AI in Business Research

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Artificial intelligence (AI) has emerged as a pivotal force in modern business transformation, garnering widespread attention from both practitioners and academics. With a notable exponential increase in AI-related studies, we provide a research framework aiming to synthesize the existing literature on AI in the business field. We conduct a comprehensive review of AI research spanning from 2010 to 2023 in 25 leading business journals according to this review framework. Specifically, we review the literature from three research perspectives: (i) AI applications, (ii) human perceptions of AI, and (iii) AI behavior. We also identify five principal research questions and offer suggestions for future research directions.

Key words: Artificial intelligence; human perception; human-AI interaction; algorithmic bias

1. Introduction

Artificial intelligence (AI) is increasingly recognized as the next general-purpose technology, heralding the advent of the fourth industrial revolution and catalyzing significant societal transformations (Brynjolfsson and Mcafee 2017). The enormous economic prospects have prompted a wide array of companies to channel substantial resources into the research and development of AI-centric technologies. Leading this surge, technology giants like Alphabet and Microsoft have pivoted towards an AI-first strategy. Simultaneously, global investments in AI reached \$91.9 billion in 2022 and are expected to rise to approximately \$200 billion by 2025 (Goldman Sachs 2023). This influx is nurturing a slew of AI innovations, now permeating diverse sectors including customer service, banking, and healthcare. A key milestone in AI development—that is, the emergence of ChatGPT in late 2022—has further sparked greater enthusiasm in AI technologies, with 2023 being heralded as the "year of AI."

AI is first conceptualized by John McCarthy in the 1950s as "the science and engineering of making intelligent machines" (Stanford HAI 2020). Initially, AI's impact is limited (Hansen et al. 1992; Goul et al. 1992), constrained by the development of hardware and algorithms. However, a resurgence in AI has emerged in recent years, fueled by advances in machine learning, especially deep learning, along with the availability of big data and enhanced computing capabilities. AI has achieved or even surpassed human performance in several areas: notably, AlphaGo defeated South Korean Go champion Lee Se-dol in 2016 (BBC 2016); machine image recognition error rates dropped below 5%, comparable to human levels (Brynjolfsson and Mcafee 2017); and ChatGPT has outperformed human crowd-workers in text annotation tasks (Gilardi et al. 2023).

The AI-driven transformation is capturing significant attention across both practice and academia, with increasing societal and economic implications. For example, AI has been demonstrated to have significant macroeconomic impacts on national economic growth (Nordhaus 2021), labor markets (Frank et al. 2019; Acemoglu and Restrepo 2019, 2020; Mann and Püttmann 2023), and income inequality (Korinek and Stiglitz 2018). Concurrently, business journals call for papers to unravel AI-related influences: *Management Science* has a special issue titled "The Human-Algorithm Connection", emphasizing the interplay between humans and AI algorithms (Caro et al. 2022); *Production and Operations Management* has a special issue titled "Responsible Data Science", focusing on the social responsibilities associated with AI and algorithmic applications (Cohen et al. 2022); *Decision Sciences* has a special issue titled "AI-Driven Decision Sciences", concentrating on AI's contributions to business decision-making (Li et al. 2023). Despite these thematic directives, there is still a noticeable lack of a systematic framework for understanding AI-related research within the context of business studies.

In this study, we introduce a structured framework to elucidate the intricate dynamics between humans and AI, as depicted in Figure 1. This framework is based on a directed cyclical interaction between humans and AI. First, humans, as creators, develop and refine AI-related products, which are then gradually deployed across various industries. The extensive applications of these AI products foster increasing interactions between humans and AI, as well as between existing organizational structures and AI. Consequently, it is crucial to thoroughly assess the impact of AI applications on human society (i.e., *AI applications*). Second, the widespread adoption of AI raises another important question: how do humans perceive AI during human-AI interactions? Given AI's transformative potential across numerous sectors, understanding consumer attitudes is vital for devising effective strategies to advertise AI and foster its broader acceptance and growth. Therefore, it is important to explore public perceptions and attitudes toward AI algorithms and systems (i.e., *human perceptions of AI*). Third, with the development of AI technologies, AI products are becoming increasingly smarter and more intelligent. In the process of humans interacting with AI, these advanced systems may display human-like behaviors, such as discrimination, irrational actions, or emotional responses, due to biased training data or other underlying factors. Such behaviors can influence the application and development of AI, as well as human perceptions of it.

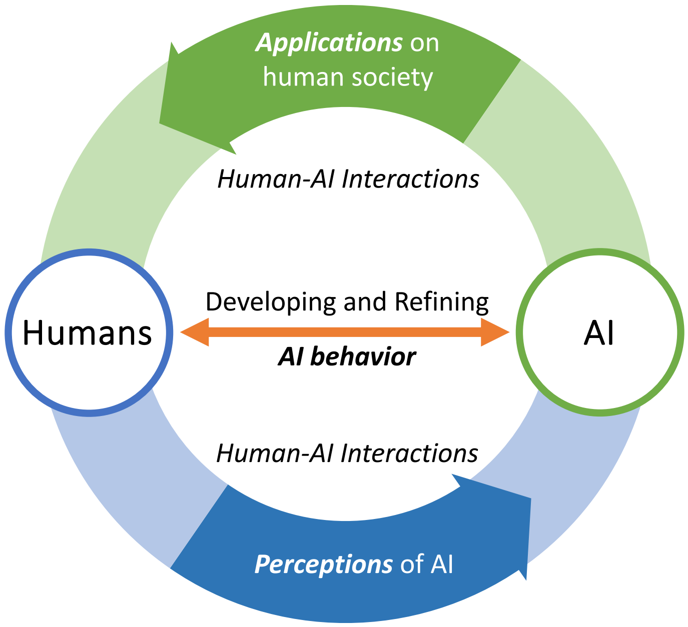

Figure 1 **The framework of AI in business**

Accordingly, exploring and identifying these behaviors in AI and related technologies is a pivotal research goal (i.e., *AI behavior*).

We adopt this framework—AI applications, human perceptions of AI, and AI behavior—to conduct a systematic literature review within the domain of business research, aiming to delineate the current landscape and future trajectory of AI research. Specifically, we focus on journals in the *Dallas (UTD) 24 List*[1] and the *Decision Sciences Journal*. We select relevant articles as follows.

- First, we construct a comprehensive list of AI-related keywords (such as "AI," "artificial intelligence," and "machine learning") to search articles published on those 25 journals via the Web of Science,[2] where the field tag *topic (TS)* is used to judge an article. In particular, searching through TS means searching for specific terms in the following fields within a record:

[1] `https://jsom.utdallas.edu/the-utd-top-100-business-school-research-rankings`.

[2] Search code on the Web of Science: (TS=("artificial intelligence" OR "AI" OR "machine" OR "deep learning" OR "algorithm*" OR "*bot" OR "*bots" OR "robo*" OR "automat*" OR "intelligen* system*") AND SO=(M SOM MANUFACTURING SERVICE OPERATIONS MANAGEMENT) OR SO=(Academy of Management Journal) OR SO=(Academy of Management Review) OR SO=(Administrative Science Quarterly) OR SO=(Information Systems Research) OR SO=(Journal of Accounting Economics) OR SO=(Journal of Accounting Research) OR SO=(Journal of Consumer Research) OR SO=(Journal of Finance) OR SO=(Journal of Financial Economics) OR SO=(Journal of International Business Studies) OR SO=(Journal of Marketing) OR SO=(Journal of Marketing Research) OR SO=(Journal of Operations Management) OR SO=(INFORMS JOURNAL ON COMPUTING) OR SO=(Management Science) OR SO=(Marketing Science) OR SO=(MIS Quarterly) OR SO=(Operations Research) OR SO=(Organization Science) OR SO=(Production and Operations Management) OR SO=(Strategic Management Journal) OR SO=(Accounting Review) OR SO=(Review of Financial Studies) OR SO=(Decision Sciences)).

title, *abstract*, *author keywords*, and *keywords plus*.[3] This process generates a total of 3,222 published articles during the period between 2010 and 2023.

- Second, we remove special types of publications such as review articles, editorial notes, and biographical items, retaining only research articles. This step results in the exclusion of 42 articles from the initial set.
- Third, we conduct a rigorous assessment of each article to determine whether its content aligns with our review framework. To diminish subjectivity in this assessment, authors independently read and evaluate all articles. Subsequently, we merge our individual assessments and engage in discussions regarding any articles marked differently, to reach a consensus on whether they should be included in our review.
- Finally, we identify 114 research articles published between 2010 and 2023. Figure 2 reports the distribution of these articles across the three topics.

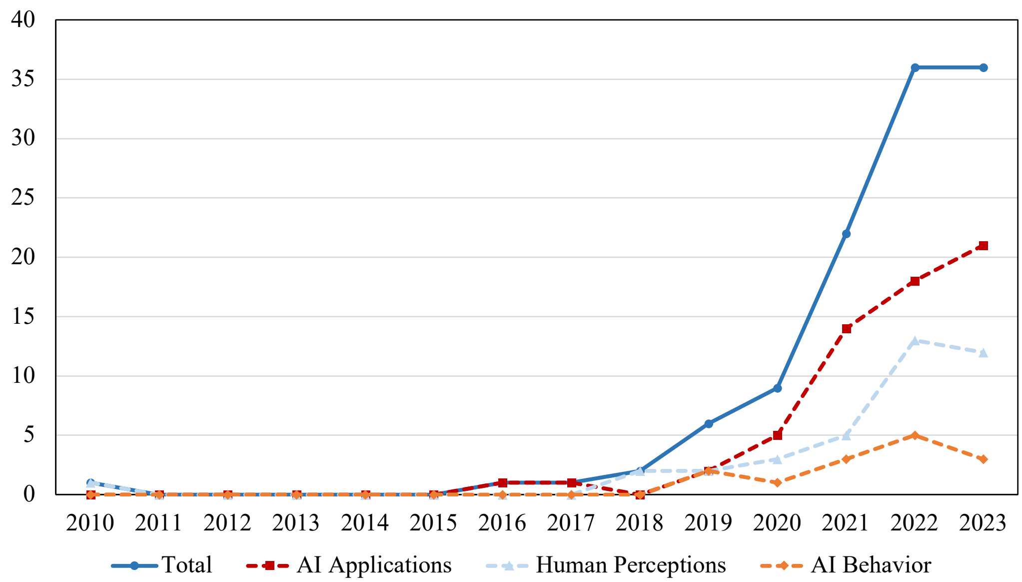

Figure 2 **Number of publications with AI-related keywords in topics**

The structure of the paper is as follows. Section 2 reviews the literature related to AI applications. Section 3 reviews the studies regarding human perceptions of AI. Section 4 discusses the research on AI behavior. Section 5 summarizes the reviewed literature and outlines several fundamental questions driving future research. Finally, section 6 offers a conclusion.

[3] This field is developed by the Web of Science and contains the words or phrases that frequently appear in the titles of an article's references, but do not appear in the title of the article itself. Ref: `https://support.clarivate.com/ScientificandAcademicResearch/s/article/KeyWords-Plus-generation-creation-and-changes?language=en_US`.

2. AI Application

This section discusses the impact of AI in the *strategic level*, *system level,* and *algorithm level* on organizational performance (Section 2.1). Then, we discuss the human-AI interaction where AI can serve an *assistant*, a *collaborator*, and a *competitor* (Section 2.2).

2.1. AI and Organizational Performance

2.1.1. Strategy. Panel A of Table 1 presents the studies of AI applications at the strategic level. For example, Lou and Wu (2021) study AI's role in accelerating drug development within biotech and pharmaceutical sectors, finding that AI significantly enhances the identification of new drug-target combinations. Zhang et al. (2023) reveal that the emergence of AI technologies would change the labor force in organizations, generally complementing high-education labor but substituting for low-education labor. Dixon et al. (2021) show that robotics investments increase overall firm employment but reduce the needs in managerial positions. Cao et al. (2023) explore how publicly traded companies adjust to the rise of AI readership. Their findings indicate that firms adapt their disclosure practices to enhance the machine readability of filings. Li et al. (2021a) discover the positive moderating role of AI innovation capabilities in the interplay between corporate social performance and market risk. On the modeling front, Li and Li (2022) develop mathematical models to analyze the repercussions of employing AI tools in automating order decisions within a decentralized supply chain, demonstrating potential profitability declines for retailers and possible detrimental effects for both suppliers and retailers in extreme scenarios. Choi et al. (2024) explore how AI-enhanced predictive capabilities influence a firm's pricing strategies under the ship-then-shop business model. Wang et al. (2023b) identify conditions under which firms benefit from disclosing their use of AI algorithms in decision-making processes to users. Gurkan and de Véricourt (2022) reveal that interactions among data volume, algorithmic enhancement, and incentive mechanisms can lead to pricing anomalies and affect social welfare, thereby suggesting that overaccumulation of data might inversely impact profits.

2.1.2. System. AI, such as chatbot, can automate complex functions involving data processing, analysis, decision-making, and action execution. Panel B of Table 1 lists the related literature. Song et al. (2017) examine the efficacy of a decision support system in facilitating auditors' evaluation of financial and nonfinancial information, finding that it enhances risk assessment performance. Mukherjee and Sinha (2020) demonstrate that the surgical robots could improve clinical performance. Schanke et al. (2021) explore the effect of anthropomorphic chatbots in retail settings, concluding that human-like chatbots positively influence transaction outcomes. Similarly, Wang et al. (2023a) find that implementing voice-activated AI systems in call centers can significantly reduce customer complaints, despite the increase in service duration. Brynjolfsson et al. (2019)

Table 1 Literature about AI impact

Literature	Application Context	Journal
	Panel A: Strategy	
Lou and Wu (2021)	Pharmaceutical firms	MISQ
Li et al. (2021a)	–	POM
Zhang et al. (2023)	–	ISR
Dixon et al. (2021)	–	MS
Cao et al. (2023)	–	RFS
Li and Li (2022)	Supply chain management	POM
Choi et al. (2024)	Consumer prediction	MS
Wang et al. (2023b)	–	MS
Gurkan and de Véricourt (2022)	–	MS
	Panel B: System	
Song et al. (2017)	Auditing	DS
Mukherjee and Sinha (2020)	Hospital	JOM
Schanke et al. (2021)	Retailing firms	ISR
Wang et al. (2023a)	Call center	POM
Brynjolfsson et al. (2019)	E-commerce platforms	MS
Cheng et al. (2020)	Traffic congestion	ISR
Deng et al. (2023)	Shelf monitoring	MISQ
Spring et al. (2022)	Law and accountancy firms	JOM
	Panel C: Algorithm	
Ferreira et al. (2016)	Demand forecasting	MSOM
Shi et al. (2020)	Inventory management	DS
Senoner et al. (2022)	Quality management	MS
Feldman et al. (2022)	Product display	OR
Chen et al. (2023a)	Revenue management	JOM
Bertsimas et al. (2022)	Hospital	MSOM
Wu et al. (2021)	Social media	ISR
Erel et al. (2021)	Director selection	RFS

Notes: MISQ: *Management Information Systems Quarterly*; POM: *Production and Operations Management*; ISR: *Information Systems Research*; MS: *Management Science*; RFS: *The Review of Financial Studies*; DS: *Decision Sciences*; JOM: *Journal of Operations Management*; MSOM: *Manufacturing & Service Operations Management*; OR: *Operations Research*; RFS: *The Review of Financial Studies.*

investigate the effect of eBay Machine Translation, an AI-driven translation tool, on cross-border transactions. They find that it boosts exports to specific regions, including Latin America, Italy, and Russia by improving translation quality. Cheng et al. (2020) analyze the benefits of implementing intelligent transportation systems in 99 U.S. urban areas, highlighting substantial reductions in traffic congestion, fossil fuel usage, and CO_2 emissions. Deng et al. (2023) find that the adoption of intelligent image processing-based shelf monitoring in a fast-moving consumer goods manufacturer significantly boosts its product sales. Spring et al. (2022) examine the deployment of AI systems in legal and accounting firms, revealing that such technologies elevate performance by reallocating human resources from mundane tasks to more strategic advisory roles.

2.1.3. Algorithm. Machine learning and deep learning algorithms exhibit powerful predictive capabilities and hold significant potential for various business decision-making scenarios. Panel C of Table 1 lists the studies that have implemented AI algorithms in real-world scenarios. For example, Ferreira et al. (2016) develop a machine learning algorithm based on modified regression trees to predict demand for new products and translate the demand forecasts into pricing. Results from a field experiment by collaborating with an online retailer, Rue La La, illustrate a profit increase of approximately 9.7%. In a similar vein, Shi et al. (2020) develop a predictive algorithm based on the random forest to manage inventory in overseas warehouses for a Chinese fashion retailer, demonstrating that the application of this algorithm in the firm significantly reduces costs by 20%. Senoner et al. (2022) introduce an innovative data-driven decision model employing explainable artificial intelligence for quality management, which has been shown to enhance manufacturing quality and reduce yield loss by 21.7% in collaboration with a high-power semiconductor manufacturer. Chen et al. (2023a) develop a discount recommendation approach based on reinforcement learning to help a budget hotel chain attract customers and demonstrate its superior performance by improving hotels' revenue per available room in a field experiment. Feldman et al. (2022) contrast machine learning algorithms against the traditional statistical approach of the multinomial logit (MNL) model in optimizing product displays on Tmall and Taobao. Yet, their large-scale field experiment indicates that the MNL approach yields a 28% increase in revenue per customer visit compared to the machine-learning method. Moreover, studies consistently demonstrate the superior performance of AI algorithms in real-world applications such as optimizing the selection of board directors for public firms (Erel et al. 2021), detecting false information on social media (Wu et al. 2021), and predicting patient flows in hospitals (Bertsimas et al. 2022).

2.2. AI-Human Interaction

2.2.1. Assistant. AI can assist human by simplifying, speeding up, or taking over tasks that are routine and laborious without participating in the process of decision-making. Panel A of Table 2 presents the related literature of AI assistant. For example, Kim et al. (2022) identify significant enhancements in students' academic outcomes when tutors are supported by AI-generated diagnoses of students' learning needs. Ko et al. (2023) reveal a significant increase in students' engagement frequency during the COVID-19 pandemic, after adopting an AI-based educational application. Moreover, in the realm of specialized training, Gaessler and Piezunka (2023) find that AI can serve as an effective training tool for chess players to enhance their strategic decision-making by substituting for scarce human training partners. Furman and Teodoridis (2020) find that automation technologies significantly enhance the generation of novel ideas among researchers by reducing the cost of executing tasks. Chen et al. (2022) show positive effects of AI knowledge systems on improving workers' job performance in three different application contexts. Bell et al. (2024) examine the efficacy of various AI algorithms in aiding experts to filter ideas in crowdsourcing contests. Wang et al. (2023c) reveal that AI aids significantly increase workers' productivity in medical chart coding tasks, with junior employees or those with specific task-based expertise benefiting more from AI assistance than their senior counterparts. In the financial investment area, Ge et al. (2021) reveal that investors adhering to AI advisors' recommendations outperform others on peer-to-peer lending platforms. Liu et al. (2024) demonstrate that lenders utilizing AI assistant experience lower delinquency rates.

While extensive literature highlights the positive effects of AI assistance, some studies present opposite results. Fügener et al. (2021) observe that groups using AI assistance in image annotation tasks underperform compared to those operating without AI, attributing to the reduction of human unique knowledge after using AI assistance. Similarly, Krakowski et al. (2023) reveal the

Table 2 Literature about AI Assistant and AI Collaborator

Literature	Application Context	Journal
	Panel A: Assistant	
Kim et al. (2022)	Home tutoring	JMR
Ko et al. (2023)	Remote education	MS
Gaessler and Piezunka (2023)	Chess	SMJ
Furman and Teodoridis (2020)	Knowledge production	OS
Chen et al. (2022)	Knowledge production	ISR
Liu et al. (2024)	Lending	ISR
Ge et al. (2021)	Lending	ISR
Bell et al. (2024)	Idea screening	MKS
Wang et al. (2023c)	Medical chart coding	MS
Fügener et al. (2021)	Image annotation	MISQ
Krakowski et al. (2023)	Chess	SMJ
	Panel B: Collaborator	
Karlinsky-Shichor and Netzer (2024)	Sales activities	MKS
Fügener et al. (2022)	Image annotation	ISR
Luo et al. (2021)	Sales skill training	JM
Tong et al. (2021)	Performance feedback	SMJ
Man Tang et al. (2022)	–	AMJ
Boyacı et al. (2024)	–	MS
Sturm et al. (2021)	Organizational learning	MISQ
Waardenburg et al. (2022)	Crime detection	OS
Te'eni et al. (2023)	Text classification	MS
Van den Broek et al. (2021)	–	MISQ
Bendoly et al. (2023)	Product design	DS

Notes: JMR: *Journal of Marketing Research*; MS: *Management Science*; SMJ: *Strategic Management Journal*; OS: *Organization Science*; ISR: *Information Systems Research*; MKS: *Marketing Science*; MISQ: *Management Information Systems Quarterly*; JM: *Journal of Marketing*; AMJ: *Academy of Management Journal*.

introduction of AI disrupts traditional competitive skills among chess players, presenting a direct contradiction to the positive outcomes noted by Gaessler and Piezunka (2023).

2.2.2. Collaborator. AI can engage in the decision-making process through dynamic interactions with human counterparts. Panel B of Table 2 reports the related literature. For example, Karlinsky-Shichor and Netzer (2024) introduce a hybrid human-machine decision-making model in a B2B (business-to-business) retail setting, demonstrating that integrating automated pricing models with salesperson insights generates profits significantly higher than either the model or the salespeople. Similarly, Fügener et al. (2022) show that human-AI collaboration surpasses individual efforts of either in classification tasks. Luo et al. (2021) assess the impact of AI coaches on sales agents' performance, identifying an inverted-U relationship where middle-ranked agents exhibit the most significant performance enhancements. Tong et al. (2021) investigate AI's role in delivering performance feedback in call centers, revealing simultaneous positive and negative impacts on workers' productivity. Man Tang et al. (2022) demonstrate that conscientious employees might experience decreased effectiveness when working alongside AI systems that possess autonomous decision-making capabilities. Moreover, Boyacı et al. (2024) develop an analytical model to explore the dynamics between human decision-makers and AI, revealing that although AI can improve decision accuracy overall, it may also elevate specific types of errors and cognitive burdens, particularly under conditions such as time pressure or multitasking. Sturm et al. (2021) demonstrate the positive effects of integrating human labor with AI technologies on organizational learning and innovation, particularly in dynamic environments. Waardenburg et al. (2022) investigate the deployment of learning algorithms by Dutch police and highlight the critical role of algorithmic brokers in interpreting AI's predictive results in criminal incidents.

In addition, several studies discuss the *human-in-the-loop* design in AI, emphasizing the role of human-AI collaboration throughout the lifecycle of AI systems. For example, Te'eni et al. (2023) develop an abstract configuration for reciprocal human-machine learning that enables iterative learning cycles between humans and machines. Van den Broek et al. (2021) delve into the integration of machine learning in organizations through a two-year ethnographic study, highlighting the interdependence of AI developers and domain experts in developing a hiring AI tool. Bendoly et al. (2023) show that the interaction between designers and generative design tools creates a double-loop learning cycle, enhancing resilience and providing a competitive edge through a unique human-AI symbiosis for firms in response to exogenous shocks, such as COVID-19.

2.2.3. Competitor. AI can even be a competitor. Lysyakov and Viswanathan (2023) examine the impact of AI competition on human decision-making by analyzing reactions to an AI system introduced for simple logo designs on a crowdsourcing platform. They observe that while successful designers enhance the quality of their work in response to AI competition, less successful ones merely increase their participation rate without improving their work quality. The competition pressure from AI is serious because numerous studies has found that AI outperforms humans (Table 3). For example, Fu et al. (2021) use the data from Prosper.com to train an AI model and compares the investing performance of humans and AI, suggesting that the AI system surpasses crowd investors in accurately forecasting loan default probabilities. Liu et al. (2023a) find that clients using robo-advisors during the financial upheaval of 2020 incur significantly fewer losses than those with traditional human investment strategies. Similarly, Coleman et al. (2022) show that Robo-Analysts' investment recommendations not only exhibit a more balanced distribution and less bias towards glamour stocks than human analysts, but also yield substantial long-term investment benefits. Pickard et al. (2020) examine the utility of automated AI interviewers in the context of auditing, revealing that it performs similarly or outperforms human interviewers when it closely resembles the interviewee in facial and vocal characteristics. Notably, their results also show an increase of up to 32% in the likelihood of employees disclosing breaches in internal controls when interviewed by an AI, compared to human interviewers. Clarke et al. (2020) explore the role of machine learning techniques in identifying fake news in financial markets, suggesting that AI algorithms can successfully identify fake news that human article commenters failed. Aubry et al. (2023) investigate the role of AI in auctions, suggesting that the trained AI algorithm predicts auction prices significantly better than the auction house. Similarly, Khern-am nuai et al. (2024) examine the impact of AI-based versus crowd-based systems on the selection of cover images for restaurants on a review platform, demonstrating the superior performance of AI, particularly for those with fewer photos, lower ratings, and initial lower engagement. Reisenbichler et al. (2022) reveal that using AI algorithms in content marketing not only generates search engine optimization content on par with that produced by expert humans, but also elevates search engine visibility while curtailing production costs.

However, AI does not outperform humans in all aspects. Peukert et al. (2023) find that automated algorithmic recommendations generally outperform human curation in the context of online news, yet human curation excels when personal data is scarce and user preferences vary greatly. Liu (2022) find that while machine learning models excel in processing hard information, loan officers are more adept at gathering soft information than AI machines. Karlinsky-Shichor and Netzer (2024) identify that although using AI algorithms to price in a B2B aluminum retailer generally enhances its profitability, human salespeople outperform in generating profits when dealing with unique or complex quotations. Luo et al. (2019) assess the effects of chatbots on sales performance within a financial services firm, revealing that AI chatbots match the efficiency of skilled employees and quadruple that of novices in sales when customers are unaware they are interacting with a

Table 3 Literature about AI competition

Superior	Literature	Application Context	Journal
NA	Lysyakov and Viswanathan (2023)	Logo design	ISR
AI	Reisenbichler et al. (2022)	Content marketing	MKS
AI	Fu et al. (2021)	Lending decisions	ISR
AI	Liu et al. (2023a)	Investment advice	POM
AI	Coleman et al. (2022)	Investment advice	AR
AI	Aubry et al. (2023)	Price prediction	JF
AI	Pickard et al. (2020)	Interview	AR
AI	Clarke et al. (2020)	Fake news detection	ISR
AI	Khern-am nuai et al. (2024)	Cover image selection	MSOM
Contingent	Peukert et al. (2023)	Online news selection	MS
Contingent	Liu (2022)	Loan information process	JAR
Contingent	Karlinsky-Shichor and Netzer (2024)	Sales activities	MKS
Equal	Wu et al. (2023)	Trust games	MS
Equal	Luo et al. (2019)	Telemarketing	MKS
Human	Cui et al. (2022)	Procurement	MSOM
Human	Lebovitz et al. (2021)	Hospital	MISQ

Notes: ISR: *Information Systems Research*; MKS: *Marketing Science*; POM: *Production and Operations Management*; AR: *The Accounting Review*; JF: *The Journal of Finance*; MS: *Management Science*; JAR: *Journal of Accounting Research*; MSOM: *Manufacturing & Service Operations Management*; MISQ: *Management Information Systems Quarterly.*

chatbot. Wu et al. (2023) develop deep neural network-based AI agents to play the trust game, discovering that the performance behavior of AI agents is similar to human decisions under certain conditions. Cui et al. (2022) conduct a field experiment on a B2B sourcing platform to compare the quotations obtained by AI and human procurement agents. Their findings reveal that firms employing solely automated chatbots for procurement are quoted higher prices compared to those using human agents, and the amalgamation of AI with chatbots results in the acquisition of the most competitive quotes. Lebovitz et al. (2021) investigate the performance of five AI tools in hospitals, revealing that none of them met expectations.

3. Human Perception of AI

Tables 4 lists the literature on human perception of AI. Van Donselaar et al. (2010) analyze the behavior of retail store managers within a supermarket chain using an automated inventory management system and find that managers often disregard the system's ordering recommendations. Leung et al. (2018) highlight that while automation machines present clear advantages, they are less appealing to consumers motivated by identity-driven purchases. de Bellis et al. (2023) find that autonomous technologies meet resistance from consumers who value manual labor as a source of meaning. Moreover, multiple studies have revealed that human-like attributes, such as emotional expression in automated machines, might affect human perceptions. For example, Bergner et al. (2023) demonstrate that chatbots designed with human conversational attributes, such as turn-taking, turn initiation, and grounding between turns, improve the consumer's perception of brand humanness, which in turn enhances consumer-brand relationships and positively affects brand loyalty and advocacy. However, Han et al. (2023) find that emotions expressed by chatbots are perceived as less genuine than those expressed by humans, leading to increased expectation discrepancies. In a similar vein, Crolic et al. (2022) uncover that anthropomorphic customer service chatbots can negatively affect satisfaction, firm evaluation, and purchase intentions when customers are angry at the outset of the interaction. In addition, Cohn et al. (2022) show that individuals are more likely to cheat when interacting with a machine compared to a human, regardless of whether the machine is equipped with human features.

Algorithm Aversion. There is a rich literature on *algorithm aversion* (Dietvorst et al. 2015); see Table 4 for a summary. Tan and Staats (2020) show that restaurant hosts often ignore algorithmic advice on customer-to-waiter assignments. Sun et al. (2022) find that warehouse packing employees frequently deviate from algorithmic guidance regarding package organization, which prolongs packing times and diminishes operational efficiency. Similarly, Commerford et al. (2022) reveal

Table 4 Literature about human perceptions of AI

Perception	Literature	Context	Journal
Negative	Van Donselaar et al. (2010)	Ordering management	MS
Negative	Leung et al. (2018)	Lab experiment	JMR
Negative	de Bellis et al. (2023)	Lab experiment	JM
Positive	Bergner et al. (2023)	Customer service	JCR
Negative	Han et al. (2023)	Customer service	ISR
Negative	Crolic et al. (2022)	Customer service	JM
Negative	Cohn et al. (2022)	Lab experiment	MS
	Algorithm Aversion		
Negative	Tan and Staats (2020)	Customer assignments	POM
Negative	Sun et al. (2022)	Package advice	MS
Negative	Commerford et al. (2022)	Auditing	JAR
Negative	de Véricourt and Gurkan (2023)	High-stakes decisions	MS
Negative	Longoni et al. (2023)	Public service	JMR
Negative	Lebovitz et al. (2022)	Healthcare	OS
Negative	Longoni et al. (2019)	Healthcare	JCR
Negative	Kyung and Kwon (2022)	Healthcare	POM
Negative	Costello et al. (2020)	Lending decisions	JAE
Negative	Habel et al. (2023)	Sales activities	JMR
Negative	Liu et al. (2023b)	Ride-hailing platform	MS
Negative	Gnewuch et al. (2023)	Customer service	ISR
Positive	Holzmeister et al. (2023)	Investment decisions	MS
Positive	Bai et al. (2022)	Task assignment	MSOM
Positive	Srinivasan and Sarial-Abi (2021)	Brand harm crisis	JM

Notes: MS: *Management Science*; JMR: *Journal of Marketing Research*; JM: *Journal of Marketing*; JCR: *Journal of Consumer Research*; ISR: *Information Systems Research*; POM: *Production and Operations Management*; JAR: *Journal of Accounting Research*; OS: *Organization Science*; JAE: *Journal of Accounting Economics*; MSOM: *Manufacturing & Service Operations Management*.

algorithm aversion in the auditing field, noting that auditors are less inclined to revise their estimates when contradicted by an AI system as opposed to a human expert. Liu et al. (2023b) explore the algorithm aversion phenomenon of drivers in a ride-hailing platform, suggesting that drivers' aversion is significantly affected by their past experiences and peer actions. Gnewuch et al. (2023) reveal that disclosing human involvement in hybrid service agents combining AI and humans results in more customers adopting human-oriented communication styles, showing the aversion of AI agents. Kyung and Kwon (2022) investigate the perception of AI on preventive healthcare, suggesting that users' acceptance and behavioral change are lower compared to interventions by human experts. Costello et al. (2020) conduct a field experiment introducing a slider feature on a lending platform, which allows lenders to modify AI recommendations. Their results show that lenders in the treatment group exhibit an 18% larger increase in their deviation from AI recommendation.

The literature also explores the mechanism behind algorithm aversion. de Véricourt and Gurkan (2023) build a theoretical model to analyze how verification bias affects the adoption and trust of human decision-makers in AI recommendations in high-stakes decisions. Habel et al. (2023) explore the factors that can mitigate or intensify salespeople's aversion to algorithms, revealing the important role of salespeople's realistic expectations regarding the algorithm's accuracy. Longoni et al. (2023) investigate public reactions to AI failures across various sectors, discovering that errors made by algorithms tend to be more broadly generalized than those committed by humans. In the healthcare industry, Lebovitz et al. (2022) highlight the opacity of AI tools as a significant barrier to effective human-AI collaboration in diagnostic radiology. Similarly, Longoni et al. (2019) explore the reasons why consumers are reluctant to adopt AI in healthcare, finding that concerns over AI's inability to recognize individual uniqueness lead to reduced willingness to use AI-provided healthcare.

While much of the literature identifies negative human perceptions of AI, several studies highlight the positive attitude. For example, Bai et al. (2022) examine the impact of algorithmic versus human-based task assignments on perceptions of fairness and productivity through a field experiment. They find that tasks assigned by algorithms are perceived as fairer, leading to enhanced productivity. Srinivasan and Sarial-Abi (2021) explore consumer reactions to brand harm crises caused by algorithmic errors and human errors, revealing that consumers respond less negatively to errors made by algorithms than those made by humans. Holzmeister et al. (2023) discover that clients prefer to delegate their investment decisions to algorithms rather than finance professionals in a lab experiment.

Dynamic Perception. The human perception of AI can be dynamic and are contingent upon various factors; see Table 5 for a list of the literature.

First, human perceptions of AI are influenced by the features of the AI itself. Castelo et al. (2023) show that consumers' responses to bot services can be as favorable as, or even superior to, those to human services, if the bots can provide superior service. Bauer et al. (2023) highlight the importance of feature-based explanations of AI systems in altering the way people use AI. Lehmann et al. (2022) reveal that the adoption of algorithmic advice by humans hinges not only on the algorithm's transparency and complexity but on its perceived appropriateness. Clegg et al. (2023) reveal that consumers generally prefer products with high-adaptive algorithms (i.e., those with higher intelligence like ChatGPT), compared with low-adaptive algorithms (i.e., pre-programmed algorithms). Bauer and Gill (2024) explore the impacts of disclosing algorithmic scoring processes on individuals' behavior. Their experiments show that revealing incorrect algorithmic scores to individuals can shape their actions to align with these scores, thus causing self-fulfilling prophecies.

Second, the perception is contingent on the specific application scenarios. Castelo et al. (2019) identify that algorithm aversion is weaker for tasks perceived as objective rather than subjective. Longoni and Cian (2022) reveal that preferences for AI-based recommendations are influenced by the tasks perceived with utilitarian and hedonic attributes. Yalcin et al. (2022) uncover that consumers react more favorably when positive decisions are made by humans rather than algorithms, but this disparity is not observed within negative decisions. In a similar vein, Garvey et al. (2023) reveal that consumers respond more positively to a human agent for a positive offer, whereas a negative offer is more tolerable when presented by AI, attributed to perceived lesser intent to harm. Adam et al. (2023) explore customer reactions to automated sales agents (ASAs) versus human sales agents (HSAs), revealing that while HSAs attract greater initial interest due to their social presence, ASAs are preferred when requiring customers' contact information.

Third, the human perception of AI also depends on individuals' own characteristics. Ge et al. (2021) demonstrate that investors who have experienced more defaults during manual investing are more likely to deviate from the recommendations from AI advisors on peer-to-peer lending platforms. Kim et al. (2022) reveal that tutors with higher levels of education and experience are less inclined to employ AI assistance in the context of tutoring services. Similarly, Dai and Singh (2020) uncover that concerns about reputation and private knowledge lead highly skilled experts to avoid using AI tools in the medical decision-making processes, thereby differentiating themselves from their less adept counterparts. Jussupow et al. (2021) investigate AI's influence on decision-making in medical settings, revealing that physicians' acceptance of AI advice hinges on complex cognitive evaluations. Moreover, Li et al. (2021b) demonstrate that a firm's adoption of AI is significantly affected by the presence of a Chief Information Officer and the diversity of its board's education and AI experience. Dietvorst et al. (2018) find that allowing individuals to make minor adjustments to algorithm-generated forecasts notably increases their likelihood of adopting these

Table 5 Literature about dynamic perceptions of AI

Perception contingent on	Literature	Context	Journal
Algorithm performance	Castelo et al. (2023)	Customer service	JCR
Algorithm explainability	Bauer et al. (2023)	Lab experiment	ISR
Algorithm transparency and complexity	Lehmann et al. (2022)	–	POM
Algorithm adaptivity	Clegg et al. (2023)	Lab experiment	JCR
Algorithm transparency	Bauer and Gill (2024)	–	ISR
Communication contents	Adam et al. (2023)	Sales activities	ISR
Task types	Yalcin et al. (2022)	Lab experiment	JMR
Task types	Longoni and Cian (2022)	Product choice	JM
Offer types	Garvey et al. (2023)	Ticket resale	JM
Task objectivity	Castelo et al. (2019)	Lab experiment	JMR
Users' education and experience	Kim et al. (2022)	Tutoring service	JMR
Users' skill levels	Dai and Singh (2020)	Healthcare	MKS
Users' investment levels	Ge et al. (2021)	Investment decisions	ISR
Board's background	Li et al. (2021b)	–	MISQ
Users' cognition	Jussupow et al. (2021)	Healthcare	ISR
Human intervention	Dietvorst et al. (2018)	Lab experiment	MS
Human intervention	Kawaguchi (2021)	Product assortment	MS

Notes: JCR: *Journal of Consumer Research*; ISR: *Information Systems Research*; JMR: *Journal of Marketing Research*; JM: *Journal of Marketing*; MKS: *Marketing Science*; MISQ: *Management Information Systems Quarterly*; MS: *Management Science*.

tools. Similarly, Kawaguchi (2021) observe that workers are more inclined to adhere to algorithmic advice when they can integrate their own forecasts into the algorithm.

4. AI Behavior

This section reviews the literature on *algorithmic bias* and *algorithmic collusion*; see Table 6 for a summary.

4.1. Algorithmic Bias

Algorithmic bias arises when algorithms make decisions that consistently disadvantage specific groups of people (Friis and Riley 2023). This bias can lead to severe consequences when implemented in critical areas such as healthcare, criminal justice, and credit scoring. Lambrecht and Tucker (2019) reveal that algorithms governing job advertisement delivery can inadvertently lead to gender discrimination in ad viewership in terms of the science, technology, engineering, and math fields. Fuster et al. (2022) show that machine learning models disproportionately disadvantage Black and Hispanic borrowers using U.S. mortgage data. Similarly, Fu et al. (2021) provide evidence that machine learning algorithms can exhibit biases related to gender and race, even when not explicitly using these attributes as inputs in prediction model training. Kelley et al. (2022) investigate the impact of antidiscrimination laws on discrimination and profitability within fintech lending. Their findings suggest that laws banning the use of gender information inadvertently heighten discrimination while only marginally affecting profitability. Zhang et al. (2021) examine the effects of Airbnb's smart-pricing algorithm on racial disparities, noting that despite a 71.3% reduction in the daily income gap between White and Black hosts following algorithm adoption, the broader racial revenue disparity exacerbated due to lower adoption rates among Black hosts. In addition, Choudhury et al. (2020) investigate prediction biases arising from human manipulation, showing that patent applicants can strategically modify content descriptions—by including irrelevant information or omitting relevant citations—to influence algorithmic decisions erroneously.

Algorithmic bias poses significant challenges, as human perceptions could swiftly shift from positive to negative upon revelations of discriminatory practices. Researchers have proposed solutions to address it. For example, Ahsen et al. (2019) introduce a bias-aware linear classification algorithm designed to correct biases in human-generated datasets, focusing particularly on the influence of clinical-risk information on radiologists' assessments of mammograms. They find that the bias-aware algorithm can effectively reduce or eliminate bias under certain conditions, although its efficacy is contingent on the variance of the error caused by the bias. Samorani et al. (2022) propose a race-aware methodology to address the racial disparities arising from machine learning-based appointment scheduling systems. They find that this approach effectively balances schedule efficiency with fairness, eliminating racial wait time disparities without compromising overall schedule cost. Choudhury et al. (2020) emphasize the necessity of combining domain expertise and specific skills with machine learning technologies to mitigate biases, particularly those arising from human manipulation. In contrast, Rhue (2023) reveal that humans may reinforce emotion recognition AI inconsistencies on demographics due to anchoring effects, highlighting the challenges in correcting algorithmic bias by including human decisions. Moreover, Fu et al. (2021) propose a debiasing technique aimed at eliminating redundant encodings, thereby rendering algorithmic training input features independent of sensitive attributes like race. They show that while this method may slightly reduce prediction accuracy, it enhances the fairness of the algorithm. Kelley et al. (2022) demonstrate that machine learning models can significantly mitigate discrimination through specific data management and modeling strategies, such as rebalancing gender distribution in training datasets and employing probabilistic gender proxy models. They demonstrate that this approach not only reduces bias but also maintains or even slightly enhances predictive accuracy and profitability. However, the effectiveness of the "equal opportunity" model in addressing algorithmic bias is debated (Hardt et al. 2016). Fu et al. (2022) critique this approach, arguing that while "equal opportunity" algorithms aim to enhance fairness, they may inadvertently disadvantage all parties, including those they are designed to protect. Through a theoretical model, they demonstrate that such fairness algorithms could reduce the overall accuracy of predictions due to the strategic behaviors of decision-makers, such as companies.

Table 6 Literature about AI behavior

Bias Type	Literature	Context	Journal
	Panle B: Algorithmic Bias		
Gender discrimination	Lambrecht and Tucker (2019)	Ads promotion	MS
Racial discrimination	Zhang et al. (2021)	Pricing	MKS
Racial discrimination	Fuster et al. (2022)	Loan	JF
Gender and racial discrimination	Fu et al. (2021)	Loan	ISR
Gender discrimination	Kelley et al. (2022)	Loan	MSOM
Algorithmic bias	Rhue (2023)	Emotion recognition	ISR
Prediction bias	Choudhury et al. (2020)	Patent identification	SMJ
Algorithmic bias	Ahsen et al. (2019)	Healthcare	ISR
Racial discrimination	Samorani et al. (2022)	Scheduling	MSOM
Algorithmic bias	Fu et al. (2022)	-	MS
	Panle B: Algorithmic Collusion		
Algorithmic collusion	Abada and Lambin (2023)	Pricing	MS
Algorithmic collusion	Meylahn and denBoer (2022)	Pricing	MSOM
Algorithmic collusion	Hansen et al. (2021)	Pricing	MKS
Algorithmic collusion	Loots and denBoer (2023)	Pricing	POM

Notes: MS: *Management Science*; MKS: *Marketing Science*; JF: *The Journal of Finance*; ISR: *Information Systems Research*; MSOM:*Manufacturing & Service Operations Management*; SMJ: *Strategic Management Journal*; POM: *Production and Operations Management.*

4.2. Algorithmic Collusion

An increasing number of firms have adopted pricing algorithms, which has caused concerns such as algorithmic collusion (Calvano et al. 2020). Abada and Lambin (2023) indicate that independent machine-learning algorithms operating in dynamic markets can unintentionally learn collusive behaviors to maximize profits, often due to imperfect exploration. They suggest that regulatory interventions or the promotion of decentralized learning may prevent these outcomes and ensure market behaviors that align with socially beneficial goals. Meylahn and denBoer (2022) explore the possibility of self-learning algorithms learning to collude in duopolies without violating competition laws. Their finding shows that algorithms can either converge to jointly maximize revenues or adopt competitive pricing based on the competitor's strategies, thus underlining the latent threat of algorithmic collusion. Furthermore, Hansen et al. (2021) provide evidence of algorithmic collusion in dynamic pricing scenarios, even when each algorithm (or firm) does not have access to competitors' pricing strategies. Loots and denBoer (2023) investigate the interplay between pricing and demand learning in a duopolistic setting using a multinomial logit model, demonstrating that algorithms can learn to set prices well above competitive levels, thereby potentially undermining consumer welfare.

5. Future Research Directions

We propose five future research directions, aimed at constructing a comprehensive research framework to guide scholars in this rapidly evolving landscape.

RQ1: What Changes Has AI Brought? Scholarly work has primarily focused on the implementation of AI in performing simple, repetitive tasks due to the initial limitations of AI technologies. However, with the rapid advancement of AI, advanced AI systems are applied in increasingly complex scenarios. For example, growing firms (e.g., H&M, Airbnb, and Chevrolet) utilize large language model tools, such as ChatGPT, to engage more deeply in customer support and sales activities, potentially replacing human workers in these contexts. While previous studies have investigated the performance of chatbots, new chatbots powered by ChatGPT may provide entirely different interaction experiences for customers, potentially resulting in varied outcomes. Therefore, it is worthwhile to reexamine the impact of advanced AI in these application contexts. Moreover, AI tools are increasingly being integrated across various industries. Examples include ChatGPT in user-generated content platforms, Copilot in coding, Suno in music, Midjourney in imaging, and Sora in video, among others. Therefore, another important research question is to investigate the changes these advanced AI tools have brought to each industry and the professions within them.

RQ2: How Humans and AI Work Together? AI and humans possess distinct qualities and capabilities (Cremer and Kasparov 2021): AI-based systems are characterized by speed, accuracy, and consistent rationality, whereas humans exhibit intuitive, emotional, and culturally sensitive competencies. Therefore, it is critical to explore how AI can augment human intelligence in decision-making processes, and how can humans and AI collaborate to enhance work efficiency and improve productivity. Although some initial investigations have been conducted in this domain, significant opportunities remain for future research considering the varying performance of AI in different application contexts (e.g., healthcare). For example, can AI tools (e.g., Med-PaLM developed by Google) assist physicians in conducting primary treatment work? Similarly, can physicians and AI collaborate to improve diagnostic capabilities during remote consultations? Furthermore, given the rapid technological advancements and the increasing intelligence of AI, it is essential to examine how humans can effectively harness and collaborate with these advanced AI tools, such as ChatGPT, to improve production efficiency.

RQ3: How Humans Perceive AI? Extensive research has explored human perceptions related to specific AI tasks and how these perceptions evolve under different conditions. Much of this research has highlighted a phenomenon known as "algorithm aversion." Although this phenomenon has been observed in various contexts, questions remain about its prevalence across all AI applications. If algorithm aversion is identified in a new context, a crucial question is to explore the conditions under which people are more likely to exhibit lower aversion or embrace AI technologies. Furthermore, human perceptions may be dynamic with the development of AI. For example, it is uncertain whether this aversion will diminish or amplify with further advancements in AI technology, such as the introduction of ChatGPT. Do customers still exhibit aversion when communicating with chatbots powered by ChatGPT? If not, what factors contribute to this change? Given that previous studies show varying perceptions of AI in different contexts, future research could investigate whether human perceptions shift with the development and application of AI in those specific contexts.

RQ4: Does AI Perform Human-like Behavior? Emerging evidence indicates that AI may manifest human-like behaviors (e.g., gender and racial discrimination) within certain contexts. Such prejudice has the potential to erode the trust that has been established in AI, altering human perceptions from acceptance to boycotts. Additionally, since most AI systems operate as black boxes, it is challenging to directly detect AI behavior prior to deployment. Consequently, a critical area for future research is to identify AI behaviors across diverse application contexts and explore their effects. Note that the human-like behavior is not inherently negative. For example, LLMs can accurately predict the outcomes of social science experiments originally conducted by humans (Hewitt et al. 2024; Li et al. 2024). This suggests that future researchers could leverage AI agents to simulate human participants in experiments, reducing the costs associated with conducting such studies. Similarly, AI agents could potentially be utilized to provide emotional value to humans (Yin et al. 2024). Therefore, a promising direction for future research is to explore the potential applications of AI exhibiting human-like behavior across various contexts.

RQ5: How to Reduce AI Bias? A pivotal direction for future research is addressing AI behavior bias. Existing literature identifies three primary sources contributing to AI bias: biased training datasets, inherent biases within algorithms, and human manipulation. Yet, other factors may also contribute to bias within AI systems, demanding a more comprehensive understanding of these sources, especially given the opacity of many AI algorithms. This knowledge is essential for developers who aim to effectively mitigate AI bias. Moreover, while several solutions to counteract AI bias have been proposed, it remains unclear how about the externality of these solutions or whether they are merely applicable on a case-by-case basis. To our knowledge, there is currently no foolproof way to ensure the unbias of AI.

6. Conclusion

This paper reviews the extant literature about AI within the domain of business research, endeavoring to delineate a roadmap for the burgeoning and intricate research terrain surrounding AI. However, we also acknowledge the limitations. First, this review does not cover a significant body of AI research within Economics, Psychology, and Social Science (e.g., Brynjolfsson and Mitchell 2017; Kleinberg et al. 2018; Obermeyer et al. 2019; Yam et al. 2021; Chen et al. 2023b), because it is constrained to publications in business research. Second, some recent studies relevant to our review framework are excluded due to the limited review period (e.g., Babina et al. 2024; Hou et al. 2024; Dong et al. 2024; Gofman and Jin 2024).

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