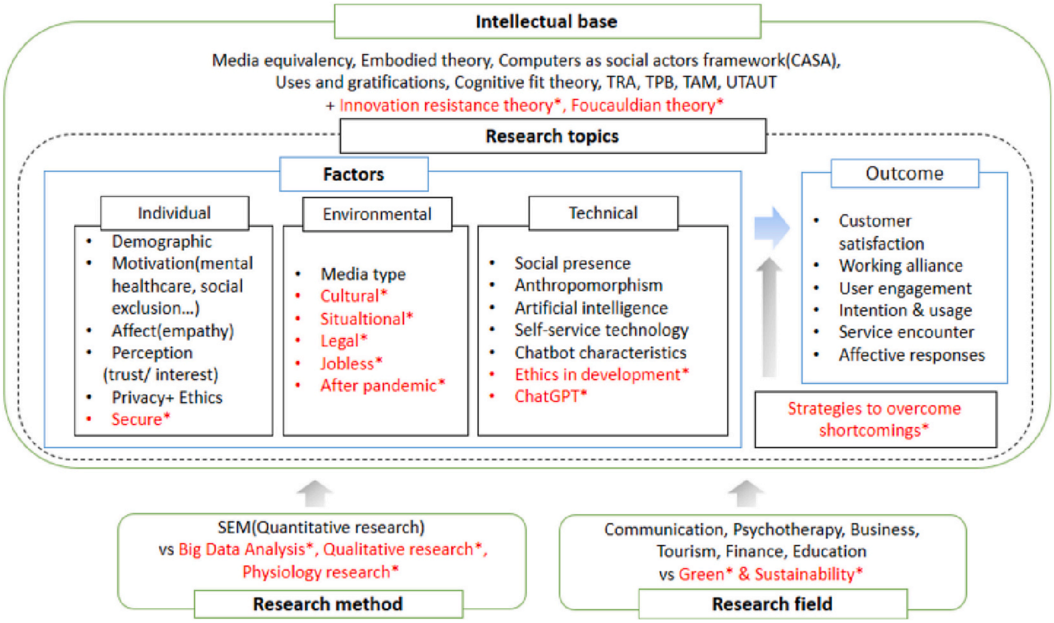

Fig. 5. Intellectual structure and research gap in the service chatbot literature.
Note: Lacking areas are marked in red fonts and *. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5.1. *Intellectual base of service chatbots*

As service chatbot research has been studied in various fields, the intellectual base theories also vary. In particular, based on the technical characteristics of service chatbots, technology adoption theories were found to be used the most. The technology acceptance model (TAM) proposed by Davis et al. (1989) along with the unified theory of acceptance and use of technology (UTAUT) proposed by Venkatesh et al. (2003) were found to be widely used as a basis for research on consumer chatbot adoption. In communication, various studies, such as those on gender stereotypes (Nass and Moon, 2000) have been conducted using theories, such as media equivalency, embodied theory, and the CASA framework to examine the partner characteristics of chatbot communication with consumers. Uses and gratifications (Levy and Windahl, 1985) and cognitive fit theory (Fitzpatrick et al., 2017) have appeared in many previous psychotherapy studies. In addition, it is expected that more studies using this theory to create psychological well-being through non-face-to-face chatbots will further proliferate. However, there is a need to expand on other research fields and theories. In particular, consumers may resist the adoption of chatbots due to various cases, such as difficulties in use by older people, securiery issues, or preference for people-oriented relationships. Therefore, there is a need to expand research using Ram (1987) innovation resistance theory. In addition, chatbots are built by the developers' machine learning. However, due to the developer's intent or any unintentional ethical problems arising during machine learning, it is necessary to examine the Foucauldian theory of Fischler (2000), which is a discourse analysis of the effect of these ethical and ideological problems on chatbot consumers.

5.2. *Factors related to service chatbot research fronts*

As a chatbot research topic, the most important technical aspect highlighted by the DCA was the research front. Various studies such as social presence, AI, and chatbot characteristics appeared, but research on the aforementioned “ethics in development” was insufficient which in turn contributed to incidents like Microsoft's chatbot “Tay” and Korea's “Lee Luda” (Olavsrud, 2020), wherein racism and misogyny appeared as an unethical learning base, and even after service was terminated, problems, like personal information leakage were raised. Furthermore, although chatGPT has appeared prevalently in big data analysis, it is nonexistent in the consumer research field, and therefore should be viewed as a new research agenda. Therefore, these issues need to be investigated in future studies.

In addition, various individual factors have been identified by previous studies. Although factors, such as perception, motivation, and emotion, have been identified, it has been shown that consumers have concerns about privacy and security. Although several previous studies have considered these problems (Biswas, 2020; Ischen et al., 2020), they appear to still occupy an immense part in big data analysis; hence, many follow-up studies are needed. In particular, even though a financial security system (Biswas, 2020) has been established to some extent based on these issues, privacy counseling in psychotherapy has not been dealt with. Hence, much research in this area is also needed in the future.

Finally, it was difficult to find studies on environmental factors. Only studies on cultural heritage (Lombardi et al., 2019) exist, while studies on various cultural factors are insufficient. This is because, due to the characteristics of chatbots, a cultural background may appear in conversations, where the characteristics accepted by ethnic groups may differ according to nuances. Situational factors may exist depending on whether it is a conversation with a chatbot on a mobile unit or kiosk. If it is a kiosk in a store, it may be difficult for other people to converse honestly. In addition, research on job loss and consumer research on non-face-to-face chatbots which have increased rapidly after COVID-19 will be increasingly needed.

5.3. *Outcome of service chatbots*

Satisfaction, intention, and usage were found to be the most frequent dependent variables, which have been shown in many consumer studies. In addition, user engagement (Kull et al., 2021; Perski et al., 2019), which has recently started to appear in consumer studies, has also begun to appear in chatbot research. Since it has a significant impact on companies and brands, it is necessary to examine more closely in the future. In addition, because chatbots have interactivity, consumers have an effective response (Ho et al., 2018) in which research has been conducted. The dependent variable, called the working alliance

(Hauser-Ulrich et al., 2020), also appeared, and this variable has been widely used in the field of psychotherapy research. A special variable is the service encounter (Larivière et al., 2017; Paluch and Wirtz, 2020). Although it has often appeared in other consumer studies, it is true that chatbots are much less responsive than humans. Therefore, some studies have been conducted on this topic. In addition it was not possible to identify all the dependent variables and determine whether additional research is needed.

5.4. Strategies to overcome the negative aspects of service chatbots

There are not many studies on how to overcome the negative aspects of chatbots. In service encounters, some responses were attempted by studying the roles of technology/employee and framework development (Larivière et al., 2017; Robinson et al., 2020). However, as mentioned before, there is a lack of research on strategies to solve security problems. In addition, there is insufficient research on strategies to overcome ethical and legal problems in chatbot development. Therefore, carefully examining these issues in the future could provide excellent implications for both consumers and businesses.

5.5. Research method and field of service chatbots

Most studies related to chatbots are SEM studies, in which the results are reported to consumers through surveys. These methods can clarify causal relationships and easily grasp the influence size or direction in detail. However, research through recently emerging big data analysis should also be conducted. Although it has been implemented in some studies (Ukpabi et al., 2019), it is necessary to introduce and analyze this method more actively for the benefits it can still provide regarding future research. In addition, an in-depth analysis of consumers using chatbots is required. If researchers attempt a qualitative approach such as why consumers use it and what problems are encountered, they can derive more diverse causes and results. When conducting a questionnaire on the use of chatbots, respondents may attempt to respond to social desirability, or where problems such as common method bias, may occur. To supplement the results, if electromyography (EMG) and electrocardiogram (ECG) used in physiology research, reaction time, and the cognitive psycnology implicit association test (Marques da Rosa et al., 2019) are used to remove bias and social desirability, more reliable results can be obtained.

Meanwhile, various research fields such as tourism, finance, and education, appeared in most of the articles. However, chatbots will also likely be used increasingly in fields such as environmental sustainability. This is because, in the future, consumers will want to use chatbots to access information such as activities that are eco-friendly and reduce global warming. As ethical and legal issues continue to be uncovered, further research is necessary.

6. Conclusion

This study aims to provide guidance in the direction of future research by identifying research trends related to chatbots in consumer studies and examining the intellectual structure through DCA, big data analysis, and comparison of issues that appear in the media. In particular, this study proposes a research method that guides future research by using the mixed method of DCA and big data analysis. The results of this study are as follows: First, research on chatbots enabled the understanding that various studies are being conducted in communication, psychotherapy, and retailing, based on the technology adoption theory. However, research on environment, sustainability, law, and policy has been insufficient. Second, unlike newspaper articles about chatbots, research on environmental factors regarding the acceptance and evaluation of chatbots are lacking compared to individual factors. Studies on chatbot bias, privacy, and ethical issues were also found to be insufficient. Therefore, research on strategies to overcome these barriers that prevent the spread of chatbots as well as on various methodologies to increase the validity and reliability of chatbots, is needed.

The implications of this study are as follows. First, through this study, it was possible to systematically establish existing research and identify the areas that lack studies on service chatbots. After COVID-19, the use of non-face-to-face service chatbots gradually increased. Therefore, research on this topic is expected to continue to become more prevalent. Based on this study, reliale findings can be derived if research is expanded by focusing on fields with insufficient analytic investigation regarding the use and implementation of chatbots. In addition, this study provided insights related to chatbots by analyzing issues that are being discussed in the media. These issues provide ideas about independent variables that were not dealt with in previous studies as well as how to manipulate the environment when designing them. For example, based on keywords found in news analyses, research can be suggested as follows: 1) Consumer risk perception such as users' anxiety about chatbot being scams and the risk that the chatbot's answer may not be true (i.e., fake news delivery); 2) With the development of chatGPT, more natural chatbots have emerged, and therefore, a study on the uncanny valley felt by consumers is necessary; 3) Design of an intervention chatbot that empathizes like a human being to overcome psychological trauma; 4) Development of a chatbot that allows crime victims to easily and conveniently report damages without worrying about retaliation; 5) Investigating various situations of chatbot failure in detail such as inaccurate response, limited mission performance (functions), and frequent disconnection due to server problems, and studies failure recovery according to each. Second, a new research method was developed to identify the research gap. Existing intellectual structure studies were identified using a single methodology. In previous studies, only co-citation analysis was used, while in recent studies, only topic modeling was performed to analyze the intellectual structure. However, in this study, both methods were combined to expand the diversity of research through new attempts. Therefore, it will be helpful to provide various ideas for future research.

The limitations of this study are as follows: For DCA, three researchers were included in the selection process of previous studies to increase the reliability of article selection, but it is possible that there may have been errors. In this regard, it is possible that more meaningful research could have been derived if the selection of prior studies using an objective program had been prioritized. Another limitation was that only WoS was included in the study. If Scopus and various other databases were included, it is possible that better implications could have been drawn. In addition, CiteSpace's visualization is another limitation since it is not revealed due to the nature of the program and its readability is poor because the interface configuration is not smooth.

This study examined the research agenda in literature using previous studies and issues that appeared in newspapers. In future research, a good study can be conducted if researchers examine the gap, in theory, factors, and outcomes from this study. Companies are expected to increase their use of chatbots given that the influence of chatbots is increasing since the occurrence of COVID-19. Furthermore, the use of chatGPT is rapidly increasing. There has been no case of research on chatGPT in the consumer field, so there is a need for future research as well as for companies to closely examine it. Therefore, by adding various studies that can derive positive outcomes from literature, new knowledge that helps companies and consumers can be generated.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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CRediT authorship contribution statement

Please indicate the specific contributions made by each author (list the authors' initials followed by their surnames, e.g., Y.L. Cheung). The name of each author must appear at least once in each of the three categories below.

Category 1

Conception and design of study: S. E. Lee, N. A. Ju, K. H Lee, acquisition of data: April 30, 2022 analysis and/or interpretation of data: April 30, 2022

Category 2

Drafting the manuscript: S. E. Lee, N. A. Ju, K. H Lee revising the manuscript critically for important intellectual content: S. E. Lee, N. A. Ju, K. H Lee

Category 3

Approval of the version of the manuscript to be published (the names of all authors must be listed): S. E. Lee, N. A. Ju, K. H Lee

Appendix A

Authors (year)	Source title	Research field	Main concepts
Araujo (2018)	Computers in Human Behavior	Communication	embodied theory/social reaction social presence/anthropomorphism/ company perception
Hill et al. (2015)	Computers in Human Behavior	Engineering & Applied Science	human computer interaction/ chatbot conversation skills/ comparison of conversations between humans and chatbots
Go and Sundar (2019)	Computers in Human Behavior	Communication	compensation effect/expectancy violation effect/ anthropomorphic visual cue/ message interactivity/purchase
Nass and Moon (2000)	Journal of Social Issues	Communication	gender stereotype/ a text-based conversational agent/ anxiety and depression
Chung et al. (2020)	Journal of Business Research	Business	Customer satisfaction, e-service, interaction, entertainment, trendiness, customization, problem solving, accuracy, credibility, communication competence
Reeves and Nass (1996)	University of Chicago Press	Psychology	media equation / media type/ politeness
Fornell and Larcker (1981)	Journal of Marketing Research	Statistics	SEM
Zarouali et al. (2018)	Cyberpsychology, Behavior, and Social Networking	Business	Consumer response, CAT model, affective, cognitive, patronage intention
Luo et al. (2019)	Marketing Science	Business	Consumer purchase, disclosure, conversational commerce
Davis et al. (1989)	Management Science	Business	attitudes, subjective norms, perceived usefulness, perceived ease of use/user acceptance
Epley et al. (2007)	Psychological Review	Business	knowledge/effectance motivation/ sociality motivation (dispositional/situational/ developmental/cultural) mind perception
Weizenbaum (1966)	Communications of the ACM	Engineering	program research on conversations with computers
Ciechanowski et al. (2019)	Future Generation Computer Systems	Psychology	human–chatbot interface (uncanny valley effect)/social presence/ anthropomorphism/willingness to collaborate with a bot
Ho et al. (2018)	Journal of Communication	Communication	media equivalency/ Computers as Social Actors (CASA) framework/ self-disclosure (emotional, relational, and psychological)
Wirtz et al. (2018)	Journal of Service Management	Business	Service robot, research agenda, privacy, ethics
Adam et al. (2021)	Electronic Markets	Business	Anthropomorphism, social presence, consumer service, commitment-consistency theory
Van den Broeck et al. (2019)	Computers in Human Behavior	Communication	Advertising effectiveness, perceived helpfulness, usefulness TAM model
van Doorn et al. (2017)	Journal of Service Research	Business	Social cognition, psychological ownership, interpersonal-attraction, satisfaction
Wirtz et al. (2018)	Journal of Service Management	Business	Ethics, privacy, markets, acceptance
Huang and Rust (2018)	Journal of Service Research	Business	Service strategy, mechanical intelligence, analytical intelligence, intuitive intelligence, empathetic intelligence
Sheehan et al. (2020)	Journal of Business Research	Business	Anthropomorphism, adoption, miscommunication, intersubjectivity, perceived humanness
Adam et al. (2021)	Electronic Markets	Business	Anthropomorphism, social presence, consumer service, commitment-consistency theory

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