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AI-driven business model innovation: A systematic review and research agenda

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ABSTRACT

Recent years have seen a surge in research on artificial intelligence (AI)-driven business model innovation (BMI), reflecting its profound impact across industries. However, the field's current state remains fragmented due to varied conceptual lenses and units of analysis. Existing literature predominantly emphasizes the technological aspects of AI implementation in business models (BMs), treating BMI as a byproduct. Additionally, there is a lack of coherent understanding regarding the scope of BMI propelled by AI. To address these gaps, our study systematically reviews 180 articles, offering two key contributions: (1) a structured analysis of evolving research dimensions in AI-driven BMI, differentiating between static and dynamic views of BMI, and (2) a framework presenting distinct research perspectives on AI-driven BMI, each addressing specific managerial focuses. This synthesis facilitates a comprehensive understanding of the field, enabling the identification of research gaps and proposing future avenues for advancing knowledge on the management of AI-driven BMI.

1. Introduction

Artificial intelligence (AI) is one of the most disruptive and groundbreaking technologies of the 21st century (Ahmad & Ghapar, 2019). The recent fanfare surrounding ChatGPT, an AI chatbot built on the GPT-3 deep learning language model, has once again fueled discussions about the impact of AI (Burger et al., 2023). To successfully capture value from AI applications, firms need appropriate business models (BMs), comprising the "architecture of the firm's mechanisms for creating, delivering, and capturing value" (Teece, 2010, p. 172). GPT-3's successor, GPT-4, has further extended the boundaries of human–machine interactions, enabling the development of innovative BMs that challenge current models (Kanbach et al., 2023). Other generative AI tools, such as Bard, Gemini, or Claude, other sophisticated large language models, and Midjourney, a tool for image generation, underscore the fast-growing relevance of generative AI across multiple domains (McKinsey, 2023). As a result, an increasing number of companies are engaging with AI technology, and managers are trying to identify the most promising BMs (Burström et al., 2021; Coskun-Setirek & Tanrikulu, 2021; Wamba-Taguimdje et al., 2020). Therefore, the potential application of AI in business processes is broad. Data-driven decision-making demonstrates a real-world application of AI that optimizes decision-making procedures and amplifies their accuracy and reliability (Battisti et al., 2022). For instance, eBay successfully implemented machine translation to enhance its operational efficiency and decision-making, resulting in essential modifications to the data utilized in decision-making and the overarching BM (Akter et al., 2022). Similarly, Vodafone enhanced its customer service across multiple channels by integrating AI-driven data analysis into its BM, resulting in the personalization of products and services (Gama & Magistretti, 2023; Sjödin et al., 2021).

According to Lee et al. (2019), more than 80 % of business executives believe that AI will allow firms to maintain or gain competitive advantages, and more than 70 % conclude that AI will create opportunities for new BMs (PwC, 2024; Soni et al., 2020; Vocke et al., 2019). Using and implementing AI in business processes requires established companies to engage in business model innovation (BMI) to leverage the value-creation potential of AI (Mariani et al., 2023). BMI can be defined as "designed, novel, and nontrivial changes to the key elements of a firm's BM and/or the architecture linking these elements" (Foss & Saebi, 2017,

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p. 216). However, according to Sjödin et al. (2021), most business leaders also feel unprepared to accelerate company-wide AI adoption and AI-driven BMI. Most organizations lack the know-how and capabilities for successful AI implementation, meaning they fail to roll out AI initiatives beyond early concepts (Björkdahl, 2020; Burström et al., 2021; Marinakis et al., 2021).

The peculiarities of AI challenges for businesses and management are complex, resulting in a diverse research landscape on AI-driven BMI. Despite a broad focus on technological aspects, management research concerns managerial challenges like AI adoption and implementation, which often necessitates changes in organizational culture due to employee resistance (Minbaeva, 2021). Furthermore, AI applications and BMI require managers and employees to adopt new routines and acquire new capabilities and skills (Jorzik et al., 2023; Sjödin et al., 2021). From a broader perspective, growing ethical challenges, regulatory uncertainty, and uncertainties associated with the application of AI require new management capabilities, while these distinct requirements necessitate both the innovation of current BMs and the emergence of novel ones (Gama & Magistretti, 2023). Due to these peculiarities and challenges, the existing literature is unclear as to how BMs change and how managers need to (re)configure their BMs to create and capture value from AI. From an analytical perspective, recent research on AI-driven BMI has often engaged in descriptive elaborations of AI-driven BMs (Mariani et al., 2023). Furthermore, while scholars have researched the phenomenon from different angles and through various conceptual lenses, they have primarily focused on a single implication of AI or a specific industry or department, leading to disparate, fractured, and contradictory views on AI-driven BMI (Chen et al., 2021; Valter et al., 2018b). Two major shortcomings have become apparent through this rapid growth and the resulting fragmented body of research (Di Vaio et al., 2020).

First, the literature investigates AI-driven BMI from a technological perspective. Many studies focus predominantly on technological challenges such as AI implementation, AI adoption, data requirements, and data security. These studies often analyze AI-specific research questions in the context of BMI. While this technology focus yields valuable insights into the organizational challenges of using AI, it creates a disparate body of research concerning the management of AI-driven BMI. At the same time, BMI often represents an evolutionary "byproduct" of AI implementation. This leads to the second shortcoming within existing research: the literature on AI-driven BMI can range from leveraging AI to increase the efficiency of an existing BM to developing disruptive AI-driven BMI. Consequently, extant research in this domain hinders a holistic understanding of AI-driven BMI management, given that research themes address different levels of the scope of AI-driven BMI. From a conceptual perspective, some studies apply static research approaches concerning the identification of constituting elements, barriers, and challenges of AI-driven BMI, while others investigate AI-driven BMI from a dynamic process perspective.

In sum, different research perspectives, conceptual lenses, units of analysis, and research foci have emerged in the AI-driven BMI research landscape in recent years, highlighting the need to synthesize key research results. In this study, we aim to fill this research gap through a structured synthesis of recent research developments in this domain with a systematic literature review. Second, in analyzing the research themes, we reconcile the different conceptual lenses and develop a conceptual framework. This framework structures the research themes within the broader BMI and innovation management literature regarding the dynamics of BMI, thereby addressing the shortcomings of the research landscape. This allows us to identify research gaps and propose future research avenues concerning the management of AI-driven BMI. Therefore, this systematic literature review is guided by the following research questions: (1) What is the content of extant research on AI-driven BMI? (2) What is the role of AI applications in driving BMI, considering the scope of AI-driven BMI? (3) What are future research directions for understanding the management of AI-driven BMI from a dynamic perspective? Although prior literature reviews have addressed the application of AI in a business context, no previous academic study has compiled the research findings related to AI-driven BMI and synthesized the characteristics of its management.

Our contribution to the literature is twofold. First, we summarize and structure the content of extant AI-driven BMI research, providing a comprehensive overview of evolving research themes and their interrelations. Through the development of a framework that synthesizes research perspectives concerning the interplay between AI and BMI, we extend the innovation management literature beyond investigations of AI applications from a technological perspective. Specifically, we organize research themes based on employing a static (e.g., describing configurations of AI-driven BMI) or dynamic approach (e.g., explaining how BMs change) to AI-driven BMI, supporting a more holistic understanding of AI-driven BMI. Our work complements recent reviews that consider AI or BMI in isolation (Gama & Magistretti, 2023; Spieth et al., 2023). Second, as we synthesize different research perspectives on AI-driven BMI, each with distinct foci and management implications, we contribute to a better understanding of the dynamics of technology-induced BMI. Our review aids researchers in organizing their research on AI-driven BMI from a conceptual point of view. We further distill research gaps and provide future research avenues and specific research questions concerning the management of AI-driven BMI that help advance knowledge in this field and provide practical implications.

2. Research on AI-Driven BMI: Establishing the groundwork and prior reviews

2.1. AI-driven BMI

Multiple and varied definitions of AI currently coexist within the literature (Eling et al., 2022; Helo & Hao, 2021). We base our research on the widely accepted definition of AI as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 17).

Along with different definitions of AI, researchers also classify AI in different ways. Some researchers divide AI by degree of intelligence (e.g., strong vs. weak AI) (Dudnik et al., 2021; Eling et al., 2022; Lee et al., 2019), while some emphasize how businesses can utilize AI (e.g., assisted vs. augmented vs. autonomous intelligence) (Garbuio & Lin, 2019; Liew, 2018). Our research follows the understanding that AI is an umbrella term for different tools, most of which are machine learning (ML) techniques (Liengpunsakul, 2021; Wan et al., 2021).

ML is a collection of mathematical methods or algorithms that independently improve and learn based on computerized data (Renz & Hilbig, 2020). It includes three types of learning: supervised, unsupervised, and reinforcement learning (Eling et al., 2022). Supervised learning trains an algorithm by using labeled data to identify connections between the input and output data. This enables the algorithm to accurately label unlabeled data based on the learned patterns (Eling et al., 2022; Lee et al., 2019). Examples of supervised learning techniques include classification (decision-tree) and regression problems, which can be used to innovate the value delivery dimension of a BM by offering predictions (Liengpunsakul, 2021). Unsupervised learning, such as clustering and dimensionality reduction, does not require predetermined outputs because the model aims to identify patterns in the raw, unlabeled data used in the BMI context to find customer segments and tailor offerings to those segments (Liengpunsakul, 2021). In reinforcement learning, a model learns and reacts to a changing environment to perform a specific task, allowing business processes to be adapted and optimized (Scheiderer et al., 2020).

Deep learning has recently gained widespread attention in both research and practice as a special form of ML (Bhattacharjee et al., 2017). Inspired by the architecture of the human brain, deep learning tries to process large volumes of data in an artificial neural network, with goals such as image classification, object recognition, or natural language processing, offering vast potential for BMI in several areas (Sarc et al., 2019). Although training a neural network is highly complex and requires immense computing power, it exceeds the performance of other ML techniques. Therefore, it may be capable of fully unlocking the potential of AI to innovate and disrupt various BMs and industries in ways that other ML techniques cannot (Bhattacharjee et al., 2017).

The number of studies exploring the interplay of AI and BMI has trended upward in recent years within the academic discourse (Burström et al., 2021; Lee et al., 2019; Mishra & Tripathi, 2021). These articles vary widely in their analytical viewpoints and range from narrow process developments to macro-scale industry disruptions. It must be acknowledged that these viewpoints can overlap and that revolutionary products can be disruptive with a time lag on an industry scale (Kohtamäki et al., 2022; Valter et al., 2018a; Warner & Wäger, 2019).

A significant number of studies primarily concentrate on the automation of processes via AI (Garrido-Baserba et al., 2020; Qvist-Sørensen, 2020), while others highlight nascent products and personalized services made possible through AI usage (Wan et al., 2021). Haftor et al. (2021) narrowed the lens to examine AI's effect on specific BMI dimensions. Other researchers prefer a more comprehensive approach, investigating multiple BMI dimensions or overarching changes (Di Vaio et al., 2020; Lee et al., 2019; Norman, 2017; Sjödin et al., 2021). Some have even delved into the impact of AI on entire ecosystems (Burström et al., 2021; Fredström et al., 2021) or entire industries (Jin & Shin, 2020; Marinakis et al., 2021). A recurring message among these studies is a call for further investigation in the area (Bertoni et al., 2022; Lee et al., 2019; Payne et al., 2021). Recent contributions to the literature have offered practical applications and use cases (Naughton, 2020; Yun et al., 2016).

As outlined above, the literature on AI-driven BMI is phenomenon-driven and largely focused on the specifics associated with AI, remaining fragmented concerning the dynamics and scope of BMI. Static and dynamic approaches have evolved in the BMI literature (Demil & Lecocq, 2010; Saebi et al., 2017). The static approach emphasizes building typologies by analyzing components of BMs, the interactions between them, and their implications, such as how configurations of BMs influence performance (Demil & Lecocq, 2010). In comparison, the dynamic approach considers how novel BMs evolve and how firms innovate their BMs. This research stream predominantly focuses on the management aspects of BMI and distinguishes between different concepts concerning BMs' innovation scope. Recently, different phenomena, such as social or circular BMI, have gained prominence in research (Klein et al., 2023; Sjödin et al., 2023). As these research areas have evolved, there has also been a shift from a static BM view (i.e., describing BMs, identifying archetypes and patterns) to one focused on dynamic BMI (i.e., investigating the process of BMI). Given the emergence of research concerning AI-driven BMI, mapping the content of AI-driven BMI research along these two approaches would be useful to assess the current state of research and advance our understanding of the specific research dimensions that have evolved regarding AI-driven BMI. Therefore, we conduct a systematic literature review aiming to organize the extant knowledge and research within the field of AI-driven BMI.

2.2. Comparing previous reviews of AI in business research

To initiate our analysis, we compared selected reviews (i.e., focus, research design, time horizon, and findings) in the research field of AI in business, highlighting the relevance and uniqueness of our research. Table 1 provides a comparison of the selected reviews.

Loureiro et al. (2021) and Nguyen et al. (2022) concentrated their reviews on AI in business, examining its applications across various domains and providing a comprehensive understanding of its impact. Letheren et al. (2020), Martínez-López and Casillas (2013), Vlačić et al. (2021), and Zeba et al. (2021) focused their reviews on specific industries, yielding explicit recommendations and future research directions in those domains.

It should be noted that multiple studies have been published in the field in the last two years, which are not covered by the reviews presented. Furthermore, none of the reviews has specifically addressed the research gaps in managing AI-driven BMI. Our research employs a systematic literature review methodology integrating BM literature with AI research. By combining these two domains, our study offers a holistic perspective on the potential synergies between AI and BMI, representing a distinctive research approach.

The above analysis underscores the differences between our research and the referenced studies in the fields of AI and BMI. By explicitly addressing the intersection of AI and BMI and employing a systematic literature review methodology, our study offers a unique and relevant contribution to the existing body of knowledge.

3. Methodology

To produce valuable insights and make a relevant contribution to the research discussion surrounding AI-driven BMI, our team of two researchers conducted a systematic literature review following the methodological approach developed by Tranfield et al. (2003). To ensure replicability, transparency, and high-quality results, this structured procedure includes implementing the following steps: planning, conducting, reporting, and dissemination (Sauer and Seuring, 2023).

3.1. Data collection

We conducted data collection to ensure relevance to our research focus. By applying rigorous selection criteria, we aimed to include high-quality studies contributing to our understanding of the intersection between AI and BMI.

We searched the titles and abstracts of published articles in English from before 2023 in four electronic databases using the keywords "business model*" OR "business-model*" OR "business model innovation" OR "value proposition*" OR "model innovat*" AND "artificial intelligence" OR "AI" OR "A.I." OR "machine learning" OR "deep learning" OR "neural network*." This initial search resulted in 3,984 articles; eliminating duplicates yielded a total of 2,132 articles. To ensure methodological rigor, we established and implemented a set of criteria to select relevant publications (Kraus et al., 2022). First, we implemented a quality filter assessment and excluded journals that did meet at least one of the following rankings: VHB $\geq$ C; JCR $\geq$ Q3; SJR $\geq$ Q3; this resulted in the exclusion of an additional 1,483 articles. We then manually screened the abstracts of the remaining 649 articles in terms of their scope, leaving 233 articles. The remaining 233 articles were assessed for full-text eligibility and were narrowed down to 167 articles. Finally, nine articles were added back to the sample after cross-referencing, resulting in a final sample of 180 articles for review.[1] Fig. 1 summarizes the selection process.

3.2. Data analysis and synthesis

Our research followed a systematic inductive approach to concept development to increase qualitative rigor while still retaining the potential to generate new ideas and concepts (Gioia et al., 2013). As a result, we clustered text components from our entire sample into meaningful concepts, themes, and aggregated dimensions. To support theory-building from data through an analysis of deeper meanings and meaningful interrelations, one researcher gathered data while the other maintained a diagnostic distance, thereby providing the benefit of a balance between distance from and proximity to the data (Glaser & Strauss, 1967). We continuously alternated between data and theory to contrast and correlate themes as they emerged from the data and

[1] The complete list of references is available on request from the authors.

Table 1
Overview of selected reviews in the field of AI in business research.

Authors (years)	SLR	Focus	Quality filters	Research Design	Databases	Keywords	Period	Sample size	Findings
Letheren et al. (2020)	–	AI for marketers	–	Essay	–	–	–	61	Recent developments of AI for marketers, consumers, and society; 24 research questions for future research
Loureiro et al. (2021)	✓	AI in business	✓	Latent Dirichlet allocation (text-mining approach); (Blei et al., 2003)	Web of Science, Scopus	"artificial intelligence," "artificial-intelligence" (in management science or management or business)	1977–2019	404	18 topics classified into four clusters; Presentation of main developmental trends and guide for future AI research
Nguyen et al. (2022)	(✓)	AI in business	(✓)	Latent semantic analysis (text-mining approach); (Landauer & Dutnais, 1997)	EBSCOhost, ProQuest	"artificial intelligence" and "business"	1998–2018	171	Key themes in academic and practitioner discourses on AI; Identification of research gaps and future research directions
Martínez-López and Casillas (2013)	–	AI in industrial marketing	–	Historical literature review (Laplaca,1997)	Scopus	"AI," "intelligent systems" (in business/management / technical-oriented subjects)	1972–2011	< 300	Focus on applications for industrial marketing; Review with conclusions and some future insights
Vlačić et al. (2021)	✓	AI in marketing	✓	Multiple correspondence analysis	Web of Science, Scopus	"marketing" and "artificial intelligence," "intelligent system(s)"	1987–2020	164	Research avenues related to AI technology in marketing, data protection, ethics, and the revolution of the labor market
Zeba et al. (2021)	✓	AI in manufacturing	✓	PRISMA and *meta*-analysis (Moher et al., 2009)	Web of Science Core Collection	"artificial intelligence" and "manufacturing"	1979–2019	836	Comprehensive study of the application of AI in manufacturing; Results present the most important topics, such as cyber–physical systems and smart manufacturing
Our review	✓	AI and BM/BMI	✓	Systematic literature review (Tranfield et al., 2003); inductive approach according to Gioia et al., 2013	EBSCOhost, Science Direct, Scopus	"business model*,","business-model*", "business model innovation," "value proposition*," "model innovat*" and "artificial intelligence," "AI," "A.I.," "machine learning", "deep learning," "neural network*"	2003–2022	180	Combining business model literature and AIComprehensive framework; Presentation of the current state of the literature, research gaps, and directions for future research

analyzed their interrelations (Charmaz, 2006). After summarizing each research paper's key findings and representative information in Microsoft Excel, we further coded and analyzed all publications using the qualitative analysis software program MAXQDA (Verbi Software, 2022). The coding procedure followed a three-step approach: open coding, axial coding, and selective coding (Pratt et al., 2006). This resulted in 2,413 coded segments and 170 initial codes. The codes were extracted from MAXQDA into the mapping tool XMind (XMind Ltd., 2022), where the findings were successively compared, analyzed, and discussed to increase the objectivity of the coding process and allow us to pay particular attention to the deeper meanings, interrelations, and emerging unexplained concepts. Overall, we extracted 117 first-order terms, which were abstracted into 32 second-order themes and further organized into six aggregated dimensions. Fig. 2 illustrates the consolidated results of our efforts, displaying our first-order concepts, second-order themes, and aggregated dimensions, which have been constructed into a data structure that demonstrates the rigor of our qualitative research.

4. Results

4.1. Descriptive analysis

The number of articles published on the interplay between BMI and AI has expanded significantly since 2016, underscoring the growing academic interest in this research field. Table 2 presents the distribution of our sample by study design and field.

Case studies were the most common study design applied in AI-driven BMI research, including both single-case and multiple-case studies. The second most prominent design was statistical analysis, followed by conceptual papers. It is notable that the distribution of study designs remained relatively constant over time.

Most of the studies we analyzed can be assigned to a single field. The areas that received the most attention were the manufacturing industry (13 %), healthcare industry (10 %), platform businesses (8 %), and marketing, fashion and media (7 %). The agriculture, education, and energy/circular economy sectors are less prominently represented but still appear in the sample. This indicates that AI-driven BMI has become a pervasive, wide-ranging field with interest beyond highly specialized application areas. Extracting findings from multiple perspectives supports generalizability, confirms the extracted findings, and demonstrates the value of AI-driven BMI.

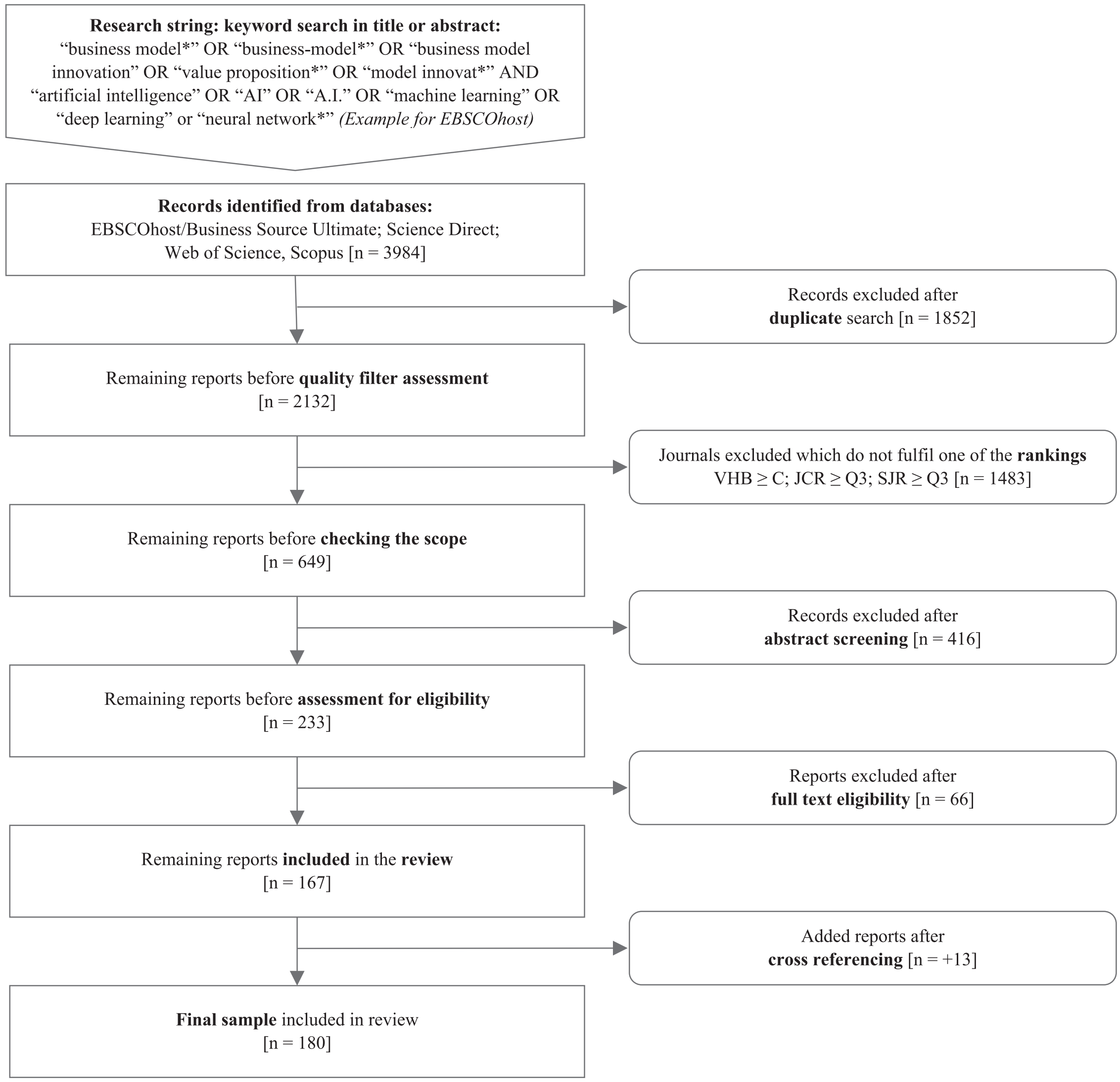

Fig. 1. Systematic literature review approach.

4.2. *Exploring the research dimensions of AI-Driven BMI*

To develop a greater understanding of AI-driven BMI, we identified six overarching dimensions that map the content of the AI-driven BMI research landscape: (1) triggers, (2) restraints, (3) resources and capabilities, (4) application of AI, (5) implications, and (6) management and organizational issues. The research dimensions build on the content identified in Fig. 2 and should not be considered separately but rather as interdependent. To contribute substantially to the literature, we related, linked, and integrated these research findings into a coherent framework describing the interrelations of the content of AI-driven BMI research (see Fig. 3).

Investigating the fragmented results within the six identified research dimensions produces a holistic perspective, illuminating the interdependencies and relationships among the dimensions. This comprehensive view of AI-driven BMI answers our first research question regarding the content of extant research on AI-driven BMI and provides valuable guidance for future conceptual and empirical research. By offering a framework that unifies the otherwise disconnected and disjointed research environment, it facilitates more informed and fruitful research endeavors.

We evaluated the research dimensions according to whether their predominant theoretical or empirical stance is a static or dynamic view of AI-driven BMI. This is essential for understanding each research dimension's contribution to the research landscape and understanding AI-driven BMI. As such, Fig. 3 illustrates that research dimensions 2 (restrains) and 3 (resources and capabilities) largely follow a static approach. By doing so, studies in these dimensions predominantly concentrate on how specific restraints and resources shape specific types of AI-driven BMI and the resulting BM configurations. However, research dimension 3 also consists of studies emphasizing a dynamic approach to AI-driven BMI, along with research dimensions 1 (triggers) and 6 (management and organizational issues). These predominantly concern the management of AI-driven BMI, focusing on how specific triggers (internal and external), capabilities, and cultural aspects influence AI-driven BMI and specific BM configurations. Thus, we can observe a shift from static to dynamic perspectives regarding triggers and management issues, while many research questions remain unanswered from a dynamic perspective, as we will outline later. The systematic literature review also shows AI applications' different roles in innovating BMs (research dimensions 4 and 5). While some studies investigate AI as an enabler of BMI, others investigate AI in the context of complex and disruptive BMI. From a conceptual perspective, studies in this (hybrid) dimension also adopt both static and dynamic approaches to understanding AI-driven BMI. Thus, the static perspective describes the functions of AI in driving BMI, while the dynamic view

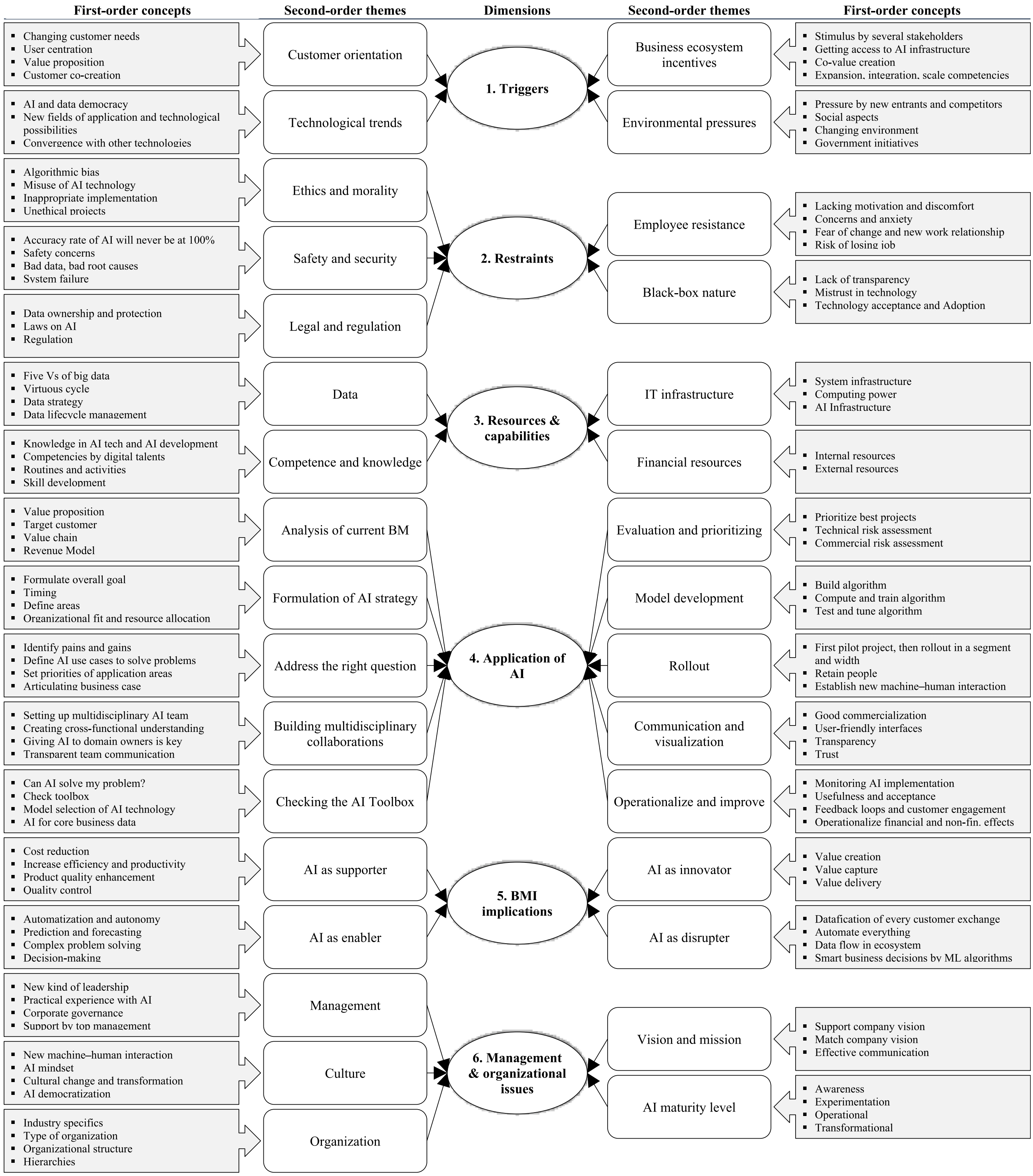

Fig. 2. AI-driven BMI dimensions derived from second-order themes and first-order concepts.

focuses on BMs' innovation processes through AI. Findings relevant to each research dimension are presented below. This aligns with the primary aim of our study, which is to synthesize the current state of knowledge on AI-driven BMI.

4.2.1. *Research dimension 1: Triggers*

The first research dimension attempts to explain why companies perceive a need for AI-driven BMI and what triggers that perceived need. Triggers and restraints (research dimension 2) are closely linked and in constant conflict. Their outcomes affect resources, implementation, and the management of corresponding initiatives.

Triggers of AI-driven BMI have various origins, such as customer or user orientation (Luo et al., 2020; Xu et al., 2019). Understanding customer needs, creating a strong value proposition, and even the

Table 2
Descriptive results – study design and field distribution (n = 180).

	2003	2012	2013	2016	2017	2018	2019	2020	2021	2022	2023	Sum	%
Study design													
Conceptual					5	5	7	7	12	4	2	**42**	23 %
Content or Thematic Analysis					1	1		1	4	5		**12**	7 %
Literature Review			1		1		1	3	9	10	2	**27**	15 %
Single/ Multiple Case Study	1			1		1	9	9	20	11	1	**53**	29 %
Statistical Analysis		1			2	1	6	5	15	12		**42**	23 %
Others							1	2	1			**4**	2 %
Sum	**1**	**1**	**1**	**1**	**9**	**8**	**24**	**27**	**61**	**42**	**5**	**180**	
Field													
Agriculture					1				3			**4**	2 %
Education					1		1	1		1		**4**	2 %
Finance					1		1	2	3	2		**9**	5 %
Healthcare/ Pharma						1	4	3	7	3		**18**	10 %
Manufacturing				1	1	2	3	6	7	3		**23**	13 %
Platform		1			1		2		9	2		**15**	8 %
Public Relations/ Public Management							1	1	1	1		**4**	2 %
Supply Chain								1	3	5		**9**	5 %
Service (incl. Tourism, Insurance, Communication)							1	4	2	4	1	**12**	7 %
Energy/ Circular Economy					1		1	1	2	1		**6**	3 %
Marketing/ Fashion/ Media			1				1	2	5	3	1	**13**	7 %
Miscellaneous					1			1	3	4		**9**	5 %
No Specific Field	1				2	5	8	5	18	12	3	**54**	30 %
Sum	**1**	**1**	**1**	**1**	**9**	**8**	**23**	**27**	**63**	**41**	**5**	**180**	

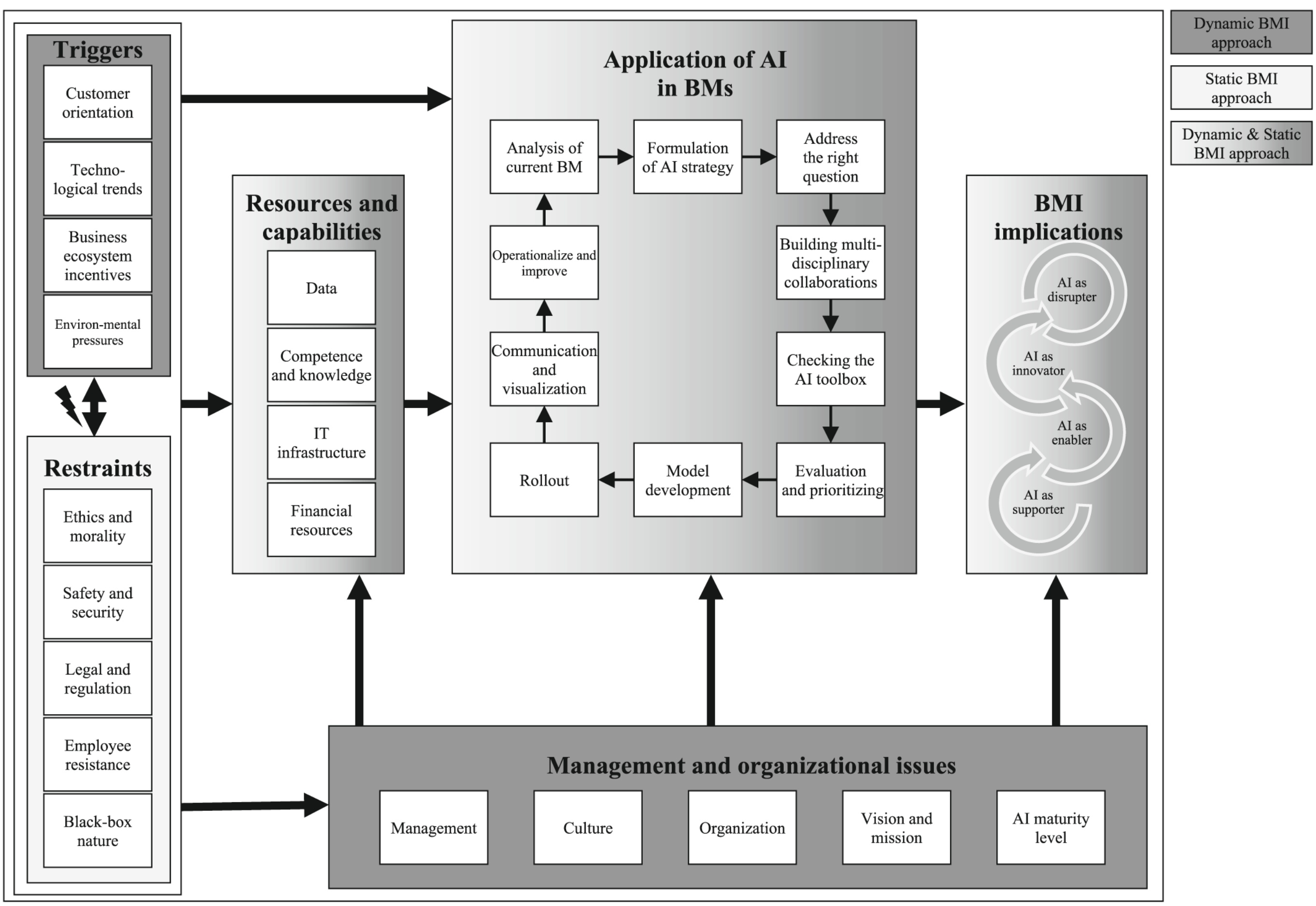

Fig. 3. Integrated view of AI-driven BMI.

implication of customer co-creation approaches are all essential elements that can trigger the BMI process (Haftor et al., 2021).

AI's technological trends, including its integration with other emerging technologies like cloud computing, blockchain, 6G, and quantum computing, unlock multiple new application fields and increase the potential for BMI (Ramakrishna et al., 2020; Yun et al., 2019). Data democratization and trends in open innovation make AI accessible to nonexperts, facilitated by platforms like GPT-3 (Marinakis et al., 2021; Rakhra & Singh, 2021; Sjödin et al., 2021).

A company's ecosystem can be a valuable instigator for AI-driven

BMI by fostering value co-creation with customers and engaging other stakeholders, such as suppliers, universities, and partners (Warner & Wäger, 2019; Xu et al., 2019). These value-creating partnerships can provide access to AI infrastructure and resources, allowing companies to integrate and scale within their ecosystems (Bosch & Olsson, 2021; Kohtamäki et al., 2022).

New market entrants, competitive forces, government initiatives, regulatory compliance, changing business environments, sustainability trends, and societal pressures also lead companies to invest in AI-driven BMI (Fatima et al., 2022; Rakhra & Singh, 2021; Volberda et al., 2021). These pressures compel companies to enhance efficiency through innovation while promoting transparency and accountability in their actions (D'Amore et al., 2022).

4.2.2. Research dimension 2: Restraints

The second research dimension examines barriers to AI implementation, including ethics, safety, legality, employee resistance, and the black-box nature of AI. Ethical concerns are often multilayered, such as algorithmic bias leading to discrimination, unintentional unethical implementations in BMs like social media bubbles, and the misuse of AI for malicious purposes (McCausland, 2021; Soriano & Torres Valdés, 2021; White & Boatwright, 2020; Wirtz & Müller, 2019). The potential for inappropriate use, such as targeted abortion advertisements and intentionally unethical projects like biological weapons, also represents cause for restraint (Breidbach & Maglio, 2020; White & Boatwright, 2020).

Safety and security concerns related to AI solutions exist in academia and society (Luo et al., 2020; Mishra & Tripathi, 2021). AI technology's inherent limitations (i.e., its inability to achieve 100 % accuracy) raise questions of culpability in many industries (Yun et al., 2019). Addressing biased, pooled, and incomplete data is crucial to ensuring the safety of AI BM applications and preventing inadequate root causes (McCausland, 2021; Mishra & Tripathi, 2021; Sarc et al., 2019). In addition, AI applications must be secured against potential system failures and hacking attacks to secure business operations (Wirtz & Müller, 2019).

In the current climate, where everything is tracked and traceable (White & Boatwright, 2020), legal requirements and regulations related to AI are critical (Marinakis et al., 2021; van Mil & Quintais, 2022). Policies regarding data ownership and protection may lead to a new understanding of privacy (Liu et al., 2019). For governments, this issue carries certain complexities that must be navigated, such as the allocation of blame even when AI-driven value propositions outperform humans, the balance between transparency and regulation, and missing necessary regulations (Liew, 2018; Naughton, 2020; Rakhra & Singh, 2021).

When corporations attempt to innovate their BMs by scaling AI solutions, employees may lack motivation and feel discomfort, resulting in the rejection of AI technology (Norman, 2017). The literature reveals several concerns and anxieties, such as insecurity, overwhelming demand, lack of responsibility, and the fear of making decisions about the implementation of AI in a BM (Liew, 2018; Minbaeva, 2021; Sena & Nocker, 2021). Recent AI-driven BMI research focuses primarily on augmenting AI to increase the value of human–machine interactions (Ehret & Wirtz, 2017). In contrast, most practitioners still focus on automating parts of the BM, stoking employees' fears of job loss (Garrido-Baserba et al., 2020).

The black-box nature of deep learning implies an information asymmetry to the user, resulting in a lack of transparency in AI models (McCausland, 2021). Particularly prominent in this respect are examples of discrimination by algorithms, and some researchers express fears of privacy invasion, resulting in mistrust and a lack of AI acceptance and integration into BMs (Talamo et al., 2021; Wirtz & Müller, 2019).

4.2.3. Research dimension 3: Resources and capabilities

The third research dimension focuses on what companies require as a foundation to implement AI-driven BMI. Without data, any effort concerning AI-driven BMI is useless (Rakhra & Singh, 2021; Zeng, 2018). A data strategy including data selection, sourcing, synthesizing, processing, data hygiene, and data costs, among many other requirements, is obligatory (Renz & Hilbig, 2020). Data lifecycle management is also necessary to manage the data stream created by sensors, Internet-of-things applications, and other connected devices in a sophisticated way (Mehmood et al., 2017). Researchers focusing on big data highlight the importance of the five Vs of data attributes: volume, value, variety, validity, and velocity (Iandolo et al., 2021; Renz & Hilbig, 2020). Furthermore, a "virtuous cycle" underlies any data strategy: more data creates better products, which attract more users and produce more data, thus creating a superior BM (Borodavko et al., 2021).

To leverage data, digital talents must be equipped with competencies like agility, psychological readiness, professional skills, and profound knowledge of AI technology (Sjödin et al., 2021; Trenerry et al., 2021). These abilities are also needed to understand the interconnections between AI and other technologies—such as cloud computing, blockchain, and quantum computing—to identify the greatest potential for AI-driven BMI (Garrido-Baserba et al., 2020; Volberda et al., 2021). Research via open sources further contributes to promoting these attempts (Nishizawa et al., 2021).

Using data is possible only when appropriate system infrastructure exists to store the data (Coyle & Nguyen, 2019; Wamba-Taguimdje et al., 2020). These complex storage systems often involve high costs associated with installation, adaptation, and maintenance (Breidbach & Maglio, 2020). However, recent developments in computing power allow for the processing of large volumes of data; in this context, cloud computing helps to mine, search, monitor, and mark the data (Mehmood et al., 2017; Niewöhner et al., 2020; Sena & Nocker, 2021).

The resources and capabilities presented above are costly and accessible only to companies with the requisite financial resources (Mäntymäki et al., 2020), whether internal or external (Garbuio & Lin, 2019; Liew, 2018). When internal resources are insufficient, external resources—such as funds from governments, associations, private investments, or academic institutions—can help facilitate AI-driven BMI (Khatab & Yousef, 2021).

4.2.4. Research dimension 4: Application of AI in BMs

The steps involved in implementing AI applications in BMs form a loop that, when repeated several times, can develop a robust new BM (Katsamakas & Pavlov, 2022). A thorough understanding of the current BM is essential before implementing AI applications. This involves examining the building blocks, including the value proposition, customer analysis, value chain, and revenue model (Dellermann et al., 2019; Di Vaio et al., 2020). The formulated AI strategy must align with the company's vision, address customer needs, and consider AI lifecycles (Bhattacharjee et al., 2017; Helo & Hao, 2021; Qvist-Sørensen, 2020). Developing ideas that address relevant questions, tackle customer pain points, and prioritize application areas with multidisciplinary AI application teams is crucial (Khatab & Yousef, 2021; Minbaeva, 2021; Sjödin et al., 2021).

Choosing appropriate AI models and technologies, evaluating and prioritizing projects, and building, training, and fine-tuning algorithms are all vital stages of the implementation process (Akter et al., 2022; Lee et al., 2019; Liengpunsakul, 2021; Wan et al., 2021). Effectively managing AI initiatives through pilot projects, implementing appealing visualization and communication, and gathering feedback for continuous improvement are also important aspects (Alshawaaf & Lee, 2021; Burström et al., 2021; Payne et al., 2021). By iterating these steps and undergoing continuous refinement, the BM can be validated, and the loop can start again (Bosch & Olsson, 2021; Dellermann et al., 2019).

4.2.5. Research dimension 5: BMI implications

In the evolving landscape of BMI enabled by AI, it is critical to outline AI's nuanced roles as a supporter, enabler, innovator, and disrupter. These roles highlight the varying degrees of influence AI exercises on

BMs, from minor enhancements to industry-altering changes.

AI, as a supporter, subtly enhances existing processes and augments human capabilities without fundamentally altering the core operations of a business (Dudnik et al., 2021; Mithas et al., 2022; Qvist-Sørensen, 2020). For instance, AI-driven quality control mechanisms in manufacturing serve to improve product quality and efficiency, embodying incremental advancements rather than radical changes (Bosch & Olsson, 2021; Dudnik et al., 2021; Wamba-Taguimdje et al., 2020). Although these changes may appear minor, AI support in critical processes can provide a competitive edge and create new opportunities for companies (Areiqat et al., 2021).

Stepping beyond mere support, AI as an enabler fundamentally redefines or creates new business processes (Akter et al., 2022). This role signifies a deeper integration of AI, where it becomes instrumental in redefining business operations. A novel illustration is the use of AI for the automation of customer segmentation and personalized marketing strategies to reshape marketing approaches (Hoffmann et al., 2023). The enabler role is characterized by AI's capacity to transform operations, showcasing AI's role in enabling new business capabilities that were previously impossible (Ahmad, Ghapar, & Abdul, 2019; Wan et al., 2021).

AI assumes the role of an innovator when it leads to the creation of new value propositions, extends prevailing BMs, or pioneers entirely new value dimensions (Mostaghel et al., 2022). This role involves leveraging AI to introduce novel products, services, or operational methods that supplement the BM (Sjøvaag & Owren, 2021). An illustration of this role is companies that integrate AI into their products, such as in the robotics industry, where robots learn to improve their performance over time, thereby redefining how value is created and delivered (Hoffmann et al., 2022; Varsha et al., 2021). Another innovative application of AI can be found in the healthcare sector, where AI is used for disease detection. This not only extends the healthcare BM but also opens pathways for personalized medicine, highlighting AI's role in driving innovation and expanding market boundaries.

At the top of AI's transformative potential lies its role as a disrupter, where AI-driven BMs challenge and redefine industry standards and practices (Garrel & Carlos, 2022). A disruptive example is the implementation of autonomous vehicles, which contests traditional conceptions of transportation and logistics (Breidbach & Maglio, 2020). Automating driving via AI-powered systems suggests new BMs for mobility and can significantly reduce accidents, restructure urban infrastructure, and reshape the automotive industry (Mishra & Tripathi, 2021; Zarifis & Cheng, 2021). This leads to new market paradigms and operational benchmarks, illustrating AI's disruptive power (Aloini et al., 2022; Gerlach et al., 2022).

4.2.6. Research dimension 6: Management and organizational issues

Management and organizational issues significantly impact the allocation of resources and capabilities, the application of AI, and its implications for BMI. The transformative nature of AI requires a new kind of leadership in AI-driven companies (Zeng, 2018). However, the fluid business environment often lacks the capabilities required to define concrete recommendations (Barro & Davenport, 2019; Schrettenbrunnner, 2020). To cultivate creative and innovative approaches, management must acquire practical experience with AI initiatives and rethink governance and hierarchy structures (Chen et al., 2022; Korherr et al., 2022; Volberda et al., 2021).

Most AI initiatives fail due to cultural deficits and a weak mindset toward new machine–human interactions (Dudnik et al., 2021; Minbaeva, 2021; Yigit & Kanbach, 2021). Establishing agile and flexible approaches, along with democratizing AI to involve the workforce in BMI activities, can overcome these cultural deficiencies (Korherr & Kanbach, 2021; Mao et al., 2021; Marinakis et al., 2021). AI-initiative rollouts should consider industry specifics and the size of the organization (Eling et al., 2022; Fredström et al., 2021; Trenerry et al., 2021; Volberda et al., 2021). Different types of organizations, such as startups and incumbents, have varying levels of adaptability and accessibility to data (Garbuio & Lin, 2019; Zaki, 2019). Additionally, each department within an organization may have different requirements for AI usage (Lee et al., 2019; Mishra & Tripathi, 2021). It is crucial to address and question these diverse needs (Schrettenbrunnner, 2020).

Formulating a coherent AI vision is an important step for companies (Yigit and Kanbach, 2021). A clear AI vision should align with the company strategy, activate stakeholders, and create collective understanding and acceptance within the organization (Liew, 2018; Liu et al., 2019; Zeng, 2018). An organization's AI maturity level is also essential for AI-driven BMI (Brem et al., 2023; Liengpunsakul, 2021). A multistep approach is suggested, starting with raising awareness, followed by AI experimentation and implementation at an operational level, leading to a high maturity level in the AI-driven BM (Helo & Hao, 2021; Qvist-Sørensen, 2020; Sjödin et al., 2021; Talamo et al., 2021; Trenerry et al., 2021).

Table 3 summarizes the key research findings of this analysis. Comparing and combining AI-driven BMI research along these six research dimensions advances our understanding of the linkages within and among the dimensions. As such a comprehensive view of AI-driven BMI has not previously been developed, this understanding offers valuable guidance for conceptual and empirical research endeavors.

4.3. A typology of AI-Driven BMI

The systematic literature review conducted in this paper provides an overview of the content of AI-driven BMI within the previously outlined research areas. The identified literature is often disconnected from the BMI literature, as much research shares an outcome-based perspective, investigating BMI as an outcome of AI applications (Mariani et al., 2023). Therefore, on the one hand, we draw on the differentiation between research insights adopting a static and dynamic perspective on AI-driven BMI, as illustrated in Fig. 3. On the other hand, we emphasize a management perspective on the interrelation between AI technology and the organizational relevance of AI. By doing so, we synthesize and organize the research themes around two thematic dimensions of AI-driven BMI research from a management perspective: first, the emergence of BMI, and second, the centrality of AI for value creation. Consequently, the resulting typology of research perspectives (Fig. 4) builds the foundation for addressing the third research question, namely identifying and outlining future research directions for managing AI-driven BMI.

The emergence of BMI refers to the extent to which BMI results from active AI-based innovation activities initiated by management and the extent to which BMI results from the evolutionary innovation of the BM based on incremental adaptations. Accordingly, this dimension suggests a process view of AI-driven BMI, which resonates with extant BMI research (Foss & Saebi, 2017; Klein et al., 2021). Emergence is defined as "a process that involves (a) the creation of novelty, (b) its growth to a salient size, and (c) its formation into a recognizable social object, process, or structure" (Seidel et al., 2017, p. 2).

This dimension is a continuum between evolutionary innovation processes and actively initiated innovation processes. The evolutionary perspective of AI-driven BMI resonates with the evolutionary BMI type described by Foss and Saebi (2017), who acknowledged that changes to BMs are emergent and occur naturally over time. Evolutionary changes in the studies of AI-driven BMI are triggered by developments in the company's environment, like technological advancements, ecosystem developments, and changing customer preferences. Burström et al. (2021) highlighted this by addressing the relevance of actively shaping and managing the ecosystem for AI-driven BMI via an ecosystem reconfiguration strategy. The evolutionary perspective views BMI as an adaptation to external changes. On the other hand, we also found literature emphasizing the role of management involvement in actively shaping AI-driven BMI, focusing on how managers can actively engage in AI integration for BMI (Jorzik et al., 2023). Several studies viewed AI-

Table 3
Summary of AI-driven BMI research findings across dimensions.

Dimension	Research Findings	Exemplary studies
Triggers	Customer demand for AI-based solutions arises from their ability to offer new value propositions	Haftor et al., 2021; Kulkov, 2021; Luo et al., 2020; Xu et al., 2019
	New AI technologies present novel opportunities for value creation	Ramakrishna et al., 2020; Trenerry et al., 2021; Yun et al., 2019
	Datafication has a pervasive impact on the entire business ecosystem, with substantial contributions from various stakeholders	Bosch & Olsson, 2021; Kohtamäki et al., 2022; Warner & Wäger, 2019
	Environmental pressures, including the adoption of AI tools by competitors, necessitate a transformation of the business model	Fatima et al., 2022; Rakhra & Singh, 2021; Renz & Hilbig, 2020
Restraints	Ethical and moral concerns must be taken into account to decelerate AI and BMI adaptation	Breidbach & Maglio, 2020; Soriano & Torres Valdés, 2021
	Addressing safety and security concerns is crucial, as they can lead to resistance during AI and business model adaptation	Marinakis et al., 2021; Sarc et al., 2019
	Legal and regulatory considerations, particularly data protection regulations, can impose restrictions on AI initiatives	Naughton, 2020; White & Boatwright, 2020
	Employee resistance may arise if they perceive AI initiatives and business model changes as a threat	Minbaeva, 2021; Ehret & Wirtz, 2017; Norman, 2017; Sena & Nocker, 2021
	AI's black-box nature often leads to a lack of overall technology acceptance	McCausland, 2021; Talamo et al., 2021
Resources and capabilities	The 5Vs of big data are prerequisites for developing robust applications	Borodavko et al., 2021; Iandolo et al., 2021
	Proficiency in AI and digital talent skills are fundamental requirements for initiating business model changes using AI solutions	Garrido-Baserba et al., 2020; Nishizawa et al., 2021
	A system infrastructure with the requisite computing power is necessary to process data and accommodate the scalability of business model implications	Coyle & Nguyen, 2019; Niewöhner et al., 2020; Wamba-Taguimdje et al., 2020
	Sufficient budget allocation is essential to finance AI projects and facilitate business model adaptations	Khatab & Yousef, 2021; Liew, 2018
Application of AI	Comprehension of the existing business model is crucial for formulating an appropriate AI strategy for a new business model	Coskun-Setirek & Tanrikulu, 2021; Di Vaio et al., 2020; Helo & Hao, 2021
	Multidisciplinary teams are necessary to facilitate the selection of appropriate AI tools, evaluate, prioritize, and deploy AI applications	Scheiderer et al., 2020; Sjödin et al., 2021
	Effective rollout, communication, visualization, and operationalization of AI initiatives are crucial for implementing long-term business model changes	Alshawaaf & Lee, 2021; Garbuio & Lin, 2019; Payne et al., 2021
BMI implications	AI process optimization supports incremental business model changes, particularly in highly complex and interrelated processes or organizations at an early AI maturity level	Areiqat et al., 2021; Mithas et al., 2022
	AI solutions enable the transformation of entire processes within a business model	Ahmad & Ghapar, 2019; Akter et al., 2022; Wan et al., 2021
	AI applications facilitate the extension of business model dimensions	Hoffmann et al., 2022; Mostaghel et al., 2022; Sjøvaag & Owren, 2021
	Integration of AI solutions can lead to the disruption of a business model	Battisti et al., 2022; Garrel & Carlos, 2022; Gerlach et al., 2022; Zarifis & Cheng, 2021; Zeng, 2018
Management and organizational issues	Effective management plays a crucial role in driving and implementing AI initiatives and facilitating BM changes	Korherr et al., 2022; Volberda et al., 2021
	Cultivating an established AI culture is essential for ensuring long-term organizational adaptations to AI within a business model	Barro & Davenport, 2019; Dudnik et al., 2021; Mao et al., 2021
	Implementing appropriate organizational structures aids in effectively managing business model changes	Eling et al., 2022; Schrettenbrunnner, 2020; Zaki, 2019
	AI company vision guides the long-term orientation toward new AI initiatives, fostering business model innovation	Liu et al., 2019; Yigit & Kanbach, 2021
	AI maturity level significantly influences the implementation and outcomes of AI initiatives, impacting the sustainable adoption of AI and corresponding business model changes	Liengpunsakul, 2021; Mäntymäki et al., 2020

driven BMI from a management perspective, advocating that the integration of AI for developing new BMs represents a management task.

The second dimension synthesized from our literature review concerns the centrality of AI to value creation. Value creation refers to the processes that aim to increase value generation within an organization (Sjödin et al., 2021). As prior BM research has identified different value creation sources, like efficiency or novelty (Amit & Zott, 2001), we distinguish between the core and peripheral relevance of AI for value creation. Accordingly, we found that studies have investigated AI as an enabler for optimizing the efficiency and efficacy of existing business processes within the BM, indicating a peripheral relevance of AI for value creation. In this stream, AI supports value creation but does not change its source. The focus of these studies is on the existing BM and business processes. In contrast, AI can also be a core component of value creation within a BM, meaning that the BM's value creation results from the application of AI (Füller et al., 2022). Consequently, at its core, the application of AI represents the source of value creation. The differentiation between AI's core and peripheral relevance for value creation aligns with the concept proposed by Amit and Zott (2001) that different factors may enhance the total value of BMs.

From an analysis of the thematic dimensions within the AI-driven BMI literature, we have identified four types of AI-driven BMI, each reflecting different research perspectives on AI-driven BMI. These perspectives are *technology implications, reconfiguration, focused BMI,* and *transformative BMI*. By describing the research insights from each

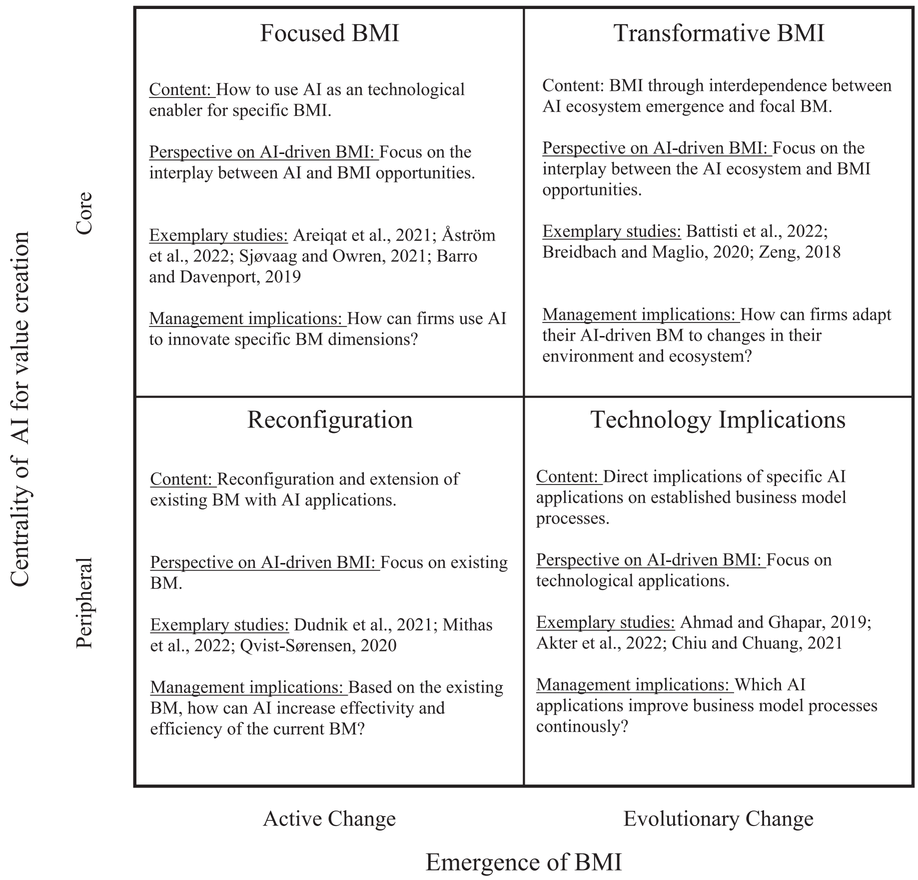

Fig. 4. Four types of AI-driven BMI that reflect different perspectives.

perspective, we will identify research gaps and outline future research directions. Below, we describe each AI-driven BMI perspective and offer an overview of research gaps within each perspective, outlining future research directions for each perspective.

4.3.1. *Technology implications*

The technology implications perspective combines a focus on AI with peripheral contributions to value creation with evolutionary change. Many studies from the technology implications perspective emphasize specific technology applications of AI aimed at innovating existing production or BM processes to operate more efficiently and effectively (Qvist-Sørensen, 2020). Accordingly, this perspective focuses on AI application opportunities within existing activities and processes. These studies emphasize a technology and process perspective, where BMI occurs naturally as the sum of incremental innovations based on AI applications over time. As new opportunities for AI applications continuously evolve, so does the potential for changes in the BM, which is assumed to be continuous. The restraints of AI for its proper application are considered, leading to investigations of barriers and enablers of AI applications. In sum, these studies focus on the technology itself and its implications, embracing the perspective that BMI depends on new technological developments and AI applications.

4.3.2. *Reconfiguration*

The reconfiguration perspective combines a focus on AI with a peripheral contribution to value creation with active AI-driven change initiated by management. Studies adopting this perspective predominantly focus on how AI applications can extend or improve the existing BM of a company (Lichtenthaler, 2018). In contrast to the technology implications perspective, the reconfiguration perspective focuses on the peculiarities of the BM rather than the peculiarities of the technology. Specifically, this perspective considers how AI can support value creation and how BM activities can be performed more efficiently. BMI evolves through reconfigurations of the existing BM, enabled by AI applications. This perspective is limited, however, to considerations of the existing BM and how managers can use AI applications to support its activities. Consequently, much of the research adopting this perspective investigates the managerial and organizational prerequisites for reconfiguring the BM. Qvist-Sørensen (2020), for instance, found that the Industrial Internet of Things and AI have the potential to reconfigure companies by providing new business opportunities while simultaneously posing a threat to existing businesses. Research utilizing this perspective emphasizes the role of managers in integrating AI applications into BMs, focusing on organizational characteristics and management capabilities for AI-driven BMI.

4.3.3. *Focused BMI*

The combination of active change and viewing AI as central to value creation in BMI results in the *focused BMI* perspective. The focused AI-driven BMI perspective is similar to the focused BMI type suggested by Foss and Saebi (2017) but describes a perspective that emphasizes how firms can use AI applications to deliberately innovate BMs with AI at the core of value creation. The literature utilizing this perspective considers both AI applications and the potential to develop innovative BMs. In contrast to the reconfiguration perspective, the focused BMI perspective emphasizes the innovation of specific dimensions of the BM (or the entire BM) with AI at the core of value creation, rather than viewing AI as supporting the value creation of the existing BM. Consequently, the focused BMI perspective offers a more entrepreneurial perspective, highlighting the interplay between recognizing opportunities for BMI related to AI applications (Weber et al., 2022).

Accordingly, the focused BMI perspective emphasizes the antecedents of AI-driven BMI. Åström et al. (2022) underscored this view by proposing a framework that identifies key activities for aligning the value-creation and value-capture dimensions of AI-driven BMI. A significant volume of research utilizing this perspective concerns the management of organizational change, new leadership skills, and building an organizational culture that embraces the use of AI in novel BMs. It investigates concrete approaches for AI-driven BMI, such as experimentation (Åström et al., 2022) and agile approaches for developing an AI culture (Sjödin et al., 2021).

4.3.4. Transformative BMI

The *transformative BMI* perspective combines a view of AI as making core contributions to value creation with evolutionary change. Most studies utilizing the transformative BMI perspective consider the business ecosystem as evolving around AI-driven BMI, emphasizing the transformative nature of AI-driven BMI and its impact on stakeholders and the broader society, as well as the development of AI ecosystems. For example, Quan and Sanderson (2018) highlighted the relevance of managers in designing AI user scenarios, data acquisition for AI, and building the AI ecosystem. This perspective considers the role of factors within a firm's environment, like technological developments, customer preferences, and societal trends, and how AI-driven BMI can address the changes and challenges within said environment. By considering the dynamic nature of ecosystems, this perspective views AI-driven BMI as evolutionary, where changes in the ecosystem evoke continuous adaptation. While AI applications are at the core of value creation, the transformative perspective of AI-driven BMI presupposes high degrees of interdependence between the focal BM and evolutionary changes in the AI ecosystem.

5. Discussion and conclusion

5.1. Implications for theory

Given the increasing interest in and application of AI associated with ongoing changes to existing BMs and the emergence of novel BMs, our study makes important contributions to both the innovation management literature and managerial practice. This study aimed to provide a synthesized overview of the current state of knowledge on AI-driven BMI to specify the link between AI applications and BMI and identify research gaps and future research avenues from a dynamic (management) perspective. We developed a conceptual framework that extends prior research by distilling the different research perspectives employed in prior research on AI-driven BMI.

Through a systematic literature review examining the intersection between AI applications in a business context and BMI, we specifically shed light on research regarding technology-driven innovation and BMI (Spieth et al., 2023). First, we summarize and structure the content of AI-driven BMI research within a singular framework (Fig. 3)—rather than focusing on AI in innovation management (Gama & Magistretti, 2023) or BMI in isolation (Spieth et al., 2023)—synthesizing different research perspectives regarding the management of AI-driven BMI (Fig. 4). Therefore, we complement recent literature reviews concerning AI and innovation (e.g., Gama & Magistretti, 2023; Mariani et al., 2023) by highlighting the interplay between AI and its broader organizational and management implications. Although we confirm the dominance of the technological perspective in the AI literature within the business context, we extend the review by Gama and Magistretti (2023), who argue for a capability perspective on AI and innovation. In the context of AI-driven BMI, we argue for a dynamic process perspective that accounts for the potential of AI to alter BMs continuously. Thus, our analysis extends the literature by contextualizing AI based on its strategic relevance to value creation and its impact on continuous BMI. We also propose a future research agenda with specific research questions.

The analysis undertaken in this study has elucidated novel insights, as demonstrated in Fig. 2. By clustering themes into second-order themes and subsequent aggregated dimensions, the findings concisely reveal the most important research themes of AI-driven BMI literature. These findings offer a comprehensive understanding and overview of all pertinent terms, establishing a robust foundation for future academic discourse.

In this context, numerous novel insights can be derived from Fig. 3, particularly in terms of how these constructs are interrelated, culminating in a novel and unique depiction. Understanding these interrelations deepens the comprehension of the subject's complexity. Of particular note is the recognition that management and organizational issues substantially influence several dimensions, including resources and capabilities, the application of AI, and the subsequent BMI implications. This insight prompts a deeper investigation into the dependencies and intersections among these dimensions, encouraging further research. To provide additional guidance, we condensed these research themes into broader research perspectives in Fig. 4, enabling future researchers to position their (empirical) research within one of these perspectives.

Second, our study enhances the BMI literature by highlighting the role of technology in the dynamics of BMI (Demil & Lecocq, 2010; Saebi et al., 2017). By distilling diverse research perspectives on AI-driven BMI, which emphasize both the emergence of BMI and the role of AI in value creation, we enrich the understanding of how AI technologies have driven continuous change in BMIs. In contrast to the static view of BMs that emerge in new areas of research, we add to the dynamic view of BMI by discussing the role of AI technology in the emergence of different research perspectives on AI-driven BMI (Demil & Lecocq, 2010). We specify how these research perspectives evolve around specific research questions (such as the management of an AI ecosystem) while also outlining the resulting research gaps. Ultimately, this contributes to increased construct clarity and enables researchers to theorize about AI-driven BMI as we build a common understanding of AI-driven BMI through the different perspectives within the field.

Finally, deriving from Fig. 4, we mark a pivotal starting point for a paradigm shift in the academic discussion. Thus, we advocate a shift that moves beyond a solely dominant technological perspective toward a more integrated view of the interplay between technology and BMI. Such a perspective supports a transition to a stronger management focus, offering fertile ground for future research to explore content and close research gaps. Specifically, we advocate a shift from an emphasis on AI technology adoption to a management-centric view of the processes of AI-driven BMI from various conceptual stances. Thus, Fig. 4 offers future researchers the opportunity to organize their (empirical) research within these broader research perspectives while also helping to clarify the conceptual positioning of future research findings. Furthermore, we propose a future research agenda intended to deepen the understanding of these complexities. This agenda, which will be outlined in the subsequent section, will articulate specific research questions that emerge from our analysis of research themes and perspectives.

Taken together, our study reviewed the current state of AI-driven BMI research by executing a systematic literature review analyzing 180 research articles concerning AI-driven BMI, creating a holistic understanding of the current literature linking the two research streams in recognition of the growing academic and practical interest in this research field. We organized the content into an interrelated framework comprising six dimensions. Subsequently, we derived two thematic dimensions to describe four distinct research perspectives on AI-driven BMI. These perspectives vary in the degree of emergence of AI-driven BMI and the degree of centrality of AI for value creation. Each perspective yielded research with distinct foci and management implications. The four perspectives extend prior research with a process perspective and by organizing AI and BMI research, highlighting the management aspect of AI-driven BMI. Based on the identified perspectives and the content of the research within the field, we propose a research agenda concerning the management of AI-driven BMI and management implications, encouraging researchers to take a process perspective in the future.

5.2. Implications for practice

Our research supports practitioners by generating a more sophisticated understanding of the interdependencies relevant to the superior management of AI-driven BMI in practice. Implementing AI-driven BMI represents a significant opportunity for organizations to create new value and gain a competitive advantage. It has important implications for managers, who must consider how AI can be leveraged to drive innovation within their organizations. Managers should be aware of the potential of AI to disrupt traditional BMs and create new opportunities for value creation. Specifically, our synthesis of different research perspectives within AI-driven BMI research may guide managers in reviewing distinct management challenges depending on the type of AI-driven BMI.

By structuring the extant literature on AI-driven BMI and highlighting the dependence of the challenges and implications of AI applications on the centrality of AI in value creation within a BM, we illuminate the necessity to pay heed to the specific challenges managers may face when seeking to actively change their BM with AI. Managing AI-driven BMs in an AI ecosystem requires an understanding of the AI environment and an outward focus. Our study helps managers identify which organizational and strategic issues they should focus on, depending on the type of AI-driven BMI.

Our proposed framework can serve as a tool to guide organizations in implementing AI-driven BMI. Fig. 4 offers managers an overview of the different research perspectives regarding AI-driven BMI and their practical implications, which can be utilized to gain a better understanding of the actions necessary for managing different types of AI-driven BMI. For example, when aiming to reconfigure specific activities within the existing BM, attention should be given to prior research covered in the *reconfiguration* and *focused BMI* perspectives. Here, we provide exemplary studies that may guide managers in actively transforming their BMs with AI, dependent on the relevance of AI for value creation.

Organizations should remain mindful of the challenges associated with AI-driven BMI, depending on the relevance of AI for value creation, such as the need for new skills and the potential impact on employees and the company culture. Organizations must carefully consider the potential benefits and risks associated with AI-driven BMI. Our study provides a foundation for this consideration.

5.3. Future research directions

Based on the assessment of the prior literature concerning AI-driven BMI and the identification of the four perspectives within the research (Fig. 4), we identified specific research gaps and propose several future research questions that may close these gaps, which are shown in Table 4.

These proposed research avenues are related to managing AI-driven BMI, an important research area that requires further exploration. Our systematic literature review found that much of the research concerning AI-driven BMI focuses on the application of AI— its triggers, restraints, and prerequisites—and views AI-driven BMI as an outcome of applying AI. Based on our analysis and the resulting perspectives on AI-driven BMI, we suggest that researchers can advance this research field by taking a process perspective that focuses on managing AI-driven BMI. Accordingly, we identified four research gaps based on evolutionary and active BMI dimensions.

From the evolutionary AI-driven BMI dimension, the first research

Table 4
Specific research gaps and proposed future research questions for AI-driven BMI.

Research gap	Avenues for future research	Conceptual lens	Proposed research questions
Managing AI-driven BMs in an AI ecosystem	Analyzing the role of BMs in democratizing data and AI	Demand-side view	Which business model configurations allow for the democratization (accessibility for everyone) of data in AI ecosystems?
	Identification of approaches for customer co-creation for AI-driven BMI	Demand-side view	How can firms integrate customers into the development of AI-driven BMI?
	Exploring the role of data access for AI-driven BMI	Configurational perspective	What are the configurations of AI-driven BMs that allow for a continuous data supply?
	AI ecosystem orchestration and governance of AI-driven business models	Ecosystem view	Which governance mechanisms allow for optimal value capture in AI-driven BMs?
Management capabilities for AI-driven BMI	Identifying critical management capabilities for AI-driven BMI	Entrepreneurial cognition	What capabilities are needed to use AI insights and data to innovate BMs?
	Identifying approaches to the integration of AI into existing business models	Ambidexterity perspective	How can managers integrate AI into existing BMs?
		Ambidexterity perspective	How do management practices (e.g., agile management) support AI-driven BMI?
	Leadership requirements for AI-driven BMI	Paradoxical leadership	What leadership skills are required for successful AI-driven BMI?
	Identification of opportunities for AI-driven BMI	Cognitive view	What management characteristics allow for the recognition of opportunities for AI-driven BMI?
Developing an organizational AI culture	Exploring internal enablers of AI-driven BMI	Organizational learning	How can managers use AI insights for continuous (business model) innovation?
		Organizational learning	How can managers assess the AI maturity of an organization?
	Identifying employee competencies for AI-driven BMI	Knowledge-based view	How can managers encourage employees to embrace AI-driven BMI?
		Knowledge-based view	What are the employee competencies, knowledge, and skills needed for AI-driven BMI?
	Understanding individual barriers for human–AI collaboration in AI-driven BMs	Technology acceptance, technological frames	How can managers gain acceptance among employees for integrating AI into the BM?
AI-driven value creation and capture	Experimentation with AI-driven BMs	Dynamic capabilities	How can managers optimize value creation through AI with suitable business models?
	Interdependencies in AI-driven business models	Positioning/ Resource-based views	How can AI lead to superior interdependencies between BM activities for creating competitive advantages?
	Assessment of the impact of AI-driven BMI	Stakeholder view	How can AI-driven business model innovation create social and/or sustainable value?
	Exploring the ethics of AI applications in AI-driven BMs	Stakeholder view	How can AI-driven BMs create and capture value that is in line with ethics principles?
		Stakeholder view	What are the implications of ethics principles on the BM design?

gap concerns the management of AI-driven BMs in an AI ecosystem (Quan & Sanderson, 2018). As this perspective assumes constant changes in a focal company's environment, further research must consider the interdependencies between environmental changes and the AI-driven adaptation of BMs. With the development of AI-driven BMs, ecosystems evolve around AI and offer opportunities for collaboration and innovation, as well as new BMs (Fallahi et al., 2022). AI ecosystems enable firms to gain access to infrastructure and resources and are also important for scaling AI-driven BMs, such as through customer value co-creation (Sjödin et al., 2021). Although most researchers have acknowledged the role of customers—e.g., for data supply and co-creation—this research is still in its infancy. By adopting an ecosystem perspective, we encourage future studies to examine the various actors in AI ecosystems and how they contribute to the development of AI-driven BMI. Furthermore, researchers should explore configurations of AI-driven BMs that account for the dynamic nature of ecosystems and investigate how governance mechanisms contribute to the creation and capture of value (Mahalakshmi et al., 2022).

The second gap we identified derives from the evolutionary dimension concerning the role of the organizational culture in supporting AI-driven BMI. Assuming constant changes in the development of AI and the dynamics of the AI ecosystem, firms with AI-driven BMs must align with the organizational culture. Prior research suggests that employees and managers need the "right" mindset for embracing AI, as fears and mistrust might hinder the effectiveness of AI in human–AI interactions (Chatterjee et al., 2022; Jorzik et al., 2023). Although this research stream investigates the barriers to using AI-driven BMs in the workplace, most studies focus on these barriers with respect to AI, neglecting the BM perspective. Based on these findings, we advocate for future research to expand beyond solely examining AI adoption barriers in isolation and instead focus on how an AI culture can enable AI-driven BMI. Here, companies might differ in their AI maturity, which refers to the extent to which their organizational culture supports AI-driven BMI. Consequently, studies should adopt a knowledge-based view to investigate the competencies and knowledge needed to create an AI culture that supports AI-driven BMs (Ma & Hu, 2021; Santana & Díaz-Fernández, 2022).

We also identified a research gap resulting from the active change management dimension. As previously outlined, researchers have devoted significant attention to the managerial capabilities (e.g., algorithm development capabilities) needed to integrate AI into existing BMs. However, this research takes a technology-centric perspective, neglecting the capabilities required to manage AI-driven change. Thus, future research must bring to the foreground the management capabilities required for managing both AI integration and BM change. Researchers addressing this gap might use an ambidexterity or paradox perspective, as managers and employees may need to handle opposing demands during AI-driven BMI. Furthermore, future studies can address how existing management approaches like agile management or entrepreneurial thinking approaches like effectuation might support the development and implementation of AI-driven BMs.

The fourth research gap we identified is within the field of value creation and capture with AI-driven BMs. We encourage researchers to investigate AI-driven BMs from a strategy perspective that explains how they can create competitive advantages. Although many researchers assume that AI-driven BMs can create competitive advantages, they do so without empirically investigating the mechanisms of those advantages. Accordingly, future studies should examine how companies can build AI-driven BMs using activities that are difficult for competitors to imitate, perhaps through a dynamic capability or interdependency perspective. By examining its strategic implications, researchers can dive deeper into the societal implications of AI-driven BMs. For instance, future studies might explore how AI-driven BMs can create societal value. A better understanding of the societal implications of AI-driven BMs is needed, as ethical concerns regarding AI are widely discussed among researchers and politicians. Studies that examine BM configurations that allow for the ethical application of AI can also contribute to political discussions. Table 4 provides an overview of the four identified research gaps, avenues for future research, and our proposed research questions that, if answered, will provide a better understanding of how to manage AI-driven BMI.

5.4. Limitations

As every research, also our work is not without limitations. First, the scope of our systematic review was limited to studies published in English, which may exclude relevant literature in other languages. A further limitation pertains to our selected keywords. While we aimed to be comprehensive, it is possible that the selected keywords may not capture every facet of the broad domains of BMI and AI, which could introduce some bias into our findings. Our focus on four specific databases may have resulted in neglecting studies that have been published in journals not available in these databases. Furthermore, our analysis neglected lower-quality journals, research from other fields, and gray literature. However, because most of the relevant research is found in the management literature in high-quality journals, the results of this study should be considered rigorous, given the high quality of the studies included.

The nature of the research method selected also limits this study (see, e.g. Kraus et al., 2024). Applying the Gioia methodology implies a certain degree of subjectivity in defining and framing the first-order concepts and second-order themes. The structured approach and the precise distribution of tasks within the team, however, helped reduce this subjectivity to a minimum. Lastly, because the proposed frameworks regarding the content and research dimensions are based on a qualitative analysis, a quantitative analysis is needed in future studies for the purpose of verifying the generalizability and applicability of our study.

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CRediT authorship contribution statement

Philip Jorzik: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Sascha P. Klein:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology. **Dominik K. Kanbach:** Writing – review & editing, Writing – original draft, Project administration, Conceptualization. **Sascha Kraus:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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