Journal of Digital Economy 1 (2022) 180–191

Contents lists available at ScienceDirect

Journal of Digital Economy

journal homepage: www.keaipublishing.com/en/journals/journal-of-digital-economy

Review article

How to realize the full potentials of artificial intelligence (AI) in digital economy? A literature review

Haiming Hang [a,*], Zhifeng Chen [b]

[a] School of Management University of Bath Bath, BA2 7AY, UK
[b] Southampton Business School, University of Southampton, Southampton, SO17 1, UK

ARTICLE INFO

Keywords:
Artificial intelligence
Literature review
Digital economy
Digital privacy

ABSTRACT

Artificial intelligence (hereafter AI) is widely considered as a driving force in the current digital economy, with many firms having already invested in AI. Since AI is unconstrainted by humans' cognitive limitations and inflexibility, and thus a key assumption in popular press is that AI is crucial for firms' success in digital economy. However, surprisingly, many managers indicate they are yet to benefit from their AI investments. To address this issue, the main purpose of this paper is to summarize the extant literature on AI in business and management fields to identify how AI can create competitive advantages and underpin the key barriers that prevent AI from realizing its full potentials. Our results suggest AI can increase revenue by improving employee productivity, increasing consumer evaluation, setting competitive price and creating unique resources. AI can also reduce cost by improving efficiency and reducing risks. However, our results also indicate that AI adoption, task nature and AI management are the key barriers preventing AI from realizing its full potentials. This is because AI lacks interpersonal skills. Thus, we encourage future research to focus on improving AI's interpersonal skills.

1. Introduction

Schwab (2017) argues that we are in the fourth industrial revolution where advances in digital technologies blur the boundary between the physical, digital, and biological spheres. What differentiates the fourth industrial revolution from previous ones are the velocity and scope of changes in the entire economic system. This is empowered by emerging technology breakthroughs in fields such as artificial intelligence (hereafter AI) (Rong, 2022; Xue and Pang, 2022).

However, humans' interaction with AI is not a recent phenomenon. It can be traced back to 1950s when Alan Turing developed the Turing Test to address the question whether machines could think (Turing, 1950). The initial intention to create AI was to use intelligent machines to augment human intelligence by overcoming humans' cognitive limitations and inflexibility (Jain et al., 2021). Thus, before 1980s AI was mainly used for simple problem solving (e.g., basic calculation in playing checkers) (Minsky, 1961). Later on, researchers in Stanford University developed expert systems to simulate the behaviour of domain experts (Feigenbaum, 1981). Technically, it was a success, with the expert system producing similar judgements as human experts with reasonable accuracy (Sebrechts et al., 1991). However, due to limitations of hardware technologies at that time, expert systems did not attract significant business interests (Jain et al., 2021). The advent of the Internet of Things (IoT) has significantly changed how AI works because it makes more and more people and devices connect to the internet. This creates large and complex data sets to train AI. This, together with the development of machine

* Corresponding author.
E-mail addresses: h.hang@bath.ac.uk (H. Hang), z.chen@soton.ac.uk (Z. Chen).

https://doi.org/10.1016/j.jdec.2022.11.003
Received 15 October 2022; Received in revised form 26 November 2022; Accepted 28 November 2022

learning and natural language processing, makes modern AI systems a driving force in various aspects of digital economy (Rong, 2022; Schwab, 2017; Xue and Pang, 2022). For example, in marketing sales AI can work with human agents to engender customer purchases (Luo et al., 2019). Customer services AI (e.g., Pepper) can respond to simple customer requests (Davenport et al., 2020). In finance, AI is now used to identify potential fraud (Costello et al., 2020) and screen customers for potential loans (Tantri, 2021). In supply chain management, AI can take orders from both suppliers and buyers (Cui et al., 2022; Li and Li, 2022). AI has also been used to develop innovative products that can increase company revenue (Rammer et al., 2022). Indeed, a recent survey of 2500 executives found that 90% of them had already invested in AI (Ascarza et al., 2021).

But can AI benefit business in digital economy? Wilson and Daugherty (2018) argued investing in AI could generate revenue much quicker, twice the speed of laggards. But among the 2500 executives surveyed, fewer than 40% of them indicated their business benefited from using AI (Ascarza et al., 2021). This is echoed by Guha et al. (2021). By interviewing with senior managers in retailing, their research suggested that the short-to-medium-term impact of AI might not be as promising as popular press suggested (Guha et al., 2021). Thus, it seems currently companies haven't taken advantages of the full potentials of AI to benefit their business. But why this is the case?

To answer this question, we need to identify how AI can create competitive advantages in digital economy and underpin the key barriers that prevent AI from realizing its full potentials. To achieve this aim, this paper reviews and synthesizes existing literature in different disciplines such as economics (e.g., Calvano et al., 2020), marketing (e.g., Davenport et al., 2020), operation management (e.g., Cui et al., 2022), accounting (e.g., Fedyk et al., 2022), finance (e.g., Gu et al., 2020), information systems (e.g., S. Zhang et al., 2021) and management (e.g., Choudhury et al., 2020). This can provide unique insights to managers about how to integrate AI in their business successfully.

The reminder of the paper is organized as follows: the next section explains our review method. This is followed by reviewing the existing conceptualizations of AI in business and management literature. We then discuss the key mechanisms AI can positively contribute to business as well as the key barriers preventing AI from realizing its full potentials in digital economy. The whole paper then concludes with suggestions for future research.

2. Literature review method

This paper uses literature review to answer our research question because review studies can synthesize piecemeal findings (Hulland and Houston, 2020) and address ambiguities in prior research by spotlighting critical unanswered questions (Palmatier et al., 2018). To provide a comprehensive coverage of the literature, we searched articles in all business and management fields via Scopus and EBSCO

Table 1
Journal list.

No. of Journals	Academic field	Journal title	AJG ranking[a]	Impact factor[b]
	Accounting	Review of Accounting Studies (RAS)	4	4.011
	Accounting	Contemporary Accounting Research (CAR)	4	4.041
	Accounting	Journal of Accounting and Economics (JAE)	4*	7.293
	Accounting	Journal of Accounting Research (JAR)	4*	4.446
	Economics	Review of Economic Studies (RES)	4*	7.833
	Economics	Quarterly Journal of Economics (QJE)	4*	19.013
	Economics	Journal of Political Economy (JPE)	4*	9.103
	Economics	American Economic Review (AER)	4*	10.540
	Entrepreneurship	Entrepreneurship Theory and Practice (ETP)	4	9.993
	Ethics	Journal of Business Ethics (JBE)	3	6.331
	Finance	Review of Financial Studies (RFS)	4*	8.414
	Finance	Review of Finance (RF)	4	5.059
	Finance	Journal of Financial and Quantitative Analysis (JFQA)	4	4.337
	General Management	Journal of Applied Psychology (JAP)	4*	11.802
	General Management	Journal of Management (JM)	4*	13.508
	General Management	Management Science (MS)	4*	6.172
	General Management	Academy of Management Review (AMR)	4*	13.865
	General Management	Academy of Management Journal (AMJ)	4*	10.979
	Information Systems	Journal of Management Information Systems (JMIS)	4	7.838
	Information Systems	Information Systems Research (ISR)	4*	5.49
	Information Systems	MIS Quarterly (MISQ)	4*	7.198
	Innovation	Research Policy (RP)	4*	9.473
	Marketing	Journal of Marketing Research (JMR)	4*	6.664
	Marketing	Journal of Marketing (JM)	4*	15.360
	Marketing	Marketing Science (MS)	4*	5.411
	Marketing	Journal of Retailing (JR)	4	11.190
	Marketing	Journal of Consumer Psychology (JCP)	4*	5.989
	Marketing	Journal of the Academy of Marketing Science (JAMS)	4*	14.904
	Marketing	Journal of Consumer Research (JCR)	4*	8.612
	Operations Management	Production and Operations Management (POM)	4	4.638
	Operations Management	Manufacturing and Service Operations Management (MSOM)	3	7.103
	Organization Studies	Organizational Behavior and Human Decision Processes (OBHDP)	4	5.606
	Strategy	Strategic Management Journal (SMJ)	4*	7.815

[a] Based on latest Academic Journal Guide 2021, published by Chartered Association of Business School.
[b] Based on latest Journal Citation Reports published by Clarivate Analytics.

databases using the following keywords: “AI”, “artificial intelligence”, and “intelligent machines”. This resulted over 17,000 articles, with 6515 articles in Scopus and 10,821 articles in EBSCO. To narrow down our review, we then limited our search to premium journals, namely, journals in Financial Times 50 list and/or UT Dallas journal list (24 journals). We concentrated on articles in premium journals because they reflect the highest quality in relevant fields and are widely cited in other articles. Through this process, we identified 92 articles for our review. In order to gather the direct evidence on the impact of AI in digital economy, we focused on empirical studies only. Thus, we excluded 19 articles that were conceptual papers/comments. As a result, our final list included 73 articles that provide empirical evidence on AI in digital economy (see Table 1).

Each member of the author team independently reviewed the title, abstract, and keywords for all the 73 articles to ensure the accuracy of our keyword search. We then developed a scheme for coding the articles, using author(s), and year of publication, journal, the main theme, theoretical lens, methodology, and main results as categories. Through this process, we found that most studies focused on either the benefits of AI or the risks of AI. Thus, we used these two schemes to code all articles. All coders achieved agreement greater than 90% and any inconsistencies were solved via discussion.

Though this process, we found our literature review covered all key disciplines in business and management studies, with 4 articles in economics, 4 in operation management, 8 in information systems, 17 in management (including entrepreneurship and business ethics), 28 in marketing, 9 in accounting and finance and 3 in organization studies. In terms of research methodology, lab and/or field experiments (42 papers) and secondary data analysis (22 papers) dominate current research on AI in digital economy. Table 2 provides details of articles by year. We summarize the key findings of extant literature in the sections below.

3. AI conceptualization

Extant literature defines AI as “programs, algorithms, systems or machines that demonstrate intelligence” (Shankar, 2018, p.vi). In other words, by using key technologies such as machine learning and natural language process, AI can “correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Haenlein and Kaplan, 2019, p. 17).

Since AI is used in various aspects of the digital economy, extent literature classifies AI into different types (Davenport et al., 2020; Huang and Rust, 2018; Kaplan and Haenlein, 2018). For example, Davenport and colleagues argue that different AIs differ on their levels of intelligence: task automation vs. context awareness. While task automation is standardized and rule-based AI applications, context awareness requires AI applications to “learn how to learn” (Davenport et al., 2020, p. 27). Thus, context awareness AI applications can address complex tasks by making context-specific responses that are beyond their initial programming by humans (Davenport et al., 2020). However, whether context awareness AI applications exist or even possible to develop is questionable (Reese, 2018). Kaplan and Haenlein (2018) classify AI into analytical AI, human-inspired AI and humanized AI. Analytical AI systems use cognitive rules to inform future decisions, with fraud detection in financial services a typical example of this. Going beyond cognitive rules, human-inspired AI systems recognize, understand human emotions, and consider them in decision making (Kaplan and Haenlein, 2018). For example, Replika as an AI system provides emotional support to customers by asking meaningful questions and adjusting to their linguistic syntax (Davenport et al., 2020). Finally, although not available yet, humanized AI systems have all cognitive, emotional and social intelligence

Table 2
(part 1) Distribution of articles published by year.

Year	JCR	JFQA	JM	JMIS	JMR	JPE	JR	MISQ	Management Science	Marketing Science
2018					1				1	
2019	1				1				2	1
2020	1					1	1			
2021		1	1					1	1	1
2022			4	1	2		1		3	
Total	2	1	5	1	4	1	2	1	7	2

part 2

Year	MSOM	OBHDP	POM	QJE	RAS	RES	RF	RFS	RP	SMJ
2018										
2019								1		
2020					1		1	1		1
2021		1								2
2022	3		2	1	1	1			2	
Total	3	1	2	1	2	1	1	2	2	3

part 3

Year	AER	AMJ	AMR	CAR	ETP	ISR	JAE	JAMS	JAR	JBE	JCP
2018											
2019											
2020	1						1				1
2021			1	1		4		1	1		
2022		1	1		1	2		10		3	1
Total	1	1	2	1	1	6	1	11	1	3	2

and are self-conscious in their interactions with others (Kaplan and Haenlein, 2018). Thus, it is very similar to context awareness AI applications proposed by Davenport et al. (2020).

Although researchers classify AI in different ways, they concur that AI as machines are unconstrained by human cognitive limitations and inflexibility (Balasubramanian et al., 2022). Thus, AI can be trained on large and complex datasets to make efficient, accurate and consistent decisions – AI's hard' data skills (Luo et al., 2019). Such skills are important for companies build competitive advantages in digital economy (Dawar and Bendle, 2018; Edelman and Abraham, 2022). For example, Edelman and Abraham (2022) argue personalized customer experience is a key competitive advantage in the current marketplace. Thus, companies need to use AI to assemble high-quality customer experience data to offer personalized service (Edelman and Abraham, 2022). This is echoed by Dawar and Bendle (2018) who suggest firms can gain competitive advantages by using AI as trusted advisors to consumers. Competitive advantages can lead to increased revenues and/or reduced cost. By can AI help companies achieve these business outcomes? The next section discusses this in detail.

4. The impact of AI on business in digital economy

4.1. Increasing revenue

Extant literature suggests AI systems can increase revenues (e.g., Brynjolfsson et al., 2019; Gu et al., 2020; Kelley et al., 2022; Mishra et al., 2022; Padigar et al., 2022) (see Table 3). For example, in Airbnb, adopting AI increases average daily revenue by 8.6% even though the average nightly rate drops by 5.7% (Z. Zhang et al., 2021). In international trade, AI increases exports by 10.9% and substantially reduces translation cost (Brynjolfsson et al., 2019).

Implementation of AI customer service chatbots generates a 0.22% abnormal stock return, with B2B firms gaining more than their B2C counterparts (Fotheringham and Wiles, 2022). Indeed, research has repeatedly demonstrated that stock market responds favourably to firms using AIs (Bahmani et al., 2022; Chen et al., 2019; Gu et al., 2020; Mishra et al., 2022; Padigar et al., 2022; Rammer et al., 2022). For example, Mishra et al. (2022) finds that focusing on AI in 10-K reports is positively associated with net profitability and return on marketing-related investment. Padigar et al. (2022) further argue that this is more evident among companies with a powerful marketing department. This is because such firms are considered as having superior marketing resources and assets to ensure the success of AI related innovations (Padigar et al., 2022). Based on the data from Germany, Rammer et al. (2022) find AI is associated with product innovations worth 16 billion Euros. It also contributes to about 6% of total annual cost savings of the German business sector (Rammer et al., 2022).

Previous research further suggests that AI systems increase revenue by improving employee productivity (e.g., Kim et al., 2022; Luo et al., 2021; Tong et al., 2021), increasing consumer responses (e.g., Crolic et al., 2022; Luo et al., 2019; Zierau et al., 2022), setting competitive price (e.g., Calvano et al., 2020; Miklós-Thal and Tucker, 2019) and creating unique resources (e.g., Gregory et al., 2021; Krakowski et al., 2022). In terms of employee productivity, Kim et al. (2022) find AI helps employees to adapt to customers' needs more effectively. Luo et al. (2021) report that AI improvs employees' performance. But middle-ranked employees improve by the largest amount, whereas both bottom and top-ranked employees show incremental gains. However, restricting the training feedback level can improve employee performance across all ranks (Luo et al., 2021). Tong et al. (2021) suggest AI increases the accuracy and consistency of the analyses of employee information, and the relevance of feedback to each employee. This helps employees achieve greater job

Table 3
Key mechanisms of AI increasing revenues.

Mechanism	Article	Field	Method	Key Findings
Improve employee productivity	Kim et al. (2022)	marketing	experiment	AI helped tutors adapt to students' learning needs and improve academic performance. But tutors who significantly contributed to the firm's revenue benefited little from AI.
	Luo et al. (2021)	marketing	experiment	Middle-ranked human agents benefited most from AI coach. But bottom- and top-ranked human agents benefit little. However, restricting the training feedback level increases performance for all agents.
	Tong et al. (2021)	management	experiment	Undisclosed AI improved employees' job performance by significantly increasing the relevance of feedback to each employee.
Increase customer evaluation	Luo et al. (2019)	marketing	experiment	Chatbots were four times more effective than inexperienced workers in engendering customer purchases. But disclosing of chatbot identity had a negative impact.
	Crolic et al. (2022)	marketing	secondary data analysis + experiment	When customers were angry, chatbot anthropomorphism had a negative effect on customer satisfaction and subsequent purchase intentions.
	Zierau et al. (2022)	marketing	experiment	Voice-based (as opposed to text-based) bots led to more positively-valenced service experiences, and more favourable behavioural firm outcomes because it promoted more flow-like user experiences.
Charge competitive price	Calvano et al. (2020)	economics	experiment	Algorithms consistently charged supercompetitive prices in an oligopoly model of repeated price competition.
Create unique resource	Krakowski et al. (2022)	management	experiment	In the context of chess, human-AI intersection created a new resource that drove performance. In addition, this resource was unrelated or even negatively related to humans' original capability.

performance, creating values for companies (Tong et al., 2021).

In terms of consumer responses, Luo et al. (2019) report that undisclosed chatbots are four times more effective than inexperienced workers in engendering customer purchases. Zierau et al. (2022) document voiced-based (as opposed to text-based) bots promote flow-like user experience, increasing consumers' brand evaluations. However, Crolic et al. (2022) caution that such effect depends on consumers' emotional states. Their research finds when consumers are angry, AI has a negative impact on consumer evaluation and subsequent purchase intentions (Crolic et al., 2022).

AI also leads to competitive pricing. Calvano et al. (2020) report using algorithms leads to setting supercompetitive prices without communicating with other firms. Echoing this, Miklós-Thal and Tucker (2019) find that algorithms-based demand forecasting not only better tailors prices to demand conditions but also leads to lower prices and higher consumer surplus.

Other researchers argue AI can help firms create unique resource (e.g., Gregory et al., 2021; Krakowski et al., 2021). For example, by focusing on AI in chess, Krakowski et al. (2021) argue human-AI interaction creates a new resource to build competitive advantage. They further argue such resource is unrelated or even negatively related to human original capability. Gregory and colleagues propose the unique resource created by AI links to data network (they call it "data network effect") (Gregory et al., 2021). In other words, advances in AI make digital platforms learn more from the data they collect from users, which, in turn, create more value to each user by offering personalized services (Gregory et al., 2021). In short, extant literature suggests AI can increase revenue in different ways ranging from improving employee productivity to creating unique resources (e.g., Gregory et al., 2021; Krakowski et al., 2021). But can AI reduce cost? The next section discusses this in detail.

4.2. Reducing cost

Extant literature suggests AI can reduce cost by improving efficiency and reducing risks (see Table 4). In terms of efficiency, Grennan and Michaely (2021) suggest AI leads to improved informational efficiency because it aggregates many data sources, including non-traditional ones (e.g., Twitter) to make investment recommendations. This is echoed by Wuttke et al. (2022) who find that AI systems improve work efficiency by 43.8%. However, this is only for a new task. For a repeated task, AI systems make employees spend 23% more time than traditional methods. This is perhaps because employees rely on new technology without fully internalizing the task (Wuttke et al., 2022). Yang (2022) argues AI systems improve productivity by reducing the share of labour force with educational qualifications of college level and below. Acemoglu and Restrepo (2020) further suggest that robots can improve work efficiency and reduce wage such that one more robot per thousand workers reduces wage by 0.42%.

In terms of reducing risks, Costello et al. (2020) find that machine-generated credit models lead to a larger decline in future portfolio-level credit risks than traditional models. This is particularly evident among borrowers who do not have social media accounts (Costello et al., 2020). In a similar vein, Senoner et al. (2022) report that AI-based models reduce yield loss by 21.7%. Tantri (2021) documents that using machine learning algorithms in lending achieves a 33% lower delinquency rate than human loan officers. Thus, research suggests AI is effective in reducing risks.

Table 4
Key mechanisms of AI reducing cost.

Mechanism	Article	Field	Method	Key Findings
Improve efficiency	Grennan and Michaely (2021)	accounting and finance	secondary data analysis	AI increased informational efficiency for investors by aggregating many data sources, including non-traditional ones (e.g., Twitter, blogs).
	Wuttke et al. (2022)	operation management	experiment	AI improved work efficiency for a new task. But it reduced efficiency for a repeated task.
	Yang (2022)	management	secondary data analysis	AI improved efficiency by reducing the share of labour force with educational qualifications of college level and below.
	Acemoglu and Restrepo (2020)	economics	secondary data analysis	AI improved work efficiency and reduced wages such that one more robot per thousand workers reduced wages by 0.42%.
Reduce risks	Costello et al. (2020)	accounting and finance	experiment	AI-generated credit model (vs. control) led to larger declines in future portfolio-level credit risk and larger increases in future sales orders.
	Senoner et al. (2022)	management	experiment	Compared with traditional model, AI-generated model led to better reduction in yield loss.
	Tantri (2021)	accounting and finance	secondary data analysis	AI achieved lower delinquency rate than human loan officers. This result is still robust when AI was explicitly prevented from discriminating against disadvantaged social classes.
Accurate prediction	Ding et al. (2020)	accounting and finance	secondary data analysis	The loss estimates generated by AI were superior to actual managerial estimates in four out of five insurance lines they examined.
	Fedyk et al. (2022)	accounting and finance	secondary data analysis	Compared with human auditors, AI led to improved audit quality and reduced fees.
	Blohm et al. (2022)	management	secondary data analysis	Investors only outperformed AI when they had extensive investment experiences and managed to suppress their cognitive biases.
	Mullainathan and Obermeyer (2022)	economics	secondary data analysis	AI made more accurate predictions because it revealed two mistakes of physicians diagnose of heart attack: over testing and undertesting.
	Cui et al. (2022)	operation management	experiment	AI buyers received higher quotes than human buyers without a smart control. However, AI delivered the most value when automation and smartness used together.

A key assumption in popular press is that AI systems can make more accurate predictions than humans because they are unconstrained by human cognitive limitations and inflexibility (Balasubramanian et al., 2022). Research in general does provide support to this assumption (e.g., Ding et al., 2020; Fedyk et al., 2022; Li and Li, 2022; Mullainathan and Obermeyer, 2022). For example, Ding et al. (2020) find that AI systems make superior estimates than human in four out of five insurance lines they examined. This is supported by Fedyk et al. (2022) who document that AI applications improve audit quality. Blohm et al. (2022) demonstrate that human investors only outperform algorithm when they have extensive investment experiences and manage to suppress their cognitive bias. In the case of health care, Mullainathan and Obermeyer (2022) find that AI systems make more accurate diagnose than physicians. This is perhaps because physicians use a simplified mental model of risk. This makes them over test those low-risk patients who do not benefit from tests and undertest those high-risk patients who suffer adverse health events afterwards (Mullainathan and Obermeyer, 2022). However, Li and Li (2022) argue AI automation cannot make accurate orders when regret is taken into consideration. Their research points out that when profit margins are high, AI automation rejects a supplier's contract. When profit margins are low, AI automation drives retailers to order more from supplies. Thus, they argue AI automation leads to a lose-lose outcome for both retailers and suppliers (Li and Li, 2022). In a similar vein, Cui et al. (2022) find that, if not equipped with a smart control, chatbots buyers receive higher quotes than human buyers.

We argue these mixed results is perhaps there are key barriers preventing AI to reach its full potentials. The next section discusses this in detail.

5. Key barriers to realize the full potentials of AI in digital economy

5.1. Adoption

At a population level, Acemoglu and Restrepo (2022) demonstrate that a shortage of middle-aged workers specializing in manual production tasks increases the adoption of AI systems. However, at an individual level, extent literature finds that people tend to hesitate to use AI due to the following reasons (see Table 5 below):

First, Dietvorst et al. (2015) find, despite algorithms outperform humans, when people see algorithms make mistakes, they more quickly lose confidence in their judgements – algorithm aversion. This is perhaps because people have the faulty assumption that algorithms, unlike their human counterparts, cannot learn from mistakes (Reich et al., 2022). In addition, Longoni et al. (2022) find that AI systems are perceived as more homogenous than humans. Therefore, failure information about one algorithm is transferred to

Table 5
Key barriers of AI adoption.

Reasons	Article	Field	Method	Key Findings
Algorithm aversion	Reich et al. (2022)	marketing	experiment	Consumers tended to avoid AI advice because they thought AI could not learn from mistakes.
	Longoni et al. (2022)	marketing	experiment	AI failures were generalized more broadly than human failures because AI systems were perceived as more homogeneous than people.
	Dietvorst et al. (2018)	management	experiment	To reduce algorithm aversion, participants needed to have control over AI outcome.
Lack feelings	Kyung and Kwon (2022)	operation management	Experiment + survey	Patients were less likely to accept advice on health behaviour change suggested by AI than human health experts because they thought AI lacked genuine care and warmth.
	Liang and Xue (2022)	information systems	Interview + survey	Physicians' resistance to AI recommendations was due to their experiential belief of face loss.
Identity loss	Uysal et al. (2022)	marketing	Interview + survey + experiment	AI anthropomorphism threatened consumers' identity and ultimately undermined their well-being.
	Leung et al. (2018)	marketing	secondary data analysis + experiment	AI hindered the attribution of identity-relevant consumption outcomes to consumers themselves.
	Granulo et al. (2021)	marketing	experiment	In symbolic consumption, uniqueness motives underpinned consumers' preference towards human (vs. robotic) made products.
	Longoni et al. (2019)	marketing	experiment	Consumers were reluctant to utilize healthcare provided by AI because they thought AI (vs. human) were less able to account for their unique characteristics and circumstances.
Privacy concern	Parket al. (2022)	information systems	experiments	Surveillance anxiety and delegation anxiety led to rejection of AI.
	Uysal et al. (2022)	marketing	Interview + survey + experiment	Data privacy concerns made consumers unwilling to use AI.
	Raveendhran and Fast (2021)	organization studies	experiment	Employees were more willingly to accept AI tracking than humans because AI tracking were considered as less judgmental.
Lack transparency	Lebovitz et al. (2022)	management	case study	Medical professionals were unengaged with AI because AI results often diverged from their initial judgment without providing underlying reasoning.
	Pachidi et al. (2021)	management	case study	Lack of transparency made employees pretend to comply with new technology while avoiding real change.

another algorithm at a higher rate than humans (Longoni et al., 2022). Taken together, these studies jointly suggest that people can easily lose their trust about AI competence, making them reluctant to use again. This is particular evident among less experienced investors who can significantly benefit from using AI recommendations (Ge et al., 2021). To overcome algorithm aversion, Dietvorst et al. (2018) propose to provide people the opportunity to modify algorithm outcomes because this makes them have a sense of control. As a result, they become more satisfied with the outcomes (Dietvorst et al., 2018).

Second, people tend to consider AI systems lack feelings. As a result, they do not want AI to make moral decisions for them (Bigman and Gray, 2018). In health care, patients are less likely to accept suggestions from AI than human health experts because they perceive AI lacks warmth and genuine care (Kyung and Kwon, 2022). As for physicians, their resistance towards AI systems is attributed to their experiential beliefs of face loss (Liang and Xue, 2022).

Third, AI is also considered as a threat to consumers' identities (Uysal et al., 2022). This is particularly evident among consumers who are strongly identified with a particular social category (e.g., fishing) (Leung et al., 2018). AI also hinders consumers' expression of their uniqueness which is an important function of symbolic consumption (Granulo et al., 2021). Supporting this, Longoni et al. (2019) find uniqueness neglect is a key reason drives consumers' resistance towards medical AI systems.

Fourth, privacy concern is another key issue preventing people using AI. Park et al. (2022) find surveillance anxiety together with delegation anxiety increases rejection of AI. Uysal et al. (2022) document that consumers' concerns about data privacy make them unwill to use AI. However, Raveendhran and Fast (2021) report that employees are more willing to accept behaviour tracking when it is conducted solely by AI rather than human. This is because employees feel AI tracking is less judgmental and allows a sense of autonomy (Raveendhran and Fast, 2021). In short, while popular press argues privacy concern is a key barrier in adopting AI, the research evidence is inconclusive.

Finally, people's resistance towards AI can also attribute to its lack of transparency. For example, Lebovitz et al. (2022) find medical professionals' hesitation of using AI is because AI tools often offer different suggestions from their own judgments without providing underlying reasoning. The lack of transparency also makes employees pretend to comply with new technology while avoiding real changes (Pachidi et al., 2021).

Another key barrier to realize the full potentials of AI is the nature of the task which we discuss below.

5.2. Task

Because AI as machine is efficient and objective, and thus people perceive it lacks subjective judgment capability (Castelo et al., 2019; Commerford et al., 2022; Lee, 2018; Longoni and Cian, 2022; Xu and Mehta, 2022) (see Table 6). For example, Castelo et al. (2019) find algorithms are trusted and relied on less for tasks that are subjective (vs. objective) in nature. In a similar vein, Lee (2018) report that algorithmic and human-made decisions are perceived equally fair and trustworthy for mechanical tasks that require objectivity. But for human tasks that involve subjective judgments, algorithmic decisions are considered less fair and trustworthy and lead to more negative emotions than human-made decisions (Lee, 2018). The lack of subjective judgment capability also makes consumers resist to AI recommendations when they choose brands/products that are hedonic in nature (Longoni and Cian, 2022). Indeed, Xu and Mehta (2022) find that when AI is used in luxury product design, it negatively impacts a brand's emotional value. Thus, for brands (e.g., luxury fashion brands) that build competitive advantages on superior emotional values, using AI reduces brand essence, leading to negative consumer evaluations (Xu and Mehta, 2022). In auditing, Commerford et al. (2022) report that when auditors receive contradictory evidence from AI (vs. a human specialist), they make smaller adjustments to management estimates. More importantly, they

Table 6
AI and task.

Focus	Article	Field	Method	Key Findings
Task nature	Castelo et al. (2019)	marketing	experiment	Consumers relied less on AI for tasks that were subjective (vs. objective) in nature. But increasing AI's perceived affective human-likeness could use AI usage for subjective tasks.
	Commerford et al. (2022)	accounting and finance	experiment	Auditors who received contradictory evidence from AI (vs. human) made smaller adjustments to managerial estimates. This was more evident when AI provided objective (vs. subjective) inputs.
	Longoni and Cian (2022)	marketing	experiment	AI was considered less competent than human in recommending products with hedonic nature.
	Xu and Mehta (2022)	marketing	experiment	AI technology had a negatively impact on the emotional value on luxury product design. but enhances the associated functional value.
Task outcome	Garvey et al. (2022)	marketing	experiment	When a product/service was better than expected, consumers respond less positively when dealing with an AI (vs. human) agent. This is because consumers perceived AI (vs. human) agents lack benevolent intentions when outcome was favourable to consumers.
	Yalcin et al. (2022)	marketing	experiment	Consumers reacted less positively when a favourable decision was made by an AI (vs. a human) agent. This is because it was easier for consumers to internalize a favourable decision outcome made by a human than AI.
Task complexity	Hodge et al. (2021)	accounting and finance	experiments	Investors were more likely to rely on recommendation of an unnamed robot-advisor. This is moderated by task complexity.

find this is more evident when objective (vs. subjective) inputs are used (Commerford et al., 2022), perhaps because they consider AI is more competent in objective tasks.

Other researchers argue that peoples' responses to AI also depend on the outcome of tasks (Garvey et al., 2022; Yalcin et al., 2022). For example, Garvey et al. (2022) find when a product/service is worse than expected, consumers respond more positively towards an AI (vs. human) agent. In contrast, when a product/service is better than expected, consumers respond less positively towards an AI (vs. human) agent (Garvey et al., 2022). In a similar vein, Yalcin et al. (2022) find consumer respond less positively towards an AI (vs. human) when they receiv a decision favourable to them. This is perhaps because compared with humans, AI lacks benevolent intentions, and thus a favourable decision made by AI is unlikely leading to feelings of gratitude (Garvey et al., 2022). Alternatively, this is perhaps because it is easier for consumers to internalize a favourable decision outcome made by a human than an algorithm (Yalcin et al., 2022).

The complexity of a task also influences people's responses to AI. For example, Hodge et al. (2021) report that investors are more likely to rely on the investment recommendations of an unnamed (vs. named) robot-advisor. This is moderated by task complexity such that investors are less likely to rely on a named robot-advisor when facing a complex task (Hodge et al., 2021). This is perhaps because naming a robot increases its humanness feature, making investors believe it is less capable of handling a complex task. Although AI can tackle complex tasks, Balasubramanian et al. (2022) argue that it also has a negative impact on routine tasks. This is because by relying on statistical analysis, machine learning may decrease the extent of causal, contextual and general knowledge associated with routines (Balasubramanian et al., 2022).

Since AI may completely transform the business models of an organization (Fountaine et al., 2019), another key challenge is how to manage AI.

5.3. Management

As discussed above, AI can help firms create unique resources (e.g., Gregory et al., 2021; Krakowski et al., 2021). But how firms can effectively manage AI to take advantages of the unique resources it creates remains unclear (Table 7).

A common assumption in extant literature is that AI works best when AI arguments humans rather than replaces humans (Davenport and Ronanki, 2018; Wilson and Daugherty, 2018). This is supported by Guha et al. (2022). By interviewing senior managers in retailing, their research finds that managers believe AI is more effective if it augments not replaces humans (Guha et al., 2022). However, the existing empirical evidence on this issue is not conclusive. For example, in the context of sale organization, Luo et al. (2021) find AI and human together outperform either AI alone or human alone because the combination of AI and human can harness the hard data skills of AI and soft interpersonal skills of humans. Echoing this, Fugener et al. (2022) report that humans and AI work together can achieve best outcomes. However, they also caution the best outcomes only happen when AI delegates work to humans but not when humans delegate tasks to AI. This is because humans are not able to assess their own capabilities correctly, and thus do not delegate well (Fuegener et al., 2022). Tong et al. (2021) find that AI and humans can be used for different users. Their research finds better outcomes resulted from using AI to provide performance feedback to veteran employees whereas using human managers to provide performance feedback to novice employees (Tong et al., 2021). However, Fügener et al. (2021) report that working with AI makes human employees feel dehumanized (they call it 'Borg'). This, in turn, leads to worse performance than human employees work alone (Fügener et al., 2021).

Zhang et al. (2021) report that the experience of interacting with AI can be summarized as liminal and ambiguous. By focusing on the retailing industry, Bonetti et al. (2022) point out that interacting with AI is a recursive process which requires co-adaption and co-alignment. As a result, the interpretation of AI advice poses a challenge. For example, Jussupow et al. (2021) finds that physicians use metacognitions to monitor and control their reasoning while assessing AI advice. Thus, they make decisions based on their own beliefs rather than the actual data from AI (Jussupow et al., 2021). Waardenburg et al. (2022) suggest, due to the untransparent nature of

Table 7
AI management.

Focus	Article	Field	Method	Key Findings
AI + human team	Guha et al. (2022a)	marketing	interview	Retail managers believed that AI was more effective if it augmented not replaced humans.
	Luo et al. (2021)	marketing	experiment	In the context of sales, AI and human together led to best sales outcomes.
	Fugener et al. (2022)	information systems	experiment	For classification tasks, AI and human together led to best outcomes. But this was only evident when AI delegated work to humans.
	Tong et al. (2021)	management	experiment	AI and human could be used for different users, with AI more suitable for veteran employees.
	Fügener et al. (2021)	information systems	experiment	Humans interacted with AI led to strong individual performance but lost human individuality.
Interact with AI	Zhang et al. (2021)	information systems	case study	Designers' experience of interacting with AI was summarized as liminal and ambiguous. This led to multiple trajectories in accordance with a multifarious temporality.
	Bonetti et al. (2022)	marketing	ethnographic study	Interacting with AI was a co-evolution process which needed to be co-envisioned, co-adapted, and co-(re)aligned.
	Jussupow et al. (2021)	information systems	experiments + interviews + survey	Physicians tended to use metacognitions to monitor and control their reasoning while assessing AI advice. Thus, they might made decisions based on beliefs rather than actual data from AI.
	Waardenburg et al. (2022)	management	case study	Knowledge brokers between AI and their users substituted AI predictions with their own judgments partly due to the lack of transparency of AI.

machine learning, the knowledge brokers between AI and their users substitute the AI advice with their own judgments.

6. Direction for future research

AI has been a key factor underlying companies' competitive advantage in digital economy (Rong, 2022; Xue and Pang, 2022). Unconstrained by human cognitive limitations and inflexibility (Balasubramanian et al., 2022), AI's 'hard' data skills can both increase revenues (e.g., Mishra et al., 2022; Padigar et al., 2022) and reduce costs (e.g., Acemoglu and Restrepo, 2020; Grennan and Michaely, 2021). However, AI's lack of interpersonal skills makes people reluctant to adopt it (e.g., Bigman and Gray, 2018; Kyung and Kwon, 2022), only outperforms humans in objective tasks (e.g., Castelo et al., 2019; Lee, 2018) and difficult to manage (e.g., Jussupow et al., 2021; Waardenburg et al., 2022). Thus, in the space below (see Table 8) we highlight key research opportunities that can help managers effectively address AI's lack of interpersonal skills.

First, a common finding in extant literature is that people consider AI as machines, and thus it lacks feeling (Bigman and Gray, 2018). In marketing, researchers have begun to focus on anthropomorphism to see how imbue AI with human features can mitigate the negative perception that AI cannot feel (e.g., Castelo et al., 2019; Uysal et al., 2022). A recent meta-analysis (Blut et al., 2021) finds that anthropomorphism has a positive effect on consumers' intentions to use AI. However, whether these results can be generalized to other groups of stakeholders (e.g., employees, investors) remain unclear. More importantly, we are not aware of any studies that directly test the impact of humanizing AI on firm values. Thus, future research needs to explore whether anthropomorphising AI can have a positive effect on firm value. In addition, future research needs to explore the key mechanism(s) underlying the impact of AI anthropomorphism on firm values. Does it improve employee productivity, create unique resources and/or reduce risks? Blut et al. (2021) also encourages future research to examine the 'dark-side' of AI anthropomorphism. For example, anthropomorphising AI may demotivate co-workers, as they may feel dehumanized (Fügener et al., 2021). In addition, consumers may feel they are not valued by companies if they are served by robots (Uysal et al., 2022). Thus, understand the negative impact of anthropomorphising AI can help companies make an informed decision about the benefits and risks of anthropomorphism. Previous research also argues AI works best when it augments humans rather than replaces humans (Luo et al., 2021; Wilson and Daugherty, 2018). Thus, a key challenge for managers is how to harness the potentials of a human + AI team? In other words, what role should AI play when it works with human employees? Is it an assistant, a monitor, a coach or a teammate (Babić et al., 2020)? In addition, given humans are not able to assess our own capabilities correctly (Fuegener et al., 2022), who should decide what role AI plays in a team? Future research can answer these questions by using

Table 8
Future research on AI.

Issues	Key Challenges	Possible Research Areas	Key Research Questions	Managerial and practical considerations
Lack of feeling	Low adoption among patients (Kyung and Kwon, 2022)	anthropomorphism	1) What is the impact of AI anthropomorphism on firm value? 2) What is the 'dark-side' of AI anthropomorphism?	1) Investing in humanizing AI 2) Keep AI's human co-workers motivated
	Not suitable for subjective tasks (Castelo et al., 2019)	empathy	1) How can artificial empathy be incorporated in AI design? 2) Can artificial empathy increase AI's warmth? 3) Which element of artificial empathy (perspective taking, empathy concern and emotional contagion) is the most effective?	1) Use human-inspired AI (e.g., Replika) to recognize and understand human emotions 2) Using AI to ask people meaningful questions and adjust to their linguistic syntax
Lack of transparency	Surveillance anxiety and low adoption (Uysal et al., 2022)	privacy	1) How people balance privacy concerns against the benefits of personalization? 2) What is the maximum private information they are willing to disclose? 3) How to effectively manage data privacy?	1) Manage consumers' private information ethically 2) Seek consumers' consent first 3) Increase transparency of how algorithms work
	Algorithm aversion (Dietvorst et al., 2015)	explanation	1) How to strike a balance between transparency and protecting commercial secrets? 2) How managers make ethical decisions on this issue?	1) Decide how much information to disclose regarding its algorithm 2) Set relevant ethical standards to manage algorithm
	Difficult to manage AI + human teams (Fügener et al., 2021)	autonomy	1) What factor(s) make people value autonomy in AI-mediated environment? 2) Do these factor(s) vary across cultures?	1) Decide how to delegate tasks among human (vs. AI) 2) Use AI to augment (not replace) human

field studies in organizations with human + AI teams.

Second, the existing literature envisions AI should be capable of feel human emotions and consider them in decision making (Davenport et al., 2020; Kaplan and Haenlein, 2018). One way to do that is to focus on artificial empathy (Liu-Thompkins et al., 2022). Liu-Thompkins and colleagues define artificial empathy as "an ability of AI agents to detect and adapt to humans' cognitive needs and emotional states" (Liu-Thompkins et al., 2022, p. 2). They further argue artificial empathy entails perspective taking, empathic concerns (e.g., emotion recognition) and emotional contagion (e.g., appropriateness appraisal, selective emotional mimicry) (Liu-Thompkins et al., 2022). Thus, future research needs to explore how the three elements of artificial empathy can be incorporated in AI design. More importantly, future research needs to explore whether imbuing AI with artificial empathy can make it outperform humans on subjective tasks, which, in turn, have a positive effect on firm value. In health care, future research can explore whether artificial empathy increases patients' adoption of AI by making patients perceive it as warm and showing genuine care. In marketing, researchers can test whether artificial empathy increases the emotional value of a brand such as a luxury fashion brand. Future research can also compare the impact of the three elements of artificial empathy to see which one is the most important to generate positive business outcomes.

Third, privacy concern is a key factor preventing people adopting AI (Park et al., 2022; Uysal et al., 2022). Davenport and colleagues point out this is perhaps because consumers are afraid that their data may be reused for the reasons different from those intended (e.g., loyalty card data used for telemarketing). Alternatively, their personal data may contain others' information (e.g., family) (Davenport et al., 2020). Thus, at an individual level, future research needs to explore how consumers/employees/investors balance their privacy concerns against the benefits of personalized recommendations. Do they consider privacy concerns as a necessary cost to pay to get their personalized offers? If yes, what is the maximum cost they are willing to sacrifice? At a policy level, Davenport et al. (2020) calls for future research to identify the best governing mechanism for data privacy management. Does it require legal regulation? Or is self-regulation sufficient? At a firm level, future research needs to explore how managers incorporate relevant ethics in their AI strategy and its implications for data management practice. Researchers interested in this area can use Xue and Pang (2022)'s framework to guide their empirical studies.

Fourth, the lack of transparency about the inputs and processes leading to AI decisions is a key barrier for medical professionals (Lebovitzet al., 2022) and employees (Pachidi et al., 2021) to adopt AI. One way to mitigate this issue is to provide explanation. For example, Marchand and Marx (2020) find that explanations of the reasoning that lead to AI recommendations outperform recommendations without explanations. However, explaining AI inputs and processes may make companies lose their commercial secrets. Thus, a key challenge for managers is how to balance business interests against AI transparency. Future research can interview managers to see what factor(s) they consider when striking a balance between transparency and commercial secrets. In addition, cross-culture studies are needed to see how different institutional environment and culture differences shape managers' decisions differently. Alternatively, researchers can use different ethical theories (Xue and Pang, 2022) to guide managers' decisions on this issue.

Finally, autonomy is important in interacting with AI because it reduces algorithm aversion (Dietvorst et al., 2018) and makes employees accept behaviour tracking (Raveendhran and Fast, 2021). However, due to AI's high predictive accuracy, Davenport and colleagues argue that consumers may feel lose a sense of autonomy because their decisions can be predicted by AI (Davenport et al., 2020). Thus, an interesting question awaits future research is that what factor(s) make consumers value perceived autonomy in AI-mediated environment. To answer this question, future research can explore individual differences to see whether certain personality traits are more important than others. Alternatively, future research can explore cultural differences to see whether autonomy is more valued in certain cultures than others. In addition, researchers can use different ethical theories to provide a normative guideline about how to incorporate autonomy in AI design.

7. Conclusion

Unconstrainted by humans' cognitive limitations and inflexibility, AI is widely considered as a key asset for firms' competitive advantage in digital economy. However, surprisingly, many managers indicate they are yet to benefit from their AI investments (Ascarza et al., 2021; Guha et al., 2021). Thus, through a literature view, the main purpose of our research is to summarize how AI can create competitive advantages in digital economy. Another goal of our research is to underpin the key barriers preventing AI realize its full potentials. Our research suggests AI's 'hard' data skills can benefit business by increasing revenue and/or reducing cost. However, our research also indicates that AI lacks interpersonal skills, leading to low adoption, difficult to manage and performance varying across tasks.

Our research extends extant literature on several fronts: first, by integrating research insights across different disciplines (e.g., economics, marketing), our research offers a more complete understanding of how AI can create values in digital economy. Second, by synthesizing existing piecemeal findings, our research spotlights an important but unanswered question in existing AI literature – how to address AI's lack of interpersonal skills. Third, more importantly, our research identifies five key areas, namely, anthropomorphism, artificial empathy, data privacy, AI explanation and autonomy that future research needs to focus to effectively address AI's lack of interpersonal skills.

Our research also has important practical implications. AI systems are unconstrained by human cognitive limitations (Balasubramanian et al., 2022). Therefore, to benefit from AI investments, managers can use AI systems to improve work efficiency. This can be done by using AI to search information (Grennan and Michaely, 2021) or augmenting existing labour force (Yang, 2022). Due to AI's high prediction accuracy, managers can also use AI to predict customer demand (Blohm et al., 2022) and manage supply chains (Cui et al., 2022). However, as AI systems are widely considered as lack of feelings (Kyung and Kwon, 2022), and thus managers need to use them on objective rather than subjective tasks (Castelo et al., 2019).

Declaration of competing interest

None.

References

Acemoglu, D., Restrepo, P., 2020. Robots and jobs: evidence from US labor markets. J. Polit. Econ. 128 (6), 2188–2244.
Acemoglu, D., Restrepo, P., 2022. Demographics and automation. Rev. Econ. Stud. 89 (1), 1–44.
Ascarza, E., Ross, M., Hardie, B.G., 2021. Why you aren't getting more from your marketing AI. Harv. Bus. Rev. 99 (4), 48–54.
Babić, R.A., De Valck, K., Sotgiu, F., 2020. Conceptualizing the electronic word-of-mouth process: what we know and need to know about eWOM creation, exposure, and evaluation. J. Acad. Market. Sci. 48 (3), 422–448.
Bahmani, N., Bhatnagar, A., Gauri, D., 2022. Hey, Alexa! what attributes of Skills affect firm value? J. Acad. Market. Sci. 1–17.
Balasubramanian, N., Ye, Y., Xu, M., 2022. Substituting human decision-making with machine learning: implications for organizational learning. Acad. Manag. Rev. 47 (3), 448–465.
Bigman, Y.E., Gray, K., 2018. People are averse to machines making moral decisions. Cognition 181, 21–34.
Blohm, I., Antretter, T., Sirén, C., Grichnik, D., Wincent, J., 2022. It's a peoples game, isn't it?! A comparison between the investment returns of business angels and machine learning algorithms. Enterpren. Theor. Pract. 46 (4), 1054–1091.
Blut, M., Wang, C., Wunderlick, N.V., Brock, C., 2021. Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI. J. Acad. Market. Sci. 49, 632–658.
Bonetti, F., Montecchi, M., Plangger, K., Schau, H.J., 2022. Practice co-evolution: collaboratively embedding artificial intelligence in retail practices. J. Acad. Market. Sci. 1–22.
Brynjolfsson, E., Hui, X., Liu, M., 2019. Does machine translation affect international trade? Evidence from a large digital platform. Manag. Sci. 65 (12), 5449–5460.
Calvano, E., Calzolari, G., Denicolò, V., Pastorello, S., 2020. Artificial intelligence, algorithmic pricing, and collusion. Am. Econ. Rev. 110 (10), 3267–3297.
Castelo, N., Bos, M.W., Lehmann, D.R., 2019. Task-dependent algorithm aversion. J. Market. Res. 56 (5), 809–825.
Chen, M.A., Wu, Q., Yang, B., 2019. How valuable is FinTech innovation? Rev. Financ. Stud. 32 (5), 2062–2106.
Choudhury, P., Starr, E., Agarwal, R., 2020. Machine learning and human capital complementarities: experimental evidence on bias mitigation. Strat. Manag. J. 41 (8), 1381–1411.
Commerford, B.P., Dennis, S.A., Joe, J.R., Ulla, J.W., 2022. Man versus machine: complex estimates and auditor reliance on artificial intelligence. J. Account. Res. 60 (1), 171–201.
Costello, A.M., Down, A.K., Mehta, M.N., 2020. Machine + man: a field experiment on the role of discretion in augmenting AI-based lending models. J. Account. Econ. 70 (2–3), 101360.
Crolic, C., Thomaz, F., Hadi, R., Stephen, A.T., 2022. Blame the bot: anthropomorphism and anger in customer–chatbot interactions. J. Market. 86 (1), 132–148.
Cui, R., Li, M., Zhang, S., 2022. AI and procurement. Manuf. Serv. Oper. Manag. 24 (2), 691–706.
Davenport, T., Guha, A., Grewal, D., Bressgott, T., 2020. How artificial intelligence will change the future of marketing. J. Acad. Market. Sci. 48, 24–42.
Davenport, T.H., Ronanki, R., 2018. Artificial intelligence for the real world. Harv. Bus. Rev. 96 (1), 108–116.
Dawar, N., Bendle, N., 2018. Marketing in the age of alexa. Harv. Bus. Rev. 96 (3), 80–86.
Ding, K., Lev, B., Peng, X., Sun, T., Vasarhelyi, M.A., 2020. Machine learning improves accounting estimates: evidence from insurance payments. Rev. Account. Stud. 25 (3), 1098–1134.
Dietvorst, B.J., Simmons, J.P., Massey, C., 2015. Algorithm aversion: people erroneously avoid algorithms after seeing them err. J. Exp. Psychol. Gen. 144 (1), 114–126.
Dietvorst, B.J., Simmons, J.P., Massey, C., 2018. Overcoming algorithm aversion: people will use imperfect algorithms if they can (even slightly) modify them. Manag. Sci. 64 (3), 1155–1170.
Edelman, D.C., Abraham, M., 2022. Customer experience in the age of AI. Harv. Bus. Rev. 100 (2), 116–125.
Fedyk, A., Hodson, J., Khimich, N., et al., 2022. Is artificial intelligence improving the audit process? Rev. Account. Stud. 27, 938–985.
Feigenbaum, E.A., 1981. Expert systems in the 1980s. In: Bond, A. (Ed.), State of the Art Report on Machine Intelligence. Pergamon-Info-tech, Maidenhead, England).
Fotheringham, D., Wiles, M.A., 2022. The effect of implementing chatbot customer service on stock returns: an event study analysis. J. Acad. Market. Sci. 1–21.
Fountaine, T., McCarthy, B., Saleh, T., 2019. Building the AI-powered organization. Harv. Bus. Rev. 63–73. July–August.
Fügener, A., Grahl, J., Gupta, A., Ketter, W., 2021. Will humans-in-the-loop become borgs? Merits and pitfalls of working with AI. Management Information Systems Quarterly (MISQ) 45 (3), 1527–1556.
Fuegener, A., Grahl, J., Gupta, A., Ketter, W., 2022. Cognitive challenges in human–artificial intelligence collaboration: investigating the path toward productive delegation. Inf. Syst. Res. 33 (2), 678–696.
Garvey, A.M., Kim, T., Duhachek, A., 2022. Bad news? Send an AI. Good news? Send a human. J. Market., 00222429211066972
Ge, R., Zheng, Z., Tian, X., Liao, L., 2021. Human–robot interaction: when investors adjust the usage of robo-advisors in peer-to-peer lending. Inf. Syst. Res. 32 (3), 774–785.
Granulo, A., Fuchs, C., Puntoni, S., 2021. Preference for human (vs. robotic) labor is stronger in symbolic consumption contexts. J. Consum. Psychol. 31 (1), 72–80.
Gregory, R.W., Henfridsson, O., Kaganer, E., Kyriakou, S.H., 2021. The role of artificial intelligence and data network effects for creating user value. Acad. Manag. Rev. 46 (3), 534–551.
Grennan, J., Michaely, R., 2021. Fintechs and the market for financial analysis. J. Financ. Quant. Anal. 56 (6), 1877–1907.
Gu, S., Kelly, B., Xiu, D., 2020. Empirical asset pricing via machine learning. Rev. Financ. Stud. 33 (5), 2223–2273.
Guha, A., Bressgott, T., Grewal, D., Mahr, D., Wetzels, M., Schweiger, E., 2022. How artificiality and intelligence affect voice assistant evaluations. J. Acad. Market. Sci. 1–24.
Guha, A., Grewal, D., Kopalle, P.K., Haenlein, M., Schneider, M.J., Jung, H., Moustafa, R., Hegde, D.R., Hawkins, G., 2021. How artificial intelligence will affect the future of retailing. J. Retailing 97 (1), 28–41.
Haenlein, M., Kaplan, A., 2019. A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. California management review, 61 (4), 5–14.
Hodge, F.D., Mendoza, K.I., Sinha, R.K., 2021. The effect of humanizing robo-advisors on investor judgments. Contemp. Account. Res. 38 (1), 770–792.
Huang, M.H., Rust, R.T., 2018. Artificial intelligence in service. J. Serv. Res. 21 (2), 155–172.
Hulland, J., Houston, M.B., 2020. Why systematic review papers and meta-analyses matter: an introduction to the special issue on generalizations in marketing. J. Acad. Market. Sci. 48 (3), 351–359.
Jain, H., Padmanabhan, B., Pavlou, P., Raghu, T.S., 2021. Editorial for the special section on humans, algorithms, and augmented intelligence: the future of work, organizations, and society. Inf. Syst. Res. 32 (3), 675–687.
Jussupow, E., Spohrer, K., Heinzl, A., Gawlitza, J., 2021. Augmenting medical diagnosis decisions? An investigation into physicians' decision-making process with artificial intelligence. Inf. Syst. Res. 32 (3), 713–735.
Kaplan, A., Haenlein, M., 2018. Siri, Siri, in my hand: who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Bus. Horiz. 62 (1), 15–25.
Kelley, S., Ovchinnikov, A., Hardoon, D.R., Heinrich, A., 2022. Antidiscrimination Laws, Artificial Intelligence, and Gender Bias: A Case Study in Nonmortgage Fintech Lending. Manufacturing & Service Operations Management.
Kim, J.H., Kim, M., Kwak, D.W., Lee, S., 2022. Home-tutoring services assisted with technology: investigating the role of artificial intelligence using a randomized field experiment. J. Market. Res. 59 (1), 79–96.

Krakowski, S., Luger, J., Raisch, S., 2022. Artificial intelligence and the changing sources of competitive advantage. Strat. Manag. J.
Krakowski, S., Luger, J., Raisch, S., 2022. Artificial intelligence and the changing sources of competitive advantage. Strategic Management Journal, forthcoming, forthcoming. https://onlinelibrary.wiley.com/doi/full/10.1002/smj.3387.
Kyung, N., Kwon, H.E., 2022. Rationally trust, but emotionally? The roles of cognitive and affective trust in laypeople's acceptance of AI for preventive care operations. Prod. Oper. Manag.
Lebovitz, S., Lifshitz-Assaf, H., Levina, N., 2022. To engage or not to engage with AI for critical judgments: how professionals deal with opacity when using AI for medical diagnosis. Organ. Sci. 33 (1), 126–148.
Lee, M.K., 2018. Understanding perception of algorithmic decisions: fairness, trust, and emotion in response to algorithmic management. Big Data & Society 5 (1), 2053951718756684.
Leung, E., Paolacci, G., Puntoni, S., 2018. Man versus machine: resisting automation in identity-based consumer behavior. J. Market. Res. 55 (6), 818–831.
Li, M., Li, T., 2022. AI automation and retailer regret in supply chains. Prod. Oper. Manag. 31 (1), 83–97.
Liang, H., Xue, Y., 2022. Save face or save life: physicians' dilemma in using clinical decision support systems. Inf. Syst. Res. 33 (2), 737–758.
Liu-Thompkins, Y., Okazaki, S., Li, H., 2022. Artificial empathy in marketing interactions: bridging the human-AI gap in affective and social customer experience. J. Acad. Market. Sci. (forthcoming).
Longoni, C., Bonezzi, A., Morewedge, C.K., 2019. Resistance to medical artificial intelligence. J. Consum. Res. 46 (4), 629–650.
Longoni, C., Cian, L., 2022. Artificial intelligence in utilitarian vs. hedonic contexts: the "word-of-machine" effect. J. Market. 86 (1), 91–108.
Longoni, C., Cian, L., Kyung, E.J., 2022. AI in the government: responses to failures. J. Market. Res., 00222437221110139
Luo, X., Qin, M.S., Fang, Z., Qu, Z., 2021. Artificial intelligence coaches for sales agents: caveats and solutions. J. Market. 85 (2), 14–32.
Luo, X., Tong, S., Fang, Z., Qu, Z., 2019. Machines vs. humans: the impact of artificial intelligence chatbot disclosure on customer purchases. Market. Sci. 38 (6), 937–947.
Marchand, A., Marx, P., 2020. Automated product recommendations with preference-based explanations. J. Retailing 96 (3), 328–343.
Miklós-Thal, J., Tucker, C., 2019. Collusion by algorithm: does better demand prediction facilitate coordination between sellers? Manag. Sci. 65 (4), 1552–1561.
Minsky, M., 1961. Steps toward artificial intelligence. Proc. IRE 49 (1), 8–30.
Mishra, S., Ewing, M.T., Cooper, H.B., 2022. Artificial intelligence focus and firm performance. J. Acad. Market. Sci. 1–22.
Mullainathan, S., Obermeyer, Z., 2022. Diagnosing physician error: a machine learning approach to low-value health care. Q. J. Econ. 137 (2), 679–727.
Pachidi, S., Berends, H., Faraj, S., Huysman, M., 2021. Make way for the algorithms: symbolic actions and change in a regime of knowing. Organ. Sci. 32 (1), 18–41.
Padigar, M., Pupovac, L., Sinha, A., Srivastava, R., 2022. The effect of marketing department power on investor responses to announcements of AI-embedded new product innovations. J. Acad. Market. Sci. 1–22.
Palmatier, R.W., Houston, M.B., Hulland, J., 2018. Review articles: purpose, process, and structure. J. Acad. Market. Sci. 46 (1), 1–5.
Park, E.H., Werder, K., Cao, L., Ramesh, B., 2022. Why do family members reject AI in health care? Competing effects of emotions. J. Manag. Inf. Syst. 39 (3), 765–792.
Rammer, C., Fernández, G.P., Czarnitzki, D., 2022. Artificial intelligence and industrial innovation: evidence from German firm-level data. Res. Pol. 51 (7), 104555.
Raveendhran, R., Fast, N.J., 2021. Humans judge, algorithms nudge: the psychology of behavior tracking acceptance. Organ. Behav. Hum. Decis. Process. 164, 11–26.
Reese, B., 2018. The Fourth Age: Smart Robots, Conscious Computer and the Future of Humanity. Atria Books, New York.
Reich, T., Kaju, A., Maglio, S.J., 2022. How to overcome algorithm aversion: learning from mistakes. J. Consum. Psychol.
Rong, K., 2022. Research agenda for the digital economy. Journal of Digital Economy 1, 20–31.
Schwab, K., 2017. The Fourth Industrial Revolution. World Economic Forum [available at. https://www.weforum.org/about/thefourthindustrialrevolutionbyklausschwab]. (Accessed 15 October 2022).
Sebrechts, M.M., Bennett, R.E., Rock, D.A., 1991. Agreement between expert-system and human raters' scores on complex constructed-response quantitative items. J. Appl. Psychol. 76 (6), 856–862.
Senoner, J., Netland, T., Feuerriegel, S., 2022. Using explainable artificial intelligence to improve process quality: evidence from semiconductor manufacturing. Manag. Sci. 68 (8), 5704–5723.
Shankar, V., 2018. How artificial intelligence (AI) is reshaping retailing. J. Retailing 94 (4) (vi-xi).
Tantri, P., 2021. Fintech for the poor: financial intermediation without discrimination. Rev. Finance 25 (2), 561–593.
Tong, S., Jia, N., Luo, X., Fang, Z., 2021. The Janus face of artificial intelligence feedback: deployment versus disclosure effects on employee performance. Strat. Manag. J. 42 (9), 1600–1631.
Turing, A.M., 1950. Computing machinery and intelligence. Mind 59 (236), 433–460.
Uysal, E., Alavi, S., Bezençon, V., 2022. Trojan horse or useful helper? A relationship perspective on artificial intelligence assistants with humanlike features. J. Acad. Market. Sci. 1–23.
Waardenburg, L., Huysman, M., Sergeeva, A.V., 2022. In the land of the blind, the one-eyed man is king: knowledge brokerage in the age of learning algorithms. Organ. Sci. 33 (1), 59–82.
Wilson, H.J., Daugherty, P.R., 2018. Collaborative intelligence: humans and AI are joining forces. Harv. Bus. Rev. 96 (4), 114–123.
Wuttke, D., Upadhyay, A., Siemsen, E., Wuttke-Linnemann, A., 2022. Seeing the bigger picture? Ramping up production with the use of augmented reality. Manuf. Serv. Oper. Manag. 24 (4), 2349–2366.
Xu, L., Mehta, R., 2022. Technology devalues luxury? Exploring consumer responses to AI-designed luxury products. J. Acad. Market. Sci. 1–18.
Xue, L., Pang, Z., 2022. Ethical governance of artificial intelligence: an integrated analytical framework. Journal of Digital Economy 1, 44–52.
Yalcin, G., Lim, S., Puntoni, S., van Osselaer, S.M., 2022. Thumbs up or down: consumer reactions to decisions by algorithms versus humans. J. Market. Res. 59 (4), 696–717.
Yang, C.H., 2022. How artificial intelligence technology affects productivity and employment: firm-level evidence from Taiwan. Res. Pol. 51 (6), 104536.
Zhang, S., Mehta, N., Singh, P.V., Srinivasan, K., 2021. Can an artificial intelligence algorithm mitigate racial economic inequality? an analysis in the context of airbnb. Market. Sci. 40 (5), 813–820.
Zhang, Z., Yoo, Y., Lyytinen, K., Lindberg, A., 2021. The unknowability of autonomous tools and the liminal experience of their use. Inf. Syst. Res. 32 (4), 1192–1213.
Zierau, N., Hildebrand, C., Bergner, A., Busquet, F., Schmitt, A., Marco Leimeister, J., 2022. Voice bots on the frontline: voice-based interfaces enhance flow-like consumer experiences & boost service outcomes. J. Acad. Market. Sci. 1–20.