Review of Managerial Science
https://doi.org/10.1007/s11846-024-00757-x

ORIGINAL PAPER

Artificial intelligence enabled product–service innovation: past achievements and future directions

Rimsha Naeem[1] · Marko Kohtamäki[1] · Vinit Parida[2]

Received: 15 June 2023 / Accepted: 11 March 2024

Abstract

This study intends to scrutinize the role of Artificial Intelligence (AI) in Product-Service Innovation (PSI). The literature on AI enabled PSI, other related innovation business models, product-service systems, and servitization has grown significantly since 2018; therefore, there is a need to structure the literature in a systematic manner and add to what has been studied thus far. Product-service innovation is used to represent the relevance of achieving innovation in business models dealing with innovation outcomes including artificial intelligence. This study used bibliographic coupling to analyze 159 articles emerging from the fields of computer sciences, engineering, social sciences, decision sciences, and management. This review depicts structures of the literature comprising five (5) clusters, namely, (1) technology adoption and transformational barriers, which depicts the barriers faced during the adoption of AI-enabled technologies and following transformation; (2) data-driven capabilities and innovation, which highlights the data-based capabilities supported through AI and innovation; (3) digitally enabled business model innovation, which explained how AI-enabled business model innovation occurs; (4) smart design changes and sustainability, which reveals the working of AI in product service environments with different design changes and transformations based on sustainability; and (5) sectorial application, which highlights industry examples. Each cluster is comprehensively analyzed based on its contents, including central themes, models, theories, and methodologies, which help to identify the gaps and support suggestions for future research directions.

Keywords Artificial intelligence · Digitalization and digital transformation · Product-service innovation · Servitization · Product-service system · Business models and strategy

JEL Classification M10 · M20 · O32

Extended author information available on the last page of the article

Published online: 18 April 2024

1 Introduction

The industrial revolution and digitalization have impacted how manufacturing companies compete today. In the business sector, innovation consistently proves to be a pivotal factor. Companies leverage innovative technologies for product maintenance, service operations, equipment repair, and gathering insights into user behavior. Digitalization in terms of service solutions and delivery systems has overcome the interdependence of manufacturers and allowed them to scale and customize at the same time (Shleha et al. 2023; Vendrell-Herrero et al. 2022). It is estimated that the current market size as of 2024 for digital transformation in global manufacturing stands at approximately USD 367.60 billion, with projections indicating a substantial increase to USD 876.10 billion over the next five years (Mordor 2023). Furthermore, considering service solution delivery through productive capability generation involving distance tracking or monitoring, controlling and optimizing the system or automation has led to the maximization of digitalization (Porter and Heppleman 2014). Therefore, leading the firms to achieve more through well-integration (Vendrell-Herrero et al. 2021).

A solution-based business model considering digital servitization (Brekke et al. 2023; Kohtamäki et al. 2019) allows manufacturers to gain a competitive advantage by using product-service innovation (PSI), providing the opportunity for data sharing knowledge and externalizing risks (Bustinza et al. 2019). According to Bustinza et al. (2019), PSI is *"an integrated product and service offering that delivers value in use" (p. 3)*. There is a need to generate customized service-based augmented innovation through such digitalization based on a solution-based servitization model (Queiroz et al. 2020). This will lead manufacturers to pursue more advanced solutions based on deep learning and AI-based capabilities (Kohtamäki et al. 2022a, b). Artificial intelligence (AI) is radically transforming the traditional way of firms to create, deliver, and capture value. Mariani et al. (2023) stated *"the adoption of AI combined with other digital technologies, supports businesses to adapt or to replace products/services, change the way they create, deliver and capture value, improve their technological capabilities" (p. 9)*. According to market research, the global market for AI in manufacturing has almost doubled from 2022 to 2023 and is expected to increase tenfold by the year 2030 (Precedence 2023).

However, the successful assimilation of AI capabilities in business models and operations is challenging (Sjödin et al. 2021; 2023). Currently, although various businesses are putting millions of people into AI technologies, 70% of these businesses generate minimal or no profit (Koetsier 2020). Eighty-five percent (85%) of AI initiatives eventually do not meet their purported promises to firms (Akula 2021). According to the IBM Global AI Adoption Index 2022, two primary obstacles hinder the advancement of AI: ensuring compliance with management tools across various data environments and addressing the shortage of skills and training in human resources necessary to develop and oversee ethical AI systems (IBM 2022). Artificial intelligence serves a crucial role in decision-making and productivity improvement, aiming to minimize human errors and maximize profitability. For instance, the McKinsey Global Institute projects that by 2030, the widespread adoption of AI will elevate global productivity by 1.2% annually, thereby expanding the global economy by $13 trillion (Bughin et al. 2018). Additionally, Accenture's report highlights that AI is to contribute $8 trillion in value to the U.S. economy by 2035 (Accenture 2016). However, some researchers believe that user perceptions about the implementation of artificial intelligence services are becoming more intriguing and demand additional research (Yang and Hu 2022).

AI is often described as the effort dedicated to creating intelligent machines, where intelligence is the attribute that permits an organization to perform correctly and predictably (Nilsson 2009). AI defines and guides a firm in today's age in the execution of tasks, simple or complex, and ways to improve business operations, manufactured products, and customer services, leading to competitive advantage (Iansiti and Lakhani 2020; Wamba et al. 2021). It is important to remember that introduction of digital technologies can enable new value creation/capture or hinder it (Trischler and Li-Ying 2022), however, it cannot be avoided as *'Innovation is at the heart of digitalization and business model' (*Bouncken et al. 2021*, p1).* The algorithms used in AI are able to provide benefits to both the firm and the customer in the servitization path (Barbieri et al. 2021). The change in bargaining power from firm to customer technological change and innovation in contrast to needs evolution in terms of the AI revolution is the cause of necessity for business model innovation (Kim 2021). In one of the recent studies, AI capacities (i.e. perceptive, predictive and prescriptive capacities) have been highlighted as the enabler for circular business model based on the journey of digital servitization (Sjödin et al. 2023).

Previously, in artificial intelligence, several bibliometric reviews have been conducted in finance (Ahmed et al. 2022), accounting/auditing (Agustí and Orta-Pérez 2022; Goodell et al. 2021; Kraus et al. 2022b), human resource management (Santana and Díaz-Fernández 2023), business-to-business marketing (Han et al. 2021) and are very narrow in perspective (Trischler and Li-Ying 2022). To comprehensively explore the topic, researchers have synergized systematic literature reviews with integrated bibliometric analysis, effectively circumventing the risk of overlooking potential advancements and novel insights, thereby making a significant contribution in the field (Kraus et al. 2022a, 2020). It is also noteworthy that all these additions are recent to the literature, and thus far, there have been no comprehensive reviews created on the role of AI in enabling PSI, product service systems (PSS), servitization, or digital servitization. The reason explained for the research prompting use of AI as an enabler of the innovation process is that business managers can overcome the challenges faced in highly volatile business environments because of rival technologies and competitive global markets (Jones et al. 2016; O'Cass and Wetzels, 2018; Spieth et al. 2014).

According to Kulkov (2021), there is a lack of AI business literature analyzing firms through theoretical concepts and frameworks. It is widely known that AI consists of machine learning, deep learning, and language recognition capabilities (Ahmed et al. 2022), but studies that exclusively include all these capabilities and methods together are lacking. Kulkov (2023) suggested that there is a lack of understanding of how to integrate the approach of business applications of AI in practice.

Furthermore, it is important to understand business model design changes for organizations with innovations such as AI to create and capture value (Sjödin et al. 2021; 2023). Teece (2018) and Stanko et al. (2023) suggest that in the context of business models, capturing value from enabling technologies or architectural innovation is more challenging than capturing value from any other modest innovation. Furthermore, acquiring such a business model can be the reason for organizational challenges, including capacity and resource limitations (Schroeder 2016). To know more about AI-enabled Product Service Innovation importance, the present study proposes research question as "*What is the role of AI in Product-Service innovation, what has been studied previously, and what future research can be done?*".

In order to contribute in literature on AIs' role in enabling business models i.e. product service systems/servitization/digital servitization, our study intends to include most of the AI models and theories in the context of product-service innovation (PSI) by identifying the structure of the literature through employing bibliographic coupling, which results in five (5) research clusters/streams, including (1) technology adoption and transformational barriers, (2) data-driven capabilities and innovation, (3) digitally enabled business model innovation, (4) smart design changes and sustainability, and (5) sectoral application. The study used content analysis of individual clusters to scrutinize the central themes, models, theories, and methodologies involved within each cluster. Further reflection on these clusters helps highlight the gaps in the related studies, which further leads to the formation of future research perspectives. The focus of this study is not limited to AI as a separate field but instead it focuses on AI's contribution in business models (Jorzik et al. 2023), including product service systems, servitization, and digital servitization (Bustinza et al. 2019).

2 Review methodology

To conduct a systematic review content analysis, we started by creating a dataset of articles by setting two search strings to search the databases. In this study, the search tool used was Elsevier's Scopus, which is considered the best for finding peer-reviewed scholarly articles (Rabetino et al. 2021). For the first search string, we use 'Artificial Intelligence', and alternative keywords like "machine learning" or "machine*learning" or "learning system*" or "neural network*" or "deep learning" or "support vector machine*" or "decision tree*" or "decision support system*" or "artificial neural network*" or "supervised learning" or "random forest" or "natural language processing" or "reinforcement learning" or "text processing" or "fuzzy logic" or "fuzzy approach" or "Bayesian network*" or "fuzzy test" or "stochastic systems" or "AI" or "LSTM".

However, to determine the relationship between the AI and PSI, we recorded a second search string. It includes keywords such as "product-service innovation" or "productservice innovation" or "servitiz*" or "servitis*" or "product-service system" or "smart product" or "smart service" or "intelligent product" or "product-service systems" or "productservice system(pss)" or "product service system" or "digital transformation framework" or "service innovation" or "sustainable product-service systems" or "sustainable product-service system" or "service transition" or "business model innovation" or "service transfusion". Hence, the most appropriate definition for understanding AI according to these research strings could be *"AI technology can provide the foundation for successful digital servitization and business model innovation; simply spending money on digital infrastructure, technologies, and data is not enough. New routines, skills, operational processes, and business models are required in making use of AI technology to create value for customers"* (Sjödin et al. 2021 p.1). Product-service innovation is a new business model in this context.

As Fig. 1 shows, the title, abstract, and keyword search of the Scopus database produced a total of 1096 publications, which were further delimited to the subject areas of computer science, engineering, business management, accounting, social science, decision sciences, economics, econometrics, and finance, resulting in 444 articles. These articles were manually scrutinized, exempting nonrelevant articles from the search, excluding pure computer science papers, and not including AI papers with nonbusiness research. The selection criteria included studies with considerable matches from both the fields of management/business/economics/econometrics/accounting/finance and computer science/decision science. The final selection yielded 200 articles. However, while uploading the data on VOSviewer, the disconnected articles were eliminated, thus providing 159 articles as connected studies for review. In this dataset, the largest number of articles were published by *Computers in Industry*, *Journal of Business Research*, and *International Journal of Production Research*. The content analysis of individual clusters scrutinizes the central themes, models, theories, and methodologies involved within each cluster (Kohtamäki et al. 2022a, b).

In the field of management, a systematic manner of review has gained increased popularity because it provides synthesis for the decision and policy-makers (Kraus et al. 2024, 2020; Sauer and Seuring 2023). We used VOSviewer software (Waltman et al. 2010) to conduct bibliographic coupling with 159 articles on AI-enabled PSIs. Bibliographic coupling is an appropriate bibliometric method for identifying the structure of the literature and understanding trends in research fields (Khanra et al. 2021; Vogel and Güttel 2013; Zupic and Čater 2015). When choosing the type of analysis and counting method in VOSviewer, we selected bibliographic coupling and the unit of analysis as documents and the counting method as fractional. Due to the small size of the dataset, we did not apply a minimum number of citations or set the resolution to 0.98 or the minimum cluster size to 21. We chose bibliographic coupling as an analysis method because it uses individual articles as a unit of analysis and functions well with a relatively limited amount of data (Xu et al. 2018). After performing the bibliometric analysis on the dataset, we move toward conducting a systematic review (Kraus et al. 2023) of the content by thoroughly reading the articles comprising each cluster and coding them accordingly based on the research content involved. The key intellectual interest that the documents in a cluster may analyze is reflected by the themes (Shiau et al. 2017; Small 1973).

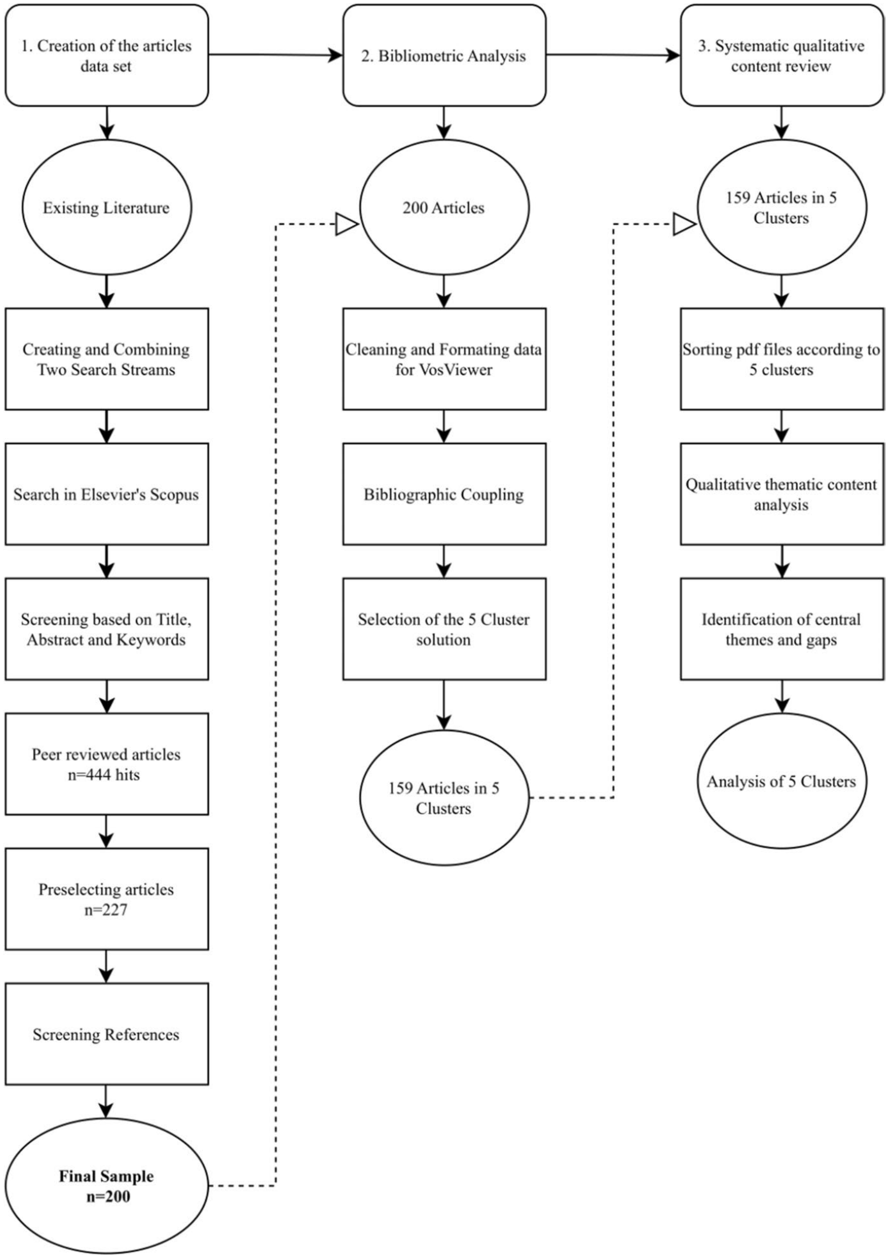

Fig. 1 Review process

3 Mapping the structure of the field

Artificial intelligence (AI) emerged as a scientific discipline in the last century, with its essence encapsulated in McCarthy's (McCarthy and Hayes 1981) definition, characterizing AI as a type of machine capable of intelligent behavior. This definition laid the groundwork for teaching computers to perform tasks more efficiently than humans, as highlighted by Rich in 1985. The concept of machine learning, an integral aspect of AI, was introduced by Arthur Samuel as early as 1959. Even after 2017, machine learning has continued to persist as a subfield within the broader domain of AI (Bhavsar et al. 2017). Hence, since 2018, the number of studies has expanded considerably and included AI-related techniques and models. According to Hahn et al. 2020, *"the use of AI can provide significant value to those companies that are willing to actively invest in and use AI in their business models. Implementing artificial intelligence in a company's business model seems to provide enormous advantages and can function as an important competitive advantage"*. However, product-service innovation can be alternately used with servitization; it is particularly useful for IT processes, where it is possible to analyze the relationship with innovation outcomes (Vendrell-Herrero et al. 2019).

The results of 159 documents and their temporal distribution can be seen in Fig. 2. A considerable number of articles were published after 2018, reaching a maximum of 36 articles published in 2021, 34 in 2021, 24 in 2020, and 16 in 2019, and a minimum of 4 in 2018, before this curve gradually increased. Currently, 41 papers have been published, 12 of which we have included. We believe that the literature is predicted to increase in the coming years. It is possible to conclude that AI in the field of product-service innovation has been an area of great interest in recent years. Here, in Fig. 3, we used the bibliographic coupling technique to form clusters on VOSviewer for the 159 articles whose information was disconnected from that of other articles. We validated the disconnect of articles, given that the theme

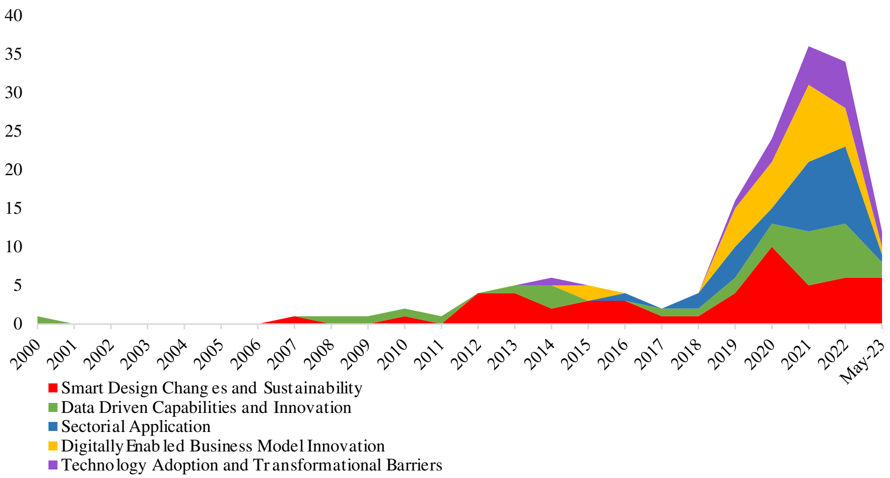

Fig. 2 Number of articles per cluster

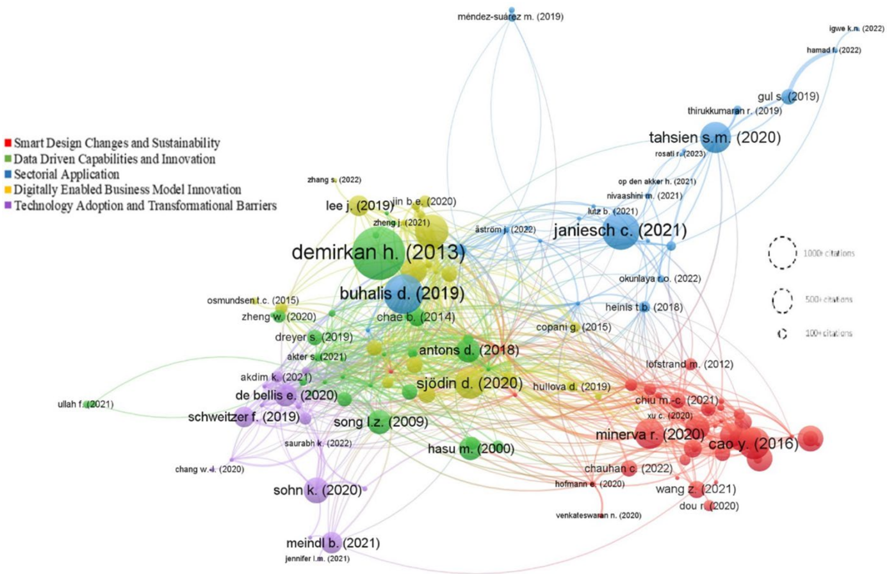

Fig. 3 Identification of the main clusters of research

formation of the clusters was not included. The figure shows the formation of clusters, which can be identified based on their color. The size of the circle for each study indicates the number of citations the study has received thus far. The distance between each circle reflects the number of shared citations in the list of references. The more visible the line is, the greater the number of similar citations the studies shared.

The analysis produced five (5) clusters, which were validated through careful reading of the papers and building themes of the clusters. However, some of the studies on the borders of the clusters may be considered well suited for the other clusters. For example, Buhalis et al. (2019), although belonging to the sectorial application based on the study performed on hospitality and tourism, is cited in the highest number of articles, it could be easily considered a part of the technology adoption and transformational barriers, as it explains the technological adoption disruption in the services.

3.1 Technology adoption and transformational barriers

"Autonomous…systems change…process profoundly by reducing or even eliminating the need for human decision-making, thereby challenging deep-rooted human–machine relationships" (de Bellis and Venkataramani Johar 2020, p. 75).

3.1.1 Central themes

In this cluster, technology adoption and transformational barriers are reflected through the challenges that occur in the adoption of AI in product/service innovation. The cluster emphasizes several key themes including the "adoption barrier" surrounding autonomous technology in shopping systems (de Bellis and Venkataramani Johar 2020), the challenges inherent in smart hospitality services (Wong et al. 2022), the utilization of voice-controlled devices (Schweitzer et al. 2019), and the complexities of "ethical digital transformation" processes (Qian et al. 2023; Saurabh et al. 2022). Additionally, the application of construal level theory was instrumental in assessing reactions toward autonomous technology "robots" (Akdim et al. 2021).

While many related studies explore "AI assist" technologies, only a handful explicitly mention them, such as Alexa and smart chatbots (Fotheringham and Wiles 2022; Hsieh and Lee 2021). Customer perception regarding the introduction of new technology is crucially tied to its recognition and acceptance to bridge the gap between service development stages (Zolfagharian and Paswan 2008). In the service sector, particularly with AI, there is significant concern about the effectiveness of AI in evaluating and predicting customers' purchase intentions and transformation of legal services fueling an ongoing debate between humans and AI (Brooks et al. 2020; Yang and Hu 2022).

3.1.2 Models and theories

The literature in this cluster was not as extensive as that in other clusters, as it contained only 18 studies. Some theories help overcome these challenges and help researchers understand the use of AI technologies in business systems. Theories such as self-extension theory (Schweitzer et al. 2019) explain how consumers feel when confronted with technology and how autonomy comes into question. This explains that the customer feels that the product becomes an extension to serve the purpose of fulfilling his or her needs. The adoption barrier of technology is addressed by using a cross-disciplinary approach. The change occurring due to this adoption leads to a delegation of decisions and further tasks to technology. Researchers obtained answers through robots or chatbots and through AI-based self-checkout. They proposed barrier reduction by targeted intervention in technology during times of usage by consumers (de Bellis and Venkataramani Johar 2020).

It is observed that Artificial Intelligence (AI) and robo-advisory services are instigating transformative shifts within the financial services sector. Through the application of artificial neural network analysis, it was discerned that perceived intelligence stands out as the foremost determinant of acceptance within the industry. Consequently, this perspective challenges the conventional linear and symmetric viewpoints prevalent in earlier literature. (Aw et al. 2023). This cluster effectively addresses technologies that are becoming self-aware, capable of making judgments, and doing activities in the name of users. To investigate obstacles to the implementation of autonomous networks, a multidisciplinary approach is used that focuses on review studies in economics, psychology, and human–computer interaction.

Researchers highlight several psychological and cultural hurdles and propose solutions to design online and physical commerce platforms that remove these obstacles (de Bellis and Venkataramani Johar 2020). To evaluate the effectiveness of AI-based intelligent devices, different theories have been proposed, e.g., the theory of planned behavior, the technology acceptance model, the unified theory of acceptance and use of technology, and the value-based adoption model for modeling user acceptance of technology for the specific purpose of using AI-based intelligent commodities (Sohn and Kwon 2020).

Disruptions in industry, economy, and society have occurred when the integration of production processes with technologies such as robotics and sensors has generated innovation. Researchers have emphasized the impact of innovativeness through bibliographic design on helping governments obtain financial stability and encouraging them to invest in technology enhancement, leading to updated academic systems and creating innovation through new methodologies and skills (Jennifer et al. 2021). The adoption of behavioral reasoning theory is used to debate autonomous vehicle use and the adoption of autonomous solutions through ethical effects in society. In addition to considering environmental benefits, there are certain risks associated with sharing roads with autonomous vehicles in comparison to human health. The immature algorithms currently used are not as developed to avoid problems in crash response (Qian et al. 2023). Challenges occur in deciding on the ethical values of AI-led technologies, and the "AI-led ethical digital transformation framework" is important for changing the current processes involved in manufacturing and introducing new processes into the business model (Saurabh et al. 2022).

3.1.3 Methodologies

This cluster is equally exploratory and experimental in nature, using qualitative methods such as case studies, single cases (17%), or no multiple cases. Surveys (22%) are included, for instance, to understand user acceptance in terms of behavioral intention to use AI-based intelligent products (Sohn and Kwon 2020), and 3 review papers (17%) include a comprehensive literature search using machine learning. Studies included, performed a temporal analysis method, taking into account the evolution of these four aspects of Industry 4.0 (Meindl et al. 2021) and consisted of interview-based studies (11%). Consequently, studies in this cluster also include experimental studies (17%), where if, how, and why utilizing a voice assistant drastically influences users' level of satisfaction and behavioral intentions and how augmented reality (AR) provides better customer satisfaction are investigated (Fan et al. 2022).

3.2 Data-driven capabilities and innovation

"Organizations that excel at connecting businesses, aggregating the data that flows among them, and extracting its value through analytics and AI will have the upper hand" (Iansiti and Lakhani 2020, p.65).

3.2.1 Central themes

This cluster effectively addresses the companies moving toward agile methods of data-based decision-making through the introduction of innovative technologies, i.e., artificial intelligence, for the companies to be operated more smartly and to have a meaningful, effective, and efficient business using “decision support service” (Demirkan and Delen 2013). The computational electronic contexts of AI are used to interact, cooperate, exchange views, and assist decision-making. AI is referred to as a technological driver that helps individuals make “guided decisions”, resulting in profitable businesses (Anton et al. 2021). Innovative companies have swiftly integrated artificial intelligence into existing service ecosystems, fundamentally altering notions of service quality and service delivery in their particular sectors. Researchers have explored through the service innovation paradigm that AI services influence “data-driven decisions”, “data-driven decision-making capabilities”, “augmented decision-making capabilities” and “technology-led innovations” (Akter et al. 2021; Chae 2014; Kandampully et al. 2022; Song et al. 2009).

3.2.2 Models and theories

One of the most prominent studies in this cluster highlights the innovation viewpoint and the role of data capture. The decision support system helps organizations make smart decisions based on data analytics. Such data management can lead to the development of new products, services, and business models. Furthermore, investing in data capabilities can lead to better performance for the firm (Demirkan and Delen 2013). Another study followed the decision support service tool with the service quality model at the service design stage. Here, it helps to collect and analyze feedback from customers in the form of improving service performance through data-driven decisions (Song et al. 2009). However, it is argued that technology-led innovations in service businesses such as hospitality businesses are often due to not only research and development but also the input of employees in generating value data on emotions are collected through employees input on a firm’s idea generation and innovation. Many large companies, including Marriott Hotels, Singapore Airlines, Disney, Southwest Airlines, and Starbucks, are utilizing the potential of their data capabilities through employees (Kandampully et al. 2022).

In another case, in the hospitality industry, the fuzzy quality function deployment framework, which receives various inputs in the form of linguistic data, from tourist perception, judgment, and evolution, has been adopted in new service development, enabling hotel managers to achieve a competitive advantage in tourist service management. The use of the fuzzy approach in service design has made it possible to measure attributes that are otherwise not easy to calculate and deal well with uncertain relationships and builds answers for “how” and “what”(Lin et al. 2011). Another example of business-to-business service innovation achieved through data capability utilization to understand firm risk and value is studied; thus, when a company gains both service innovation and product innovations, it should combine them to generate hybrid innovations with a decision at the strategy level, thus causing an increase in firm value from business to business (Dotzel et al. 2019).

Activity theory/systems are used in innovation capacity to study the historical background and object orientation of technological development and a firm's ability to innovate with data. This helps in the study of tensions and conflicts in organizational structures to determine support and knowledge sharing (Hasu and Engeström 2000). Akter et al. (2021) agree that AI relies on big data sources that further use machine learning and deep learning to identify patterns and learning processes. Furthermore, service analytics and data-driven decision-making capabilities are dependent on AI applications. The use of the theory of micro-foundations of dynamic capabilities confirms that the related literature is connected with the big data analytics literature. Another study explains that digital dynamic capabilities in the context of AI and their role in changing the business model via digital servitization are bound to rearrange their activity system and therefore cause changes in their value creation process (Čirjevskis 2022). This helps firms make critical strategic and operational service decisions based on and improve firm performance (Barile et al. 2021).

AI capabilities, such as data processing or cognition or augmented reality, are considered a form of numerous smart services, and using AI during service provision enhances service evaluation and service satisfaction (Gäthke 2020; Leung and Loo 2022). Another study used Ackoffs's pyramid based on data information knowledge wisdom, hence increasing the efficiency of augmented decision-making capabilities. Users of AI technology interact through a viable system approach, complex adaptive systems, and information technology-enabled service inventions, such as a process of variation selection and retention, thus increasing the overall potential of system and data management (Chae 2014). The positive relationship between unstructured data and the potential of a firm to enable service innovation capabilities informs that data analysis using techniques such as 'entity matching classification using text' and keywords in context analysis using machine learning can eliminate biases in data and enhance performance (Kohler et al. 2014).

3.2.3 Methodologies

The studies included in this cluster did not primarily use one specific dominant methodology; rather, they had a good mix of methodologies. In the total categorization, this cluster had 4 single case studies (13%), 3 multiple case studies (9%), 4 survey studies (13%), 3 interview studies (9%), 2 questionnaire-based studies (6%), 5 experiment-based studies (16%), 5 quantitative studies (16%) and 7 studies (22%) with framework design and development. However, this cluster is important in context because it includes five review studies, with a bibliometric review of AI and its types by Mariani et al. (2023) and of the role of unsupervised machine learning in smart services by Nahr and Heikkilä (2022). Experiment-based surveys are conducted to perform quantitative assessments within businesses to study the impact of AI-based technology in business ecosystems (Agarwal et al. 2022).

3.3 Digitally enabled business model innovation

"Business model innovation (BMI) depends on changes; if there is no change, there is no need for BMI. In other words, when there happen changes, BMI should be done" (Kim 2021,p.1).

3.3.1 Central themes

This cluster holds the key understanding of how AI technology is being used in business model innovation, not only in the PSS but also in relevant studies, including those on servitization and digital servitization. The business model evolution and the extent to which digitalization (maximum point) is reached using AI-enabled capabilities. The papers include business models frequently cited by business and management researchers. Prominent researchers in this cluster, Sjödin et al. (2020, 2021), emphasized digital servitization and business model innovation. In this cluster, the emerging themes include "servitization", "digital servitization" and "product service systems (PSS)" and the conversion of standard products and services to smart solutions (Y. Chen et al. 2021).

The research stream further probe into business model digital transformation with AI (Burström et al. 2021). The emerging themes in this cluster further include "service innovation"(Osmundsen et al. 2015; Qvist-Sørensen 2020); "business model innovation" due to AI; and how the techno-economic era started to dramatically change around the 2010s and the need for adaptiveness evolution in technological change to survive to follow dynamic management (Kim 2021) and "innovation strategies" (Kamalaldin et al. 2021; Yan et al. 2019). Furthermore, it also addresses how the parallel transformation of an AI-based business model affects "customer cocreation, "value creation" and "ecosystems" (Burström et al. 2021; Sjödin et al. 2021; Wirtz and Kowalkowski 2022). The theme of "ecosystem strategies", such as the orchestrator strategy, dominator strategy, complementary strategy, and protector strategy, helps guide suppliers in the configuration of appropriate ecosystem strategies (Kamalaldin et al. 2021).

3.3.2 Models and theories

The literature in this cluster shows a strong orientation around servitization, digital servitization, and business model innovation (BMI) with AI-enabled capabilities and methods. Researchers advance the literature on innovation and business models by highlighting the distinctions among innovation kinds (i.e., BMI, product and process innovation) as well as the related behavior. The knowledge-based theory of innovation indicates that the type of knowledge required for a BMI can impact relevant search behavior, involving the exploration of new combinations and causing changes in the firm value chain. However, this approach is different from process innovation, which is complex and difficult (Snihur and Wiklund 2019).

Then, the research stream focuses on usage of service marketing prediction model (decision tree), which helps independent distributors identify barriers while beginning the servitization journey. To detect servitization readiness, three main problems are addressed, namely, conflict with stakeholders, misalignment between and management in deciding on servitization strategies, and lack of knowledge within the ecosystem (Hullova et al. 2019). Additionally, the retail industry comprises disruptive business-model advancements. Researchers have investigated three industry disruptors that include born-digital brands, AI-powered demand forecasting, product design and collaborative consumption (Jin and Shin 2020). Probabilistic event-decision tree modeling is used for the economic assessment and to determine the best decision for the firm to take by having the information on events, which allows for better risk assessment in smaller periods and, accordingly, adjusting the returns. Thus, creating a win–win situation that will help make the business model sustainable for both customers and suppliers (Copani and Rosa 2015).

Other studies used the microservice innovation approach to ensure the customization of the digital offering and make the offering scalable. It provides insight into the different phases, activities, and organizational principles of business model innovation (Sjödin et al. 2020). Business ecosystem and business model innovation lenses are used to determine the integration of the innovation process into the firm ecosystem. Integrating AI with altered marketing strategies may perform poorly when transformations are not connected to experienced players or other companies in the broad collection of ecosystem linkages. Organizations that are unable to create a fit-for-purpose environment over an AI-based business plan could collapse in the long term (Burström et al. 2021).

Sjödin et al. (2021) explained the scaling of AI capabilities by using the coevolutionary framework and underscoring the mechanisms for business model transformation and feedback loops. It is recommended that for firms to innovate their business models, they focus on agile cocreation, delivery operations based on data, and scalable ecosystem incorporation. Using the dynamic model and the dynamic complexity of a mobile digital platform, the competitive strategy feedback loops that form the foundation of a mobile business strategy are depicted. It was stressed that businesses must strive to comprehend and capitalize on artificial intelligence feedback loops that influence the company model for business enhancement (Katsamakas and Pavlov 2022). In the machine tool industry, through servitization and machine learning processes, manufacturers benefit by uplifting the business model and adding value by reducing unnecessary downtime (Alegeh et al. 2019). For instance, Chen et al. (2021) focused on the changes in business models through the AI solution provided in the case company, which resulted in gaining value with multiple capture mechanisms, causing discontinuous and continuous changes between business models.

3.3.3 Methodologies

This cluster is mostly exploratory in nature and involves the use of qualitative methods such as case studies, single case studies (28%), or multiple case studies (24%). Interview-based studies (17%) have also been conducted; for instance, to understand how companies have succeeded in implementing AI and transforming business models, researchers have conducted more than 30 interviews involving critical key employees to learn about how they fully applied AI and altered business strategies

(Burström et al. 2021). Only one study used the survey method, one used an experimental method, and three used review papers with one bibliometric analysis (Ávila-Robinson et al. 2022). Multiple exploratory case studies were taken from different industries, manufacturing, telecommunications, energy, and mining (Sjödin et al. 2020), and two interview-based studies (Szabó et al. 2022; Wirtz and Kowalkowski 2022) were performed through purposive sampling, which considered interviews conducted by experts in the industry.

3.4 Smart design changes and sustainability

Smart PSS is defined as "An IT-driven value co-creation business strategy consisting of various stakeholders as the players, intelligent systems as the infrastructure, SCPs(Smart Connected Products) as the media and tools, and their generated services as the key values delivered that continuously strives to meet individual customer needs in a sustainable manner" (Cong et al. 2022, p.1).

3.4.1 Central themes

This cluster was formed through closely located articles in VOSviewer (Fig. 3). These articles mostly address the smart changes that occur through the introduction of AI to businesses. However, the articles are mostly based on engineering and computer research. The themes included are "smart product-service systems", an evolving technology services marketing model that utilizes smart, linked items and provided services to function as a solution package to increase individual user satisfaction (Cong et al. 2022). In smart PSS, "smartness" in a data-driven design helps in the data analysis of large datasets and extracts important results through the use of artificial intelligence (AI) (Z. Wang et al. 2021). AI is used to predict satisfaction levels, recommendation systems, and closed-loop smart design for the engineering lifecycle through machine learning (Chiu et al. 2021; Cong et al. 2022; Zheng et al. 2020).

The PSS takes the form of "industrial smart PSS" (Zheng et al. 2020), "result-oriented PSS" (Sassanelli et al. 2022), and "warehouse PSS" (Zhang et al. 2020), and the concept of "sustainable product-service systems" has been proposed (Xing et al. 2013). Businesses aim for synergy in innovative products/services while maintaining high-quality products/services through collaborative innovation processes and "product and service design changes" (Tseng et al. 2019; Zheng et al. 2020). For instance, creation of a smart manufacturing marketing strategy during the industrial revolution was determined by exceeding consumer expectations and sophisticated algorithms. Thus, offering an efficient, unique product approach with increased performance increasing the cost and production effectiveness (Dou et al. 2020).

3.4.2 Models and theories

In this cluster, the literature consists of theories supporting AI-enabled design changes in PSS in contrast to traditional PSS. The traditional decision-making methods usually do not consider fuzziness or randomness in the data. Therefore, fuzzy theory and group decision-making techniques are incorporated into the supermatrix approach and fuzzy-stochastic environment to obtain accurate and informed results (D. Chen et al. 2015; Geng et al. 2010). Importance–performance analysis is performed to prove that the customer satisfaction evaluation is revised through Kano model integration and further used to identify improvements in PSS strategies to avoid inefficiencies (Geng and Chu 2012). Furthermore, another study employed a model based on service innovation, an agent-based approach, to clarify the uncertainties related to the cost and benefits of contracts via stochastic data analysis. Stochasticity helps in understanding machine learning methods, and its application in analyzing servitization-based contracts through quantifiable numbers contributes to the development of sustainable PSS strategies (Farsi and Erkoyuncu 2021).

The literature highlights the lifecycle approach in the design theory of smart PSS, used to help develop a sustainable model (Zheng et al. 2020). The concept of a digital twin intertwined with AI is used in this cluster to develop smart and sustainable strategies, including smart design, smart manufacturing, smart distribution, smart operation, smart reconfiguration, reuse and recycling strategies (Minerva et al. 2020). In regard to understanding the intangibility of services and therefore assessing and prioritizing client requirements, traditional product design methods are restricted. To overcome this issue, quality function deployment is applied to a service environment by combining fuzzy logic and the analytic hierarchy process to reduce errors (Haber and Fargnoli 2020) and testing approach through data mining and algorithm clustering in PSS design to improve product service innovation (Shimomura et al. 2018).

Studies in this cluster leverage established fuzzy and artificial network models to understand the intricacies of customer advancement within sustainable supply chain systems. A comprehensive examination of the interrelationship hierarchical approach is facilitated through methodologies such as the fuzzy delphi method, fuzzy significant analysis, and the analytic hierarchy method. These tools, as demonstrated by Tseng et al. (2019), provide a structured framework for analyzing complex decision-making processes in sustainable supply chains. Furthermore, the integration of fuzzy theory and cooperative decision-making approaches within artificial network processes offers a robust solution for addressing ambiguity, unpredictability, and diversity in decision-making. This is exemplified through the utilization of supermatrix techniques, as highlighted by Geng et al. (2010), which enable the identification of engineering significance parameters crucial for PSS planning and optimization. By aligning these parameters with sustainability objectives, researchers can discern optimal PSS design specifications aimed at maximizing customer satisfaction while minimizing environmental impact.

The intersection of design changes and sustainability within Product-Service Systems (PSS) has become a focal point in recent research endeavors. particularly AI, to drive PSS modifications geared towards enhancing sustainability while maintaining efficiency and effectiveness. Consequently, there has been a pronounced increase in studies exploring how AI-enabled design changes can be leveraged to instill PSS with sustainable attributes. This includes initiatives such as optimizing resource allocation in smart waste management systems (Pourabbasi and Shokouhyar 2022), enhancing the durability and recyclability of smart bicycle designs, and streamlining improving delivery solutions through smart box innovations (Zheng et al. 2020) and improving health systems (Teixeira et al. 2012). While PSS inherently holds promise for promoting sustainability, it's acknowledged that this potential is not automatically realized without deliberate design interventions. (Xing et al. 2013), the decision support system model is used to align with PSS design. Hence, researchers are actively engaged in developing predictive maintenance algorithms and lifecycle assessment models tailored to evaluate the environmental impact of PSS design alterations. These efforts aim to ensure that sustainability considerations are integral to every stage of the PSS lifecycle, from conception and design to deployment and eventual disposal (Chauhan et al. 2022; Chiu et al. 2021; Cong et al. 2022; Zheng et al. 2020).

In this context, the emphasis on sustainable design changes in Smart PSS underscores the need for interdisciplinary collaboration. Decision support systems are being deployed to align design strategies with sustainability goals, enabling the customization of PSS configurations to meet the diverse needs of customers while optimizing environmental outcomes (M. Chen and Shen 2020). Moreover, the integration of smart product service components emerges as a critical enabler, fostering innovation and adaptability in the pursuit of sustainable PSS solutions that effectively address the complexities of modern socio-environmental challenges (Z. Chen and Ming 2020).

3.4.3 Methodologies

This cluster included 51 studies, which was larger than the other clusters. There is a distinctive use of qualitative research; almost 57% of the studies were case studies based on a single case (55%) or multiple case studies (2%). The effectiveness of the PSS conceptual design is tested in these case studies, and the proposed methods are validated to reach that point (Chiu et al. 2021; Geng et al. 2010). The application of these theories has been demonstrated in industries such as stainless steel manufacturing, crane machines, textile firms, and autonomous vehicles (D. Chen et al. 2015; Z. Chen and Ming 2020; Tseng et al. 2019; X. Wang and Durugbo 2013).

However, there were equal parts of the questionnaire (8%) and interviews (8%), for instance, individual customers were followed by weighting fuzzy clustering, and another included customer feedback gathering through questionnaires and interviews to improve their service innovation (Dou et al. 2020; Tseng et al. 2019). The survey (10%) and framework development approaches (18%) included the fuzzy best–worst method and data envelopment analysis for identifying smart product service components associated with service deployment, asset compatibility, and innovative capabilities (Z. Chen and Ming 2020). In another study, a complex support vector machine concept was developed to design a customized PSS that matched the requirements of the client (Long et al. 2013).

3.5 Sectorial application

In terms of AI, the purpose of sectorial application is to "…gather, process, arrange and disseminate information to target users, the emergence and applications of the state-of-the-art technologies for information services delivery" (Igwe and Sulyman 2022, p. 148).

3.5.1 Central themes

This cluster, positioned from the top-center to the right-center of Fig. 3, encompasses a diverse range of topics, primarily focusing on the sectorial application of AI-enabled PSIs and product service systems. Technological advancements such as autonomous devices and artificial intelligence are paving the way for the creation of smart environments. Researchers explore various service management scenarios, with particular emphasis on the tourism and hospitality industry. They anticipate future disruptions in extrasensory service experiences, hyper-personalized experiences, and beyond-automation experiences (Buhalis et al. 2019). Within this cluster, emerging industry trends include the development of "smart libraries," advancements in "electronics," enhancements in "library services," and the integration of "virtual coaching" (Gul and Bano 2019; Hamad et al. 2022; Igwe and Sulyman 2022; Janiesch et al. 2021; Okunlaya et al. 2022; op den Akker et al. 2021). Furthermore, intelligent libraries exhibit a positive correlation with service innovation and quality (M. Chen and Shen 2020).

Furthermore, themes such as "predictive," "predictive power," and "predictive model" are prominent, emphasizing the utilization of AI techniques, machine learning, deep learning, and fuzzy approaches to generate missing information and accurately predict missing values. Additionally, studies in this cluster explore leveraging AI to counter cyber-attacks (Janiesch et al. 2021; Paredes et al. 2021; Rosati et al. 2022) and detect abnormal behavior in smart devices and networks (Tahsien et al. 2020).

3.5.2 Models and theories

The literature in this cluster follows the main methodological influences in this stream originating from the applicability of machine learning models and deep learning models. Such as, predictive maintenance, as highlighted by Rosati et al. (2022), entails forecasting maintenance activities, while behavior pattern recognition, as exemplified by Hao et al. (2018), involves activity prediction and recognition, facilitating guided decision-making processes. These applications of AI hold promise in significantly reducing costs and enhancing product availability with precision. Moreover, as underscored by Tahsien et al. (2020), AI's capacity to enable new data-driven services and support novel business models should fall under important consideration.

Researchers explore significant technological innovations through the prism of value co-creation, aiming to inform service innovations (Buhalis et al. 2019).

Employing deep learning, an efficient and reliable intelligent service warehousing platform has been developed and validated using hospital data. However, there is a recognized need to enhance the availability and effectiveness of this service platform (Chang et al. 2021). Smart libraries represent the next generation of libraries, integrating smart technologies, intelligent user interactions, and advanced services. Gul and Bano (2019) assert that the rapid development of smart libraries is driven by advancements in smart technologies, enhancing their functional capacities and benefiting library users. The adoption of smart technology in libraries bridges the gap between traditional library services and the evolving needs of users (Hamad et al. 2022).

Servitization has gained substantial interest from the manufacturing industry because of its ability to deliver a competitive advantage. Alternative pricing models, including pay-per-usage models, are required for advanced services; machine learning models capture value and enable the effective assessment of depreciation and the development of pay-per-usage methods for a large variety of industrial support items and product-service systems (Heinis et al. 2018). Another study created an artificial intelligence library services innovative framework to provide a unique perspective on how AI technology may be leveraged to produce value-added creative library services and automated processes by incorporating digitalization structure elements and exploring them by utilizing a service innovation concept (Okunlaya et al. 2022).

3.5.3 Methodologies

This cluster methodologically contains single case studies (17%) and multiple case studies (14%). Only some of the studies contained quantitative studies in which questionnaires (7%) were developed to obtain data and considerable experimental research (28%) was conducted. Exploratory review studies (10%) were conducted using qualitative content analysis to investigate the extant literature. Okunlaya et al. (2022) used content analysis to find an effective way to innovate library services through AI service innovation and delivery. Extensive literature was collected on smart libraries by using Clarivate Analytics, Web of Science, and the Sciverse Scopus (Gul and Bano 2019).

A small number of exploratory interviews (3%) were also used to determine the suitability of strategies for business models (Häckel et al. 2022). As this cluster grows, multiple influences of models and analysis techniques are also observed (28%). All five clusters discussed thus far are compared in Table 1, for better visual representation.

4 Research agenda

The content analysis of the five (5) clusters led to careful considerations about AI-enabled PSIs. Based on these considerations, this study identify the gaps and further build suggestions to help future research.

Table 1 Comparing the five clusters

	AI-enabled PSI				
	Technology adoption and transformational barriers	Data-driven capabilities and innovation	Digitally enabled business model innovation	Smart design changes and sustainability	Sectorial application
Central themes	Adoption barrier Autonomous technology AI-assisted technologies Technology adoption Human versus AI Ethical digital transformation Robots	Guided decisions Augmented decision-making capabilities Technology-led innovations Data-driven decision-making capabilities Service innovation capability	Business model innovation Servitization Digital servitization Service innovation Technology acceptance Ecosystem strategies Customer cocreation Value creation	Smart PSS Closed Loop Design Industrial smart PSS Result-oriented PSS Warehouse PSS Sustainable PSS Product and service design changes	Smart libraries Electronics Library services Virtual coaching Predictive power Service innovation Tourism and hospitality
Models and theories	Construal level Theory (Akdim et al. 2021) (Conceptual theory, Decision Tree for Adoption of technology, Self-extension theory) (Schweitzer et al. 2019) Cross-disciplinary approach (de Bellis and Venkataramani Johar 2020) (Theory of Planned Behavior, Technology Acceptance Model, Unified Theory of Acceptance, and Use of Technology and Value-based Adoption Model) (Sohn and Kwon 2020)	Decision Support System (Demirkan and Delen 2013) Complex adaptive systems (Chae 2014) Fuzzy Quality Function Deployment (Lin et al. 2011) Dynamic Capability theory (Akter et al. 2021) Complexity Theory Approach (Chae 2014) Activity theory/system (Hasu and Engeström, 2000) (5-S Model, Service marketing theory, New Product Development, Service Innovation Model) (Song et al. 2009)	Service marketing prediction model (Hullova et al. 2019) Service Innovation approach (Sjödin et al. 2020) Servitization (Alegeh et al. 2019) Business ecosystem and Business-model innovation (Burström et al. 2021) Co-evolutionary processes and feedback loops(Sjödin et al. 2021) Portfolio Model (Li 2020) Machine learning algorithms (Zhang et al. 2022) Knowledge-based Theory (Snihur and Wiklund 2019) Disruptive business model (Li 2020) Service-dominant logic (Manser Payne et al. 2021) Feedback Loops (Katsamakas and Pavlov 2022)	Decision support system (Pourabbasi and Shokouhyar 2022) Analytic network process (Geng et al. 2010) Quality function deployment (Haber and Fargnoli 2020) Digital twin concept (Minerva et al. 2020) Design theory (Zheng et al. 2020) Fuzzy Stochastic environment (D. Chen et al. 2015) Fuzzy Theory (Geng et al. 2010) Kano model (Geng and Chu 2012) Agent-based approach (Farsi and Erkoyuncu 2021) (Capability-based view, Dynamic capability theory, strategic capability theory, circular economy) (Chauhan et al. 2022) Productivity paradox theory (Kumar et al. 2023) Dynamic capability theory (Abou-Foul et al. 2023)	Pay-per-usage (Heinis et al. 2018) Machine learning(Rosati et al. 2022) Deep learning (Rosati et al. 2022) Knowledge innovation approach (Hao et al. 2018) Intelligent service warehousing platform (Chang et al. 2021) Regional innovation systems (Moutinho 2016)

Table 1 (continued)

	AI-enabled PSI				
	Technology adoption and transformational barriers	Data-driven capabilities and innovation	Digitally enabled business model innovation	Smart design changes and sustainability	Sectorial application
Methodologies	Multiple case studies Single case studies Bibliometric reviews Questionnaire Experimental study Surveys	Multiple case studies Single case studies Bibliometric reviews Questionnaire Experimental study Surveys Systematic literature	Multiple case studies Single case studies Interview Surveys Systematic literature	Multiple case studies Single case studies Interview Surveys Systematic literature	Multiple case studies Single case studies Interview Surveys Experimental study
Examples of studies (5 most cited in each cluster, order based on the number of citations)	(de Bellis and Venkataramani Johar 2020) (Sohn and Kwon 2020) (Meindl et al. 2021) (Schweitzer et al. 2019) (Hsieh and Lee 2021)	(Demirkan and Delen 2013) (Song et al. 2009). (Hasu and Engeström, 2000) (Antons and Breidbach 2018) (Dotzel and Shankar 2019)	(Sjödin et al. 2020) (Li 2020) (Snihur and Wiklund 2019) (Sjödin et al. 2021) (Burström et al. 2021) (Lee et al. 2019)	(Cao et al. 2016) (Minerva et al. 2020) (Geng and Chu 2012) (Dzitac et al. 2017) (Geng et al. 2010)	(Buhalis et al. 2019) (Janiesch et al. 2021) (Tahsien et al. 2020) (Heinis et al. 2018) (Okunlaya et al. 2022)

4.1 Technology adoption and transformational barriers

4.1.1 Central themes gap

Following the context analysis, a lack of common terminology related to "AI assist" technologies is found, where only a few were directly referred to as such (e.g., Alexa and smart chatbots) (Fotheringham and Wiles 2022; Hsieh and Lee 2021), suggesting a lack of standardized terminology. There is literature on customer perception and acceptance (Zolfagharian and Paswan 2008), but there is a need for a more in-depth exploration of the factors influencing these factors. Understanding the psychological and sociological factors contributing to the acceptance or rejection of AI-driven innovations and ethical considerations would be crucial for businesses and policy-makers. The debate between humans and AI (Yang and Hu 2022) was mentioned, but there is room for a more in-depth exploration of how human-AI collaboration can be optimized in product service innovation.

Challenges related to AI in product/service innovation are mentioned with examples in autonomous technology, smart hospitality services, voice-controlled devices, and ethical digital transformation. A research gap exists in the exploration of a broader spectrum of AI applications considering various industries and sectors. This approach can help in understanding the commonalities and differences in innovation challenges across different domains.

4.1.2 Models and theories gaps

Models and theories such as construal level theory (Akdim et al. 2021), the theory of planned behavior, the technology acceptance model, and the unified theory of acceptance and use of technology (Sohn and Kwon 2020) have made significant contributions to the findings of the cluster, but these views are simplistic in nature and do not provide information at the organizational level or, in our case, address business models and their architecture effectively. There is an urgent need for additional studies, which include dynamism and technology-based frameworks for AI and explain how, with time, the evolving nature of innovation can be captured and related complexities simplified. Researchers need to establish more rigorous and comparable models and theories for assessing the effectiveness of AI technologies and their challenges/barriers to adoption into business models.

4.1.3 Methodologies gaps

Different industries and domains may have unique dynamics and challenges related to AI adoption. Relying on a single method, such as a qualitative case study, could lead to findings that are specific to the context studied but may not be broadly applicable. Conducting quantitative research involving multiple companies helps reduce the impact of biases associated with a single supplier. This approach provides a more balanced and comprehensive view of user opinions, fostering a more accurate understanding of the implications of AI in service scenarios.

4.1.4 Future directions

It is suggested that researchers come together and find common terminology for referencing AI-assisted technologies. Future research should investigate the specific challenges organizations encounter during the implementation of AI in product service innovation. This can involve examining issues related to infrastructure, employee training, the integration of AI into existing business processes, and ethical considerations since the research stream was not as elaborate as others. Future research could focus on identifying strategies to enhance the integration of AI into service businesses without causing customer concerns or fostering more harmonious coexistence. (Zolfagharian and Paswan 2008). Future studies should highlight successful cases of AI integration in service businesses, identifying best practices that can guide businesses in optimizing human-AI collaboration (Yang and Hu 2022). This aligns with the call for exploring strategies for more seamless integration.

In addition to autonomous shopping systems, researchers must concentrate on research problems concerning related technologies such as autonomous products, e.g., autonomous vehicles. This future research agenda contributes to a better grasp of autonomous technology-based products (de Bellis and Venkataramani Johar 2020). Possible disadoption of technology was missing from the research, and challenges related to autonomy and control at the organizational level were not addressed in detail (Akdim et al. 2021). Instead of using traditional predictive analysis techniques, smart manufacturing industries could move toward explainable AI techniques and models in future research (Eddy et al. 2021). It is urged to researchers to conduct in-depth studies on the dynamic nature of AI innovation, emphasizing technological frameworks. Explore how businesses can effectively capture and adapt to the evolving landscape of AI over time. Comprehensive models and theories for assessing the effectiveness of AI technologies in various business models have been established. Identify and analyze specific challenges and barriers that impact the adoption of AI, providing actionable insights for businesses.

Furthermore, application of multiple methodologies is suggested, including field experiments and surveys, to avoid generalizing the results to the setting in which the research was conducted. The studies are restricted by their scope, which mostly focuses on qualitative methodology with a single case study. The use of these data was also constrained by the reality that the data collected were obtained from a single AI supplier; hence, the user's opinion may be overlooked. Quantitative exploratory research is suggested that considers additional companies and offers a new level of findings. Different assessment tools may be used; for example, survey strategies can offer comprehensive views of industry leaders regarding the importance of AI technology in business model development.

4.2 Data-driven capabilities and innovation

4.2.1 Central themes gaps

There is a gap in fully exploring the potential of the data-driven business model paradigm, including understanding its role in reshaping traditional product service-based business models. Akter et al. (2021) suggest that service innovation in terms of the AI climate promotes market performance and service analytics capabilities. However, considering only the service innovation paradigm is insufficient. Due to the lack of exploration of data capabilities, especially in the context of big data, contributions to enhancing AI applications in business models are lacking. A comprehensive understanding of how AI services contribute to data-driven decision-making in decision support services" (Demirkan and Delen 2013) and to technology-led innovations (Anton et al. 2021) need further investigation.

4.2.2 Models and theories gaps

There is a gap in detailing the specific models or frameworks for utilizing AI-driven data capabilities and decision support systems (Demirkan and Delen 2013) in making critical strategic and operational service decisions. For instance, the practical aspects of integrating AI into decision-making models for improved firm performance need further exploration. While the study explores the link between activity theory (Hasu and Engeström 2000) and a firm's ability to innovate with data, a comprehensive link to contemporary challenges in leveraging data for strategic decision-making and innovation is missing. However, studies explaining the techniques, algorithms, or best practices for handling unstructured data capabilities (Kohler et al. 2014) with AI while considering innovation are lacking. There is a gap in detailing the specific frameworks for effectively integrating emotional data into the innovation process. The practical challenges and strategies for leveraging employee-generated emotional data (Kandampully et al. 2022) for idea generation and innovation have not been thoroughly explored.

4.2.3 Methodologies gaps

There is a lack of comparative research across platforms that build data capabilities through AI. There is a need for empirical research on data-based devices over time, i.e., longitudinal studies. Moreover, a lack of consensus-building among stakeholders is found, which hinders the identification of critical factors that influence decision making processes.

4.2.4 Future directions

Researchers need to explore beyond the service innovation paradigm to fully understand the potential of data-driven business models in reshaping traditional business models. Consider diverse perspectives and implications for a more comprehensive analysis. Better theories based on data-enabled AI systems, i.e., game theories, instead of using activity theory with a firm's ability to innovate with data (Hasu and Engeström, 2000), can provide holistic and optimal strategies for decision-making and innovation. The scale used to discern service innovation must be evaluated in various sociocultural situations to determine whether the conceptualization and operationalization of service innovativeness are context specific. By focusing on unstructured data capabilities (Kohler et al. 2014), researchers can bridge the gap between AI-driven design innovations and the challenges associated with managing diverse data types. Researchers can explore how advancements in augmented reality design elements, driven by AI innovations, align with and potentially contribute to addressing challenges related to data interoperability and the effective integration of emotional data (Kandampully et al. 2022).

Future research might include superior design elements such as avatars and content, in addition to greater AI-enabled innovations. Other variables, such as utility, simplicity of use, and amusement, that have been proven to be important for service assessment in the augmented reality context might enhance the conceptual model. Delphi interviews can explore the perspectives of stakeholders regarding the transition to a more automated system, considering factors such as technological readiness. By combining cross-platform comparative research, longitudinal studies on data-based devices, and consensus-building efforts, future research can offer a holistic view of the evolving landscape of AI-driven data capabilities.

4.3 Digitally enabled business model innovation:

4.3.1 Central themes gaps

There is limited coverage of innovation strategies (Snihur and Wiklund 2019) related to the dramatic changes in the techno-economic era. (Kim 2021). There are gaps in the industrial ecosystem between the front and back ends of AI-enabled products and services, and there is a lack of individual impact studies on developing AI-based innovation at the organizational level (Burström et al. 2021). Insufficient examination of ecosystem strategies has been performed (Kamalaldin et al. 2021). and configuring appropriate strategies in AI-enabled business models.

4.3.2 Models and theories gaps

There is an inadequate understanding of the complexities involved in the integration of AI in servitization, especially about independent distributors, stakeholder conflicts, and servitization readiness (Hullova et al. 2019). A lack of detailed exploration of economic assessment techniques is highlighted, specifically probabilistic event-decision tree modeling, and its role in supporting sustainable business models (Copani and Rosa 2015). There is limited understanding of the organizational principles and scalability factors associated with the microservice innovation approach in business model innovation in terms of AI (Sjödin et al. 2020). Furthermore, highlighting inadequate exploration of challenges and strategies related to integrating AI into business ecosystems, including potential pitfalls when AI transformations are not connected to experienced players (Burström et al. 2021). There are gaps in utilizing dynamic models, particularly in understanding the coevolutionary framework, feedback loops, and dynamic complexity in the context of AI-driven business model transformation (Sjödin et al. 2021).

4.3.3 Methodology gaps

Findings from just a qualitative investigation of industrial sector incumbents conducted beyond a brief time period led to observe only a small portion of the development (Burström et al. 2021). AI-enabled business models are possibly more critical than classical business models; however, researchers have not assessed the comprehensiveness of these models through additional investigations. Business model innovation concepts may differ between business-to-business and business-to-customer innovation. The case companies are substantial, well-known, and globally competitive manufacturing companies (Sjödin et al. 2021).

4.3.4 Future directions

There is an opportunity for researchers to investigate consecutive relationships across innovation strategies to determine whether there is an ideal order during which various innovation kinds must be explored, such as improving the business model as well as products before actually introducing new procedures (Snihur and Wiklund 2019). Future research needs more themes around bridging gaps in industrial ecosystems through AI-based innovation (Burström et al. 2021). Future research should focus on enhancing the examination of ecosystem strategies (Kamalaldin et al. 2021), specifically by providing detailed insights into the configuration of strategies in AI-enabled business models.

Future studies should examine the viability of event decision tree models for business model evaluation against the actual results of innovation initiatives (Copani and Rosa 2015). Future research could demonstrate many forms of developing business model paradigms in the framework of an artificial intelligence-based business model, and several distribution formats, such as software as a service and platform as a service, could be explored and compared with each other in terms of efficiency and performance. For instance, future understanding of the organizational principles and scalability factors associated with the microservice innovation approach in business model innovation in terms of AI (Sjödin et al. 2020) can lead to better performance and explore how these models adapt and transform over time. Scholars are invited to investigate the results under different circumstances and to broaden conclusions in the context of AI.

Qualitative and quantitative methods could be employed to provide a better understanding of these complexities and inform strategies for effective AI integration in servitization initiatives (Hullova et al. 2019). Researchers are invited to conduct in-depth longitudinal studies employing both qualitative and quantitative methods to comprehensively understand the innovation and impact of AI-enabled business models within the industrial sector over extended time periods to observe complete development (Burström et al. 2021).

4.4 Smart design changes and sustainability

4.4.1 Central themes gaps

The shift in PSS themes signifies a broader trend toward incorporating smart technologies; however, with every new trend comes a new terminology that serves a purpose and is then no longer used. Smart PSS are more common than “industrial smart PSS” (Zheng et al. 2020), “result-oriented PSS” (Sassanelli et al. 2022), “warehouse PSS” (Zhang et al. 2020); moreover, the concept of “sustainable product-service systems” needs further exploration. The focus on smart PSS (Z. Wang et al. 2021) and AI-driven design changes needs to include a more thorough analysis of consumer perspectives and their impact on market acceptance, adoption rates, and overall consumer behavior to support product service innovation.

4.4.2 Models and theories gaps

The suggested models and theories need to be expanded to address additional engineering design challenges that require decision-making while considering the relevance of decision variables in various engineering elements as well as assessments from various viewpoints in upcoming studies (Geng et al. 2010). There is limited understanding of the impact of AI on improving quality function deployment (Haber and Fargnoli 2020) and inadequate exploration of AI-enabled design theory applications (Zheng et al. 2020). There are gaps in understanding how AI-based models resolve or contribute to productivity paradox issues (Kumar et al. 2023) by making sustainable changes in design. Researchers should explore the ethical theories surrounding AI applications in smart PSS (Z. Wang et al. 2021), and explaining how consumers perceive and interact with AI-driven innovations is crucial for designing user-friendly, ethically sound systems that align with societal values and expectations.

4.4.3 Methodologies gaps

Only a limited amount of empirical research exists on the mediators and moderators of AI in service systems. Also, observing that limited firms have effectively used AI due to a lack of knowledge of AI and its potential benefits for the creation of business models. It was highlighted that not every sector has new studies on how to employ sophisticated supervised learning algorithms (Liu et al. 2020) to improve the design of smart businesses.

4.4.4 Future directions

This research stream observed a shift in PSS themes; therefore, researchers are called to explore the long-term sustainability and adoption patterns of new terminologies in the context of smart technologies. Researchers need to investigate the reasons behind the creation of new terminologies and assess their effectiveness and longevity. There is a need to analyze how the introduction of new terminology influences communication and understanding in the industry. Future themes can include comparative studies of various PSS types (smart PSS, industrial smart PSS, result-oriented PSS, warehouse PSS, and sustainable PSS) and of the role of AI. Researchers need to conduct in-depth examinations of the specific characteristics, advantages, and challenges associated with each type of PSS. Additionally, it is urged to investigate the market demand and acceptance rates of different AI-enabled PSS types across industries and regions. Furthermore, we explore how consumer perceptions impact AI-based design acceptance and adoption of smart PSS in the market (Z. Wang et al. 2021).

Researchers need to explore more complex decision-making scenarios. This could involve introducing scenarios that involve multidimensional decision variables, considering diverse viewpoints, or addressing intricate challenges within engineering design (Geng et al. 2010). There is a need for advanced theories other than quality function deployment and design theory so that future research can holistically assess how AI influences decision-making from various perspectives within engineering design processes. (Haber and Fargnoli 2020; Zheng et al. 2020). Future research can investigate the contribution of AI-based models to resolving productivity paradox issues and driving sustainable changes in the design landscape (Kumar et al. 2023).

Future literature could improve the utilization of data mining technologies and integrate qualitative and quantitative evaluations. Quantitative work in identifying the changes in the design of AI-based business models needs to be done to better understand the impact of these changes on the performance of companies. Future experimental research exploring novel AI algorithms is suggested, and it is hoped that this study will provide informative advice for smart PSS interactive models. These novel studies have still not been fully explored in every sector. Future studies should use a questionnaire or knowledge discovery approach to identify the problem areas of actual service by employing sophisticated supervised learning algorithms (Liu et al. 2020).

4.5 Sectorial application

4.5.1 Central themes gaps

This research stream observed a lack of developed sectorial application themes of AI within the context of business models, not limited to hospitality, tourism, or smart libraries (Gul and Bano 2019; Hamad et al. 2022; Igwe and Sulyman 2022; Janiesch et al. 2021; Okunlaya et al. 2022; op den Akker et al. 2021). The lack of diversity of sectors in this section needs to be addressed. AI-based innovations in sectorial applications can be developed such that all systems utilize customization. There is generalizability of the machine learning model and a lack of ability to predict future datasets (M. Chen and Shen 2020). Tourism and hospitality services persist across various degrees of infrastructure, institutions, and sociocultural limitations for enabling AI. The sectorial application of AI in the business model context is still lacking. There are severe constraints on the training data due to probable disruptions and innovations (Buhalis et al. 2019).

4.5.2 Models and theories gaps

Model-based AI practicality should be expanded by rendering it applicable to various service-centric business strategies and therefore by supplementing the model with additional techniques to evaluate key service aspects (Häckel et al. 2022). There is a need for further investigation into alternative pricing structures, such as pay-per-usage, to capture the value of AI-driven services and facilitate effective assessment of depreciation, especially concerning a broader range of industrial support items and product-service systems (Heinis et al. 2018). While the study by Okunlaya et al. (2022) introduces an innovative framework for AI-driven library services, there is a research gap in exploring the broader applications of such frameworks.

There is a gap in theoretical constructs for examining the distinct dynamics and patterns between start-ups and established innovative businesses, particularly through a design-oriented lens. The need extends to the evaluation of AI-enabled business models, necessitating focused attention on start-ups versus established companies (Kulkov 2021).

4.5.3 Methodologies gaps

For the AI-based product-service model, quantitative studies, ideally those involving the integration of deductive and inductive reasoning via the dynamic pattern recognition method, are needed. There is a need for qualitative research that considers customer perceptions and must be considered for upcoming research so that the market size and acceptability of technology among different sectors can be recognized. A framework that precisely explains how various business models interact when AI is involved is needed (Åström et al. 2022).

4.5.4 Future directions

More inclusive research, including but not limited to "smart libraries", "electronics", "library services", and "virtual coaching" (Gul and Bano 2019; Hamad et al. 2022; Igwe and Sulyman 2022; Janiesch et al. 2021; Okunlaya et al. 2022; op den Akker et al. 2021), is needed. Future research can investigate ways to overcome the current limitations and uncertainties in predicting future data trends within sectorial applications of AI (M. Chen and Shen 2020). Research should aim to identify specific areas where AI can bring transformative changes and enhance operational efficiency. This includes understanding how AI can optimize customer experiences, streamline operations, and contribute to sustainable tourism practices (Buhalis et al. 2019). Future research should focus on the integration of supplementary techniques, providing insights into optimizing AI models for robust evaluation of key elements within service-centric frameworks (Häckel et al. 2022).

Future research should explore extensive alternative pricing structures, such as AI-enabled pay-per-usage, to comprehensively understand their effectiveness in capturing the value of AI-driven services (Heinis et al. 2018). Imitating AI-based library services (Okunlaya et al. 2022), future research can investigate how similar frameworks can be adapted and applied in different contexts, industries, or service sectors. Furthermore, researchers are suggested to continue developing new theories and building new theoretical constructs to study industrial AI-enabled data. It will be necessary to evaluate AI-enabled business models for start-ups and companies to analyze their efficacy and uncover market benefits and open sectors (Kulkov 2021).

Future research should explore the integration of mixed methods, combining qualitative and quantitative approaches across sectors. AI-enabled metaheuristic methods could be one of the leading breakthroughs including but not limited to particle swarm optimization, ant colony optimization for service selection and scheduling (Cao et al. 2016), simulated annealing, tabu search, and differential evolution, may be utilized to aid in the selection of suitable hyperparameters by using machine learning models to increase consistency and evaluate forecasting power (Table 2).

4.6 Managerial/practical implications

Managers can develop cross-industry adoption strategies that go beyond simplistic models and theories to understand AI adoption challenges across various sectors. Businesses should be able to recognize the transformative potential of data-driven business models and understand AI's impact on decision-making for effective integration into strategic processes. The study emphasizes the need for businesses to evolve innovation strategies in response to dynamic technoeconomic changes, aiding managers in navigating rapid transformations. Managers can gain insights into consumer perspectives on AI-driven smart design changes, helping shape product-service strategies that align with market acceptance and adoption rates. This research underscores the importance of inclusive research across diverse sectors, guiding managers in tailoring AI applications to specific industry needs.

4.7 Limitations to the study

As with all related research, the present study is not immune to limitations. The search string used to find the articles was subjected to bias. This study used bibliometric coupling from a single database in Scopus. Furthermore, it examined other databases, however, the search string produced almost the same results as Scopus which contained the most number of articles. This paper discussed the disconnects of the articles while feeding the data into VOSviewer, but bibliometric approaches do not capture why authors cite other works (Zupic & Čater 2015). This

Table 2 Synthesizing the gaps in the literature and future research directions regarding the five clusters and methodologies

Cluster	The identified gaps in the research	Suggestions for future research
Technology adoption and transformational barriers	The lack of standardized AI terminology hampers clear communication	Investigate challenges in AI implementation: Explore infrastructure, training, and ethical issues.
	&Models and theories lack organizational-level effectiveness for business applications	Enhance AI integration in service businesses: Focus on customer concerns.
	The gap in understanding of AI evolution calls for comprehensive studies	Research into successful AI integration cases: Identify optimal human-AI collaboration.
	Human-AI collaboration needs deep exploration in product service innovation	Formulate model for innovation attributes: Generate theories covering diverse organizational contexts.
	Diverse methodologies are essential to avoid limitations in industry-specific findings	Expand research on autonomous technology: Address disadoption, autonomy challenges, and organizational control
Data-driven capabilities and innovation	Limited exploration of the transformative impact of data-driven business model	Explore beyond the service innovation paradigm
	Incomplete understanding of AI services in data-driven decision-making	Develop better theories for data-enabled AI
	Lack of detailed methodologies for AI-driven data capabilities	Evaluate service innovativeness in diverse contexts
	Limited exploration of big data's role in enhancing AI applications	Bridge the gap in AI-driven design innovations
	Insufficient longitudinal studies on data-based devices' evolution	Investigate AI-driven augmented reality for data interoperability
	Lack of consensus-building on critical factors in decision processes	Need for comparative research on AI-driven data capabilities

Table 2 (continued)

Cluster	The identified gaps in the research	Suggestions for future research
Digitally enabled business model innovation	Limited coverage of innovation strategies related to techno-economic changes Gaps in the industrial ecosystem between customer-facing and back-end AI products Inadequate understanding of complexities in AI integration in servitization Lack of exploration of economic assessment techniques in AI-enabled business models Insufficient examination of challenges and strategies in integrating AI into business ecosystems	Investigate consecutive relationships across innovation strategies Focus on bridging gaps in industrial ecosystems through AI Examine the viability of event decision tree models Explore various forms of developing AI-based business model paradigms Conduct in-depth longitudinal studies on the impact of AI-enabled business models
Smart design changes and sustainability	Shift in PSS themes lacks exploration of new terminologies Limited understanding of AI's impact on engineering design Novel studies on AI applications in business models design have not been fully explored Inadequate exploration of AI-enabled design theory applications. Unresolved paradoxical issues related to design changes and sustainability	Explore sustainability and adoption patterns of new terminologies Conduct comparative studies on various PSS types and the role of AI Investigate how consumer perceptions impact AI-based design acceptance and adoption Develop advanced theories for assessing AI's influence on decision-making Utilize data mining technologies for better qualitative and quantitative integration

Table 2 (continued)

Cluster	The identified gaps in the research	Suggestions for future research
Sectorial application	Limited exploration of AI applications across diverse sectors	Inclusive research exploring AI applications in "smart libraries," "electronics," and "virtual coaching"
	Generalizability of AI models without accounting for sector-specific variations	Overcoming limitations in predicting future data trends in sectorial AI applications
	Insufficient theoretical constructs for AI in various business models.	Identification of specific areas for transformative changes and operational efficiency with AI
	Lack of comprehensive frameworks for understanding AI-enabled business interactions	Integration of supplementary techniques to optimize AI models for robust evaluation
	Limited understanding of the distinct dynamics between start-ups and established businesses in AI contexts	Exploration of alternative pricing structures and development of new theoretical constructs for industrial AI-enabled data

disconnect occurs between two authors because a third author is not citing those studies. One of the limitations of this review includes the rapid development of articles in the coming months. The selected articles were limited to certain time, as the number of predicted articles significantly increased from 200 articles selected in Scopus till 2024. The additional papers could significantly change the existing analysis; therefore, the analysis was limited to May 2023. Furthermore, limitations to future research are not included in the scope of this paper.

5 Conclusion

This study aimed to extend the literature in terms of AI-enabled PSIs. In doing so, this research conducted a bibliometric literature review, identifying the five research streams, revealing the current position of the research in each stream, and identifying how the streams interact with each other. These findings helped in identifying the different AI-enabled technological disruptions in product-service innovation, allowing the gathering of data to be interpreted in a meaningful manner. On the basis of our bibliometric analysis, this study developed coherent central themes, analyzed models and theories of the content reviewed, and developed methodologies based on the research streams. The clusters were labeled (1) technology adoption and transformational barriers, (2) data-driven capabilities and innovation, (3) digitally enabled business model innovation, (4) smart design changes and sustainability, and (5) sectorial application.

Our review indicated that AI in the field of product-service innovation (PSI) has great potential for future research. In (1) technology adoption and transformational barriers, the call for a cross-industry comparative analysis aligns with the need to go beyond simplistic models and theories, emphasizing the importance of understanding AI adoption challenges across various sectors. Future research should not only compare challenges but also consider organizational-level implications, addressing business models and architectures across different industries. This comparative approach can provide insights into the contextual differences and similarities in AI adoption challenges. Developing user-friendly labels can enhance understanding and acceptance, addressing a key aspect highlighted in the literature. There is generalizability in the setting of the research and a lack of diversity in models and theories. Modern problems need modern solutions. Multiple methodologies are suggested to avoid generalizability. There is a need for additional studies related to ethical considerations and other issues related to infrastructure, employee training, and the integration of AI into existing business processes.

In (2) data-driven capabilities and innovation, the central themes reveal a need for deeper exploration into the transformative potential of the data-driven business model and a more detailed understanding of AI's impact on decision-making. Theoretical gaps highlight the necessity for detailed methodologies and frameworks to effectively integrate AI-driven data capabilities into strategic decision-making processes. Methodologically, there is a call for comparative research and longitudinal studies to comprehensively assess the evolving impact of AI. Future research should extend beyond the service innovation paradigm, embrace diverse domains and employ advanced theories such as game theories. Further emphasis should be placed on evaluating service innovation scales in varied sociocultural contexts, ensuring contextual specificity. This holistic approach will foster a more comprehensive understanding of the intricate dynamics between AI, data capabilities, and innovative business models.

In (3) digitally enabled business model innovation, the gaps in current research highlight the limited coverage of innovation strategies in the face of dramatic changes in the techno-economic era, urging scholars to explore a more comprehensive landscape. Methodological shortcomings emphasize the need for a more extensive assessment of the impact of AI-enabled business models. In terms of models and theories, there is a need for a deeper understanding of the intricacies involved in AI integration within servitization and the scalability factors for organizations. Future research directions should prioritize investigating the ideal order of exploring various kinds of innovation and delving into economic assessment techniques. Additionally, an exploration of business model innovation concepts across different business scenarios is essential. Finally, in-depth longitudinal studies are recommended to comprehend the evolving dynamics of AI-enabled business models, calling for scholars to explore diverse circumstances for a more holistic understanding.

In (4) smart design changes and sustainability, the evolution of Product-Service Systems (PSS) toward smart technologies necessitates comprehensive exploration of new terminologies' sustainability and industry-wide adoption. While "smart PSS" dominate, other variants, such as "industrial smart PSS", "result-oriented PSS", "warehouse PSS", and "sustainable PSS", require further analysis. Future research should scrutinize consumer perspectives on AI-driven design changes for insights into market acceptance and adoption rates, informing innovative product-service strategies. Existing models and theories require expansion to address emerging engineering design challenges comprehensively, including the impact of AI on quality function deployment and productivity paradox resolution. Ethical exploration of AI applications in smart PSS is vital, as it emphasizes the need to understand consumer perceptions and interactions when designing ethical and user-friendly systems. The methodological gaps highlight the limited empirical research on AI in service systems, hindering effective AI utilization in business models. Future research recommendations underscore the need for exploring long-term sustainability and adoption patterns of new terminologies and thorough examination of specific PSS types, characteristics, and challenges. Future research should integrate data mining technologies and employ sophisticated supervised learning algorithms to gain insight into the impact of AI-based business models on company performance.

In (5) sectorial application, significant gaps persist in understanding the sectorial applications of AI within business models, calling for more inclusive research spanning diverse sectors. Theoretical constructs for examining the dynamics between start-ups and established businesses are lacking, especially from a design-oriented perspective. Methodologically, there is a need for both quantitative studies employing dynamic pattern recognition in AI-based product-service models and qualitative research addressing customer perceptions across sectors. The development of a comprehensive framework explaining how various business models interact when AI is involved is imperative. Future research should also explore alternative pricing structures, such as AI-enabled pay-per-usage, to understand their effectiveness. Additionally, investigations should explore adapting successful AI-based frameworks across different contexts and industries, drawing inspiration from models such as AI-based library services. Finally, methodologically, there is a call for additional mixed methods that integrate qualitative and quantitative approaches, employing metaheuristic methods for parameter selection in AI models. These future research directions aim to fill existing gaps and contribute to the understanding of AI's role in diverse business contexts.

Funding Open Access funding provided by University of Vaasa. The authors did not receive support from any organization for the submitted work and have no financial or proprietary interests in any material discussed in this article

Data availability statement Our manuscript has no associated data.

Declarations

Conflict of interest The authors have no conflict of interests to declare that are relevant to the content of this article.

References

Abou-Foul M, Ruiz-Alba JL, López-Tenorio PJ (2023) The impact of artificial intelligence capabilities on servitization: the moderating role of absorptive capacity-A dynamic capabilities perspective. J Bus Res 157:113609. https://doi.org/10.1016/j.jbusres.2022.113609

Accenture (2024) Accenture Technology Vision 2024: "Human by Design" Technologies Will Reinvent Industries and Redefine Leaders by Supercharging Productivity and Creativity. Retrieved from https://newsroom.accenture.com/news/2024/accenture-technology-vision-2024-human-by-design-technologies-will-reinvent-industries-and-redefine-leaders-by-supercharging-productivity-and-creativity

Agarwal GK, Simonsson J, Magnusson M, Hald KS, Johanson A (2022) Value-capture in digital servitization. J Manuf Technol Manag 33(5):986–1004. https://doi.org/10.1108/JMTM-05-2021-0168

Agustí MA, Orta-Pérez M (2022) Big data and artificial intelligence in the fields of accounting and auditing: a bibliometric analysis. Span J Finance Account/Rev Esp Financ Contab 52(3):412–438. https://doi.org/10.1080/02102412.2022.2099675

Ahmed S, Alshater MM, El Ammari A, Hammami H (2022) Artificial intelligence and machine learning in finance: a bibliometric review. Res Int Bus Finance 61:101646

Akdim K, Belanche D, Flavián M (2021) Attitudes toward service robots: analyses of explicit and implicit attitudes based on anthropomorphism and construal level theory. Int J Contemp Hosp Manag. https://doi.org/10.1108/IJCHM-12-2020-1406
Akker H, Cabrita M, Pnevmatikakis A (2021) Digital therapeutics: virtual coaching powered by artificial intelligence on real-world data. Front Comput Sci. https://doi.org/10.3389/fcomp.2021.750428
Akter S, Hani U, Mariani M, Wamba SF (2021) How to build an AI climate-driven service analytics capability for innovation and performance in industrial markets? Ind Mark Manag 97:258–273
Akula V (2021) Council Post: Why your AI project is failing to deliver value. Forbes. https://www.forbes.com/sites/forbestechcouncil/2021/04/13/why-your-ai-project-is-failing-to-deliver-value/
Alegeh N, Longstaff AP, Shagluf A, Fletcher S (2019) Accuracy in detecting failure in ballscrew assessment towards machine tool servitization. Int J Mech Eng Robot Res 8(5):667–673. https://doi.org/10.18178/ijmerr.8.5.667-673
Anton E, Protz L, Oesterreich TD, Schuir J, Teuteberg F (2021) A business model taxonomy for start-ups in the electric power industry-the electrifying effect of artificial intelligence on business model innovation. Int J Innov Technol Manag. https://doi.org/10.1142/S0219877021500048
Antons D, Breidbach CF (2018) Big data, big insights? Advancing service innovation and design with machine learning. J Serv Res 21(1):17–39. https://doi.org/10.1177/1094670517738373
Åström J, Parida V, Reim W (2022) Value creation and value capture for AI business model innovation: a three-phase process framework. Rev Manag Sci 16(7):2111–2133. https://doi.org/10.1007/s11846-022-00521-z
Ávila-Robinson A, Islam N, Sengoku S (2022) Exploring the knowledge base of innovation research: towards an emerging innovation model. Technol Forecast Soc Change 182:121804. https://doi.org/10.1016/j.techfore.2022.121804
Aw ECX, Chuah SHW, Zha T (2023) My new financial companion! Non-linear understanding of Robo-advisory service acceptance. Serv Ind J. https://doi.org/10.1080/02642069.2022.2161528
Barbieri C, Adrodegari F, Baccarin G, Rapaccini M, Saccani N (2021) The role of AI platforms for the servitization of manufacturing companies. In: West S, Meierhofer J, Ganz C (eds) Smart services summit. Progress in IS. Springer, Cham. https://doi.org/10.1007/978-3-030-72090-2_9
Barile S, Bassano C, Piciocchi P, Saviano M, Spohrer JC (2021) Empowering value co-creation in the digital age. J Bus Ind Mark. https://doi.org/10.1108/JBIM-12-2019-0553
Bhavsar P, Bouaynaya N, Dera D, Polikar R, Safro I (2017) Machine learning in transportation data analytics. Data Anal Intell Transp Syst 2017:283–307. https://doi.org/10.1016/B978-0-12-809715-1.00012-2
Bouncken RB, Kraus S, Roig-Tierno N (2021) Knowledge- and innovation-based business models for future growth: digitalized business models and portfolio considerations. Rev Manag Sci 15(1):1–14. https://doi.org/10.1007/s11846-019-00366-z
Brooks C, Gherhes C, Vorley T (2020) Artificial intelligence in the legal sector: pressures and challenges of transformation. Cambridge J Reg Econ Soc 13(1):135–152. https://doi.org/10.1093/cjres/rsz026
Bughin J, Seong J, Manyika J, Chui M, Joshi R (2018) Notes from the AI frontier: modeling the impact of AI on the world economy. McKinsey Global Institute 4. Retrieved from https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-modeling-the-impact-of-ai-on-the-world-economy
Buhalis D, Beldona S, Bogicevic V, Harwood T, Hofacker C, Viglia G (2019) Technological disruptions in services: lessons from tourism and hospitality. J Serv Manag 30(4):484–506. https://doi.org/10.1108/JOSM-12-2018-0398
Burström T, Lahti T, Parida V, Wincent J (2021) AI-enabled business-model innovation and transformation in industrial ecosystems: a framework, model and outline for further research. J Bus Res 127:85–95. https://doi.org/10.1016/j.jbusres.2021.01.016
Bustinza OF, Baines T, Gomes E, Vendrell-Herrero F (2019) Product–service innovation and performance: the role of collaborative partnerships and R&D intensity. R&D Manag 49(1):33–45
Brekke T, Lenka S, Kohtamäki M, Parida V, Solem BA (2023) Overcoming barriers to transformation in manufacturing firms. A path-dependence perspective of digital servitization. Rev Manag Sci 15:1–28. https://doi.org/10.1007/s11846-023-00641-0
Cao Y, Gao Y, Kang L, Wang S (2016) A TQCS-based service selection and scheduling strategy in cloud manufacturing. Int J Adv Manuf Technol 82(1–4):235–251. https://doi.org/10.1007/s00170-015-7350-5

Chae B (2014) A complexity theory approach to IT-enabled services (IESs) and service innovation: business analytics as an illustration of IES. Decis Support Syst 57(1):1–10. https://doi.org/10.1016/j.dss.2013.07.005

Chang CH, Chiu PF, Chu WCC, Hsu TC, Hung CL (2021) A smart service warehousing platform supporting big data deep learning modeling analysis. J Internet Technol 22(2):483–489. https://doi.org/10.3966/160792642021032202022

Chauhan C, Dhir A, Parida V (2022) Linking circular economy and digitalisation technologies: a systematic literature review of past achievements and future promises. Technol Forecast Soc Change 177:121508. https://doi.org/10.1016/j.techfore.2022.121508

Chen D, Chu X, Li Y, Sun X (2015) A new product service system concept evaluation approach based on Information Axiom in a fuzzy-stochastic environment. Int J Comput Integr Manuf 28(11):1123–1141. https://doi.org/10.1080/0951192X.2014.961550

Chen M, Shen C-W (2020) The correlation analysis between the service quality of intelligent library and the behavioral intention of users. Electron Lib 38(1):95–112. https://doi.org/10.1108/EL-07-2019-0163

Chen Y, Parida V, Visnjic I, Zhang Z (2021) On the road to digital servitization—The (dis)continuous interplay between business model and digital technology. Int J Oper Prod Manag 41(5):694–722. https://doi.org/10.1108/IJOPM-08-2020-0544

Chen Z, Ming X (2020) A rough–fuzzy approach integrating best–worst method and data envelopment analysis to multi-criteria selection of smart product service module. Appl Soft Comput J 94:106479. https://doi.org/10.1016/j.asoc.2020.106479

Chiu MC, Akman G, Gupta S, Huang JH (2021) Developing a personalized recommendation system in a smart product service system based on unsupervised learning model. Comput Ind 128:103421. https://doi.org/10.1016/j.compind.2021.103421

Čirjevskis A (2022) Exploring coupled open innovation for digital servitization in grocery retail: from digital dynamic capabilities perspective. J Risk Financ Manag 15(9):411. https://doi.org/10.3390/jrfm15090411

Cong J, Bian Y, Chen C-H, Li J, Li X, Zheng P (2022) A machine learning-based iterative design approach to automate user satisfaction degree prediction in smart product-service system. Comput Ind Eng 165:107939. https://doi.org/10.1016/j.cie.2022.107939

Copani G, Rosa P (2015) DEMAT: sustainability assessment of new flexibility-oriented business models in the machine tools industry. Int J Comput Integr Manuf 28(4):408–417. https://doi.org/10.1080/0951192X.2014.924160

de Bellis E, Venkataramani Johar G (2020) Autonomous shopping systems: identifying and overcoming barriers to consumer adoption. J Retail 96(1):74–87. https://doi.org/10.1016/j.jretai.2019.12.004

Demirkan H, Delen D (2013) Leveraging the capabilities of service-oriented decision support systems: putting analytics and big data in cloud. Decis Support Syst 55(1):412–421. https://doi.org/10.1016/j.dss.2012.05.048

Dotzel T, Shankar V (2019) The Relative effects of business-to-business (vs. business-to-consumer) service innovations on firm value and firm risk: an empirical analysis. J Market 83(5):133–152. https://doi.org/10.1177/0022242919847221

Dou R, Huang R, Liu J, Nan G (2020) Less diversity but higher satisfaction: an intelligent product configuration method for type-decreased mass customization. Comput Ind Eng 142:106336. https://doi.org/10.1016/j.cie.2020.106336

Dzitac I, Filip FG, Manolescu MJ (2017) Fuzzy logic is not fuzzy: world-renowned computer scientist Lotfi A. Zadeh. Int J Comput Commun Control 12(6):748–789

Eddy D, Grosse I, Krishnamurty S (2021) Realization of system robustness by clustering to predict new product performance levels. Smart Sustain Manuf Syst 5(1):30. https://doi.org/10.1520/SSMS20200030

Fan A, Lu Z, Mao ZE (2022) To talk or to touch: unraveling consumer responses to two types of hotel in-room technology. Int J Hosp Manag 101:103112. https://doi.org/10.1016/j.ijhm.2021.103112

Farsi M, Erkoyuncu JA (2021) An agent-based approach to quantify the uncertainty in product-service system contract decisions: a case study in the machine tool industry. Int J Prod Econ 233:108014. https://doi.org/10.1016/j.ijpe.2020.108014

Fotheringham D, Wiles MA (2022) The effect of implementing chatbot customer service on stock returns: an event study analysis. J Acad Market Sci. https://doi.org/10.1007/s11747-022-00841-2

Geng X, Chu X (2012) A new importance-performance analysis approach for customer satisfaction evaluation supporting PSS design. Expert Syst Appl 39(1):1492–1502. https://doi.org/10.1016/j.eswa.2011.08.038

Geng X, Chu X, Xue D, Zhang Z (2010) An integrated approach for rating engineering characteristics' final importance in product-service system development. Comput Ind Eng 59(4):585–594. https://doi.org/10.1016/j.cie.2010.07.002

Goodell JW, Kumar S, Lim WM, Pattnaik D (2021) Artificial intelligence and machine learning in finance: identifying foundations, themes, and research clusters from bibliometric analysis. J Behav Exp Fin 32:100577

Gul S, Bano S (2019) Smart libraries: an emerging and innovative technological habitat of 21st century. Electron Lib 37(5):764–783. https://doi.org/10.1108/EL-02-2019-0052

Gäthke J (2020) The impact of augmented reality on overall service satisfaction in elaborate servicescapes. J Serv Manag 31(2):227–246. https://doi.org/10.1108/JOSM-05-2019-0151

Haber N, Fargnoli M (2020) The management of customer requirements in a product-service system context: a case study in the medical equipment sector. Int J Serv Oper Manag 37(2):145–169. https://doi.org/10.1504/IJSOM.2020.110336

Hahn C, Traunecker T, Niever M, Basedow GN (2020) Exploring AI-driven business models: conceptualization and expectations in the machinery industry. In: 2020 *IEEE International conference on industrial engineering and engineering managemen*t (IEEM) (567–570). IEEE.

Hamad F, Al-Fadel M, Fakhouri H (2022) The provision of smart service at academic libraries and associated challenges. J Librarianship Inf Sci. https://doi.org/10.1177/09610006221114173

Han R, Dwivedi YK, Lam HK, Tan KH, Wang Y, Zhan Y (2021) Artificial intelligence in business-to-business marketing: a bibliometric analysis of current research status, development and future directions. Ind Manag Data Syst 121(12):2467–2497

Hao J, Bouzouane A, Bouchard B, Gaboury S (2018) Activity inference engine for real-time cognitive assistance in smart environments. J Ambient Intell Humaniz Comput 9(3):679–698. https://doi.org/10.1007/s12652-017-0467-7

Hasu M, Engeström Y (2000) Measurement in action: an activity-theoretical perspective on producer-user interaction. Int J Human Comput Stud 53(1):61–89. https://doi.org/10.1006/ijhc.2000.0375

Heinis TB, Loy CL, Meboldt M (2018) Improving usage metrics for pay-per-use pricing with IoT technology and machine learning: IoT technology and machine learning can identify and capture advanced metrics that make pay-per-use servitization models viable for a wider range of applications. Res Technol Manag 61(5):32–40. https://doi.org/10.1080/08956308.2018.1495964

Hsieh SH, Lee CT (2021) Hey Alexa: examining the effect of perceived socialness in usage intentions of AI assistant-enabled smart speaker. J Res Interact Mark 15(2):267–294. https://doi.org/10.1108/JRIM-11-2019-0179

Hullova D, Frishammar J, Laczko P (2019) Independent distributors in servitization: an assessment of key internal and ecosystem-related problems. J Bus Res 104:422–437. https://doi.org/10.1016/j.jbusres.2019.01.012

Häckel B, Karnebogen P, Ritter C (2022) AI-based industrial full-service offerings: a model for payment structure selection considering predictive power. Decis Support Syst 152:113653. https://doi.org/10.1016/j.dss.2021.113653

Iansiti M, Lakhani KR (2020) Competing in the age of AI: strategy and leadership when algorithms and networks run the world. Harvard Business Press, Cambridge

IBM (2022) Global AI Adoption Index 2022. Retrieved from: https://www.ibm.com/downloads/cas/GVAGA3JP

Igwe KN, Sulyman AS (2022) Smart libraries: changing the paradigms of library services. Bus Inf Rev. https://doi.org/10.1177/02663821221110042

Janiesch C, Zschech P, Heinrich K (2021) Machine learning and deep learning. Electron Markets 31(3):685–695. https://doi.org/10.1007/s12525-021-00475-2

Jennifer LM, Adolfo EM, Francisco TH (2021) Challenges for universities in the face of the global trend of Industry 4.0. Rev Cienc Soc 27((Special Issue 4)):306–318

Jin BE, Shin DC (2020) Changing the game to compete: innovations in the fashion retail industry from the disruptive business model. Bus Horiz 63(3):301–311. https://doi.org/10.1016/j.bushor.2020.01.004

Jones JN, Cope J, Kintz A (2016) Peering into the future of innovation management: as the world changes, innovation professionals consider what the future holds for innovation and innovation management. Res Technol Manag 59(4):49–58

Jorzik P, Yigit A, Kanbach DK, Kraus S, Dabić M (2023) Artificial intelligence-enabled business model innovation: competencies and roles of top management. In: IEEE transactions on engineering management.

Kamalaldin A, Hullova D, Parida V, Sjödin D (2021) Configuring ecosystem strategies for digitally enabled process innovation: a framework for equipment suppliers in the process industries. Technovation. https://doi.org/10.1016/j.technovation.2021.102250

Kandampully J, Bilgihan A, Sharma A, Van Riel ACR (2022) Toward holistic experience-oriented service innovation: co-creating sustainable value with customers and society. Cornell Hosp Q. https://doi.org/10.1177/19389655221108334

Katsamakas E, Pavlov OV (2022) Artificial intelligence feedback loops in mobile platform business models. Int J Wireless Inf Netw 29(3):250–256. https://doi.org/10.1007/s10776-022-00556-9

Khanra S, Dhir A, Parida V, Kohtamäki M (2021) Servitization research: a review and bibliometric analysis of past achievements and future promises. J Bus Res 131:151–166. https://doi.org/10.1016/j.jbusres.2021.02.034

Kim IHS (2021) The comprehensive unified paradigm for business model innovation. Technol Anal Strateg Manag. https://doi.org/10.1080/09537325.2021.2011190

Koetsier J (2020) How amex uses AI to automate 8 billion risk decisions (and achieve 50% less fraud) Forbes. Retrieved from https://www.forbes.com/sites/johnkoetsier/2020/09/21/50-less-fraud-how-amex-uses-ai-to-automate-8-billion-risk-decisions/?sh=415b82941a97

Kohler M, Feldmann N, Fromm H, Kimbrough SO (2014) Service innovation analytics: leveraging existing unstructured data to assess service innovation capability. Int J Inf Syst Model Des 5(2):1–21. https://doi.org/10.4018/ijismd.2014040101

Kohtamäki M, Baines T, Gebauer H, Oghazi P, Parida V (2019) Digital servitization business models in ecosystems: a theory of the firm. J Bus Res 104:380–392

Kohtamäki M, Henneberg S, Parida V, Rabetino R, Sjödin D (2022a) Managing digital servitization toward smart solutions: framing the connections between technologies, business models, and ecosystems. Ind Mark Manag 105:253–267

Kohtamäki M, Whittington R, Vaara E, Rabetino R (2022b) Making connections: harnessing the diversity of strategy-as-practice research. Int J Manage Rev. https://doi.org/10.1111/ijmr.12243

Kraus S, Bouncken RB, Yela AA (2024) The burgeoning role of literature review articles in management research: an introduction and outlook. Rev Manag Sci 18:299–314. https://doi.org/10.1007/s11846-024-00729-1

Kraus S, Breier M, Dasí-Rodríguez S (2020) The art of crafting a systematic literature review in entrepreneurship research. Int Entrep Manag J 16:1023–1042. https://doi.org/10.1007/s11365-020-00635-4

Kraus S, Breier M, Lim WM, Dabić M, Kumar S, Kanbach D, Mukherjee D, Corvello V, Piñeiro-Chousa J, Liguori E, Palacios-Marqués D (2022a) Literature reviews as independent studies: guidelines for academic practice. Rev Manag Sci 16(8):2577–2595

Kraus S, Durst S, Ferreira JJ, Veiga P, Kailer N, Weinmann A (2022b) Digital transformation in business and management research: an overview of the current status quo. Int J Inf Manage 63:102466. https://doi.org/10.1016/j.ijinfomgt.2021.102466

Kraus S, Mahto RV, Walsh ST (2023) The importance of literature reviews in small business and entrepreneurship research. J Small Bus Manag 61(3):1095–1106

Kulkov I (2021) Next-generation business models for artificial intelligence start-ups in the healthcare industry. Int J Entrepreneur Behav Res. https://doi.org/10.1108/IJEBR-04-2021-0304

Kulkov I, Bertello A, Ferraris A, Ivanova-Gongne M, Kulkova J, Makkonen H, Rohrbeck R (2023) Technology entrepreneurship in healthcare: challenges and opportunities for value creation. J Innov Knowl 8(2):100365

Kumar P, Dutot V, Sharma SK (2023) Artificial intelligence (AI)-enabled CRM capability in healthcare: the impact on service innovation. Int J Inf Manag 69:102598. https://doi.org/10.1016/j.ijinfomgt.2022.102598

Lee J, Baucus M, Roy D, Suh T (2019) Emerging technology and business model innovation: the case of artificial intelligence. J Open Innov Technol Market Complex. https://doi.org/10.3390/joitmc5030044

Leung R, Loo PT (2022) Co-creating interactive dining experiences via interconnected and interoperable smart technology. Asian J Technol Innov 30(1):45–67. https://doi.org/10.1080/19761597.2020.1822748

Li F (2020) The digital transformation of business models in the creative industries: a holistic framework and emerging trends. Technovation 92–93:102012. https://doi.org/10.1016/j.technovation.2017.12.004

Lin LZ, Chang TJ, Chen WC (2011) Using FQFD to analyze island accommodation management in fuzzy linguistic preferences. Expert Syst Appl 38(6):7738–7745. https://doi.org/10.1016/j.eswa.2010.12.135

Liu S, Hao X, Ma C, Zhang S (2020) State prediction and servitisation of manufacturing processing equipment resources in smart cloud manufacturing. Int J Internet Manuf Serv 7(4):329–344. https://doi.org/10.1504/IJIMS.2020.110232

Long HJ, Jiang ZB, Shen J, Wang LY, Wu MX (2013) Product service system configuration based on support vector machine considering customer perception. Int J Prod Res 51(18):5450–5468. https://doi.org/10.1080/00207543.2013.778432

Manser Payne EH, Dahl AJ, Peltier J (2021) 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. https://doi.org/10.1108/JRIM-12-2020-0252

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. https://doi.org/10.1016/j.jbusres.2022.113364

McCarthy J, Hayes PJ (1981) Some philosophical problems from the standpoint of artificial intelligence. In: Readings in artificial intelligence. Morgan Kaufmann, Burlington, pp 431–450. https://doi.org/10.1016/B978-0-934613-03-3.50033-7

Meindl B, Ayala NF, Frank AG, Mendonça J (2021) The four smarts of Industry 4.0: evolution of ten years of research and future perspectives. Technol Forecast Soc Change. https://doi.org/10.1016/j.techfore.2021.120784

Minerva R, Crespi N, Lee GM (2020) Digital twin in the IoT context: a survey on technical features, scenarios, and architectural models. Proc IEEE 108(10):1785–1824. https://doi.org/10.1109/JPROC.2020.2998530

Mordor Intelligence Private Limited (2024) Digital transformation in manufacturing industry size & share analysis—growth trends & forecasts (2024–2029). Retrieved from https://www.mordorintelligence.com/industry-reports/digital-transformation-market-in-manufacturing

Moutinho RFF (2016) Absorptive capacity and business model innovation as rapid development strategies for regional growth. Investig Econ 75(295):157–202. https://doi.org/10.1016/j.inveco.2016.03.005

Nahr N, Heikkilä M (2022) Uncovering the identity of electronic markets research through text mining techniques. Electron Markets 32(3):1257–1277. https://doi.org/10.1007/s12525-022-00560-0

Nilsson NJ (2009) The quest for artificial intelligence. Cambridge University Press, Cambridge. https://doi.org/10.1017/CBO9780511819346

O'Cass A, Wetzels M (2018) Contemporary issues and critical challenges on innovation in services. J Prod Innov Manag 35(5):674–681

Okunlaya RO, Alias RA, Syed Abdullah N (2022) Artificial intelligence (AI) library services innovative conceptual framework for the digital transformation of university education. Libr Hi Tech. https://doi.org/10.1108/LHT-07-2021-0242

Osmundsen TC, Andreassen Jaatun EA, Heggem GF, Kulseng BE (2015) Service innovation from the edges: enhanced by telemedicine decision support. Pers Ubiquit Comput 19(3–4):699–708. https://doi.org/10.1007/s00779-015-0857-9

Paredes CM, González-Potes A, Ibarra-Junquera V, Martínez-Castro D (2021) Detection and isolation of DoS and integrity cyber attacks in cyber-physical systems with a neural network-based architecture. Electronics 10(18):2238. https://doi.org/10.3390/electronics10182238

Porter ME, Heppelmann JE (2014) How smart, connected products are transforming competition. Harv Bus Rev 92(11):64–88

Pourabbasi M, Shokouhyar S (2022) Towards a framework to design product service system-based mobile phone waste management: a social media data analysis perspective. Int J Comput Integr Manuf. https://doi.org/10.1080/0951192X.2022.2078510

Precedence Research (2023) Artificial Intelligence (AI) in Manufacturing Market Size, Report By 2032. Retrieved from https://www.precedenceresearch.com/customization/3090#

Qian L, Huang Y, Liang Y, Yin J (2023) The role of values and ethics in influencing consumers' intention to use autonomous vehicle hailing services. Technol Forecast Soc Change 188:122267. https://doi.org/10.1016/j.techfore.2022.122267

Queiroz SA, Cauchick Miguel PA, Ganga GM, Mendes GH, Oliveira MG, Silva JH (2020) Servitization and performance: impacts on small and medium enterprises. J Bus Ind Mark 35(7):1237–1249
Qvist-Sørensen P (2020) Applying IIoT and AI - Opportunities, requirements and challenges for industrial machine and equipment manufacturers to expand their services. Cent Eur Bus Rev 9(2):46–77. https://doi.org/10.18267/j.cebr.234
Rabetino R, Federico J, Kohtamäki M (2021) A (Re)view of the philosophical foundations of strategic management. Int J Manag Rev 23:151–190
Rich E (1985) Artificial intelligence and the humanities. Comput Humanit 19:117–122. https://doi.org/10.1007/bf02259633
Rosati R, Cecchini G, Frontoni E, Mancini A, Romeo L, Tonetto F, Viti P (2022) From knowledge-based to big data analytic model: a novel IoT and machine learning based decision support system for predictive maintenance in Industry 4.0. J Intell Manuf. https://doi.org/10.1007/s10845-022-01960-x
Santana M, Díaz-Fernández M (2023) Competencies for the artificial intelligence age: visualization of the state of the art and future perspectives. Rev Manag Sci 17(6):1971–2004
Sassanelli C, Arriga T, D'adamo I, Terzi S, Zanin S (2022) Industry 4.0 driven result-oriented PSS: an assessment in the energy management. Int J Energy Econ Policy 12(4):186–203. https://doi.org/10.32479/ijeep.13313
Sauer PC, Seuring S (2023) How to conduct systematic literature reviews in management research: a guide in 6 steps and 14 decisions. Rev Manag Sci 12:1–35
Saurabh K, Arora R, Mishra D, Ramkumar M, Rani N (2022) AI led ethical digital transformation: framework, research and managerial implications. J Inf Commun Ethics Soc 20(2):229–256. https://doi.org/10.1108/JICES-02-2021-0020
Schroeder R (2016) Big data business models: challenges and opportunities. Cogent Soc Sci 2(1):1166924
Schweitzer F, Belk R, Jordan W, Ortner M (2019) Servant, friend or master? The relationships users build with voice-controlled smart devices. J Mark Manag 35(7–8):693–715. https://doi.org/10.1080/0267257X.2019.1596970
Shiau WL, Dwivedi YK, Yang HS (2017) Co-citation and cluster analyses of extant literature on social networks. Int J Inf Manag 37(5):390–399
Shimomura Y, Ishii T, Nakamura T, Nemoto Y (2018) A method for identifying customer orientations and requirements for product–service systems design. Int J Prod Res 56(7):2585–2595. https://doi.org/10.1080/00207543.2017.1384581
Shleha W, Vaillant Y, Vendrell-Herrero F (2023) Entry mode diversity and closing deals with international customers: the moderating role of advanced servitization. Int Bus Rev. https://doi.org/10.1016/j.ibusrev.2022.102053
Sjödin D, Kohtamäki M, Parida V, Wincent J (2020) An agile co-creation process for digital servitization: a micro-service innovation approach. J Bus Res 112:478–491. https://doi.org/10.1016/j.jbusres.2020.01.009
Sjödin D, Palmié M, Parida V, Wincent J (2021) How AI capabilities enable business model innovation: scaling AI through co-evolutionary processes and feedback loops. J Bus Res 134:574–587. https://doi.org/10.1016/j.jbusres.2021.05.009
Sjödin D, Parida V, Kohtamäki M (2023) Artificial intelligence enabling circular business model innovation in digital servitization: conceptualizing dynamic capabilities, AI capacities, business models and effects. Technol Forecast Soc Change 197:122903. https://doi.org/10.1016/j.techfore.2023.122903
Small H (1973) Co-citation in the scientific literature: a new measure of the relationship between two documents. J Am Soc Inf Sci 24(4):265–269
Snihur Y, Wiklund J (2019) Searching for innovation: product, process, and business model innovations and search behavior in established firms. Long Range Plann 52(3):305–325. https://doi.org/10.1016/j.lrp.2018.05.003
Sohn K, Kwon O (2020) Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products. Telemat Inform. https://doi.org/10.1016/j.tele.2019.101324
Song LZ, Di Benedetto CA, Song M (2009) A staged service innovation model. Decis Sci 40(3):571–599. https://doi.org/10.1111/j.1540-5915.2009.00240.x
Spieth P, Ricart JE, Schneckenberg D (2014) Business model innovation–state of the art and future challenges for the field. R&D Manag 44(3):237–247
Stanko MA, Rindfleisch A (2023) Digital manufacturing and innovation. J Prod Innov Manag 40(4):407–432. https://doi.org/10.1111/jpim.12686
Szabó I, Fodor S, Ternai K (2022) Affordances in blockchain-based financial recommendations concerned with life events and personalities. Enterp Inf Syst 16(12):2081935

Tahsien SM, Karimipour H, Spachos P (2020) Machine learning based solutions for security of Internet of Things (IoT): a survey. J Netw Comput Appl. https://doi.org/10.1016/j.jnca.2020.102630
Teece DJ (2018) Profiting from innovation in the digital economy: enabling technologies, standards, and licensing models in the wireless world. Res Policy 47(8):1367–1387
Teixeira E, Tjahjono B, Alfaro S, Julião J (2012) Harnessing prognostics health management and product-service systems interaction to support operational decisions. J Manuf Technol Manag 24(1):78–94. https://doi.org/10.1108/17410381311287490
Trischler MFG, Li-Ying J (2022) Digital business model innovation: toward construct clarity and future research directions. Rev Manag Sci 17(1):3–32. https://doi.org/10.1007/s11846-021-00508-2
Tseng ML, Chiu AS, Lim MK, Tan K, Wu KJ (2019) Reprint of: Service innovation in sustainable product service systems: improving performance under linguistic preferences. Int J Prod Econ 217:159–170. https://doi.org/10.1016/j.ijpe.2019.09.013
Vendrell-Herrero F, Darko CK, Ghauri P (2019) Knowledge management competences, exporting and productivity: uncovering African paradoxes. J Knowl Manag 24(1):81–104. https://doi.org/10.1108/JKM-07-2018-0433
Vendrell-Herrero F, Bustinza OF, Opazo-Basaez M (2021) Information technologies and product-service innovation: the moderating role of service R&D team structure. J Bus Res 128:673–687. https://doi.org/10.1016/j.jbusres.2020.01.047
Vendrell-Herrero F, Bustinza OF, Lafuente E, Vaillant Y (2022) Product lifespan: the missing link in servitization. Prod Plann Control 33(14):1372–1388
Vogel R, Güttel WH (2013) The dynamic capability view in strategic management: a bibliometric review. Int J Manag Rev 15:426–446
Waltman L, Noyons ECM, van Eck NJ (2010) A unified approach to mapping and clustering of bibliometric networks. J Informetr 4(4):629–635
Wamba SF, Bawack RE, Carillo KDA, Guthrie C, Queiroz MM (2021) Are we preparing for a good AI society? A bibliometric review and research agenda. Technol Forecast Soc Change 164:120482
Wang X, Durugbo C (2013) Analysing network uncertainty for industrial product-service delivery: a hybrid fuzzy approach. Expert Syst Appl 40(11):4621–4636. https://doi.org/10.1016/j.eswa.2013.01.062
Wang Z, Chen CH, Khoo LP, Li X, Zheng P (2021) A graph-based context-aware requirement elicitation approach in smart product-service systems. Int J Prod Res 59(2):635–651. https://doi.org/10.1080/00207543.2019.1702227
Wirtz J, Kowalkowski C (2022) Putting the "service" into B2B marketing: key developments in service research and their relevance for B2B. J Bus Ind Mark. https://doi.org/10.1108/JBIM-02-2022-0085
Wong IA, Huang J, Lin Z, Jiao H (2022) Smart dining, smart restaurant, and smart service quality (SSQ). Int J Contemp Hosp Manag 34(6):2272–2297. https://doi.org/10.1108/IJCHM-10-2021-1207
Xing K, Qian W, Wang HF (2013) A sustainability-oriented multi-dimensional value assessment model for product-service development. Int J Prod Res 51(19):5908–5933. https://doi.org/10.1080/00207543.2013.810349
Xu X, Brown S, Chen X, Gong Y, Jia F, Xu Y (2018) Supply chain finance: a systematic literature review and bibliometric analysis. Int J Prod Econ 204:160–173
Yan MR, Cruz Flores NJ, Su YY, Wang CH (2019) Targeting open market with strategic business innovations: a case study of growth dynamics in essential oil and aromatherapy industry. J Open Innov Technol Market Complex 5(1):7. https://doi.org/10.3390/joitmc5010007
Yang C, Hu J (2022) When do consumers prefer AI-enabled customer service? The interaction effect of brand personality and service provision type on brand attitudes and purchase intentions. J Brand Manag 29(2):167–189. https://doi.org/10.1057/s41262-021-00261-7
Zhang F, Ding K, Hui J, Li J, Zhu B (2020) Uncertain demand modeling of warehouse product service system based on interval number optimization. Int J Comput Integr Manuf 33(2):133–141. https://doi.org/10.1080/0951192X.2020.1718761
Zhang S, Liu J, Zhang W (2022) Optimization of artificial intelligence model for badminton teaching and training with wireless network support. Secur Commun Netw. https://doi.org/10.1155/2022/8925907
Zheng P, Li X, Peng T, Wang Y, Zhang G (2020) Industrial smart product-service system development for lifecycle sustainability concerns. IET Collaborative Intell Manuf 2(4):197–201. https://doi.org/10.1049/iet-cim.2020.0056
Zolfagharian M, Paswan A (2008) Do consumers discern innovations in service elements? J Serv Mark 22(5):338–352. https://doi.org/10.1108/08876040810889111

Zupic I, Čater T (2015) Bibliometric methods in management and organization. Organ Res Methods 18(3):429–472. https://doi.org/10.1177/1094428114562629

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

Authors and Affiliations

Rimsha Naeem[1] · Marko Kohtamäki[1] · Vinit Parida[2]

✉ Rimsha Naeem
rimsha.naeem@uwasa.fi

Marko Kohtamäki
marko.kohtamaki@uwasa.fi

Vinit Parida
vinit.parida@ltu.se

1 University of Vaasa, School of Management, PO Box 700, 65101 Vaasa, Finland

2 Luleå University of Technology, Entrepreneurship & Innovation, 97187 Luleå, Sweden