



Connecting artificial intelligence to value creation in services: mechanism and implications

Minjun Kim¹

Received: 10 April 2023 / Accepted: 2 October 2023 / Published online: 31 October 2023
© The Author(s) 2023

Abstract

Artificial intelligence (AI) is transforming services by providing personalized solutions, enhancing customer experience, and reducing operational costs. To tackle the challenges posed by the extensive and diverse literature on AI services, a comprehensive review was conducted using text mining techniques on journal articles. Twelve key research topics were identified, and the enabler–interface–business framework was developed. In addition, a value creation mechanism for AI services consisting of 6Cs (i.e., connection, collection, and computation, communication, control, and co-creation) was proposed. The study provides a complete overview of AI services, facilitating academic discussion and industrial transformation.

Keywords Artificial intelligence · Service innovation · Literature review · Text mining · Machine learning · Data driven

1 Introduction

Technological advances change the nature of services, the service experience of customers, the roles of service providers, and the relationship between service providers and customers (van Doorn et al. 2017). In recent years, artificially created intelligence capable of learning, connecting, and adapting (artificial intelligence, hereafter referred to as AI) brings about innovation and revolution in the service sector (Huang and Rust 2018; Noor et al. 2022). Some examples of AI implementation in the service sector include automation of service processes using AI robots in restaurants (Molinillo et al. 2023), transforming customer services into self-services using chatbots or virtual assistants (Ruan and Mezei 2022), and customization of customer preferences based on big data and machine learning (Lee and Lee 2020). AI can assist service providers in reducing operational expenses and increasing

✉ Minjun Kim
minjun@kumoh.ac.kr

¹ School of Industrial Engineering, Kumoh National Institute of Technology, Gumi 39177, Republic of Korea

profitability (Belk et al. 2023; Davenport and Ronanki 2018), while playing a significant role in the expansion and innovation of the service sector (Neuhofer et al. 2020; Prentice et al. 2020).

Such positive effects spark much interest on AI services from the academic sector (Lins et al. 2021; Mariani et al. 2023). In the existing studies, AI services are defined from various perspectives. The core of AI services highlighted by the studies is to provide effective and efficient solutions through AI to support service providers in performing their tasks (Huang and Rust 2021; Ostrom et al. 2019). Here, the tasks include simple and repetitive tasks; complex and systematic tasks; and social, emotional, and interactive tasks of the service provider (Huang and Rust 2022). AI-based solutions include direct (i.e., AI performs tasks of service providers) and indirect (i.e., AI provides information to support the tasks of service providers) interactions with customers.

The value of AI services is created through a harmonious combination of technologies and services (Davenport et al. 2020; Huang and Rust 2021; Rust 2020). Thus, it becomes essential to understand the AI algorithms for services (i.e., what AI algorithms to be utilized), scope of AI application in services (i.e., what service tasks will be supported or performed through AI), clarification of roles between AI and customers (i.e., how to utilize AI for customer engagement), and design of customer experience utilizing AI (i.e., how to enhance customer experience by utilizing AI) (Ostrom et al. 2019). To this end, it is necessary to understand the links between AI and service innovation, identify the application areas of the AI services, and recognize the success factors as well as challenges prior to such implementations. Although several scholars, such as Meurisch and Mühlhäuser (2021) and Li et al. (2021), attempted to understand AI services through literature reviews, existing reviews are selective and limited in scope. They focus only on a few service sectors (i.e., hospitality and tourism) and specific viewpoints of AI services (i.e., data privacy). In short, these reviews are insufficient for comprehensively understanding the full spectrum of AI services, as they do not consider multiple perspectives.

This study contributes to the understanding of the commonality and diversity in research, as well as future research directions for AI services, by employing a machine learning approach to review a large volume of research articles on AI services. Using keywords associated with AI services, this study collected 211 published articles from the Web of Science and Scopus databases. The core of the text corpus must be fully grasped. Hence, this study utilized several metrics to quantify the statistical and semantic importance of word features. This study also utilized unsupervised machine learning algorithms, including spectral clustering (Von Luxburg 2007), latent Dirichlet allocation (LDA) (Blei et al. 2003), and non-negative matrix factorization (NMF) (Lin 2007). Spectral clustering was utilized to discover the key research topics of 211 articles, whereas LDA and NMF were employed to confirm and interpret the clusters.

This study conducted an analysis of articles to extract important keywords, basic statistics, key research topics, and the relationships among the topics. Specifically, 12 key topics of AI service literature were identified. By combining these quantitatively derived findings with a qualitative review of the machine-suggested key references, an overview of AI services was presented from the perspectives of

technological enablers, interfaces, and businesses. Additionally, a value creation mechanism for providing AI services was proposed, considering the data-based value creation mechanism of smart services, including connection, collection, computation, control, communication, and co-creation. The overview and value creation mechanism can help identify, synthesize, and integrate various aspects and related knowledge of AI services, from abstract to concrete concepts of AI services. Lastly, theoretical and managerial implications of AI services were identified from the findings, and future research issues were suggested accordingly.

A common ground should be established for central concepts in science (Fortunato et al. 2018). To integrate the perspectives and capabilities for AI services, this study presented a systematic view of dispersed knowledge by integrating it into a robust conceptualization and identifying the commonality and diversity in related literature. The findings provide an overview of the existing studies on AI services. This overview is expected to serve as a baseline in promoting academic discussion and industrial transformation toward successful AI service development. Additionally, this study is unique; it performed a bibliometric and systematic literature review based on machine learning approaches (i.e., automatic literature review vs. manual literature review). Such an approach helps address the gap between existing works on AI technological development and service innovation by incorporating studies on AI services across various fields, including technology, engineering, and business. This contribution is clear compared with existing studies that perform literature review on AI services (e.g., Li et al. 2021; Meurisch and Mühlhäuser 2021). The contribution of the machine learning approach is shown in Fig. 1, which depicts an overview of the research topics on AI services. Moreover, the machine learning approach has the additional benefits of not requiring the removal of past approaches (i.e., literature review by experts) or causing conflicts in its implementation. This approach offers an advantage for future review research.

The rest of paper is organized as follows. In Sect. 2, the literature of AI services is reviewed. In Sect. 3, the approach to analyzing the research articles is elaborated. In Sect. 4, an overview of AI services is presented based on the findings of data analysis. In Sect. 5, a mechanism for offering AI services and future research issues for AI services are proposed. In Sect. 6, the theoretical and managerial implications of the findings as well as research limitations are discussed.

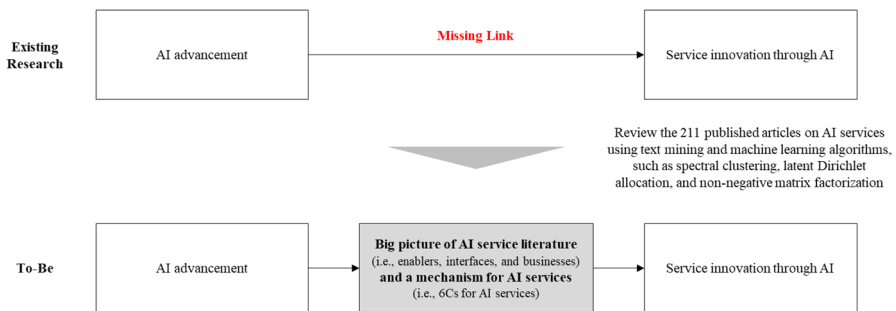


Fig. 1 Research overview

2 Literature review: AI services

The advancement of Industry 4.0 technologies, such as the Internet of Things, cloud computing, and big data, have greatly contributed to the rapid growth of the AI. AI can be defined as an intelligence that imitates the human brain and refers to the set of technologies that implement various human competencies, including cognition and thinking, problem solving, prediction and judgment, and system optimization, using technologies from areas of machine learning, big data, and natural language processing (Poole and Mackworth 2010; Russell et al. 2015). The utilization of AI has the potential to increase profits and reduce costs for businesses, ultimately leading to the expansion of the service sectors (e.g., Belk et al. 2023; Davenport et al. 2020; Loureiro et al. 2023).

Owing to this versatility, research on AI services continues to garner much interest from an increasingly large number of researchers (e.g., Kelly et al. 2022). Previous studies define AI services from various perspectives. For example, Baek et al. (2021) focused on the potential and technical aspects of AI and defined an AI service as a service offered to customers using machines that are enabled with intelligent abilities, such as human competencies in cognition, learning, and decision-making. Huang and Rust (2021) categorized AI into mechanical, thinking, and feeling AIs based on their intelligence level. According to these AIs, they defined AI services by the category of tasks supported that allow customer engagement. Mechanical AI is used for service standardization (e.g., supporting simple tasks), thinking AI supports service personalization (e.g., supporting complex tasks), and feeling AI enhances relationships between service providers and customers (e.g., supporting emotional tasks). The performed or supported tasks of service providers can vary depending on the implemented AIs.

Ostrom et al. (2019) identified three types of AI services based on their role in customer encounter: AI-supported, AI-augmented, and AI-performed service encounters. They also explained the types of customer encounters suitable for each AI service. In AI-supported services, AI provides support in the decision-making process of service providers without directly interacting with customers (e.g., aiding the diagnosis of a patient's disease). In AI-augmented services, AI directly interacts with customers based on the information obtained through AI (e.g., real-time language translation). In AI-performed services, AI directly interacts with customers and collaborates in creating the overall service experience (e.g., decision-making through a chatbot). Meurisch and Mühlhäuser (2021) classified AI services into three categories based on their level of proactivity: reactive, proactive, and autonomous. Reactive services respond to customer requests, proactive services offer information or functions without being requested by customers, and autonomous services make decisions without customer input and confirmations. Wirtz et al. (2018) defined an AI service agent, which is an interface within a system that allows for autonomous and adaptable interaction between service provider and customers. To summarize the results of the aforementioned studies, AI services can be defined based on their potential technological functionality (Baek et al. 2021), their role in supporting or replacing service providers

(Huang and Rust 2021), and the types and modes of interaction with customers (Meurisch and Mühlhäuser 2021; Ostrom et al. 2019; Wirtz et al. 2021).

The use of AI in service offerings, processes, or networks can result in the diversification, redesign, or expansion of AI services, leading to increased complexity (Xu et al. 2020). As AI services become more complex, a number of challenges arise in various aspects and levels, such as the identifying front- and back-end activities (Kirkpatrick 2017), structuring capabilities (Aker et al. 2021), and managing or configuring enabler technologies for AI services (Kumar et al. 2023; Payne et al. 2021a). These challenges require additional research before AI services can be developed in practice. The present knowledge on these topics remains less mature or practical than those on other innovation research topics. Therefore, existing knowledge on AI services should be reviewed and integrated to address such limitations and provide useful information for future research. Viewing AI services from multiple perspectives and levels is particularly essential owing to their complexity, which underscores the need to integrate existing knowledge.

A prerequisite to the development of successful AI services is identifying and synthesizing various perspectives and knowledge to analyze and consolidate multiple aspects and levels. Although recent studies review the literature on existing AI services (e.g., Li et al. 2021; Meurisch and Mühlhäuser 2021), they have limitations in that they selectively limit the scope and cannot include all sources or diversity. Therefore, they offer only a limited range of information and knowledge on AI services. Moreover, previous studies tend to focus on the application of AI for service innovation (e.g., Akdim and Casaló 2023); they do not provide a holistic overview of the research topics related to AI services, from the implementation of technologies to realization of service objectives. Understanding the full spectrum of AI services, from technology development to service innovation, plays an important role in facilitating AI service development. Furthermore, previous studies do not consider recent research articles published between 2020 and 2022, despite the significant increase in articles on relevant topics during this period. To overcome the aforementioned limitations, this study employed a new approach of implementing text mining and machine learning algorithms to analyze the massive volume of research articles. This was in consideration of the massive challenges faced by researchers in performing large-scale literature reviews and consolidations.

3 Method

This study employed text mining and machine learning algorithms to develop the understanding of AI services based on the original method of Lim and Maglio (2018). The method consists of four steps: (1) collecting journal article data, (2) extracting significant word features, (3) clustering journal articles (i.e., extracting topics of AI services) and identifying keywords related to the topics, and (4) interpreting the topics. Sections 3.1–3.4 describe how the author implemented the aforementioned steps in the analysis of AI service literature.

3.1 Step 1: collecting data

Step 1 involves the collection of text data from the scientific literature that contain information about AI services. Only the title, abstract, and keywords set by the authors are used as data for analysis to reduce noise, increase signal strength, maximize efficiency, and overcome the problem related to the limited accessibility of the full texts (e.g., Lim and Maglio 2018; Noh et al. 2015). In addition, this step integrates various types of data from different sources and deletes outliers of data.

In this study, journal article data related to AI services were collected from the Web of Science and Scopus databases of SCIE (1945–), SSCI (1987–), and Emerging Sources Citation Index (2015–). The search field input consisted of “topic (i.e., terms used in the Web of Science “TS” and Scopus “TITLE-ABS-KEY” fields),” and various articles were downloaded using the keywords related to AI services, up to January 31, 2023. The following search query was selected for the study: “Topic=(“artificial intelligence in service” OR “AI in service” OR “AI service” OR “artificial intelligence service” OR “AI based services” OR “AI-based service” OR “artificial intelligence-based service” OR “AI agent service” OR “AI-driven service” OR “artificial intelligence agent service” OR “artificial intelligence driven service” OR “AI-powered service” OR “AI powered service” OR “artificial intelligence-powered service” OR “artificial intelligence powered service”).” Papers on academic conferences, book chapters, reviews, surveys, and editorials were excluded; only journal articles were collected. As a result, 463 journal articles (Web of Science: 158, Scopus: 305) were collected. After excluding 10 articles that only contained the title and no other information (e.g., no abstract), 144 articles that overlapped in the two sets of databases and 98 articles that were not related to AI services (i.e., topics on artificial insemination, cow fertility, and heifer among the results obtained by searching AI services), the remaining 211 articles were scoped for analysis.

3.2 Step 2: extracting significant word features

Step 2 aims to extract significant word features for explaining specific theme of literature (i.e., AI services). The text corpus (i.e., document-term matrix) is then pre-processed to remove potential sources of noises as follows. This step eliminates letters not found on the alphabet and stop words (e.g., “or,” “within,” and “it”). The entire text is also transformed to lowercase (e.g., “AI” to “ai”). Customized rules are applied (e.g., non-contextual words commonly used in journal articles, such as “result” and “paper,” are eliminated). Lastly, all words are lemmatized (e.g., “processes” to “process”).

Step 2 also creates a document-term matrix embedded with term frequency–inverse document frequency (TF–IDF) for the word feature selection. This is because many studies using text mining techniques employ a TF–IDF measure instead of simple frequency (e.g., Kim and Trimi 2023). When calculating the significance value of a word, the TF–IDF value lowers the value by the frequency of the word’s appearance in other articles; the value increases when the word only appears

in the selected article. In the matrix embedded with TF-IDF, words that frequently appear only in certain articles (e.g., acronyms defined by the authors) or frequently used in all articles (e.g., “work,” “study”) are excluded, and only the words that represent the general topics (e.g., “chatbot,” “quality,” and “learning”) are extracted to identify the significant word features. The significant word features can be selected by defining the number of words that represent the topic of each article (hyperparameter 1) and the number of articles where the representative words appear (hyperparameter 2). Lim and Maglio (2018) proposed the five metrics for the optimization of the hyperparameter setting.

In this study, the text corpus (i.e., 211 documents with 4748 word features), was then prepared and preprocessed for subsequent analysis. Python libraries (i.e., TextBlob for text analysis and NLTK for stop word elimination and lemmatization) were employed for text preprocessing. After preprocessing, the five metrics for extracting significant word features of AI services were used. Figure 2 shows the optimization results for hyperparameter setting. The substantial difference between the average significance of the eight-keyword case and the seven-keyword case is illustrated by the three graph lines (i.e., gray, yellow, and purple). The results highlight the substantial difference between the average significance of the seven-keyword case and

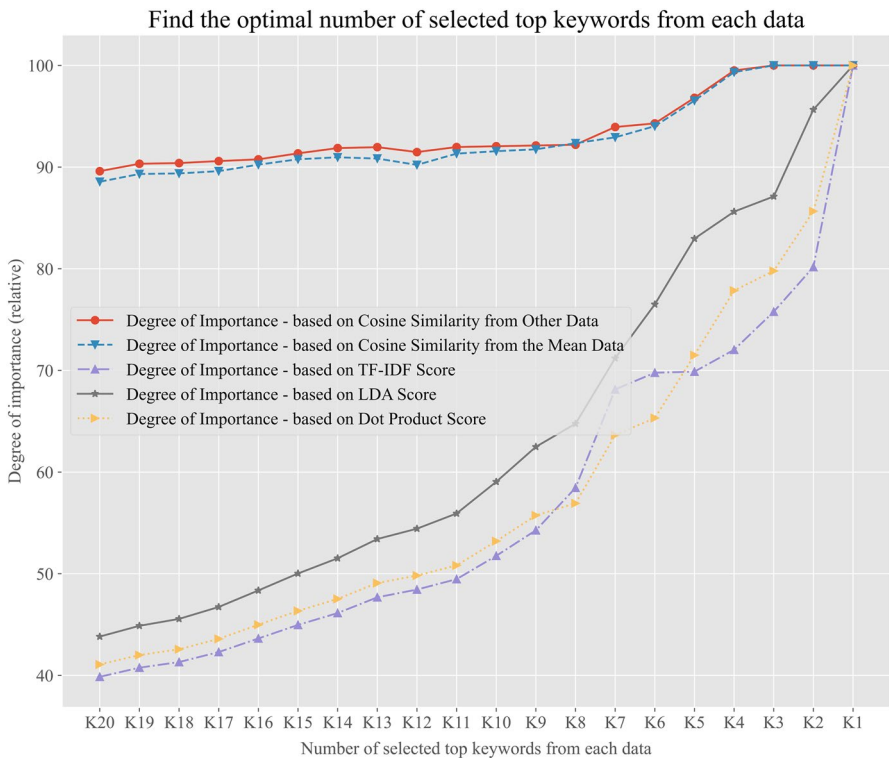


Fig. 2 Changes in importance according to significant word extraction from each article. (Color figure online)

the eight-keyword case, signifying the latter's inclusion of numerous nonsignificant keywords. Consequently, seven was selected as the minimum number of keywords from each article (hyperparameter 1). Furthermore, opting for a hyperparameter 2 value greater than two may result in the exclusion of numerous words that frequently occur exclusively in specific articles, as observed during the pilot study. Thus, the representative words in no less than two articles were selected (hyperparameter 2). In summary, 225 words out of the initial 4748 words were selected as significant word features.

3.3 Step 3: identifying AI service topics

Step 3 aims to identify key research topics of literature. Spectral clustering is applied under the assumption that one article has only one core topic. This technique is based on graph partitioning to distinguish clusters in a latent space. The graph partitioning problem in spectral clustering is an NP-hard problem that requires the application of a heuristic algorithm. Specifically, each run returns a distinct set of clustering results and an ideal number of clusters cannot be determined straightforwardly. Subsequently, silhouette coefficient values (Rousseeuw 1987) of the data are averaged to measure the clusters that are part of the text corpus.

In this study, scikit-learn Python library was employed to use spectral clustering algorithm and iterations for computing silhouette coefficients. For each set of 20 cases, the average of 100 iterations was computed. The precise number of clusters from 2 to 20 was tested based on the finding that the value of the mean silhouette coefficient decreases monotonously from cluster number 11 (Fig. 3). Next, the data of each cluster were manually evaluated, that is, the cluster results were verified and the top articles in each cluster examined. Two clusters that have less than 10 articles and focus on the same topics as the other clusters were reassigned to other clusters. Finally, nine were chosen as the ideal number of clusters.

Step 3 also involves understanding and naming each cluster to define key research topics of literature. The visualization proposed by Longabaugh (2012) is utilized to point out the clusters (Fig. 4). In the binary adjacency matrix, the yellow squares denote individual clusters; the size and density of the clusters indicate the amount and homogeneity (i.e., cosine similarity of clusters) of data, respectively. In addition, topic modeling algorithms like NMF and LDA are used to determine the top 30 representative keywords for each cluster and validate the spectral clustering results for each scenario with different topic numbers. LDA is a generative probabilistic model to recognize topics from sets of words across documents. NMF is a matrix factorization method for extracting latent factors from the original features with non-negativity constraints. Lastly, the topics are reviewed through expert interviews. The experts can be asked questions regarding the comprehensiveness of the extracted topics of AI services, such as whether the extracted topics are sufficient to represent the overview and mechanisms of AI services and what additional topics can be considered to reflect the characteristics of AI services. The results of the expert interviews are used to add, delete, divide, and merge topics of AI services.

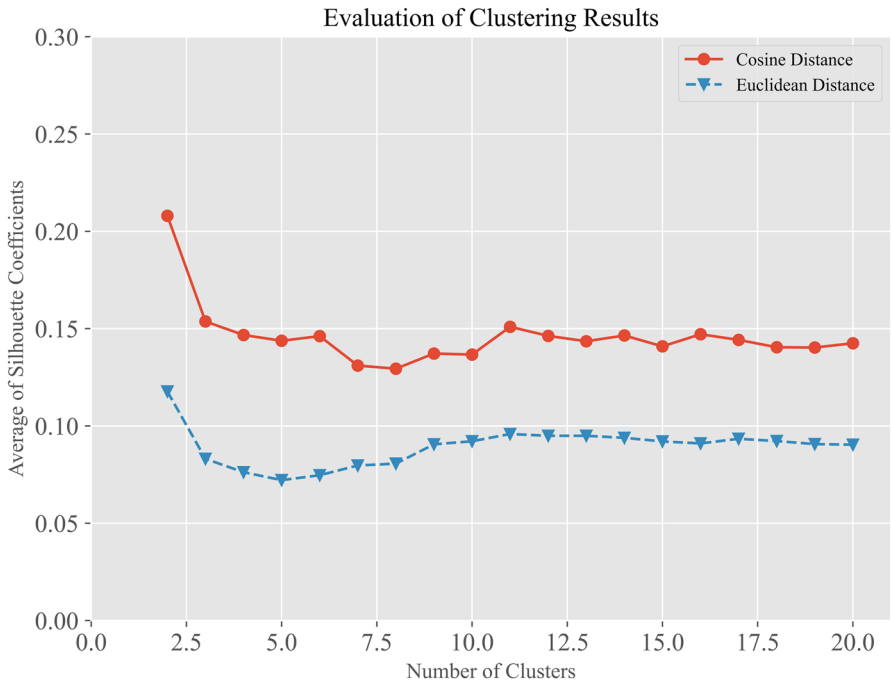


Fig. 3 Changes in silhouette coefficients according to the number of clusters

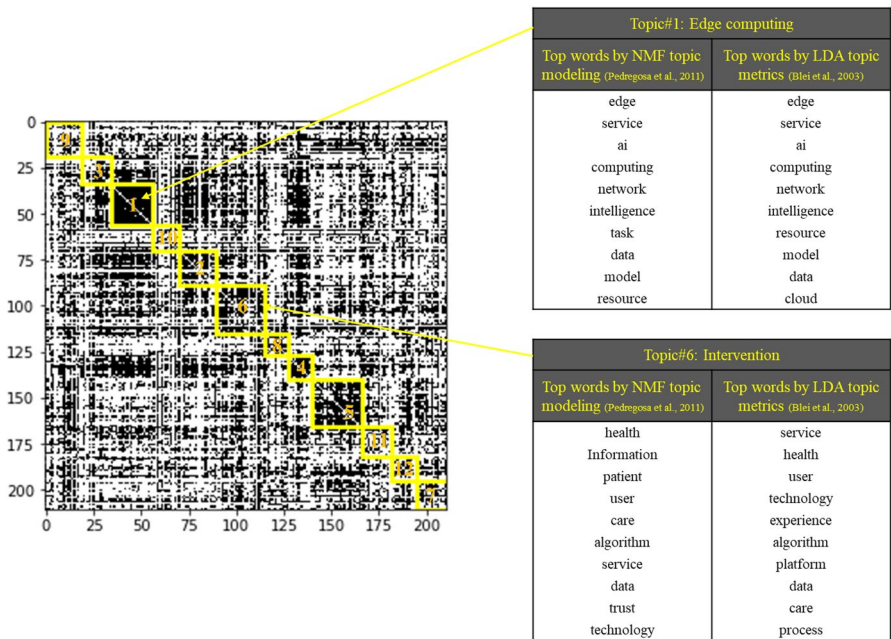


Fig. 4 Interpretation of clustering results. (Color figure online)

In this study, nine clusters were identified using Longabaugh (2012) method, NMF, and LDA. In addition, two experts were recruited for the interviews. One had more than 6 years of experience in the industrial engineering department at a university, specializing in designing AI services in chemical and healthcare industries and developing algorithms for AI service operations. The other expert had over 6 years of experience working for a global AI service company in South Korea, focusing on operating AI services and designing user experiences of AI services. The experts emphasized the importance of business topics in AI services and recommended further subdividing one cluster (i.e., business topic) into multiple subtopics to consider various aspects of business topics, such as service, society, customers, marketing strategy, and goals. As a result, the nine clusters were changed to 12 clusters to incorporate business aspects of AI services. In addition, another round of expert interviews was conducted to validate the results. The results on topic identification are elaborated in Sect. 4.2.

3.4 Step 4: interpreting AI service topics

Step 4 aims to interpret the clustering results by conducting network analysis. The centroids (i.e., those of the TF-IDF-embedded document vectors) in every cluster are determined, and the cosine similarities between them are computed. The similarity scores are generally high, and all clusters (nodes) are connected because they are all closely related. Consequently, only the top three most highly related clusters are singled out for each cluster, and they are connected to examine the most important relationships between research topics. The results demonstrate that nodes in the center are connected to several others, thus the strong relationship values. To the contrary, nodes in the boundaries are connected through nodes in the center, hence the weak relationship values. The nodes in the center represent the concepts that connect those in the periphery. To deepen the findings and highlight a future research direction, qualitative analysis is performed.

In this study, network Python library was used to conduct network analysis, and the outcomes of text mining and the literature gathered were investigated. The interpretation results are elaborated in Sect. 4.3.

4 Results

4.1 Statistics of the AI service literature

Table 1 shows the basic statistics of the 211 collected articles, including their country (i.e., the affiliated institution of the corresponding author) and journal of publication. China, the USA, and South Korea are the top three countries with the most numbers of published articles on AI services. Authors from China and South Korea tend to focus on technological development for the implementation of AI services, whereas those from the USA tend to focus on the methods for providing AI services (e.g., robots and chatbots) or investigate the relationship between AI services

Table 1 Basic statistics of the AI service literature

Country	Frequency	Journal	Frequency
China	55	<i>IEEE Access</i>	7
USA	25	<i>Sensors</i>	6
South Korea	25	<i>Applied Sciences</i>	5
Australia	10	<i>Journal of Service Research</i>	5
United Kingdom	7	<i>Journal of Hospitality Marketing and Management</i>	4
Germany	7	<i>Sustainability</i>	4
Italy	6	<i>Frontiers in Psychology</i>	3
Finland	6	<i>Psychology and Marketing</i>	3
Taiwan	6	<i>IEEE Internet of Things Journal</i>	3
India	5	<i>Journal of Service Management</i>	3

and firm performance. The interdisciplinary nature of research on AI services is reflected in the variety of journals that publish related articles. Service-related journals like *Journal of Service Research*, *Journal of Service Management*, and *Journal of Hospitality Marketing and Management* publish articles on AI services. In addition, technology-related journals such as *Sensors* and *Applied Sciences* contribute to the literature on AI services. These results emphasize the need for collaboration across disciplines to advance research on AI services.

Figure 5 shows the publication trend of 211 collected articles, including publication counts and total citation per year. Analyzing the annual publication count from 2016 to 2023, spanning approximately 8 years, reveals a consistent growth pattern in the quantity of articles related to AI services. This escalating yearly publication

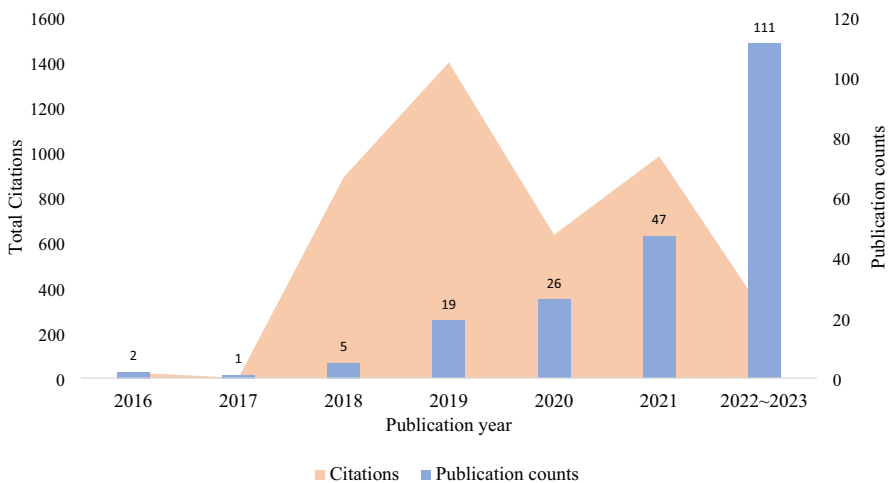


Fig. 5 Publication trend of AI service literature

trend underscores the rapid expansion of literature on AI services. Furthermore, the growing number of citations provides evidence of the substantial popularity of AI service topics, particularly attributed to the advancements facilitated by Industry 4.0 technologies and the increased availability of data assets. In short, the number of publications and the increasing number of citations signify a robust and growing interest among researchers in the field of AI services, underscoring the relevance of the present review.

4.2 Key topics (12) in the AI service literature

Table 2 lists the 12 topics (i.e., clusters) identified from the analysis of the AI service literature. Enclosed in parentheses are the numbers of scientific articles that discuss each topic.

Four topics on the enablers of AI services are as follows. Edge computing (Topic 1) addresses the provision of AI services based on edge computing (Li et al. 2022a), services architectures for edge devices (Valadares et al. 2022), and efficient processing and cooperative transmission for edge inference (Yang et al. 2020). Cloud platform (Topic 2) addresses the use of sensors and cloud servers for data collection. In particular, this topic covers sensing technologies necessary for supporting efficient data collection (Kwon and Seo 2022) and frameworks for virtual sensor configurations to collect data via multiple devices (Alberterst et al. 2021). Learning technology (Topic 3) addresses the machine learning algorithms can be used in various AI service areas (e.g., smart city service and healthcare service), such as deep learning models for image classification and segmentation (Lee et al. 2022b; Tseng et al. 2021) and federated learning models for privacy protection of AI services (Rodríguez-Barroso et al. 2020). Network quality (Topic 4) addresses the quality for data collection, analysis, and utilization for AI services. Specifically, this topic covers 6G technologies for the implementation of AI services (Letaief et al. 2019; Wu et al. 2022) and future issues and challenges on network quality improvement to provide AI services (Park and Park 2020). Topics 1, 2, and 4 focus on AI technologies to enhance the experience of service delivery (e.g., service delivery in real time and information delivery to the customers), whereas Topic 3 focuses on AI technologies for service value creation to satisfy customer needs (e.g., x-ray image detection models for a cancer patient and learning algorithm for customer's privacy protection).

Four topics focus on the interfaces of AI services. Service agent (Topic 5) indicates the AI chatbots or voice-enabled virtual assistants that help address customer requirements. This topic covers the use of AI chatbots and voice-enabled virtual assistants in various service fields, such as handling of customer complaints (Riikkinen et al. 2018), identification of the characteristics of these agents (Ashfaq et al. 2020; Cai et al. 2022), examination of customer acceptance models (Cai et al. 2022), investigation of the effectiveness of different interaction styles between service agents and customers (Vassilakopoulou et al. 2023), and identification of negative aspects of service agents (Castillo et al. 2021). Intervention (Topic 6) describes the continued interaction via on-going systems (e.g., online system and

Table 2 12 key topics of AI service literature

Group	Topics	Top 10 keywords (NMF, LDA)
Enabler (69)	<ol style="list-style-type: none"> 1. Edge computing (22) 2. Cloud platform (19) 3. Learning technologies (15) 4. Network quality (13) 5. Service agent (26) 	<p>Edge, service, computing, network, intelligence, task, data, model, resource, system</p> <p>Cloud, IoT, system, attack, sensing, device, data, sensor, security, distribution</p> <p>image, privacy, deep, learning, data, performance, segmentation, network, facial, model</p> <p>Network, wireless, communication, mobile, model, technology, system, architecture, application, IoT</p> <p>Chatbots, agent, satisfaction, user, interaction, relationship, communication, engagement, experience, trust</p>
Interface (80)	<ol style="list-style-type: none"> 6. Intervention (26) 7. Failure and recovery (16) 	<p>Health, patient, care, algorithm, experience, information, application, trust, process, platform</p> <p>Failure, recovery, task, context, social, information, data, response, labor, strategy</p>
Business (62)	<ol style="list-style-type: none"> 8. Service robot (12) 9. Business strategy (19) 10. Business model (15) 	<p>Robot, appearance, interaction, acceptance, social, HRI, acceptance, type, attitude, anthropomorphism</p> <p>Strategy, financial, perceived, customer, value, risk, intention, development, system, decision-making</p> <p>Business, model, platform, system, taxonomy, management, learning, technology, information, performance</p>
	<ol style="list-style-type: none"> 11. Application across industries (15) 12. Characteristics of AI service (13) 	<p>Application, industry, transformation, digital, innovation, learning, model, education, enterprise, legal</p> <p>Technology, human, system, adoption, analytical, data, ethic, task, protection, customer</p>

smartphone-based system) to support customer task of AI services. Most of the studies in this topic relate to healthcare or education services, including the intervention methods to improve the health of patients (Joerin et al. 2019) and educate the health improvement in family (Zhao and Fu 2022) and how and when to deliver data analysis results to the customers (e.g., data chart and monitoring information) (Yu et al. 2022). Failure and recovery (Topic 7) presents solutions to recovery and response for failures arising out of inappropriate interaction between AI and customers. This topic covers the identification of the contexts that lead to failures of AI services (Huang and Philp 2021) and service recovery plans of AI services (Chen et al. 2022; Xu and Liu 2022) as well as how to accurately understand customer requirement for prevention of failures (Li et al. 2022b) and how to solve the problems using AI emotion expression, highlighting the needs for empathy (Esmailzadeh and Vaezi 2022; Peng et al. 2022). Service robots (Topic 8) shows the robot to support or enhance customer tasks of AI services. This topic covers the potential use of robots for improving customer experience (Ghazal et al. 2021) and various types of robot and interaction types for improving acceptance of these robots in services (Song and Kim 2022; Yao et al. 2022; Zhang et al. 2021).

Four topics related to the business of AI services encompass various themes for improving and enhancing the business aspects of AI services. Business strategy (Topic 9) outlines the actions and decisions a firm's plans to take to reach its goals and objectives, including marketing, finance, design, operations, and other areas. This topic covers the strategies and future research issues of business model planning of AI services (Kitsios and Kamariotou 2021), the improvement of customer acceptance and satisfaction of AI services (Atwal and Bryson 2021), strategies for enhancing the value co-creation process of AI services (Payne et al. 2021b), design strategies for AI-based service business models (von Garrel and Jahn 2022), and strategies for achieving sustainability and circular economy in AI services (Rajput and Singh 2019). Business model (Topic 10) pertains to the understanding and categorization of various business models for service firms. This topic covers platformization and ecosystem transformation for providing AI services (Liu et al. 2020), the taxonomy of business models of AI services (Anton et al. 2021), and digital transformation or servitization closely related to AI services and servitization (Kim et al. 2023; Payne et al. 2021a). Application across industries (Topic 11) relates to perspectives on AI service development from case studies in various sectors, including education (Ouyang and Jiao 2021), hospitality (Hussein Al-shami et al. 2022), energy (Marinakis et al. 2021), construction (Gec et al. 2023), sports (Chin et al. 2022), and healthcare (Megaro et al. 2022) sectors. Characteristics of AI services (Topic 12) covers the identification of AI characteristics in the perspectives of business models and their application for enhancing customer engagement (Huang and Rust 2018, 2021) in the context of service robots considering system, customer, and service encounter (Flavián and Casaló 2021). Additionally, this topic identifies potential challenges of AI for enhancing the experience of service delivery (Chi et al. 2020), customer intention to use AI services in the perspective of technology readiness and awareness (Flavián et al. 2022), and an overview of AI in the business context considering societal impact of AI, organizational impact of AI, AI systems, and AI methodologies (Loureiro et al. 2021).

Utilizing the publication counts of AI service articles in the recent 3 years (2020–2022), trends of key topics were analyzed across three groups (i.e., enabler, interface, and business). Considering the limited number of papers available until 2019, the analysis was restricted to the last 3 years. Given the increasing annual count of AI service articles, the analysis focused on trends based on the proportional values of paper counts for each year rather than the absolute number of papers in specific key research topics. The trends of the 12 key topics within the three groups are illustrated in Fig. 6.

In the enabler group, edge computing topic (Topic 1) shows a relatively high recent publication count compared with other topics due to the increasing importance of real-time analysis and utilization in AI services. Three topics of cloud platform (Topic 2), learning technologies (Topic 3), and network quality (Topic 4) serve as fundamental components in implementing AI service. They exhibit a gradual decline or relatively stable publication count. In the interface group, topics of service agent (Topic 5), intervention (Topic 6), and failure and recovery (Topic 7) have witnessed a surge in recent publications. This surge is attributed to the direct interaction between customers and service providers, playing a pivotal role in customer satisfaction. In particular, service agent topic has consistently seen a high publication count from 2020 to 2022, likely influenced by the emergence and potential utilization of voice assistants (e.g., Amazon Alexa). Conversely, service robot topic garnered significant interest in 2021 but experienced a decline in related publications in 2022. Lastly, in the business group, no distinct trend has been identified, which shows that business-related topics continue to receive steady and consistent attention. In summary, topics in the enabler group (Topics 1–4), forming the foundation for AI services, and the topics in the interface group (Topics 5–8), facilitating direct customer interactions, demonstrate adaptability to evolving technological trends. By contrast, the topics in the business group (Topics 9–12) display stability regardless of technological fluctuations.

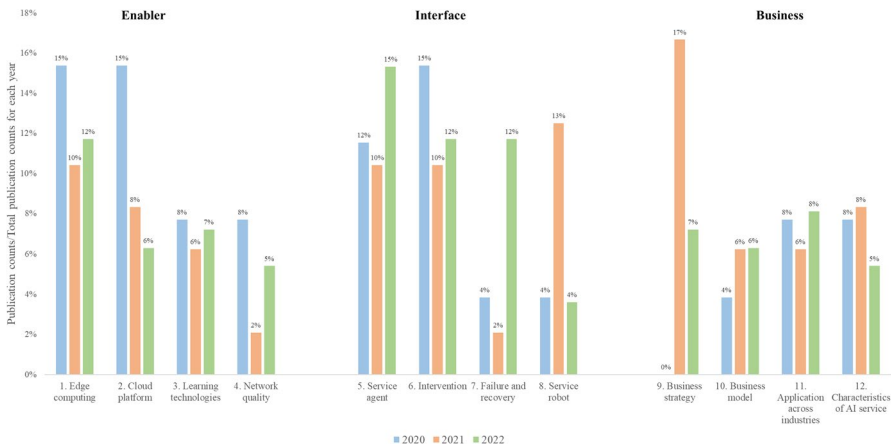


Fig. 6 Publication trend of key topics related to AI services

4.3 Enabler–interface–business framework

This section presents an overview of the literature on AI services by integrating the aforementioned findings. The overview and outcomes of AI service innovation in terms of management practices have been questioned (Füller et al. 2022). Figure 7 illustrates this overview captured in the literature.

Service companies are motivated to adopt AI technologies for service development thanks to technological advances, such as the rise of network technologies, edge computing, cloud platforms, and deep learning technologies. They also have a need to advance service operations and enhance customer experiences using interfaces, such as service robots, service agents, and interventions. Additionally, failure and recovery of interfaces should be considered during service operations. For AI service development, companies recognize opportunities for AI services by benchmarking cases of AI service innovation across various industries and identifying the characteristics of AI services. Based on these opportunities, they develop various business models or strategies with new technologies and use them for developing AI services, such as platform transformation, data annotation models, and personalized service models. Specific methods for AI service design, analysis, and evaluation have been developed for these companies. Through AI service provision, companies aim to achieve innovation and contribute to the circular economy.

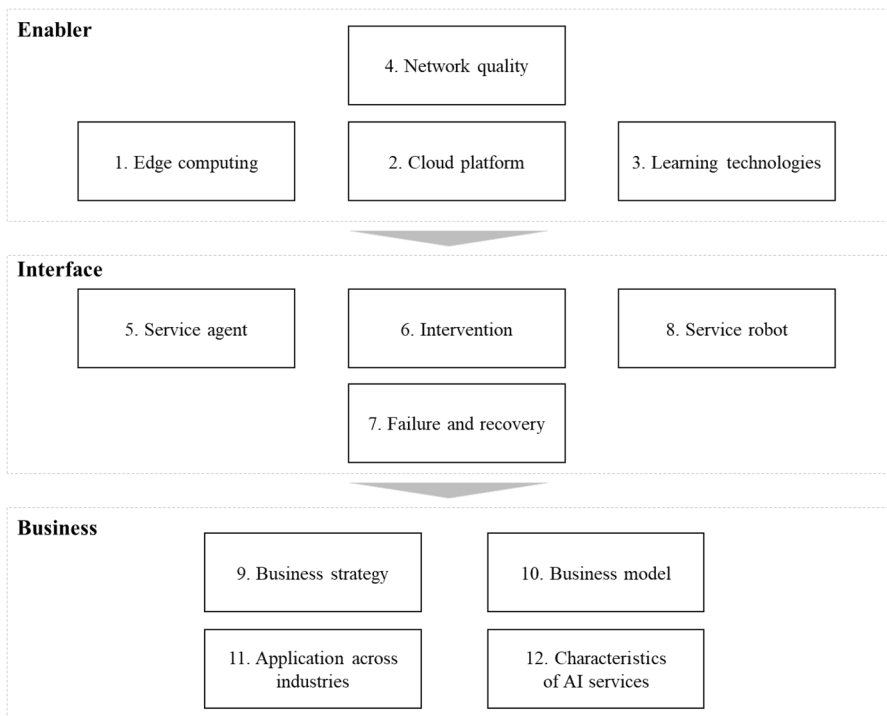


Fig. 7 Enabler–interface–business framework for AI service innovation

Figure 8 illustrates the network of relationships among the 12 key topics on AI services. Each node represents a topic, with the size of the node indicating the percentage of articles covering that topic relative to all articles. The color represents three topic groups, and the lines connecting the nodes represent the relationships among the topics.

The three topics (Topics 1, 2, and 4) in the technological enabler group are interconnected (upper side of Fig. 8) as they are highly related technologies for the development and implementation of AI services. Additionally, they are connected with the business aspects of AI services (Topics 11 and 12) because these technologies play an important role in the planning of business models and determining the role of AI in services. Business-related topics (Topics 9–12) are connected to all topics of interfaces (i.e., failure and recovery, service agent, intervention, and service robot) because interfaces function as the interaction channel between service providers and customers, which is key to improving customer satisfaction of AI services. As failure and recovery (Topic 7) largely impact the satisfaction levels on the service robot or agent (e.g., Huang and Philp 2021), this topic is connected to the two topics (Topics 5 and 8) in the interface group. Lastly, intervention (Topic 6) shows no connections among the interface-related topics as this topic has low relations to the actions of the robots or agents.

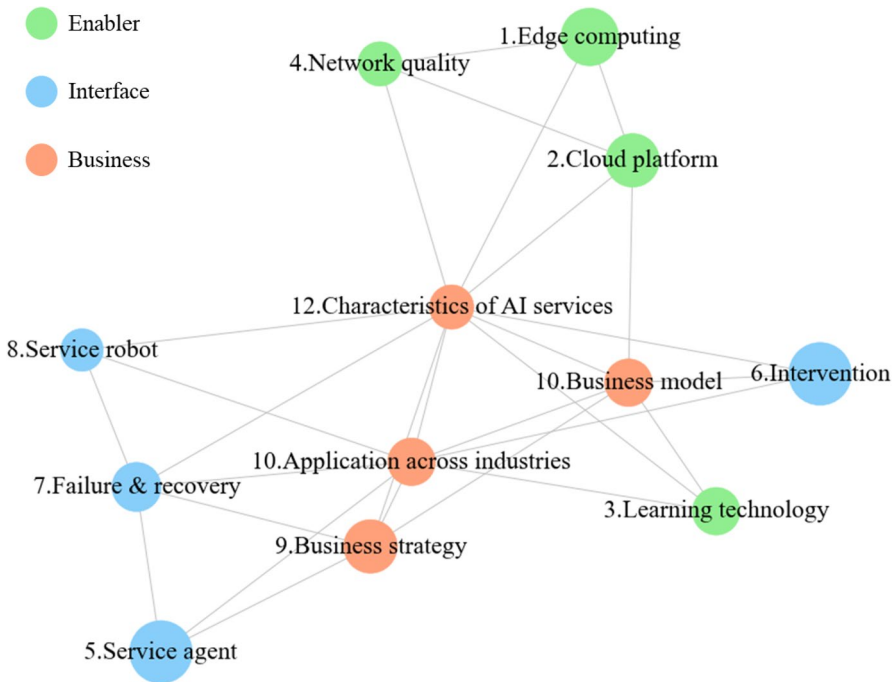


Fig. 8 Relationship among the 12 key topics

5 Discussion

This section proposes a mechanism for providing AI services based on the 12 key topics and their relationships (Sect. 5.1) and discusses the future research issues for key topics (Sect. 5.2).

5.1 Value creation mechanism of AI services

In offering AI services, AI consolidates various techniques (e.g., deep learning, federated learning, and edge computing) to deliver and perform intelligent competencies and plays a critical role in facilitating and supporting the mutual interactions between customers and service providers. In terms of creating service values based on the intelligent competencies, AI services can be regarded as a branch of smart services. Lim and Maglio (2018) proposed a representation model for data-based value creation mechanism of smart services. In this study, the author reconstructed the mechanism (see Fig. 9) in the context of AI services. The lines correspond to the interactions among data and information. In addition, Fig. 9 depicts the closed-loop mechanism of AI services. Data and information interactions within the service are iterative. Stakeholders can build their relationships and enhance value co-creation continuously through a cycle of monitoring and learning. The direction of the advancement of AI services is obvious. Value co-creation can be further developed by incorporating AI technologies for connection, collection, computation, control, and communications.

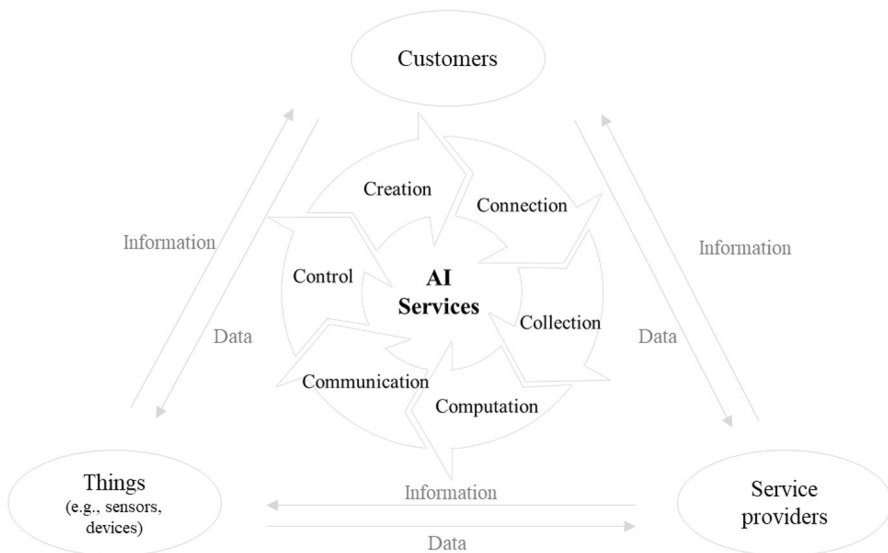


Fig. 9 Value creation mechanism of AI services

AI service comprises the following six attributes for creating value: (1) connection between customers and things (e.g., sensors and devices), (2) collection of data from customers and connected things, (3) computation and analysis of data through AI-related technologies and algorithms (e.g., cloud computing, edge computing, and deep learning), (4) wireless communication between customers and things, (5) control over customer environments or decisions, and (6) value co-creation between service providers and customers. Table 3 describes in detail these six attributes, which this study calls the 6Cs. The first five attributes are the technological resources for AI services. They should incorporate technologies for connection, collection, computation, control, and communication so as to cater for variability around service operations, including customer-introduced variability and be intelligent. The first to three attributes (i.e., connection, collection, and computation) closely reflect the enabler topics (Topics 1–4), whereas the fourth and fifth attributes (i.e., communication and control) relate to the interface topics (Topics 5–8). The last attribute (i.e., co-creation) represents the objective of applying the various resources, which is the business topic (Topics 9–12). The first five attributes actually contribute to the rising opportunities for active value co-creation. Encounters for value co-creation expand as the connection between customers, providers, information, and technologies tightens. Informational or intellectual resources for value co-creation grows with the collection and computation of high-quality data. The efficient control and communication within the AI service boost the frequency and intensity of value co-creation.

Based on the 6Cs attributes and 12 key topics, the provider's activities for delivering AI services can be summarized as follows. First, the providers should identify and understand the AI technologies that can be used or implemented along with their usefulness for services (Topics 1–4). Technological enablers of AI services include the technologies for connection of things, collection of data via connected things, and computation and analysis of the collected data. Next, the scope of tasks to be supported or replaced by enabler technologies should be determined, including the appropriate technologies selected for the tasks to be performed. Utilizing such technologies enables the understanding of customer contexts and identification of useful information to the customers. Based on such contexts and information, the interfaces (Topics 5–8) suitable for supporting communication or control can be identified and determined. In addition, interaction types (i.e., direct and indirect) and frequency (i.e., reactive, proactive, and autonomous) between AI and customers should be selected by considering customer requirements and preferences. Based on the selected enabler technologies and interfaces, the providers can then plan various business strategies and models (Topics 9 and 10; e.g., platform, data annotation, and personalized service models) and offer these models to the customers to co-create the values of AI services. Lastly, the effectiveness, usability, and expected benefits of the delivered AI services should be evaluated to improve the quality of AI services (e.g., quality evaluation, recovery model, and business performance management).

Table 3 6Cs of AI services

6Cs	Description
Connection	Connected things include <i>tangible goods directly used by customers and dedicated infrastructures generally required by customers and providers</i> . These goods and infrastructures can be connected to other objects. The development of a connected network of people and things, which is the base infrastructure for AI services, is the groundwork for collection and communication for AI services. In fact, <i>a connected network represents the network of "data sources" for AI services</i> . The source of data is directly relevant to their use (i.e., purpose of the AI service) and the scope and potential of the AI service
Collection	Collection of data include condition traces of engineering systems, event logs of business processes, health and behavioral records of people, and bio-signals of animals. <i>Data are the core resources for context awareness given our capability for continuous monitoring of and learning from data</i> . Data use contributes to the effectiveness and efficiency of process for AI services
Computation	Computational processes involve <i>the use of specific AI algorithms and expert knowledge for decision-making</i> . Computation is a <i>prerequisite for data and information communications in a connected network</i> because these processes transform raw data into standardized data or information that enable machine-understandable data. The key functions of AI services (including context awareness, predictive and proactive operations, adaptation, real-time and interactive decision-making, diagnosis, and control) can be created only through computation of specific data. This process frequently requires several pre-tasks for data analytics, such as analysis planning, data cleaning, anonymization, aggregation, integration, and storage. Two of the key requirements of computation in AI services are cloud or edge computing availability and security, given the distributed nature of connections in stakeholders of AI services
Communication	Communication contexts include <i>machine-to-machine actuation and machine-to-human guidance</i> . Thus, the aspects of this attribute encompass the aspects of communicating machine-understandable data and human-understandable information, such as in visualization methods and other information delivery methods through auditory, olfactory, gustatory, and tactile stimulation in physical, virtual, and augmented reality. Interactions tend to be unique in each AI service interface, although the same goods, infrastructures, and stakeholders can be involved in multiple AI service interfaces. The key to designing or developing AI services is to improve the unique interactions between customers and providers, given AI technologies for connection, collection, and computing are fulfilled in such AI services. Thus, <i>a communication technology that facilitates interactions is crucial to any AI service and considered the circulating blood of the AI services</i>
Control	Control includes the <i>typical machine-to-machine actuation, human-to-machine control, and the recently available automation of human-to-human transactions</i> and workflows enabled by smart contracts, that is, self-executing scripts in a blockchain network of different parties. Control in traditional and modern services <i>can be distinguished in terms of variability</i> , with the former reducing variability (e.g., ATMs that cover limited options) and the latter accommodating variability (e.g., AI-based financial services that invest on their own)

Table 3 (continued)

6Cs	Description
Co-creation	Co-creation of value between customers and providers. Value creation is the core purpose and central process in economic exchange. Any type of service involves value co-creation that assembles various stakeholders to jointly produce a mutually valued outcome. <i>The development and use of AI ultimately aim for an enhanced or new value creation.</i> Based on the concept of the AI service, this study distinguishes between data and information from the perspective of value. Data are traces and evidence of interactions within an AI service and the raw materials and ingredients of information. Information is the content created by data analysis delivered to customers and providers for a specific decision-making purpose. Value is not created until information is used for a specific decision-making purpose; that is, value is created through information use

5.2 Future research issues for AI services

This section focuses on the challenges for AI services derived from the results of quantitative analysis (i.e., text mining, machine learning, and network analysis) and qualitative analysis (i.e., review of titles and abstracts of representative articles).

The enabler topics (Topic 1–4) are closely related to “data,” the basis for which AI services operate. AI services analyze the data from customers and their contexts and enhance the interaction between the customers and providers. In particular, the core of the value creation of AI services lies in understanding the contexts and status of customers via the activities related to data and providing customized services for performing the tasks of AI services (Lim et al. 2018). Therefore, the providers should accurately identify the data-related activities during lifecycles of AI services (e.g., data collection, analysis, delivery, and protection) and effectively manage them through AI-based infrastructures. Recently, various types of data (e.g., customer actions, expressions, and biological signal) can be collected from multiple sources. Service providers simultaneously analyze and use the collected data for providing AI services, such as offering customized services based on the analysis of customer emotions and the change of the emotions. To successfully implement these services, a systematic methodology should be developed that can support the management and analysis of multiple types of data. In particular, the quality of data collection and analysis must be managed. In this database, several scholars highlighted the importance of data management and explored the effects of data management (Meurisch and Mühlhäuser 2021; Wu et al. 2022). Therefore, further studies are needed to help the providers improve their efficiency and effectiveness of data-related activities based on the AI technologies. Lastly, in many examples of AI services, the interactions between customers and providers happen in real time (e.g., AI agent provides instant response to customer inquiries). Therefore, a fast turnaround is required for analyzing and utilizing the collected data as well as a fast decision process. Li et al. (2022a) highlighted the importance in the development of mobile edge computing to enhance such decision-making process and went as far as to mention that the AI services need to be provided over a 6G network.

The interface topics (Topic 5–8) are closely related to the “means, methods, and considerations to better deliver AI services to customers.” The key factor of interfaces is to properly understand customers and timely provide customized or personalized information to them (Song and Kim 2022). To this end, the speed of data collection analysis and the quality of the utilized data as previously mentioned need to be ensured. Adequate information must be provided to the customers at their desired points in time. Furthermore, research on the level of anthropomorphism exhibited by the interfaces should be conducted, that is, the extent to which they show human-like characteristics. Several studies on service agents (Topic 5) and service robots (Topic 8) state that interfaces that have human-like characteristics, including psychological features (e.g., emotions and speech styles) and non-psychological features (e.g., appearance and movements), improve customer intention and satisfaction (e.g., De Visser et al. 2017). Yang et al. (2020) demonstrated that the influence of anthropomorphism level of an interface on customer satisfaction can vary based on the characteristics of AI services (e.g., friendly responses vs. simply providing information). In more detail, for AI services where empathy is a critical factor (e.g., social scenario), increasing the level of anthropomorphism in the interface can lead to higher customer satisfaction. On the contrary, for AI services that primarily provide information (e.g., non-social scenario), the impact of anthropomorphism on customer satisfaction is less significant. Therefore, research is necessary to categorize AI services based on their intended purposes and to determine the appropriate level of anthropomorphism for the interface in each category. Lastly, further research is needed to investigate multi-modal interactions. Although current service agents and robots are primarily activated through voice or touch interactions, technological advancements enable the collection of diverse data and the exploration of various types of interactions (e.g., Di Nuovo et al. 2018). For instance, a gesture-based interaction is potentially more effective than an audio-based interaction for service robots. In this case, multi-modal interaction can be considered for gesture-initiated interactions in addition to visual and touch interactions. In short, suitable interaction types for various interfaces should be explored and the patterns or paths for multi-modal interactions must be optimized.

The topics in business group (Topics 9–12) is closely related to the “planning, development, evaluation, and improvement of AI services.” First, a systematical methodology that can support the development of AI services is required that can create and deliver real values rather than aiming for the development of services that simply adopt AI technologies. This methodology should consider the holistic lifecycle of AI services, from the purpose of services to clear problem statements, plans for AI-based solutions, offering of the services, and even improvements in customer satisfaction. Second, an evaluation methodology should be developed for measuring the quality of AI services. In particular, the importance of the Quality of Experience (QoE) for AI services is also increasing, beyond the only application of technologies for AI services (Nguyen and Malik 2022). This triggers the growing need in the development of enabler technologies that can be used for the assessment of QoE. They are technologies that can develop high-quality AI services with a focus on customer experience rather than on the development of AI services that are highly regarded only from the technical perspective. Despite the recent studies that propose

methodology for evaluating QoE of AI services (e.g., Ameen et al. 2021), they are limited because they do not consider the whole scope of AI services and only focus on the quality evaluation of AI agents (i.e., voice-activated assistants). Therefore, a QoE evaluation for AI services that can be implemented in various interfaces, such as robots or intervention techniques, must be developed. In situations where customers of AI services provide information to “experts” (e.g., providing medical diagnosis information to doctors or providing equipment status information to onsite engineers), the experts tend to take actions with a stronger trust of their past experiences or intuitions, rather than the results provided by AI (Lee et al. 2022a). Thus, research on evaluation framework for expert-targeted AI services is also necessary.

Further research is needed to develop business models for small- and medium-sized enterprises (SMEs). Although AI has the potential to fundamentally transform business activities, such as improving efficiency, internal processes, or developing business models, how AI can effectively and efficiently support SMEs to develop and operate business models remains unanswered (Abu-Rumman et al. 2021). In this context, the competition to take the lead in the new AI market is expected to intensify, making it crucial to design methodologies for developing business models that can help understand customers and satisfy them through AI services (Baek et al. 2021). von Garrel and Jahn (2022) suggested a framework for guiding manufacturing SMEs in designing various business models. The findings may serve as references for developing business models.

6 Conclusion

The development of AI services has recently gained much attention in both research and government policies. However, to date, there is no integrated and conceptual review of the various concepts related to AI services. To provide an overview of existing studies on AI services, a literature review was conducted using machine learning algorithms to analyze journal articles on AI services. As a result, 12 key topics were derived from the literature review, and an overview of AI service literature was identified considering the aspects of enablers, interfaces, and businesses. Additionally, a mechanism for providing AI services (i.e., 6Cs for AI services) was proposed. Moreover, theoretical and business implications for future research that will help implement AI in practical service innovations were discussed.

This research contributes theoretically to the service literature. Although innovation in AI services is critical, AI services have yet to be reviewed from multiple perspectives. This study contributes to AI-driven service innovations by consolidating knowledge on AI services scattered throughout a large volume of literature and analyzing it in an organized fashion. In particular, the study considers AI services not only from the perspective of technological application but also from a broader viewpoint that expands across “enabler-interface-business,” presenting an overview of AI service literature. This overview provides detailed information on the activation, exploration, and integration of existing studies on AI services and is expected to serve as a baseline for promoting more related studies by various researchers. Furthermore, this study will drive further research on AI services based on the findings. The existing literature does not

cover all aspects of AI services, but the overview presented in this study considers various aspects and levels of AI services, offering a value creation mechanism to conceptualize research on AI services.

Regarding the practical implications, the machine learning-based literature review approach employed in this study provides a guideline for many researchers to conduct literature reviews on specific concepts in a wider scope and gain an overview of the relevant topic. The results of this study can be regarded a successful example of collecting, analyzing, and interpreting large-scale text data. This methodology is unique in that it aims to minimize the subjectivity of the experts engaged in the literature review and ensure a higher degree of comprehensiveness in processing and interpreting texts on specified concepts. Compared with the results derived from literature reviews of previous studies, no differences are found in the empirical results of this study. This implies that the results of the semi-automatic analysis of text big data are reasonable and clearly reveal the framework of existing literature reviews. Thus, by adopting the proposed machine learning-based literature review approach, researchers will be able to investigate the evolving overview of research topics and gain an understanding of its surroundings. Furthermore, the approach is expected to help researchers gain insights into other interdisciplinary topics across engineering, science, sociology, and humanities.

This research clearly contributes to literature, but it also has some limitations. First, the results of the study can change with the data used. That is, if the sources or the collection periods of the data changes, the results will also change. All scientific data available from the databases of Web of Science and Scopus are considered in this study. As such, future studies may extend or reduce the scope and sources of data to other database or domains (e.g., innovation research or journals on operational management) depending on the objectives of the research. For example, data from news or on patents may be analyzed to further understand the technical aspects required for AI services. Second, the machine learning-based approach for literature review does not offer detailed information on each key topic. The analysis focuses more on the identification and classification of the topics rather than on the interpretation of the details of each article. Therefore, a structured literature review on certain topics is required for more detailed reviews on specific aspects of AI services (e.g., interface architecture or service quality evaluation systems).

Acknowledgements This work was supported by the National Research Foundation of Korea grant funded by the Korea government (MSIT) (No. 2022R1G1A1008312) and the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2021S1A5A2A03065747).

Funding This work was funded by the National Research Foundation of Korea grant funded by the Korea government (MSIT) (No. 2022R1G1A1008312).

Data availability The data that support the findings of this study are available from the first author [minjun@kumoh.ac.kr] upon request.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line

to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Abu-Rumman A, Al Shraah A, Al-Madi F, Alfalah T (2021) Entrepreneurial networks, entrepreneurial orientation, and performance of small and medium enterprises: are dynamic capabilities the missing link? *J Innov Entrep* 10(29):1–16
- Akdım K, Casaló LV (2023) Perceived value of AI-based recommendations service: the case of voice assistants. *Serv Bus* 17(1):81–112
- Akter S, Wamba SF, Mariani M, Hani U (2021) How to build an AI climate-driven service analytics capability for innovation and performance in industrial markets? *Ind Mark Manag* 97:258–273
- Alberternst S, Anisimov A, Antakli A, Duppe B, Hoffmann H, Meiser M, Muaz M, Spieldenner D, Zinnikus I (2021) Orchestrating heterogeneous devices and AI services as virtual sensors for secure cloud-based IoT applications. *Sensors* 21(22):7509
- Ameen N, Tarhini A, Reppel A, Anand A (2021) Customer experiences in the age of artificial intelligence. *Comput Hum Behav* 114:106548
- Anton E, Oesterreich TD, Schuir J, Protz L, Teuteberg F (2021) A business model taxonomy for startups in the electric power industry—the electrifying effect of artificial intelligence on business model innovation. *Int J Innov Technol Manag* 18(3):2150004
- Ashfaq M, Yun J, Yu S, Loureiro SMC (2020) I, Chatbot: modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telemat Inform* 54:101473
- Atwal G, Bryson D (2021) Antecedents of intention to adopt artificial intelligence services by consumers in personal financial investing. *Strateg Change* 30(3):293–298
- Baek CH, Kim SY, Lim SU, Xiong J (2021) Quality evaluation model of artificial intelligence service for startups. *Int J Entrepreneurial Behav Res*. <https://doi.org/10.1108/IJEBR-03-2021-0223>
- Belk RW, Belanche D, Flavián C (2023) Key concepts in artificial intelligence and technologies 4.0 in services. *Serv Bus* 17:1–9
- Blei DM, Ng AY, Jordan MI (2003) Latent Dirichlet allocation. *J Mach Learn Res* 3(Jan):993–1022
- Cai R, Cain LN, Jeon H (2022) Customers' perceptions of hotel AI-enabled voice assistants: does brand matter? *Int J Contemp Hosp Manag* 34(8):2807–2831
- Castillo D, Canhoto AI, Said E (2021) The dark side of AI-powered service interactions: exploring the process of co-destruction from the customer perspective. *Serv Ind J* 41(13–14):900–925
- Chen A, Pan Y, Li L, Yu Y (2022) Are you willing to forgive AI? Service recovery from medical AI service failure. *Ind Manag Data Syst* 122(11):2540–2557
- Chi OH, Denton G, Gursoy D (2020) Artificially intelligent device use in service delivery: a systematic review, synthesis, and research agenda. *J Hosp Mark* 29(7):757–786
- Chin JH, Do C, Kim M (2022) How to increase sport facility users' intention to use AI fitness services: based on the technology adoption model. *Int J Environ Res Public Health* 19(21):14453
- Davenport TH, Ronanki R (2018) Artificial intelligence for the real world. *Harv Bus Rev* 96(1):108–116
- Davenport T, Guha A, Grewal D, Bressgott T (2020) How artificial intelligence will change the future of marketing. *J Acad Mark Sci* 48(1):24–42
- De Visser EJ, Monfort SS, Goodyear K, Lu L, O'Hara M, Lee MR, Parasuraman KF (2017) A little anthropomorphism goes a long way. *Hum Factors* 59(1):116–133
- Di Nuovo A, Broz F, Wang N, Belpaeme T, Cangelosi A, Jones R, Esposito R, Cavallo F, Dario P (2018) The multi-modal interface of robot-era multi-robot services tailored for the elderly. *Intell Serv Robot* 11:109–126
- Esmailzadeh H, Vaezi R (2022) Conscious empathic ai in service. *J Serv Res* 25(4):549–564
- Flavián C, Casaló LV (2021) Artificial intelligence in services: current trends, benefits and challenges. *Serv Ind J* 41(13–14):853–859

- Flavián C, Pérez-Rueda A, Belanche D, Casaló LV (2022) Intention to use analytical artificial intelligence (AI) in services—the effect of technology readiness and awareness. *J Serv Manag* 33(2):293–320
- Fortunato S, Bergstrom CT, Börner K, Evans JA, Helbing D, Milojević S, Petersen AM, Radicchi F, Sinatra R, Uzzi B, Vespignani A, Waltman L, Wang D, Barabási AL (2018) Science of science. *Science*. <https://doi.org/10.1126/science.aao0185>
- Füller J, Hutter K, Wahl J, Bilgram V, Tekic Z (2022) How AI revolutionizes innovation management—perceptions and implementation preferences of AI-based innovators. *Technol Forecast Soc Change* 178:121598
- Gec S, Kočovski P, Lavbič D, Stankovski V (2023) Multi-party smart contract for an AI services ecosystem: an application to smart construction. *Concurr Comput* 35:e6895. <https://doi.org/10.1002/cpe.6895>
- Ghazal M, Yaghi M, Gad A, El BaryAlhalabi GM, Alkhedher M, El-Baz AS (2021) AI-powered service robotics for independent shopping experiences by elderly and disabled people. *Appl Sci* 11(19):9007
- Huang B, Philp M (2021) When AI-based services fail: examining the effect of the self-AI connection on willingness to share negative word-of-mouth after service failures. *Serv Ind J* 41(13–14):877–899
- Huang MH, Rust RT (2018) Artificial intelligence in service. *J Serv Res* 21(2):155–172
- Huang MH, Rust RT (2021) Engaged to a robot? The role of AI in service. *J Serv Res* 24(1):30–41
- Huang MH, Rust RT (2022) AI as customer. *J Serv Manag* 33(2):210–220
- Hussein Al-shami SA, Mamun AA, Ahmed EM, Rashid N (2022) Artificial intelligent towards hotels' competitive advantage. An exploratory study from the UAE. *Foresight* 24(5):625–636
- Joerin A, Rauws M, Ackerman ML (2019) Psychological artificial intelligence service, Tess: delivering on-demand support to patients and their caregivers: technical report. *Cureus* 11(1):e3972
- Kelly S, Kaye SA, Oviedo-Trespalacios O (2022) What factors contribute to acceptance of artificial intelligence? A systematic review. *Telemat Inform* 77:101925. <https://doi.org/10.1016/j.tele.2022.101925>
- Kim M, Trimi S (2023) Transforming data into information for smart services: integration of morphological analysis and text mining. *Serv Bus* 17:257–280
- Kim M, Lim C, Hsuan J (2023) From technology enablers to circular economy: Data-driven understanding of the overview of servitization and product–service systems in Industry 4.0. *Comput Ind* 148:103908. <https://doi.org/10.1016/j.compind.2023.103908>
- Kirkpatrick K (2017) AI in contact centers. *Commun ACM* 60(8):18–19
- Kitsios F, Kamariotou M (2021) Artificial intelligence and business strategy towards digital transformation: a research agenda. *Sustainability* 13(4):2025
- Kumar P, Sharma SK, Dutot V (2023) Artificial intelligence (AI)-enabled CRM capability in healthcare: the impact on service innovation. *J Inf Manag* 69:102598
- Kwon HM, Seo J (2022) Effect of compressed sensing rates and video resolutions on a posenet model in an aiot system. *Appl Sci* 12(19):9938
- Lee SM, Lee D (2020) “Untact”: a new customer service strategy in the digital age. *Serv Bus* 14(1):1–22
- Lee C, Kim S, Kim J, Lim C, Jung M (2022a) Challenges of diet planning for children using artificial intelligence. *Nutr Res Pract* 16(6):801–812
- Lee H, Lee N, Lee S (2022b) A method of deep learning model optimization for image classification on edge device. *Sensors* 22(19):7344
- Letaief KB, Chen W, Shi Y, Zhang J, Zhang YJA (2019) The roadmap to 6G: AI empowered wireless networks. *IEEE Commun Mag* 57(8):84–90
- Li M, Yin D, Qiu H, Bai B (2021) A systematic review of AI technology-based service encounters: implications for hospitality and tourism operations. *Int J Hosp Manag* 95:102930
- Li J, Lin F, Yang L, Huang D (2022a) AI service placement for multi-access edge intelligence systems in 6G. *IEEE Trans Netw Sci Eng*. <https://doi.org/10.1109/TNSE.2022.3228815>
- Li C, Zhou Y, Chao G, Chu D (2022b) Understanding users' requirements precisely: a double Bi-LSTM-CRF joint model for detecting user's intentions and slot tags. *Neural Comput Appl* 34(16):13639–13648
- Lim C, Maglio PP (2018) Data-driven understanding of smart service systems through text mining. *Serv Sci* 10(2):154–180
- Lim C, Kim MJ, Kim KH, Kim KJ, Maglio PP (2018) Using data to advance service: managerial issues and theoretical implications from action research. *J Serv Theory Pract* 28(1):99–128
- Lin CJ (2007) Projected gradient methods for nonnegative matrix factorization. *Neural Comput* 19(10):2756–2779

- Lins S, Pandl KD, Teigeler H, Thiebes S, Bayer C, Sunyaev A (2021) Artificial intelligence as a service. *Bus Inf Syst Eng* 63(4):441–456
- Liu P, Jiang W, Wang X, Li H, Sun H (2020) Research and application of artificial intelligence service platform for the power field. *GEI* 3(2):175–185. <https://doi.org/10.1016/j.gloei.2020.05.009>
- Longabaugh B (2012) Visualizing adjacency matrices in python. <http://sociograph.blogspot.com/2012/11/visualizing-adjacency-matrices-in-python.html>
- Loureiro SMC, Guerreiro J, Tussyadiah I (2021) Artificial intelligence in business: state of the art and future research agenda. *J Bus Res* 129:911–926
- Loureiro SMC, Bilro RG, Neto D (2023) Working with AI: can stress bring happiness? *Serv Bus* 17(1):233–255
- Mariani MM, Machado I, Nambisan S (2023) Types of innovation and artificial intelligence: a systematic quantitative literature review and research agenda. *J Bus Res* 155:113364
- Marinakos V, Koutsellis T, Nikas A, Doukas H (2021) AI and data democratisation for intelligent energy management. *Energies* 14(14):4341
- Megaró A, Carrubbo L, Polese F, Sirianni CA (2022) Triggering a patient-driven service innovation to foster the service ecosystem well-being: a case study. *TQM J*. <https://doi.org/10.1108/TQM-02-2022-0072>
- Meurisch C, Mühlhäuser M (2021) Data protection in AI services: a survey. *ACM Comput Surv* 54(2):1–38
- Molinillo S, Rejón-Guardia F, Anaya-Sánchez R (2023) Exploring the antecedents of customers' willingness to use service robots in restaurants. *Serv Bus* 17(1):167–193
- Neuhöfer B, Magnus B, Celuch K (2020) The impact of artificial intelligence on event experiences: a scenario technique approach. *Electron Mark* 31(3):601–617
- Nguyen TM, Malik A (2022) A two-wave cross-lagged study on AI service quality: the moderating effects of the job level and job role. *Br J Manag* 33(3):1221–1237
- Noh H, Jo Y, Lee S (2015) Keyword selection and processing strategy for applying text mining to patent analysis. *Expert Syst Appl* 42(9):4348–4360
- Noor N, Hill SR, Troshani I (2022) Developing a service quality scale for artificial intelligence service agents. *Eur J Mark* 56:1301–1336
- Ostrom AL, Fotheringham D, Bitner MJ (2019) Customer acceptance of AI in service encounters: understanding antecedents and consequence. In: Maglio PP, Kieliszewski CA, Spohrer JC, Lyons K, Patricio L, Sawatani Y (eds) *Handbook of service science*, vol II. Springer, Cham, pp 77–103
- Ouyang F, Jiao P (2021) Artificial intelligence in education: the three paradigms. *Comput Educ* 2:100020
- Park JS, Park JH (2020) Future trends of IoT, 5G mobile networks, and AI: challenges, opportunities, and solutions. *J Inf Process* 16(4):743–749
- Payne EH, Dahl AJ, Peltier J (2021a) Digital servitization value co-creation framework for AI services: a research agenda for digital transformation in financial service ecosystems. *J Res Interact Mark* 15(2):200–222
- Payne EH, Peltier J, Barger VA (2021b) Enhancing the value co-creation process: artificial intelligence and mobile banking service platforms. *J Res Interact Mark* 15(1):68–85
- Peng C, van Doorn J, Eggers F, Wieringa JE (2022) The effect of required warmth on consumer acceptance of artificial intelligence in service: the moderating role of AI-human collaboration. *J Inf Manag* 66:102533
- Poole DL, Mackworth AK (2010) *Artificial intelligence: foundations of computational agents*. Cambridge University Press, Cambridge
- Prentice C, Lopes SD, Wang X (2020) The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty. *J Hosp Mark Manag* 29(7):739–756
- Rajput S, Singh SP (2019) Connecting circular economy and industry 4.0. *Int Int J Inf Manag* 49:98–113
- Riikkinen M, Saarijärvi H, Sarlin P, Lähteenmäki I (2018) Using artificial intelligence to create value in insurance. *Int J Bank Mark* 36(6):1145–1168
- Rodríguez-Barroso N, Stipcich G, Jiménez-López D, Ruiz-Millán JA, Martínez-Cámara E, González-Seco G, Luzón MV, Veganzones MA, Herrera F (2020) Federated learning and differential privacy: software tools analysis, the Sherpa.ai FL framework and methodological guidelines for preserving data privacy. *Inf Fusion* 64:270–292
- Rousseeuw PJ (1987) Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *J Comput Appl Math* 20:53–65

- Ruan Y, Mezei J (2022) When do AI chatbots lead to higher customer satisfaction than human frontline employees in online shopping assistance? Considering product attribute type. *J Retail Consum Serv* 68:103059
- Russell S, Dewey D, Tegmark M (2015) Research priorities for robust and beneficial artificial intelligence. *AI Mag.* 36(4):105–114
- Rust RT (2020) The future of marketing. *Int J Res Mark* 37(1):15–26
- Song CS, Kim YK (2022) The role of the human-robot interaction in consumers' acceptance of humanoid retail service robots. *J Bus Res* 146:489–503
- Tseng KK, Zhang R, Chen CM, Hassan MM (2021) DNetUnet: a semi-supervised CNN of medical image segmentation for super-computing AI service. *J Supercomput* 77:3594–3615
- Valadares DCG, De Oliveira Filho TB, Meneses TF, Santos DF, Perkusich A (2022) Automating the deployment of artificial intelligence services in multiaccess edge computing scenarios. *IEEE Access* 10:100736–100745
- Van Doorn J, Mende M, Noble SM, Hulland J, Ostrom AL, Grewal D, Petersen JA (2017) Domo arigato Mr. Roboto: emergence of automated social presence in organizational frontlines and customers' service experiences. *J Serv Res* 20(1):43–58
- Vassilakopoulou P, Haug A, Salvessen LM, Pappas IO (2023) Developing human/AI interactions for chat-based customer services: lessons learned from the Norwegian government. *Eur J Inf Syst* 32(1):10–22
- von Garrel J, Jahn C (2022) Design framework for the implementation of AI-based (service) business models for small and medium-sized manufacturing enterprises. *J Knowl Econ.* <https://doi.org/10.1007/s13132-022-01029-3>
- Von Luxburg U (2007) A tutorial on spectral clustering. *Stat Comput* 17(4):395–416
- Wirtz J, Patterson PG, Kunz WH, Gruber T, Lu VN, Paluch S, Martins A (2018) Brave new world: service robots in the frontline. *J Serv Manag* 29(5):907–931
- Wirtz J, Kunz W, Paluch S (2021) The service revolution, intelligent automation and service robots. *Eur Bus Rev* 29(5):38–44
- Wu W, Zhou C, Li M, Wu H, Zhou H, Zhang N, Shen X, Zhuang W (2022) AI-native network slicing for 6G networks. *IEEE Wirel Commun* 29(1):96–103
- Xu X, Liu J (2022) Artificial intelligence humor in service recovery. *Ann Tour Res* 95:103439
- Xu Y, Shieh CH, van Esch P, Ling IL (2020) AI customer service: task complexity, problem-solving ability, and usage intention. *Australas Mark J* 28(4):189–199
- Yang K, Shi Y, Yu W, Ding Z (2020) Energy-efficient processing and robust wireless cooperative transmission for edge inference. *IEEE Internet Things J* 7(10):9456–9470
- Yao Q, Wu Z, Zhou W (2022) The impact of social class and service type on preference for AI service robots. *Int J Emerg Mark* 17(4):1049–1066
- Yu G, Tabatabaei M, Mezei J, Zhong Q, Chen S, Li Z, Li J, Shu L, Shu Q (2022) Improving chronic disease management for children with knowledge graphs and artificial intelligence. *Expert Syst Appl* 201:117026
- Zhang M, Gursoy D, Zhu Z, Shi S (2021) Impact of anthropomorphic features of artificially intelligent service robots on consumer acceptance: moderating role of sense of humor. *Int J Contemp Hosp Manag* 33(11):3883–3905
- Zhao J, Fu G (2022) Artificial intelligence-based family health education public service system. *Front Psychol* 13:898107

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.