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Henrik C. Schleth, Franz Breu, Dominik K. Kanbach & Sascha Kraus

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AI-driven business model innovation in service industries: a systematic review

服务业中人工智能驱动的商业模式创新: 系统性综述

Henrik C. Schleth[a], Franz Breu[a], Dominik K. Kanbach[a,b] and Sascha Kraus [c,d]

[a]HHL Leipzig Graduate School of Management, Leipzig, Germany; [b]Faculty of Management, University of Warsaw, Warsaw, Poland; [c]School of Economic Disciplines, University of Siegen, Siegen, Germany; [d]Department of Business Management, University of Johannesburg, Johannesburg, South Africa

ABSTRACT

This study offers an integrative understanding of how Artificial Intelligence (AI) drives Business Model Innovation (BMI) in the service industry. Drawing from a systematic review of 113 articles, we identify seven key considerations for integrating AI into service-centric models. Our findings show that AI automates tasks and enhances human-like service interactions, enabling new revenue opportunities. Yet, success hinges on navigating ethical concerns and relational complexities tied to automation and personalization. By examining the interplay between value creation, proposition, and capture, we present a holistic framework that links technological capabilities with customer experience and organizational readiness. Our study provides actionable insights for researchers and practitioners, emphasizing the need to balance efficiency with human-centered values and trust-building. These findings guide service organizations in leveraging AI for sustainable advantage while offering a foundation for future research on the transformative role of AI in service-centric business models.

本研究通过整合分析揭示了人工智能（AI）如何推动服务业的商业模式创新 (BMI)。基于对113篇文献的系统性综述,我们归纳出将人工智能融入服务导向型模式的七大关键考量。研究发现，人工智能既能自动化处理任，又能提升类人服务交互体验，从而创造新的收入机会。然而，成功实施的关键在于化解自动化与个性化进程中涉及的伦理问题及关系复杂性。通过剖析价值创造、价值主张与价值获取的动态交互，我们构建了技术能力、客户体验与组织准备度三维联结的整体框架。本研究为学者与实践者提供可操作性见解，强调需在效率提升与以人为本的价值观及信任构建间寻求平衡。这些发现既为服务机构运用AI获取可持续竞争优势提供指引，也为未来研究AI在服务导向型商业模式中的变革性作用奠定基础。

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关键词
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CONTACT Sascha Kraus sascha.kraus@uni-siegen.de School of Economic Disciplines, University of Siegen, Unteres Schloß 3, 57072 Siegen, Germany

Introduction

The disruptive nature of Artificial Intelligence (AI) is profoundly impacting the service industry, changing how organizations create, deliver, and capture value (Jorzik et al., 2024; Kong et al., 2023; Lee et al., 2019; Spring et al., 2022). These advances highlight the strategic importance of continuously innovating business models to remain competitive in a dynamic environment (Jorzik et al., 2024; Kanbach et al., 2024).

In contrast to the manufacturing industry, the dynamic and interactive nature of the service industry opens up unique opportunities for value co-creation through AI (Galvagno & Dalli, 2014; Grönroos & Voima, 2013; Uriarte et al., 2026). For example, hotels use AI-driven robotic concierges to personalize interactions with guests, while restaurants use automated systems such as cooking robots to address labor shortages and rising operating costs (Park, 2024; Tavakoli & Mura, 2018). These innovations show that AI is a key driver for transforming business models in the service industry (Huang & Rust, 2018; Knani et al., 2022; Vishwakarma et al., 2024).

However, innovating AI-driven business models brings challenges for service organizations, particularly between automated efficiency and personalized customer focus (Trincado-Munoz et al., 2024). While automation makes processes more efficient and reduces costs, it can reduce the quality of interpersonal interactions crucial for many services (Cai et al., 2022; Flavián & Casaló, 2021; Hildebrand & Bergner, 2021). Equally, AI-enhanced personalization based on extensive datasets raises ethical questions about privacy and fairness that could affect customer trust (Aw et al., 2022; Pereira et al., 2022; Vatankhah et al., 2024).

Overcoming these tensions requires a balanced and comprehensive approach to integrating AI into business models in the service industry (Lin et al., 2024). In this regard, recent researchers describe the Business Model Innovation (BMI) framework as a valuable basis for addressing the potential and challenges of AI (Jorzik et al., 2024). By focusing on value creation, value proposition, and value capture, the BMI framework enables a systematic analysis of business models in the context of AI (Doborjeh et al., 2022; Filser et al., 2021). While foundational contributions, such as Roy et al. (2025) and Spieth et al. (2023), provide valuable strategic and organizational perspectives on AI-driven BMI, they offer limited insights into the critical tensions, particularly pronounced in service contexts. Therefore, addressing this adds substantial value as it extends existing frameworks and offers insights into how AI can effectively drive BMI in dynamic and human-centric scenarios.

Although researchers started investigating AI's impact on BMI in the service industry, the current literature remains fragmented and leaves important gaps. Particularly striking is the isolated consideration of the individual BMI dimensions, which often neglects interdependencies (Boustani et al., 2023; Dalvi-Esfahani et al., 2023; Huang & Sénécal, 2023; Li et al., 2023). Existing studies often focus on customer-oriented aspects but ignore strategic and organizational factors that are crucial for the effective integration of AI (Flavián & Casaló, 2021). Furthermore, sector-specific approaches limit the generalizability of results, leaving other service sectors without suitable strategies (Battisti et al., 2022; Lalicic & Weismayer, 2021). Finally, tensions between automation and personalization are often insufficiently considered, leading to unbalanced and ineffective approaches in the long term (Cai et al., 2022; Flavián & Casaló, 2021; Hildebrand & Bergner, 2021).

To address these research gaps, our study systematically analyzes the literature on the impact of AI on BMI in the service industry. Specifically, we examine how tensions between automation, personalization, and ethical considerations simultaneously influence strategic alignment, organizational readiness, and service-oriented value co-creation processes. By focusing on the interconnected roles of AI in value creation, value proposition, and value capture, we seek to identify critical considerations for effective BMI in human-centric service settings. We aim to answer the following research question:

What are the key considerations when integrating AI for BMI in the service industry?

By answering this question, the study contributes to the scientific discussion on AI-driven BMI and responds to other scientists' calls for a more comprehensive understanding of this intersection. It extends holistic frameworks, as presented by Jorzik et al. (2024), by centering on the service industry's unique interplay between automation, personalization, and ethical constraints. In doing so, it provides researchers and practitioners with insights to successfully overcome the challenges of AI integration in dynamic and human-centric contexts (Battisti et al., 2022; Jiménez-Barreto et al., 2021; Lalicic & Weismayer, 2021).

AI-Driven BMI in the service industry

Business models increasingly face shorter lifespans due to rapid technological advancements and evolving customer expectations. This is particularly relevant in the context of AI-enabled technologies that offer opportunities to reshape how services are created, delivered, and monetized (Dwivedi et al., 2023; Mariani et al.&, 2023). This underscores the imperative for frameworks such as BMI depicted by Clauss (2017), describing the process of deliberately reconfiguring existing business models or developing entirely new approaches to creating, delivering, and generating value (Filser et al., 2021; Kraus et al., 2020). It distinguishes between the three interrelated BMI dimensions: value creation innovation, new proposition innovation, and value capture innovation. Value creation innovation focuses on how firms generate value by leveraging new capabilities, technologies, partnerships, and processes. New proposition innovation involves creating and delivering unique offerings, entering new customer segments and markets, adopting novel distribution channels, and improving customer relationships. Finally, value capture innovation addresses strategies for establishing new revenue streams and managing cost structures tied to delivering the value proposition. If one dimension is modified, it is also necessary to make modular changes to the other dimensions (Clauss, 2017).

While the theoretical underpinnings of BMI are well established, the literature on AI-driven BMI in the service industry has substantially grown. Still, it remains primarily isolated within the three main BMI dimensions and neglects their interdependent nature (Boustani et al., 2023; Dalvi-Esfahani et al., 2023; Huang & Sénécal, 2023; Li et al., 2023). Studies often focus on operational efficiency gains through automation or customers' subjective experience of interacting with AI-driven service interfaces without holistically examining how these changes influence one another. Recent studies reveal how AI can optimize service workflows and reduce processing time and error rates. However, few of these works explore whether such operational efficiency translates into a more compelling value proposition or a more profitable financial model (Dicuonzo et al., 2023; Guo et al., 2024; Mor & Gupta, 2021; Pham et al., 2024). Equally, explorations of customer-centric

AI adoption delve deep into personalization and intuitive design features and pay less attention to the organizational restructuring or strategic cost management practices required to sustain these capabilities profitably (Flavián & Casaló, 2021; Gupta et al., 2022; Kumar et al., 2023; Shumanov et al., 2021). Similarly, research frequently emphasizes pricing innovation, data monetization, or cost-saving opportunities. Still, it rarely articulates how these models depend on the firm's underlying ability to create and deliver new forms of value through AI-driven capabilities or the corresponding shifts in customer value perceptions (Chen et al., 2024; Gursoy et al., 2019; Spring et al., 2022). This fragmented perspective is also reflected in recent literature reviews on AI in service industries, which offer valuable overviews of technological developments, adoption patterns, and customer interactions (Bakir et al., 2025; Khanfar et al., 2025; Vishwakarma et al., 2024). However, these reviews do not explicitly examine how AI impacts the interconnected BMI dimensions.

As a result, there remains a critical need for more integrative research that illuminates the dynamic interplay between value creation, value proposition, and value capture.

Research methodology

Research approach and data structure

The findings presented in Section 4 were derived from a systematic literature review (SLR), a method increasingly adopted to provide integrated insights to decision-makers and policymakers (Kraus et al., 2024; Sauer & Seuring, 2023). To ensure methodological transparency and reproducibility, we followed the guidelines by Tranfield et al. (2003), Kraus et al. (2022), and Öztürk et al. (2024). Our approach included three steps: Step (1) involved identifying the need for a review and framing the research objectives. Step (2) focused on conducting the review. Step (3) entailed synthesizing and presenting the findings within an integrated framework.

To address the intersection of AI, BMI, and the service industry, we conducted a mutually independent scoping review in Google Scholar and Web of Science. We used both databases to capture a wide range of research papers and other publications with the aim of refining our search terms. This was supplemented by manually screening articles published in selected peer-reviewed journals. Afterward, we elaborated on the results within the research group and identified the most frequently studied contexts for AI-driven BMI in high-quality journals. We thus focused on these widely examined sectors to capture key advancements and current research trends. This led to a search string with the terms 'AI' OR 'Artificial Intelligence' AND 'Hospitality' OR 'Tourism' OR 'Travel' OR 'Hospital' OR 'Healthcare' OR 'Financial Servic*' OR 'Banking' OR 'Insurance' OR 'Asset Management' OR 'Payment*' OR 'Professional Servic*' OR 'Consulting' OR 'Retail' OR 'Servic* Industr*' (see Figure 1) within their title, abstract and keywords. The final systematic search was then conducted in EBSCO, which offers comprehensive coverage of high-quality and peer-reviewed journals and its strong alignment with the study's focus on AI, BMI, and the service industry. In comparison with Google Scholar and Web of Science, it further possesses robust search, filter, and export functions that are suitable for transparent and reproducible SLR for our interdisciplinary topic. A total of 13,582 articles were retrieved.

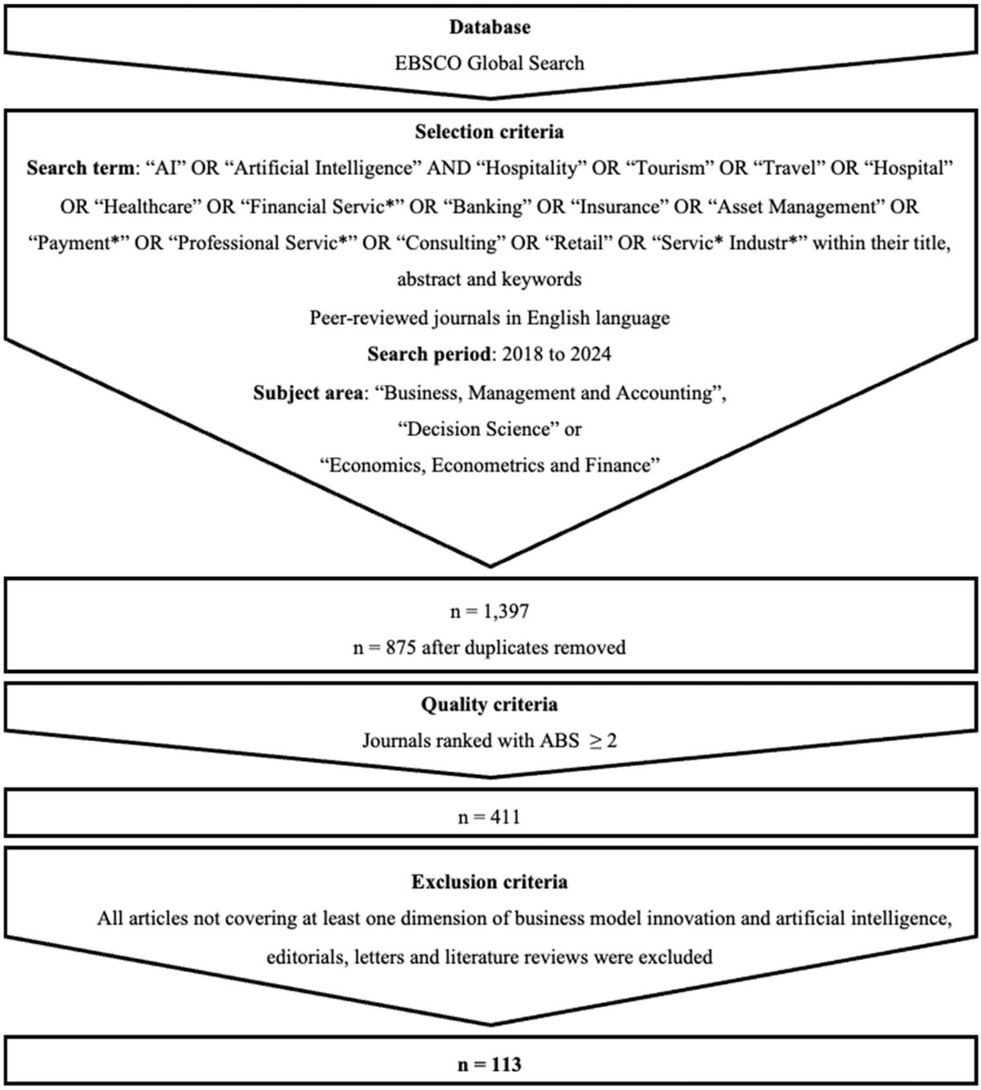


Figure 1. Systematic literature review approach.

However, we found the terms were insufficiently precise to meet the research objective, so we extended the search string with 'Business Model Innovation' in the articles' full text. After reviewing their titles and abstracts, we concluded that the search string was not sufficient to meet the research objective, as most articles were not specifically concerned with BMI. Consequently, we returned to our initial search string. To ensure the relevance and quality of the articles, we applied predefined inclusion and exclusion criteria. For this, we categorized articles based on their journals' SCImago subject area and limited the search to journals categorized in 'Business, Management and Accounting,' 'Decision Science' or 'Economics, Econometrics, and Finance' (Kraus et al., 2020; Mariani & Borghi, 2023). The search was constrained to English-language, peer-reviewed journal articles published between 2018 and 2024, reflecting the rise in AI capabilities impacting

AI-driven BMI following Vaswani et al.'s (2017) groundbreaking publication introducing the Transformer architecture (Jimma, 2023; Knani et al., 2022; Kong et al., 2023; Okagbue et al., 2023). After duplicates were removed, 875 articles remained.

As suggested by Tranfield et al. (2003) and Kraus et al. (2022), we introduced a quality threshold of at least 2 in the CABS Academic Journal Guide 2024 to ensure that we limit our search to articles with sufficient quality. To ensure that the articles aligned with the research objective, we reviewed the titles and abstracts of the remaining 411 articles. All articles not covering at least one dimension of BMI and AI, as well as editorials, letters, and literature reviews, were excluded. As a result, 113 articles remained for our review. We gathered descriptive statistics such as publication year, journal quality, research methodology, as well as sector and technology examined.

For the analysis of the research papers, we applied an inductive approach, as suggested by Gioia et al. (2013). We uploaded the full texts into MAXQDA to facilitate the organization of material during the comprehensive manual coding and analysis process. Following Gioia et al. (2013), we identified and openly coded 1st-order concepts to systematically capture all relevant ideas directly emerging from the data to ensure no significant topic was overlooked. Subsequently, we organized them into 2nd-order themes that serve as theory-centered categories and patterns. If necessary, overarching theoretical dimensions were derived from these themes to capture the central concepts and relationships. To develop the final coding system, we adopted an iterative and inductive process that was in line with our research objective (Gioia et al., 2013). By going back and forth between the data and the codes, we manually coded the remaining research papers to derive our results. The data structure displayed in Figure 2 synthesizes the results from our coding process. The aggregated dimensions were integrated into a

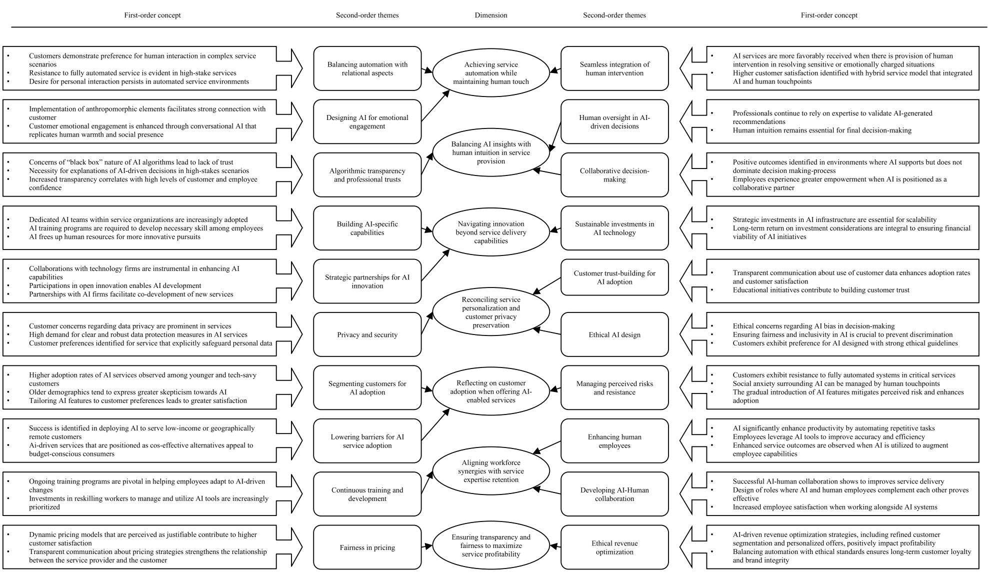


Figure 2. Data structure derived from 1st order concepts, 2nd order themes, and aggregated dimensions.

holistic framework, highlighting the interrelationships of AI-driven BMI in the service industry.

Findings

Descriptive results

The annual distribution of publications shows that most of the 113 articles were published after 2020, most notably in CABS 3 ranked journals (see Figure 3). The sample includes 69 articles that applied a quantitative and empirical approach, most commonly adopting scenario-based online experiments and surveys concerning past experiences with respective AI applications (Hildebrand & Bergner, 2021). The prevalence of this approach is comprehensible due to its comparatively good feasibility in investigating AI (Frank & Otterbring, 2023; Huang & Sénécal, 2023).

Less prevalent, 17 articles applied a qualitative and empirical approach, predominantly utilizing a single-site case study methodology and sector-specific or service-specific interviews (Dicuonzo et al., 2023; Spring et al., 2022;). Additionally, 15 articles applied a mixed-methods and empirical approach (Akdim et al., 2023; Van Doorn et al., 2023). 12 articles applied a conceptual approach, most commonly proposing AI-infused solution concepts to solve service-specific challenges (Dai & Tayur, 2022; Micu et al., 2022).

Regarding the geographic distribution of data gathered by empirical research, data predominantly originates from Asia (43 articles), North America (28 articles), and Europe (21 articles).

Concerning the service sectors investigated in the sample, hospitality and tourism (44 articles) were most prevalent, while research exploring AI in retail (23 articles) and healthcare (21 articles) also received relatively large attention. Less research was conducted in the context of financial services (13 articles), professional services (3 articles), and sector-independent services (9 articles).

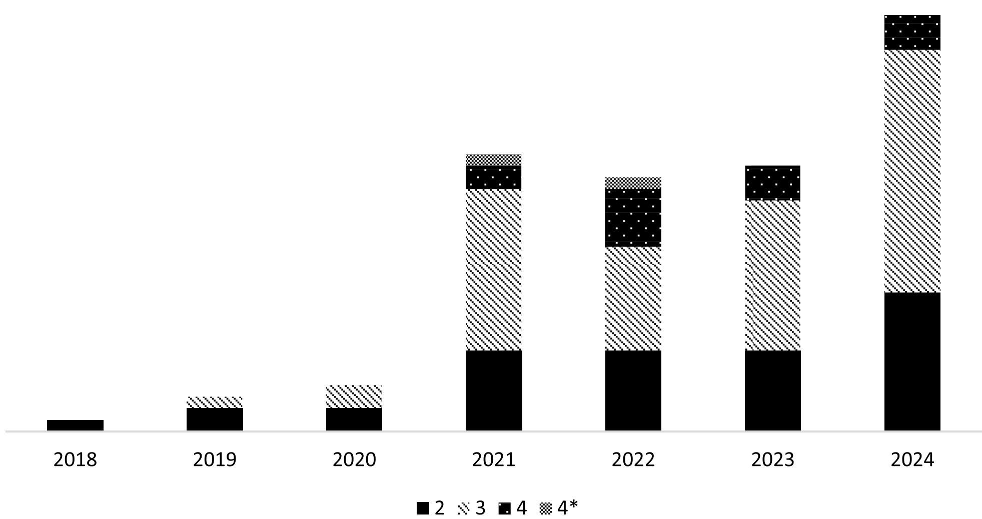


Figure 3. Sample distribution and journal ranking quality (CABS Academic Guide 2021. Database search conducted in December 2024.

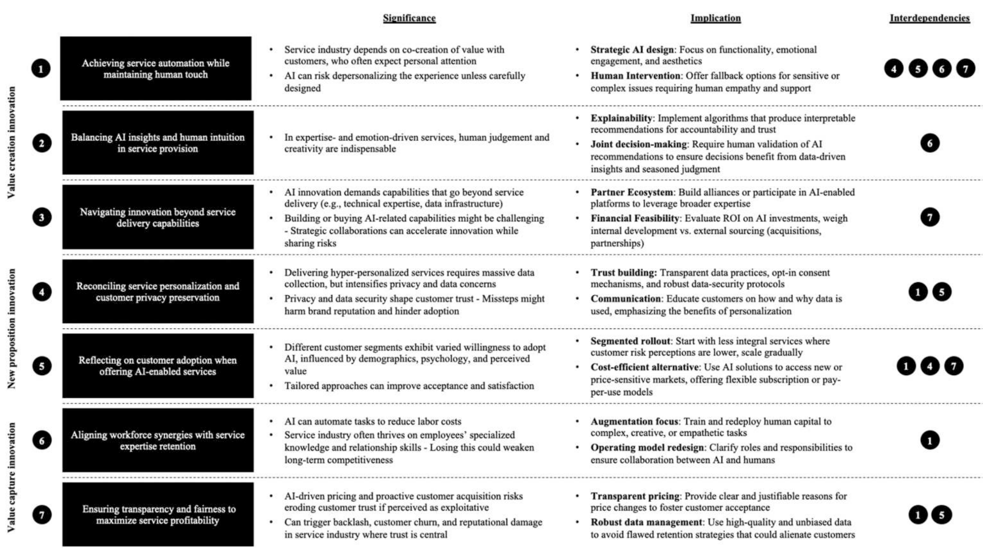
Results

To deepen our understanding of AI-driven BMI in the service industry, we developed 7 key considerations for innovating service-centric business models. By doing so, we synthesized previously isolated research efforts on value creation, value proposition, and value capture innovation into an integrated framework. This framework acknowledges the interplay between these BMI dimensions, captures AI's multifaceted opportunities, and highlights critical trade-offs and challenges. Specifically, it emphasizes the importance of aligning technological advancements with human-centric elements of service delivery, fostering trust and transparency in customer interactions, and ensuring organizational readiness to balance innovation with ethical and operational considerations.

We refer to our inductively derived aggregated dimensions as considerations to underscore the essential and interdependent aspects of AI integration into service business models rather than static solutions (Figure 4).

Value creation innovation

The evolution of AI substantially impacts value creation innovation in the labor-intensive service industry, allowing service organizations to automate formerly exclusively human-to-human interaction (Dicuonzo et al., 2023; Mariani & Borghi, 2023). This includes chatbots enabled by natural language processing (NLP), offering 24/7 support, faster responses, and reduced waiting times (Gursoy et al., 2019; Spring et al., 2022; Van Doorn et al., 2023). Additionally, physical robots help maintain service continuity under unpredictable circumstances (e.g. natural disasters), especially in high-touch service sectors (e.g. hospitals) (Moore et al., 2022; Srivastava et al., 2022). Additionally, leveraging the advanced analytical capabilities of AI enables service organizations to optimize their service delivery by extending and improving human capabilities (Blöcher & Alt, 2021;



			Significance	Implication	Interdependencies
Value creation innovation	1	Achieving service automation while maintaining human touch	• Service industry depends on co-creation of value with customers, who often expect personal attention • AI can risk depersonalizing the experience unless carefully designed	• **Strategic AI design**: Focus on functionality, emotional engagement, and aesthetics • **Human Intervention**: Offer fallback options for sensitive or complex issues requiring human empathy and support	4 5 6 7
	2	Balancing AI insights and human intuition in service provision	• In expertise- and emotion-driven services, human judgement and creativity are indispensable	• **Explainability**: Implement algorithms that produce interpretable recommendations for accountability and trust • **Joint decision-making**: Require human validation of AI recommendations to ensure decisions benefit from data-driven insights and seasoned judgment	6
	3	Navigating innovation beyond service delivery capabilities	• AI innovation demands capabilities that go beyond service delivery (e.g., technical expertise, data infrastructure) • Building or buying AI-related capabilities might be challenging - Strategic collaborations can accelerate innovation while sharing risks	• **Partner Ecosystem**: Build alliances or participate in AI-enabled platforms to leverage broader expertise • **Financial Feasibility**: Evaluate ROI on AI investments, weigh internal development vs. external sourcing (acquisitions, partnerships)	7
New proposition innovation	4	Reconciling service personalization and customer privacy preservation	• Delivering hyper-personalized services requires massive data collection, but intensifies privacy and data concerns • Privacy and data security shape customer trust - Missteps might harm brand reputation and hinder adoption	• **Trust building:** Transparent data practices, opt-in consent mechanisms, and robust data-security protocols • **Communication**: Educate customers on how and why data is used, emphasizing the benefits of personalization	1 5
	5	Reflecting on customer adoption when offering AI-enabled services	• Different customer segments exhibit varied willingness to adopt AI, influenced by demographics, psychology, and perceived value • Tailored approaches can improve acceptance and satisfaction	• **Segmented rollout**: Start with less integral services where customer risk perceptions are lower, scale gradually • **Cost-efficient alternative**: Use AI solutions to access new or price-sensitive markets, offering flexible subscription or pay-per-use models	1 4 7
Value capture innovation	6	Aligning workforce synergies with service expertise retention	• AI can automate tasks to reduce labor costs • Service industry often thrives on employees' specialized knowledge and relationship skills - Losing this could weaken long-term competitiveness	• **Augmentation focus**: Train and redeploy human capital to complex, creative, or empathetic tasks • **Operating model redesign**: Clarify roles and responsibilities to ensure collaboration between AI and humans	1
	7	Ensuring transparency and fairness to maximize service profitability	• AI-driven pricing and proactive customer acquisition risks eroding customer trust if perceived as exploitative • Can trigger backlash, customer churn, and reputational damage in service industry where trust is central	• **Transparent pricing**: Provide clear and justifiable reasons for price changes to foster customer acceptance • **Robust data management**: Use high-quality and unbiased data to avoid flawed retention strategies that could alienate customers	1 5

Figure 4. AI-driven business model innovation in the service industry.

Lei et al., 2021; Van Doorn et al., 2023). Expert systems infused with machine learning (ML) and deep learning (DL) algorithms are utilized to process human employees' expertise along with customer information. This enables more timely and accurate decisions, leading to improved service outcomes, employee efficiency, and associated costs (Dalvi-Esfahani et al., 2023; Johnson et al., 2022; Spring et al., 2022). Additionally, these algorithms enable a shift to more proactive service provision by predicting customers' needs and offering preventive and personalized recommendations. This mitigates costly coping activities and fosters strong customer relationships by demonstrating an understanding of customers' preferences (Bermudéz et al., 2023; Dicuonzo et al., 2023; Leone et al., 2021; Mor & Gupta, 2021). Ultimately, this translates into higher levels of operational excellence, adaptability, and scalability by decoupling service provision from limitations of workforce capacity (Dicuonzo et al., 2023; Guo et al., 2024; Mor & Gupta, 2021; Pham et al., 2024). Nevertheless, as service-centric business models are characterized by their strong dependence on human expertise and relationships, the integration of AI requires careful consideration to preserve essential human elements that define service creation and customer experience (Akdim et al., 2023; Cai et al., 2022; Della Corte et al., 2023).

Consideration 1: achieving service automation while maintaining human touch

Given the co-creative nature of the service industry, innovating value creation through AI requires a careful balance between automation and preserving personal and relational aspects of service provision. Our findings reveal that AI-enabled services designed to be functionally effective, emotionally engaging, and visually appealing foster seamless customer interactions. However, these capabilities pose a critical challenge as they risk undermining genuine emotional connection and service authenticity (Flavián & Casaló, 2021; Hildebrand & Bergner, 2021; Huang & Sénécal, 2023; Lei et al., 2021; Mariani & Borghi, 2021). This challenge reflects a tension consistent with Service-Dominant logic, which understands value as being co-created through interaction and integration of operant resources (Vargo & Lusch, 2008). Our analysis emphasizes that AI plays different, context-dependent roles within these processes and does not represent a uniform type of resource. In simple, highly scripted applications, AI is treated as an operand resource, a tool that is configured once and then applied to customers. In more adaptive, conversational situations, it acts as a non-human operant resource that actively shapes and personalizes the interaction through which value is co-created. Rather than replacing the human touch, AI should be designed to complement it by interactions that meet customers' service expectations (Hildebrand & Bergner, 2021; Lei et al., 2021; Ruiz-Equihua et al., 2025). Therefore, hybrid service models, where human employees remain available for sensitive or complex situations, become increasingly important (Lei et al., 2021; Pillai & Sivathanu, 2020). Equally, the transparent disclosure of AI within service provision is crucial as it strengthens customer trust (Aw et al., 2022; Kyung & Kwon, 2022; Sohn, 2024). Ultimately, AI-driven service automation should not be seen as a replacement for human contact but as reshaping service experiences through meaningful human-AI interactions. In this manner, Service-Dominant logic provides a guideline for classifying AI integration possibilities and elucidates the challenges faced by organizations in reconciling scalable automation with authentic, trust-based interactions in AI-driven service encounters.

Consideration 2: balancing AI insights and human intuition in service provision

Especially in highly expertise-driven service sectors, a key tension between algorithmic rationality and human intuition is emerging as AI increasingly supports decision-making (Dalvi-Esfahani et al., 2023; Johnson et al., 2022; Spring et al., 2022). While our findings highlight the value of AI's analytical and predictive capabilities, they point to risks of an over-reliance on AI, leading to the potential depreciation of human intuition and expertise often cherished in service interactions (Dai & Tayur, 2022; Micu et al., 2022). This aligns with socio-technical systems theory, emphasizing the joint optimization of technological tools and human action (Baxter & Sommerville, 2011). Against this, AI is not a substitute for human intuition but must be integrated into decision-making processes to ensure responsible and informed service outcomes. Traceability and explainability of algorithmic decisions are particularly important as they allow employees and customers to understand the rationale behind recommendations of AI, fostering accountability and trust (Bermudéz et al., 2023; Dalvi-Esfahani et al., 2023). Our analysis suggests that hybrid intelligence models, in which human employees provide critical insights, validate AI's recommendations, and intervene with professional judgment, are crucial for service quality (Dai & Tayur, 2022; Micu et al., 2022). Thus, socio-technical systems theory helps to explain that in AI-enabled services, joint optimization depends on how hybrid intelligence arrangements are configured.

Consideration 3: navigating innovation beyond service delivery capabilities

Our analysis reveals that AI-driven value creation requires additional capabilities exceeding conventional service delivery processes and expertise (Cao, 2021; Spring et al., 2022). This includes substantial investments into technology acquisition, specialized talent, and ongoing operating costs, while risks such as overinvestments without integration, mismatches of capabilities, or heavy reliance on external partners arise (Luo et al., 2021; Mor & Gupta, 2021). From a dynamic capabilities perspective, it is essential to develop the agility to reconfigure acquired AI-related resources in line with changing service requirements (Teece, 2007). Some service organizations build AI capabilities by entering partnerships with technology providers, participating in open innovation, and making acquisitions (Belanche et al., 2019; Cao, 2021). Others participate in AI-enabled platforms that serve as orchestrators within service ecosystems to benefit from co-created value (Battisti et al., 2022; Leone et al., 2021). These different approaches represent distinct configurations of dynamic capabilities, each involving trade-offs between control, integration complexity, and dependence on ecosystem partners. It further highlights the increasing need to balance innovation-driven exploration with efficient service delivery. This tension underscores the organizational ambidexterity required to succeed in AI-enabled service provision.

Value proposition innovation

Utilizing AI allows service organizations to innovate value propositions by offering highly tailored and personalized services, thereby creating more engaging and fulfilling customer journeys. Leveraging AI's advanced analytical and predictive capabilities enables organizations to constantly capture and respond to changing customer preferences, behaviors, and needs (Flavián & Casaló, 2021; Gupta et al., 2022; Kumar et al., 2023;

Shumanov et al., 2021). These stem from AI's ability to collect, process, and analyze data to an extent that exceeds human capabilities due to constraints of scale, complexity, and real-time processing (Boustani et al., 2023; Guo et al., 2024; Rodgers et al., 2021). AI applications such as biometrics (e.g. eye movement), tracking systems (e.g. in-store movement), and wearables (e.g. health trackers) are applied to collect diverse and real-time data at scale (Dicuonzo et al., 2023; Guo et al., 2024; Gupta et al., 2022; Rodgers et al., 2021). Subsequently, ML and DL algorithms are utilized to deliver hyper-personalized services and shift value propositions and underlying revenue models into more dynamic and customer-centric service offerings (Boustani et al., 2023; Micu et al., 2022). This includes transforming from traditionally effort-based to subscription or pay-per-use models by incorporating human employees' knowledge and expertise into AI-driven applications. Consequently, AI ensures steady revenue streams and improves customer satisfaction by offering more flexible and on-demand service options (Luo et al., 2021; Spring et al., 2022). However, the successful implementation of a new value proposition is strongly influenced by adequately considering customers' perceived privacy and trust as well as service expectations. Effectively addressing these factors while leveraging AI to deliver experiences that differentiate from competitors is essential.

Consideration 4: reconciling service personalization and customer privacy preservation

Service personalization comes with critical considerations, as privacy and security are paramount with the extensive use of customers' data. Our findings suggest that customers' adoption of AI in the service industry, characterized by its nature of intimate and trusting relationships, is strongly impacted by the perceived risks and trust towards privacy and data protection (Aw et al., 2022; Kyung & Kwon, 2022; Sohn, 2024). These dynamics resonate with privacy calculus theory, which considers that individuals weigh the expected benefits of personalization against the potential costs to privacy. However, our analysis shows that this weighing is not a one-time, purely rational assessment, but rather an ongoing process that also involves perceptions of transparency, control, and ethical use of data, especially when hyper-personalized offers are perceived as intrusive or manipulative (Belanche et al., 2019; Culnan & Armstrong, 1999; Moore et al., 2022). Therefore, our findings underscore developing trust-building strategies that emphasize privacy and security, implementing transparent data usage policies to foster adoption and educate customers when offering AI-enabled service personalization (Belanche et al., 2019; Mariani & Borghi, 2021; Moore et al., 2022; Sohn, 2024). As a result, while AI enables value proposition innovation with highly personalized services, customers' continuous trust and acceptance are contingent upon sustained data privacy and security measures. In this way, privacy calculus theory not only helps to classify customers' risk-benefit considerations but also explains why hyper-personalization initiatives can still fail if customers feel they are losing control or being treated unfairly. This underscores that the value of AI-driven personalization depends on trustworthy data management.

Consideration 5: reflecting on customer adoption when offering AI-enabled services

Customer adoption of AI-enabled services is strongly influenced by psychological, sociological, and demographic factors, posing a critical challenge for service organizations to innovate through automation (Belanche et al., 2019; Shahzad et al., 2025; Shi et al., 2021; Shumanov et al., 2021). Our findings suggest that adoption is highly context-dependent. For instance, Huang et al. (2021) suggest implementing AI into less integral parts of service offerings due to lower perceived risk and resistance by customers, while Deng et al. (2024) propose service scenarios with extensive human interaction as preferable, as social anxiety mediates customers' preferences for human service provision. Additionally, our sample suggests AI-enabled service offerings as a cost-efficient alternative to address customers and markets with limited access or financial resources (Belanche et al., 2019; Dai & Tayur, 2022; Nourallah, 2023). Nevertheless, our findings underscore a broader lack of consensus on where and how AI should be integrated into service provision. In light of this, adopting a contingency-based perspective becomes essential (Ginsberg & Venkatraman, 1985). Our findings indicate that AI should be deployed differently across service contexts. Extensive automation fits routine, low-risk or price-sensitive interactions, whereas in core, emotionally charged or high-stakes services, AI needs to take a supporting role alongside human employees. Rather than relying on one-size-fits-all solutions, AI must be aligned with specific customer profiles, service contexts, and market conditions to foster meaningful adoption and realize the full benefits of AI-enabled innovation.

Value capture innovation

Implementing AI offers the opportunity to transform and streamline service delivery and thereby capture financial value from innovation (Chen et al., 2024; Gursoy et al., 2019; Spring et al., 2022). The capability of AI to mimic human-like cognitive behavior enables service organizations to automate activities previously limited to human employees' execution (Gursoy et al., 2019; Mariani & Borghi, 2021; Pillai & Sivathanu, 2020). Considering the industry's traditionally labor-intensive business models, AI allows service organizations to unprecedently reduce cost structures by replacing human labor in service provision (Dicuonzo et al., 2023; Gursoy et al., 2019; Spring et al., 2022). Additionally, the advanced analytical capabilities of AI are anticipated to optimize the profitability of revenue streams when utilized to develop dynamic pricing models and proactive customer acquisition and retention strategies (Cao, 2021; Kumar et al., 2023; Pillai & Sivathanu, 2020). Our findings show that AI is employed to dynamically adjust service prices in response to rapidly changing market dynamics and customer preferences to support profit margin optimization (Cao, 2021). Additionally, ML and DL algorithms predict customers' (re)-purchasing behavior and customize advertising and cross-selling efforts to achieve higher conversion rates, thus contributing to revenue assurance. This is important to optimize value capture within the service industry due to its rapidly changing market conditions, demand fluctuations, and competitor activities (Boustani et al., 2023; Shumanov et al., 2021). However, aligning technological advancements in AI with effective human collaboration and ethical consideration is crucial to substantial financial success.

Consideration 6: aligning workforce synergies with service expertise retention

While AI's cost-saving potential is evident, preserving human expertise in the knowledge-driven service industry is essential (Fruehwirt & Duckworth, 2021). Drawing on knowledge-based theory, which conceptualizes knowledge as the most significant resource, our findings highlight that AI should be viewed as a complement to human expertise (Grant, 1996). Specifically, AI can augment employees by liberating their capacity through automation to focus on activities requiring ingenuity and problem-solving capabilities to improve overall service quality (Mariani & Borghi, 2021; Van Doorn et al., 2023). However, this requires designing operating models that facilitate effective service sequencing and seamless collaboration between AI and human employees by defining clear roles and responsibilities, emphasizing human leadership (Micu et al., 2022; Van Doorn et al., 2023). Continuous training and talent management are critical to maintaining and enhancing service expertise, including the development of hybrid skills for working with and critically assessing AI outputs (Cao, 2021; Spring et al., 2022; Zhao et al., 2025). Without such strategies, service organizations risk eroding the valuable human expertise that differentiates their value propositions (Frank & Otterbring, 2023; Spring et al., 2022). In conclusion, realizing AI's transformative potential depends on technological integration and the strategic preservation, augmentation, and continuous development of human expertise to achieve cost efficiency and exceptional customer experiences. Critically, the long-term value of AI-driven BMI hinges on how AI reshapes, rather than reduces, the underlying knowledge base.

Consideration 7: ensuring transparency and fairness to maximize service profitability

AI-enabled dynamic pricing and customer retention offer considerable potential to optimize revenues, but their effectiveness hinges on customers' trust in the fairness and transparency of these applications. Our findings suggest that customers are susceptible to pricing adjustments, and any perception of price gouging potentially diminishes customers' trust and loyalty (Aw et al., 2022; Lei et al., 2021). Similarly, customer retention efforts based on inadequate or biased data result in declining revenue streams (Pereira et al., 2022; Leone et al., 2021). This underscores the importance of trust-based perspectives, emphasizing that customer engagement is mainly contingent on perceptions of fairness, ethical conduct, and procedural transparency (Morgan & Hunt, 1994). Therefore, guaranteeing dynamic pricing changes are interpretable and justifiable for customers to foster continuous acceptance is essential and requires sophisticated data management capabilities that support responsible and context-aware use of customer information (Bermudéz et al., 2023; Dalvi-Esfahani et al., 2023; Leone et al., 2021; Pereira et al., 2022). Our analysis indicates that transparency and fairness mechanism are not merely ethical add-ons but conditions for the effectiveness of AI-based value capture. Ultimately, transparency and fairness are strategic conditions for profitable value capture in AI-enabled services. Without cultivating trust, organizations risk undermining the very mechanisms intended to improve financial performance.

Discussion

Our study provides valuable insights into the multifaceted impact of AI on BMI in the service industry, as it highlights the interdependencies between value creation, value proposition, and value capture. Our integrated framework demonstrates that AI can drive efficiency, hyper-personalization, and dynamic pricing strategies simultaneously.

Nonetheless, the synthesis reveals tensions challenging the uncritical adoption of AI-driven BMI. The emphasis on automation in value creation is counterbalanced by ongoing concerns about the decline of human interactions, which are only partially addressed in the current literature (Cai et al., 2022; Flavián & Casaló, 2021). Similarly, AI-enabled personalization can change value propositions but raises significant privacy and trust issues (Aw et al., 2022; Kyung & Kwon, 2022). Lastly, while AI promises to optimize value capture through dynamic pricing and cost reduction, it also introduces risks of perceived unfairness and ethical ambiguity, especially when algorithmic decisions lack transparency (Lei et al., 2021; Pereira et al., 2022). Given these critical evaluations, our findings highlight AI's transformative potential and serve as a cautionary tale. They encourage scholars and practitioners to reflect on the inherent trade-offs and complexities of integrating AI into service business models. Our integrative approach underscores that incorporating AI is a dynamic process requiring continuous alignment between technological capabilities and human-centric values, which are at the core of service delivery.

Theoretical contribution

This research's theoretical contribution is synthesizing 7 key considerations on AI-driven BMI in the service industry into a holistic framework, which highlights the dynamic and interconnected nature of value creation, value proposition, and value capture. It demonstrates that AI can simultaneously drive, mediate, and constrain innovating business models in the service industry.

Our findings reveal that AI enables the automation of labor-intensive activities, augments human capabilities, and transforms cost and revenue models (Dicuonzo et al., 2023; Guo et al., 2024; Pham et al., 2024). However, these opportunities must be considered in a broader context as operational optimizations (value creation) might reshape customer experiences (value proposition) and require new cost and revenue approaches (value capture) (Chen et al., 2024; Spring et al., 2022). By highlighting these interdependencies, this study moves isolated theoretical discussions prevalent in existing research to an integrated perspective. It suggests AI-driven BMI as a multi-directional reconfiguration of strategic, relational, and operational elements and offers researchers a holistic view of how AI-driven transformations impact the various facets of service-centric business models.

Additionally, our study emphasizes ethical and relational tensions often underdeveloped in existing research (Trincado-Munoz et al., 2024). By making these trade-offs explicit, our study shows that service automation must be supported by mechanisms that maintain trust and emotional commitment. The framework places significant emphasis on the utilization of AI-driven BMI as a process characterized by tension, wherein the considerations of efficiency, personalization, and value capture are to be evaluated in relation to relational and ethical concerns. This approach diverges from the conventional perspective of considering these concerns as purely technological improvements. This broadens the scholarly discourse by highlighting new ways to fine-tune business model innovation. It extends S-D logic by positioning AI as an operant resource that reconfigures value co-creation processes (Vargo & Lusch, 2008). Additionally, it supports socio-technical systems theory by emphasizing the importance of balancing technological capabilities with human-centric service design (Baxter & Sommerville, 2011).

Lastly, our findings highlight that innovating service-centric business models move beyond technological investments and require strategic alignment of organizational structures, expertise, and culture (Johnson et al., 2022; Spring et al., 2022). This adds greater theoretical depth to current debates by highlighting the organizational complexity of AI-enabled services that require coordination between frontline employees, management, and algorithmic systems. This underscores the importance of deliberate alignment between human judgment and algorithmic capabilities, reinforcing the relevance of dynamic capabilities theory (Teece, 2007). Our results link capability-building paths with dynamic capabilities and organizational ambidexterity by showing how different configurations embody different trade-offs between exploring AI-driven innovations and exploiting reliable, efficient services (Teece, 2007). Furthermore, our findings contribute to the knowledge-based view as we offer a more nuanced understanding of how organizations can evolve internal capabilities while leveraging AI for sustained service innovation (Grant, 1996). Additionally, we enrich privacy calculus theory and a contingency perspective by showing that benefit-risk assessments of AI-enabled personalization are ongoing and context-dependent, shaped by transparency, perceived control, task criticality customers' emotional and social needs, and resource constraints (Culnan & Armstrong, 1999; Ginsberg & Venkatraman, 1985).

Overall, by underlining these interdependencies, the AI-driven BMI framework narrows the gap in the literature and contributes to a better understanding of the impact of AI on service-centric business models. In this way, the study guides scholars in understanding the influence of AI on BMI and provides a theoretically grounded basis for future research on the trade-offs and boundary conditions of AI-driven BMI in services.

Practical contribution

Our study provides top service industry managers with a cohesive guideline for implementing AI across the interrelated BMI dimensions. It translates our findings into practical recommendations that support top managers in innovating service-centric business models.

First, it encourages practitioners to deploy AI to automate labor-intensive activities while preserving empathy through clear escalation paths for human employees. This approach enables customers to receive empathic support in sensitive service contexts, allowing service organizations to increase operational efficiency and secure customers' trust and loyalty.

Second, our findings highlight the importance of balancing AI insights with human expertise in service provision. Even though AI facilitates improved predictive accuracy and decision speed, top managers must design processes and training programs to enable employees to engage critically and foster closer collaboration with AI. In doing so, service organizations ensure the preservation of service professionals' expertise, which is critical for maintaining customer satisfaction in complex service interactions.

Third, service organizations should evaluate whether to build AI capabilities in-house, partner with specialist firms, or acquire such capabilities to optimize resource allocation and safeguard intellectual property rights.

Fourth, our study provides insights into designing new value propositions through hyper-personalization and data-driven customer interactions. However, it cautions top managers to adopt hyper-personalization responsibly, with robust data governance and transparent privacy policies, to sustain customer trust. Trust-building measures such as demonstrating data security, ethical use, and algorithmic explainability are crucial. Addressing customer concerns about data misuse and algorithmic biases will increase adoption rates for AI-driven service offerings.

Fifth, we provide recommendations to retain service expertise. Even if AI enables streamlining labor-intensive manual activities and reduces personnel expenses, our findings highlight that top managers must proactively manage workforce transitions by reinvesting cost savings in employee development so service professionals can focus on complex, high-value customer interactions. This includes clearly defining roles, talent management, and continuous training.

Sixth, ensuring data integrity is critical for long-term success. Rigorous data management and early detection of flawed AI predictions help prevent biases, preserve customer relationships, and protect revenue streams.

Our insights enable service organizations to move from standalone AI implementations toward strategic deployments that reconcile technological advancements with human-centric service principles. In doing so, they are positioned to maintain a competitive advantage in the rapidly evolving service industry.

Limitations

Our study is not without limitations. First, we acknowledge that the search terms, even though extensively elaborated, are based on a mutually independent scoping review and the research team's expertise. This implies a degree of subjectivity and might lead to other researchers using different search terms to analyze the impact of AI on BMI. As in all qualitative research, subjectivity also exists in coding and interpreting results. Second, we restricted our review to peer-reviewed publications with a quality threshold of CABS $\geq$ 2. Even though this ensures academic rigor, it may exclude substantive insights from industry white papers, conference proceedings, or emerging journals. After screening two-thirds of the sample, theoretical saturation was reached when constructing our framework (Gioia et al., 2013). Hence, the value of any possibly missed contributions is presumably limited. Third, our decision to focus on articles published between 2018 and 2024 and capture the most recent technological advancement excludes earlier studies that may offer the historical context of AI-driven BMI in the service industry. Equally, any research on AI currently faces limitations due to the continuous advancements in AI technologies (e.g. generative AI). Nevertheless, a comprehensive understanding of theoretical concepts in management research is required. Fourth, our study might be limited in its depth of service- and technology-specific findings as we prioritize the breadth of our analysis by integrating studies from multiple service sectors. Fifth, the articles in our sample predominantly originate from Asia, North America, and Europe. Therefore, the findings might not represent other markets (e.g. Africa and South America) and restrict our study's generalizability. Lastly, our research offers key considerations for AI-driven BMI, but it does not reflect the applicability to service organization's characteristics such as size, resource availability, or cultural readiness. Thus, generalizing our findings to all service organizations must be carefully considered.

Future research directions

Building upon our study's insights and limitations, further research is required to deepen the theoretical and practical understanding of AI-driven BMI in the service industry.

First, more evidence is needed on how and when automation can replace human interactions without sacrificing empathy and trust. Field experiments, quasi-experiments, and cross-cultural comparisons could clarify how cultural norms, emotional factors, and task complexity influence preferences for chatbots or service robots, especially in contexts where interpersonal warmth is crucial.

Second, examining the interaction between AI-derived insights and human judgment is essential. Multiple case studies or process-tracing methods could elucidate how frontline employees assess and decide whether to act on AI recommendations. This would illuminate organizational cultures and technological enablers that support collaborative human-AI models, particularly in services where professional expertise is vital.

Third, future research should investigate how service organizations acquire and develop AI capabilities to foster innovation. Comparative case studies could explore situations where internal development, strategic alliances, or platform participation have led to competitive advantages. Action research could reveal challenges encountered when transitioning to AI-driven business models, such as management failures or skills shortages.

Table 1. Future research questions.

Key considerations	Future research questions
Achieving service automation while maintaining human touch	• How do emotional needs shape customer openness to automated vs. human-led services? • Under what conditions do AI tools enhance trust in service contexts?
Balancing AI insights and human intuition in service provision	• Which organizational cultures best help employees balance personal judgment with AI input? • How does AI explainability impact employees' readiness to accept algorithmic suggestions?
Navigating innovation beyond service delivery capabilities	• What factors guide a firm's choice between building AI in-house, forming alliances, or joining platforms? • What dynamic capabilities are essential for AI-enabled BMI? • How do resource limitations influence the speed and success of AI-driven innovation?
Reconciling service personalization and customer privacy preservation	• At what data usage threshold do customers perceive hyper-personalized services as intrusive or unethical? • Can transparent data policies and ongoing consent ease privacy concerns in AI-enabled services?
Reflecting on customer adoption when offering AI-enabled services	• How do psychographic segments balance cost, convenience, and perceived risk when evaluating AI-enabled services? • Do the same AI solutions yield similar adoption across cultural and socioeconomic contexts?
Aligning workforce synergies with service expertise retention	• How do AI-induced role changes affect employee satisfaction in services? • Do collaborative AI tools support knowledge sharing among service employees?
Ensuring transparency and fairness to maximize service profitability	• How can ethics boards or protocols address biases in AI-driven pricing strategies? • Does algorithmic transparency build lasting customer trust and loyalty?

Fourth, closer scrutiny is required to address the tension between hyper-personalization and privacy. AI-based personalization relies on extensive consumer data, raising ethical and regulatory concerns about surveillance and data misuse. Scenario-based experiments could identify thresholds at which customers perceive such data practices as intrusive. Longitudinal surveys might determine whether transparent data policies and frequent consent mechanisms sustain trust over time.

Fifth, understanding variations in consumer characteristics would add depth to the study of AI adoption in services. Discrete choice experiments can illuminate how individuals weigh cost, convenience, and perceived risk. Cross-country field studies could show whether the exact AI-based solutions resonate similarly across different social or economic contexts.

Sixth, scholars could examine how to preserve human expertise in knowledge-intensive service settings increasingly supported or augmented by AI. While automation handles repetitive tasks, these changes may reshape professional roles, collaborative structures, and skill requirements. Mixed-method research could reveal how these shifts impact employee well-being, the cultivation of expertise, and overall service outcomes.

Seventh, ensuring fairness and transparency in deploying AI to optimize profitability remains a critical concern. Dynamic pricing and targeted customer retention initiatives can backfire if perceived as exploitative or biased. Multi-method approaches, such as algorithm audits combined with consumer experiments, would help uncover potential discrimination and assess how to effectively address issues related to non-transparent or unfair pricing mechanisms (Table 1).

Conclusion

By reviewing the intersection of AI and BMI in the service industry, our study emphasizes the interconnected nature of the dimensions value creation, value proposition, and value capture. We identify 7 key considerations that describe the thoughtful integration of AI into service-centric business models. Collectively, our insights demonstrate that the innovation of service business models with AI should be managed holistically. By embracing the interconnected nature of the BMI dimensions, our study contributes to the academic discussion and managerial practice on AI-driven BMI in the service industry.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Sascha Kraus http://orcid.org/0000-0003-4886-7482

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Appendix

Aggregated dimension	2nd order theme	In-vivo excerpts
Achieving service automation while maintaining human touch	Balancing automation with relational aspects	*'The majority of consumers still express preference for human financial advisors, due to the lack of a 'human touch' of robo advisors and human's greater ability to understand and personalize advice'* (Hildebrand & Bergner, 2021)
	Designing AI for emotional engagement	*'Warmth has a positive impact in mitigating the negative emotional reactions from an interaction failure'* (Huang & Sénécal, 2023)
	Seamless integration of human intervention	*'Practitioners should contemplate how to combine chatbot and human resources effectively to deliver the best customer service'* (Lei et al., 2021)
Balancing AI insights with human intuition in service provision	Human oversight in AI-driven decisions	*'We envision a future in which physicians routinely use AI to supplement their decision-making; we do not believe that physicians will be completely replaced by AI'* (Dai & Tayur, 2022)
	Algorithmic transparency and professional trust	*'Providing clear, comprehendible explanations for the suggestions made by CDSS can improve the HCP's understanding of the system's rationale, leading to more precise and reliable recommendations'* (Dalvi-Esfahani et al., 2023)
	Collaborative decision-making	*"Augmentation entails humans and machines 'combin[ing] their complementary strengths, enabling mutual learning and multiplying their capabilities'mpa#rdquo;* (Spring et al., 2022)
Navigating innovation beyond service delivery capabilities	Building AI-specific capabilities	*'Retailers are also aggressively hiring AI experts to build their technology teams'* (Cao, 2021)
	Strategic partnerships for AI innovation	*'The technology service provider adopts a strategy of horizontal collaborations with other providers in order to improve its AI competencies and provide increasingly sophisticated AI-based solutions'* (Leone et al., 2021)
	Sustainable investments in AI technology	*'The benefits of AI adoption might not immediately be reflected on the financial statement due to the learning curve of AI technologies and initial investment, but hospitals will benefit from AI adoption in the long term'* (Pham et al., 2024)
Reconciling service personalization and customer privacy preservation	Privacy and security	*'The significant role of perceived security identified in the study adds to the human-computer interaction body of knowledge, highlighting that consumer-digital voice assistant relationship development resembles that of human-human interactions, which requires the presence of security and a sense of non-threatening'* (Aw et al., 2022)
	Customer trust-building for AI adoption	*'This study also calls for managerial efforts to reduce users' resistance to AI through active customer communication and to make AI applications more trustworthy'* (Kyung & Kwon, 2022)

(*Continued*)

Continued.

Aggregated dimension	2nd order theme	In-vivo excerpts
	Ethical AI design	*'For management, differences in personality traits can enhance customer targeting and communications, and if applied ethically, can improve consumer outcomes by better matching products and services, and reducing search costs'* (Shumanov et al., 2021)
Reflecting on customer adoption when offering AI-enabled services	Segmenting customers for AI adoption	*'They need to be conceived as distinct per target markets: while Z and Y generations are far more open towards applications and less fearful towards information sharing, operating on platforms, etc, the older generations are more biased and may be afraid of not being comfortable in interacting with an unknown and maybe complex machine'* (Della Corte et al., 2023)
	Lowering barriers for AI service adoption	*'Although human financial advisors do not focus on YRIs due to their low incomes and modest investments, the increase in YRIs' rate of investing their savings represents a good opportunity for FRAs to enter the market'* (Nourallah, 2023)
	Managing perceived risks and resistance	*'This is especially recommended for countries with high levels of uncertainty avoidance (like Portugal in the present case) because, in these countries, customers need to be secure when adopting an innovation that involves uncertainty. That is, customers need to have a very positive opinion about financial robo-advisors in order to decide to use them'* (Belanche et al., 2019)
Aligning workforce synergies with service expertise retention	Continuous training and development	*'Thus, when introducing AT to work together with workers, organizations should not only provide a collaborative complementary narrative but also offer training so workers can acquire new skills and perform tasks that cannot be carried out by AT in the joint work'* (Van Doorn et al., 2023)
	Enhancing human employees	*'The large amount of data being collected through in-store customer tracking systems and analyzed with AI platforms has the potential to improve marketers' understanding of customer behavior and improve both demand prediction and supply chain management'* (Micu et al., 2022)
	Developing AI-Human collaboration	*'In a nutshell, if the AT–worker teamwork operates in a way that can tap into the unique and complementary competences and skill sets of both AT and human workers, the quality of worker–consumer interaction is likely enhanced by the presence of AT'* (Van Doorn et al., 2023)
Ensuring transparency and fairness to maximize service profitability	Fairness in pricing	*'Customers should be provided with quick and accurate information to locate a particular product in the store and do product comparisons very easily, as interactivity is important to engage the customers with a dynamic and seamless shopping experience'* (Pillai & Sivathanu, 2020)
	Ethical revenue optimization	*'Matching consumer personality with congruent advertising messages can lead to more effective consumer persuasion for most personality type'* *'Regulation and the creation of disincentives to malfeasance are urgently required to ensure that personality information is not misused'* (Shumanov et al., 2021)