

The Role of Artificial Intelligence in Modern Business Management: A Conceptual Study of Opportunities and Challenges

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<i>Type: Article</i> <i>Received: 22 July 2026</i> <i>Revised: 25 Aug2026</i> <i>Accepted: 19 Sept 2026</i> <i>Published: 23 Oct 2026</i>	Artificial intelligence (AI) has moved from the periphery of experimental computing to the centre of managerial practice, reshaping how organisations make decisions, allocate resources, engage customers and manage people. Despite the rapid growth of scholarship on the subject, the literature remains fragmented across functional silos, and the opportunities and risks of AI are frequently examined in isolation from one another. This conceptual study synthesises existing literature to examine the role of AI in modern business management and to articulate an integrated understanding of its opportunities and challenges. Drawing on the technology–organisation–environment framework, the resource-based view, dynamic capabilities theory and the automation–augmentation perspective, the paper develops a conceptual model comprising five interrelated components: AI adoption enablers, AI applications across management functions, the dual effects of AI (opportunities and challenges), organisational outcomes, and moderating governance mechanisms. The model proposes that AI generates sustainable value only when technological capability is matched by organisational readiness, responsible governance, effective human–AI collaboration and continuous workforce development. The discussion elaborates the implications of the model for strategic decision-making, operations, marketing, human resource management and finance, and considers the ethical, social and implementation challenges that accompany adoption. The paper contributes a theoretically grounded and integrative framework that can guide future empirical research and support managers who seek to adopt AI responsibly and effectively. Keywords: Artificial Intelligence; Business Management; Decision-Making; Human–AI Collaboration; AI Governance; Conceptual Model; Digital Transformation

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Introduction

Few technologies have attracted as much managerial attention in recent years as artificial intelligence. Once confined to research laboratories and a narrow set of industrial applications, AI is now embedded in credit scoring, demand forecasting, recruitment, customer service, logistics planning, fraud detection and product design. Scholars have described the current moment as a new phase of technological change in which machines increasingly perform cognitive tasks that were previously regarded as the exclusive preserve of human judgement (Brynjolfsson & McAfee, 2014; Makridakis, 2017). Industry evidence points in the same direction: global consultancies have estimated that AI could add substantial economic value across sectors, while surveys of executives indicate that a growing proportion of organisations regard AI as strategically important to their future competitiveness (Bughin et al., 2017; Ransbotham et al., 2017).

Artificial intelligence is commonly understood as the capability of a system to interpret external data correctly, to learn from that data and to use what it has learned to accomplish specific goals through flexible adaptation (Kaplan & Haenlein, 2019). The field has a long intellectual history, marked by periods of enthusiasm and disappointment (Haenlein & Kaplan, 2019), but its recent resurgence is attributable to the convergence of three developments: the availability of very large data sets, substantial increases in computing power, and advances in machine learning techniques, particularly deep learning (Jordan & Mitchell, 2015; Russell & Norvig, 2021). For business managers, the significance of these developments lies less in the technical detail than in the economic logic they create. Agrawal et al. (2018) argue that AI can be understood as a dramatic fall in the cost of prediction, and that when prediction becomes cheap, organisations will use it more widely and will rethink the decisions, processes and business models that depend on it.

The implications for management are far-reaching. Management has traditionally been described as a set of activities concerned with planning, organising, directing and controlling organisational resources, and many of these activities rely on the collection, interpretation and communication of information. AI systems can automate routine administrative work, generate predictions that inform planning, monitor performance continuously and personalise interactions with customers and employees at a scale that human managers cannot match (Kolbjørnsrud et al., 2016; Davenport & Ronanki, 2018). At the same time, AI raises questions that go to the heart of managerial responsibility. If an algorithm recommends whom to hire, whom to lend to or how to price a product, who is accountable for the outcome? How should organisations respond when systems reproduce historical bias, when their reasoning is opaque, or when their deployment threatens established patterns of employment? These questions indicate that AI is not merely a technical tool to be installed; it is an organisational phenomenon that changes decision rights, skills requirements, power relationships and ethical obligations (Berente et al., 2021; Kellogg et al., 2020).

Academic research has responded vigorously. Studies have examined AI in marketing (Davenport et al., 2020), service delivery (Huang & Rust, 2018), human resource management (Tambe et al., 2019), supply chain management (Toorajipour et al., 2021) and organisational decision-making (Jarrahi, 2018; Shrestha et al., 2019). Parallel streams of research have investigated the business value of AI capabilities (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020), the ethics of algorithmic systems (Mittelstadt et al., 2016; Floridi et al., 2018) and the human consequences of automation (Acemoglu & Restrepo, 2019; Frey & Osborne, 2017). However, these streams have developed largely in parallel. Studies of opportunity tend to be written from a performance perspective, while studies of risk are written from ethical, legal or sociological perspectives, and relatively few attempts have been made to integrate the two within a single conceptual structure that managers and researchers can use.

This paper addresses that need. Its purpose is to examine the role of AI in modern business management through a conceptual lens and to develop an integrative model that explains how organisational enablers, functional applications, opportunities, challenges and governance mechanisms interact to shape organisational outcomes. A conceptual approach is appropriate for three reasons. First, the phenomenon is evolving faster than empirical research can codify, so theoretical synthesis can provide direction where large-scale evidence is still limited. Second, the existing evidence is dispersed across disciplines, and integration requires systematic conceptual work. Third, a well-specified conceptual model generates propositions that can be tested empirically in subsequent research (Dwivedi et al., 2021).

Section 2 reviews the literature, Section 3 identifies the research gap and objectives, Section 4 presents the conceptual model, Section 5 justifies its components, Section 6 discusses the opportunities, challenges and implications, and Section 7 concludes with contributions, limitations and future research directions.

Literature Review

The literature on AI in business management is extensive and interdisciplinary. This section organises the existing scholarship into four themes: the conceptual foundations of AI in organisations, the application of AI across management functions, the opportunities attributed to AI, and the challenges and risks associated with its adoption. The section concludes with a comparative table that summarises selected influential studies.

Conceptual Foundations of AI in Organisations

A first stream of research seeks to clarify what AI is and how it differs from earlier generations of information technology. Traditional enterprise systems execute rules that have been explicitly programmed by humans. By contrast, machine learning systems infer patterns from data and improve their performance through experience, which allows them to handle tasks that are difficult to specify in advance (Jordan & Mitchell, 2015). This distinction has important managerial consequences. Berente et al. (2021) argue that AI differs from conventional technologies because of its autonomy, its capacity to learn and its inscrutability, and that these characteristics make it a distinct object of management. Autonomy raises the question of how much discretion should be delegated to machines; learning means that systems change after deployment, complicating oversight; and inscrutability makes it difficult for managers to understand why a system has produced a particular output.

Researchers have also proposed typologies that help managers to locate AI within their organisations. Davenport and Ronanki (2018) distinguish three broad types of business application: process automation, cognitive insight and cognitive engagement. Process automation substitutes for structured back-office activities, cognitive insight uses algorithms to detect patterns in large volumes of data, and cognitive engagement employs natural language and conversational interfaces to interact with customers and employees. Huang and Rust (2018) offer a complementary typology based on the kinds of intelligence that AI can display, namely mechanical, analytical, intuitive and empathetic intelligence, and argue that the boundary of tasks that AI can perform is moving progressively from the mechanical towards the empathetic. Taken together, these typologies show that AI is not a single technology but a family of capabilities with different organisational implications.

AI Across Management Functions

A second stream of research documents applications of AI within specific management functions. In strategic decision-making, AI can process far larger and more varied data sets than human analysts and can identify patterns that are not visible to unaided cognition (Duan et al., 2019). Jarrahi (2018) argues that AI is particularly well suited to decision contexts characterised by high complexity, whereas human judgement remains superior in contexts characterised by uncertainty and equivocality, in which goals are ambiguous and interpretations are contested. This leads to the proposition that the most effective organisational decisions will emerge from a symbiosis between human and artificial intelligence rather than from either alone. Shrestha et al. (2019) similarly show that the appropriate decision-making structure, ranging from full delegation to algorithms through to hybrid and aggregated human–AI arrangements, depends on the specificity of the decision domain, the size of the alternative set and the speed of decision-making required.

In operations and supply chain management, AI supports demand forecasting, inventory optimisation, route planning, predictive maintenance and supplier risk assessment. Early work by Min (2010) catalogued the potential of AI techniques in supply chain management, and a recent systematic review by Toorajipour et al. (2021) confirms that applications have expanded considerably, with the literature clustering around demand and sales forecasting, supplier selection, logistics and inventory control. In marketing and customer management, AI enables segmentation, personalisation, dynamic pricing and conversational service. Davenport et al. (2020) propose a multidimensional framework in which AI shapes marketing strategy, customer interaction and the nature of the marketing task itself, while Huang and Rust (2018) examine how AI is reconfiguring service delivery and the division of labour between employees and machines.

In human resource management, AI is used in recruitment screening, talent analytics, workforce planning and employee engagement. Tambe et al. (2019) provide a balanced assessment, noting that the complexity of HR outcomes, the limited size of many HR data sets, the ethical and legal constraints on the use of personal data, and employee reactions to algorithmic decisions all create challenges that are less pronounced in domains such as consumer analytics. In finance, risk management and compliance, machine learning has long been used for credit scoring, algorithmic trading and the detection of fraudulent transactions (Ngai et al., 2011). More recent work extends these applications to anti-money-laundering surveillance, regulatory reporting and the automation of audit procedures. Across these functions, the literature consistently suggests that AI is most effective when it is integrated with existing processes and expertise rather than introduced as an isolated tool (Fountaine et al., 2019).

Opportunities Associated with AI

The opportunities attributed to AI in the literature can be grouped into efficiency, decision quality, innovation and competitive advantage. Efficiency gains arise when AI automates repetitive tasks, reduces error rates and accelerates processes. Kolbjørnsrud et al. (2016) anticipate that AI will take over a large share of the administrative coordination and reporting work that currently occupies managers, thereby freeing them to concentrate on judgement-intensive activities such as creative thinking, experimentation and the development of people. Improvements in decision quality follow from the ability of AI to generate more accurate predictions and to consider a wider range of information. Agrawal et al. (2018) emphasise that better prediction does not remove the need for judgement but increases its value, because human decision-makers must determine which outcomes matter and how to trade them off.

Innovation represents a further opportunity. Verganti et al. (2020) argue that AI is changing the way organisations approach innovation and design, because it enables data-driven problem-solving and expands the range of solutions that can be explored. Empirical studies of AI projects suggest that AI-based transformation can enhance business process performance, support new product and service development and strengthen firm-level outcomes (Wamba-Taguimdje et al., 2020). Mikalef and Gupta (2021) show, on the basis of survey data, that organisations with a strong AI capability, composed of tangible resources such as data and technology, human resources such as technical and business skills, and intangible resources such as an appropriate culture and the willingness to take risks, report higher organisational creativity and performance. These findings support the view that AI creates value when it is treated as a bundle of complementary organisational resources, rather than as a stand-alone technology.

Evidence concerning the human dimension of AI is encouraging but conditional. Wilson and Daugherty (2018) report, from a study of a large sample of companies, that the greatest performance improvements occurred when humans and machines worked together, with each complementing the other's strengths. This collaborative-intelligence perspective suggests that the primary opportunity for managers lies in redesigning work so that human skills such as leadership, empathy and creativity are combined with machine strengths such as speed, scale and consistency.

Challenges and Risks of AI Adoption

A parallel body of research stresses that AI also generates significant challenges. Ethical concerns are prominent. Mittelstadt et al. (2016) map the ethical debate surrounding algorithms and identify epistemic concerns, such as inconclusive and inscrutable evidence, and normative concerns, such as unfair outcomes and threats to autonomy and privacy. The risk of algorithmic bias has been demonstrated empirically. Obermeyer et al. (2019) found that a widely used healthcare algorithm systematically underestimated the health needs of Black patients because it used past healthcare cost as a proxy for need, illustrating how apparently neutral design choices can embed structural inequalities. A review of 84 AI ethics guidelines by Jobin et al. (2019) found convergence around the principles of transparency, justice and fairness, non-maleficence, responsibility and privacy, although the interpretation and implementation of these principles varied substantially.

Opacity and trust form a second cluster of challenges. Burrell (2016) distinguishes three forms of opacity in machine learning systems: deliberate secrecy by organisations, technical illiteracy among those affected, and the inherent mismatch between high-dimensional mathematical optimisation and human styles of interpretation. Research on explainable AI seeks to address these problems (Adadi & Berrada, 2018; Arrieta et al., 2020), but explanation techniques remain imperfect. Trust is equally critical. Glikson and Woolley (2020) review empirical research on human trust in AI and show that trust is shaped by the tangibility and transparency of the system, its reliability and the behaviour it displays. Dietvorst et al. (2015) document algorithm aversion, whereby people lose confidence in algorithmic forecasts more quickly than in human forecasts after observing an error, even when the algorithm is superior on average. Managers must therefore address both excessive scepticism and excessive reliance.

Workforce and labour market consequences constitute a third cluster. Frey and Osborne (2017) estimated that a large share of occupations in the United States was susceptible to computerisation, a finding that has stimulated both alarm and critique. Acemoglu and Restrepo (2019) offer a more nuanced framework in which technology both displaces labour from existing tasks and reinstates labour through the creation of new tasks, so that the net effect depends on the balance between these forces. Within organisations, Kellogg et al. (2020) show that algorithms can become instruments of managerial control, recommending, restricting, recording, rating, replacing and rewarding workers, thereby altering the balance of power in employment relationships. Raisch and Krakowski (2021) frame the underlying tension as the automation–augmentation paradox: automation and augmentation are interdependent, and attempts to pursue one in isolation may undermine the other over time.

Finally, privacy, data governance and implementation challenges deserve attention. AI systems depend on large volumes of data, much of it personal, which raises concerns about surveillance, consent and security (Zuboff, 2019) and requires compliance with regulatory regimes such as the European Union's General Data Protection Regulation (Voigt & Von dem Bussche, 2017). Practical obstacles include data quality, integration with legacy systems, scarcity of skilled personnel and the cost of development and maintenance. Fountaine et al. (2019) observe that organisations often fail to realise the benefits of AI not because the technology is inadequate but because of cultural and organisational barriers, including siloed structures, risk aversion and a lack of leadership commitment. Brock and von Wangenheim (2019) similarly caution that unrealistic expectations and insufficient attention to data foundations are common causes of failed AI initiatives.

Summary of Selected Studies

Table 1 summarises ten influential studies that illustrate the main conceptual and empirical contributions to the field. The table highlights the diversity of foci, from decision-making and organisational capabilities to human resources, ethics and the governance of AI, and it indicates the contribution of each study to the development of the conceptual model presented later in this paper.

Table 1. *Summary of Selected Studies on Artificial Intelligence in Business Management*

Author(s) and year	Focus and approach	Key contribution
Davenport & Ronanki (2018)	Practitioner-oriented study of AI initiatives in organisations	Identifies three types of business application (process automation, cognitive insight, cognitive engagement) and recommends beginning with lower-risk projects.
Jarrahi (2018)	Conceptual analysis of AI and organisational decision-making	Argues that AI suits complexity while humans excel under uncertainty and equivocality; proposes human–AI symbiosis.
Shrestha et al. (2019)	Conceptual framework of decision-making structures	Shows that full delegation, hybrid and aggregated human–AI arrangements suit different decision contexts.
Raisch & Krakowski (2021)	Theoretical analysis of AI and management	Introduces the automation–augmentation paradox: the two are interdependent over time.
Wamba-Taguimdje et al. (2020)	Case-based study of AI transformation projects	Links AI projects to improved process performance, innovation and firm performance.
Mikalef & Gupta (2021)	Survey-based empirical study of AI capability	Demonstrates that tangible, human and intangible AI resources enhance creativity and firm performance.
Tambe et al. (2019)	Conceptual analysis of AI in human resource management	Identifies challenges of HR data, ethical constraints and employee reactions.
Kellogg et al. (2020)	Review of algorithmic management at work	Shows how algorithms recommend, restrict, record, rate, replace and reward workers.
Jobin et al. (2019)	Content analysis of 84 AI ethics guidelines	Finds convergence on transparency, fairness, non-maleficence, responsibility and privacy.
Berente et al. (2021)	Conceptual framework for managing AI	Highlights autonomy, learning and inscrutability as defining features requiring distinct management.

Note. Compiled by the author from the sources cited.

Research Gap and Objectives

Research Gap

The preceding review reveals a substantial and growing body of knowledge, but also several gaps that justify the present study. The first gap concerns fragmentation. Research on AI in management is typically organised by function (for example marketing, human resources or supply chain) or by discipline (for example information systems, ethics or labour economics). As a result, there is limited understanding of how developments in one area relate to those in another and how the organisational conditions that enable AI in one function may constrain it in another. Managers, however, confront AI as an enterprise-wide phenomenon and must make decisions about investment, governance and skills that cut across functions (Benbya et al., 2020).

The second gap concerns the separation of opportunities and challenges. Performance-oriented studies tend to emphasise the benefits of AI, whereas critical studies concentrate on its risks. Few frameworks treat opportunities and challenges as two simultaneous and interdependent effects of the same adoption process, even though the evidence suggests that they are closely connected. For example, the same data-intensive capability that enables personalisation also creates privacy risks, and the same automation that raises productivity may displace workers (Acemoglu & Restrepo, 2019; Zuboff, 2019). A model that treats these effects as separate risks understating the trade-offs that managers actually face.

The third gap concerns the role of moderating mechanisms. Much of the literature acknowledges that governance, ethical frameworks, human oversight and workforce development matter, but these factors are often treated as background conditions or normative recommendations rather than as explicit components of an explanatory model. Consequently, little theoretical guidance exists on how such mechanisms influence the relationship between AI adoption and organisational outcomes (Berente et al., 2021; Raisch & Krakowski, 2021).

The fourth gap is methodological: much of the evidence is based on case studies, practitioner reports or cross-sectional surveys, and there are few integrative conceptual frameworks from which testable propositions can be derived (Dwivedi et al., 2021). Finally, much of the existing research has been conducted in advanced economies, and the conditions facing organisations in emerging markets, which may include different infrastructural constraints, regulatory environments and labour market structures, remain comparatively under-theorised.

Research Objectives

In light of these gaps, the study pursues the following objectives:

1. To examine the conceptual foundations of AI and its role in the major functions of modern business management.
2. To identify and synthesise the principal opportunities that AI creates for organisations.
3. To identify and synthesise the principal challenges and risks associated with AI adoption in business contexts.
4. To develop an integrative conceptual model that explains how enablers, functional applications, opportunities, challenges and moderating mechanisms jointly influence organisational outcomes.
5. To justify the model theoretically and to derive implications for managers, policymakers and future research.

Conceptual Model

Figure 1 presents the conceptual model developed in this study. The model is organised as a left-to-right causal flow supported by an overarching layer of governance. It consists of five components. Component A, AI adoption enablers, comprises the technological, organisational and environmental conditions that determine whether and how an organisation can adopt AI. Component B, AI application in management functions, represents the concrete domains in which AI is deployed: strategy and decision-making, operations and supply chain, marketing and customer engagement, human resource management, and finance, risk and compliance. Component C, the dual effects of AI, distinguishes the opportunities and challenges that result from such deployment. Component D, organisational outcomes, captures the ultimate consequences in terms of sustainable competitive advantage, organisational performance and long-term stakeholder trust. Component E, moderating and governing mechanisms, comprises responsible AI governance, human–AI collaboration and change management, which condition the relationship between AI application and its effects.

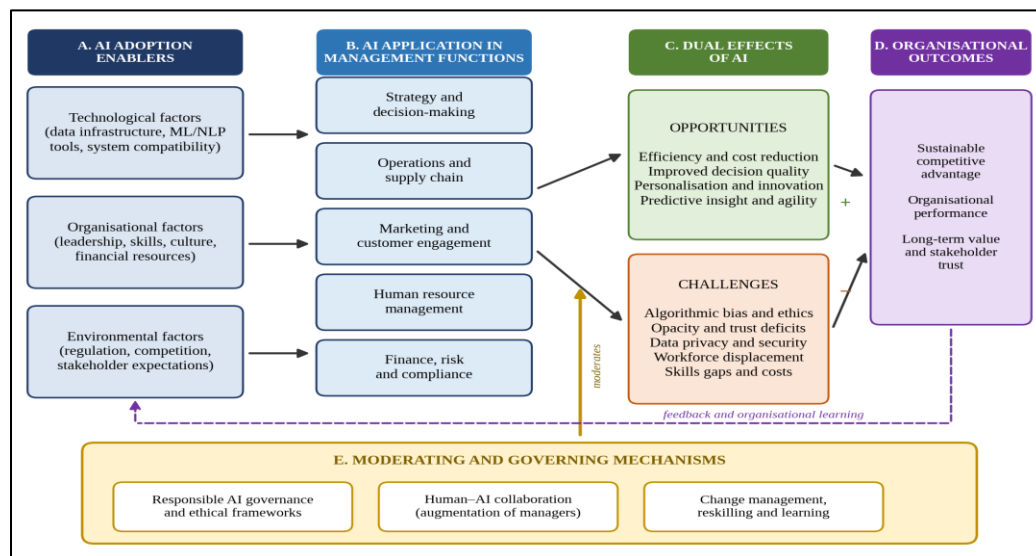


Fig. 1. Conceptual Model of the Role of AI in Modern Business Management

Note. “+” indicates a positive contribution of opportunities to outcomes; “–” indicates that unmanaged challenges detract from outcomes. Source: Developed by the author.

The arrows in Figure 1 denote the proposed direction of influence. Enablers (A) shape the breadth and quality of AI applications (B). Applications in turn generate opportunities and challenges simultaneously (C). Opportunities contribute positively to organisational outcomes (D), whereas challenges, if left unmanaged, detract from them. The moderating mechanisms (E) are depicted as acting on the link between applications and their dual effects: effective governance, collaboration and change management are expected to amplify opportunities and to attenuate challenges. Finally, the dashed feedback loop indicates that outcomes alter the enabling conditions over time, because successful or unsuccessful experience affects investment, skills, culture and stakeholder expectations. On this basis, the model yields four propositions that are developed in Section 5: (P1) stronger enablers are associated with broader and more effective AI application; (P2) AI application simultaneously increases opportunities and challenges; (P3) governance, human–AI collaboration and change

management strengthen the relationship between AI application and opportunities while weakening the relationship between AI application and challenges; and (P4) the net outcome of AI adoption depends on the balance of realised opportunities and unmanaged challenges.

Justification of the Conceptual Model

Each component of the model is grounded in established theory and supported by the literature reviewed above. This section justifies the components in turn and highlights the subthemes that constitute each.

Component A: AI Adoption Enablers

The inclusion of enablers is grounded in the technology–organisation–environment (TOE) framework (Tornatzky & Fleischer, 1990), which holds that the adoption of technological innovations is influenced by the characteristics of the technology, the internal features of the organisation and the external environment. Three subthemes follow directly from this framework.

The first subtheme is technological readiness, which includes data availability and quality, computing infrastructure, interoperability with legacy systems and access to appropriate algorithms and tools. AI systems are only as good as the data on which they are trained, and Brock and von Wangenheim (2019) emphasise that weak data foundations are a principal cause of unsuccessful AI projects. The second subtheme is organisational readiness, which encompasses leadership commitment, technical and managerial skills, culture, financial resources and structural flexibility. The resource-based view (Barney, 1991) supports this subtheme by suggesting that sustainable advantage arises from resources that are valuable, rare, difficult to imitate and organised for exploitation. Mikalef and Gupta (2021) operationalise this logic by showing that AI capability is a composite of tangible, human and intangible resources. Fountaine et al. (2019) reinforce the point by arguing that culture and organisational capability, rather than technology, are the decisive barriers to scaling AI.

The third subtheme is environmental pressure, which includes regulation, competitive intensity, customer expectations and the availability of external expertise and partners. Regulatory regimes such as data protection law shape what organisations may do with data (Voigt & Von dem Bussche, 2017), while competitive dynamics may compel adoption even where internal readiness is limited. Individual-level adoption research, notably the technology acceptance model (Davis, 1989) and the unified theory of acceptance and use of technology (Venkatesh et al., 2003), adds that employee perceptions of usefulness, ease of use and social influence affect whether adopted systems are actually used. These considerations support proposition P1: the stronger the technological, organisational and environmental enablers, the broader and more effective the application of AI across management functions.

Component B: AI Application in Management Functions

The second component reflects the observation that AI is deployed not in the abstract but within concrete managerial activities. The five functional domains included in the model were selected because they are the most extensively documented in the literature and because together they span the principal value-creating and control activities of the firm. Strategy and decision-making is included because AI changes how information is processed and how choices are made (Duan et al., 2019; Jarrahi, 2018; Shrestha et al., 2019). Operations and supply chain management features because predictive and prescriptive analytics have been shown to improve forecasting, logistics and inventory decisions (Min, 2010; Toorajipour et al., 2021). Marketing and customer engagement is included because AI is transforming personalisation, pricing and service interaction (Davenport et al., 2020; Huang & Rust, 2018). Human resource management is included because AI is increasingly used in recruitment, performance evaluation and workforce analytics, and because these applications raise particularly sensitive ethical questions (Tambe et al., 2019). Finally, finance, risk and compliance is included because it is among the earliest and most mature domains of AI use, notably in fraud detection and credit assessment (Ngai et al., 2011).

Component C: The Dual Effects of AI

The distinctive feature of the model is that opportunities and challenges are presented side by side as simultaneous effects of the same application. This design responds directly to the second research gap and is supported by the literature in several ways. On the opportunity side, the model identifies efficiency and cost reduction (Kolbjørnsrud et al., 2016), improved decision quality (Agrawal et al., 2018), personalisation and innovation (Verganti et al., 2020) and predictive insight and organisational agility (Wamba-Taguimdje et al., 2020). On the challenge side, it identifies algorithmic bias and ethical risk (Mittelstadt et al., 2016; Obermeyer et al., 2019), opacity and trust deficits (Burrell, 2016; Glikson & Woolley, 2020), data privacy and security concerns (Zuboff, 2019), workforce displacement (Acemoglu & Restrepo, 2019; Frey & Osborne, 2017) and skills gaps and implementation costs (Fountaine et al., 2019).

Treating the two sets of effects as coupled rather than independent is justified because they share common causes. Greater use of personal data enhances personalisation but heightens privacy exposure. Greater automation of tasks improves efficiency but may erode skills and reduce employee autonomy (Kellogg et al., 2020; Raisch & Krakowski, 2021). Greater algorithmic autonomy accelerates decisions but weakens human oversight. This coupling supports proposition P2: the application of AI simultaneously increases both opportunities and challenges, and the two cannot be separated analytically without distorting the picture available to managers.

Component D: Organisational Outcomes

The fourth component captures the outcomes that matter to organisations and their stakeholders. Sustainable competitive advantage is included on the basis of the resource-based view (Barney, 1991) and dynamic capabilities theory (Teece et al., 1997). The latter holds that advantage in turbulent environments derives from the ability to sense opportunities, seize them and reconfigure resources accordingly. AI contributes to each of these processes, since it enhances environmental scanning, supports faster decisions and enables the reconfiguration of processes, but only if the organisation can integrate it into routines and learning systems. Organisational performance, comprising financial and operational measures as well as innovation and creativity, is supported by empirical evidence linking AI capability to firm outcomes (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020).

The inclusion of long-term value and stakeholder trust distinguishes the model from purely performance-oriented frameworks. Organisations that deploy AI in ways that employees, customers and regulators perceive as unfair or intrusive risk reputational damage, legal liability and loss of legitimacy, even where short-term efficiency improves. The inclusion of trust as an outcome therefore reflects both the ethical literature (Floridi et al., 2018; Jobin et al., 2019) and the empirical evidence on the fragility of trust in algorithmic systems (Dietvorst et al., 2015). This supports proposition P4: net organisational outcomes depend on the balance between realised opportunities and unmanaged challenges, rather than on the mere fact of AI adoption.

Component E: Moderating and Governing Mechanisms

The final component is the most important for explaining why organisations with similar technologies obtain divergent results. Three mechanisms are identified. The first is responsible AI governance, which includes ethical principles, accountability structures, risk assessment, auditing and explainability practices. Floridi et al. (2018) propose that a good AI society should rest on the principles of beneficence, non-maleficence, autonomy, justice and explicability, and Jobin et al. (2019) show that similar principles recur across a wide range of guidelines. Governance converts such principles into organisational routines, and explainability techniques (Arrieta et al., 2020) provide some of the technical means through which transparency and accountability can be achieved.

The second mechanism is human–AI collaboration. The augmentation perspective (Jarrahi, 2018; Wilson & Daugherty, 2018) holds that AI performs best as a complement to human capability. Shrestha et al. (2019) show that decision structures should be designed deliberately, with clear allocation of authority between humans and machines. Raisch and Krakowski (2021) caution that augmentation and automation are interdependent, so that managers must plan for both. The third mechanism is change management, reskilling and learning. Because AI changes tasks, skills and roles, organisations must invest in training, communication and participation if employees are to accept and use the technology effectively (Tambe et al., 2019; Venkatesh et al., 2003). Dynamic capabilities theory (Teece et al., 1997) further suggests that organisations need systematic learning processes to adapt as technologies and contexts evolve.

These mechanisms are placed as moderators because they are expected to influence the strength of the relationships in the model rather than to serve as stand-alone outcomes. Specifically, proposition P3 states that stronger governance, collaboration and change management enhance the translation of AI applications into opportunities and reduce the translation of AI applications into harmful challenges. The feedback loop completes the model by recognising that outcomes reshape enablers over time, consistent with the view of organisational capabilities as cumulative and path-dependent (Teece et al., 1997).

Detailed Discussion

AI and Strategic Decision-Making

The most profound managerial implication of AI concerns the quality and structure of decision-making. AI augments human cognition by processing volumes of data that would be impossible for individuals to analyse, thereby supporting more evidence-based strategic choices (Duan et al., 2019). Yet the model implies that the contribution of AI is not uniform across decision types. Jarrahi (2018) argues that AI excels where complexity arises from the sheer number of variables, whereas uncertainty and equivocality require human intuition and sense-making. Consequently, managers should avoid the temptation to apply algorithms indiscriminately. Instead, they should assess each decision domain according to the criteria proposed by Shrestha et al. (2019), namely the specificity of the decision space, the size of the alternative set and the need for speed and scalability, and then choose between full delegation, sequential human–AI collaboration or aggregation of human and machine recommendations.

Leyer and Schneider (2021) suggest that managers perceive AI both as a threat and as an opportunity, and that its effect on managerial roles depends on whether it is used to automate or to augment decisions. The present model supports the augmentation interpretation: the greatest strategic value arises when AI expands the range of options managers consider and sharpens their predictions, while humans retain responsibility for defining objectives, weighing trade-offs and interpreting context (Agrawal et al., 2018). It follows that the strategic capability that AI makes scarce is not computation but judgement, and organisations should invest accordingly in the development of managerial judgement alongside technical capacity.

Operational Efficiency and Supply Chain Management

In operations, AI delivers some of the most measurable benefits. Predictive models improve demand forecasts and reduce inventory costs, optimisation algorithms improve routing and scheduling, and condition-monitoring systems anticipate equipment failure before it disrupts production (Toorajipour et al., 2021). Such applications generally fall within the cognitive insight and process automation categories described by Davenport and Ronanki (2018) and typically involve lower ethical sensitivity than applications that evaluate individuals. This helps to explain why many organisations begin their AI journey in operations. Operational applications nonetheless depend on integrated, high-quality data across organisational boundaries and can create fragile dependencies if models fail under conditions that differ from their training data, so algorithmic recommendations should be combined with scenario planning and human review.

Marketing, Customer Engagement and Service

AI has transformed the way organisations understand and interact with customers. Recommendation systems, dynamic pricing and predictive customer analytics allow firms to tailor offers at the level of the individual, while chatbots and virtual assistants extend service availability (Davenport et al., 2020). Huang and Rust (2018) argue that as AI acquires analytical and, increasingly, intuitive and empathetic capabilities, the allocation of tasks between employees and machines in service encounters will shift, with employees concentrating on the most complex and emotionally demanding interactions. These developments create clear opportunities for personalisation and efficiency, but they also intensify the tension between personalisation and privacy that the model identifies. Customers may welcome relevant recommendations but resist forms of profiling that they perceive as intrusive or manipulative (Zuboff, 2019). Organisations must therefore be transparent about data use, offer meaningful consent and avoid exploitative design practices. Trust, once lost, is difficult to rebuild, and the model positions trust explicitly as an organisational outcome for this reason.

Human Resource Management and the Future of Work

Human resource management illustrates the dual effects of AI more vividly than any other function. AI can reduce administrative burden, identify talent more efficiently and support personalised development. At the same time, algorithmic screening and evaluation can reproduce historical bias, undermine perceived fairness and diminish employee autonomy (Tambe et al., 2019; Kellogg et al., 2020). The evidence from other domains that biased proxies can produce discriminatory outcomes at scale (Obermeyer et al., 2019) is a reminder that human resource applications require rigorous validation, regular auditing and transparent communication with those affected. Lee (2018) shows that people's perceptions of algorithmic decisions depend on the task: algorithms are judged less favourably when they perform tasks that are perceived as requiring human skills, such as hiring and work evaluation, than when they perform mechanical tasks. This finding implies that the acceptability of AI in human resource management cannot be assumed and must be actively earned.

At a broader level, AI raises fundamental questions about the future of work. Estimates of the susceptibility of occupations to automation have been influential (Frey & Osborne, 2017), but the task-based analysis of Acemoglu and Restrepo (2019) indicates that the net employment effect depends on whether new tasks are created at a pace sufficient to offset displacement. For organisations, the practical implication is to plan workforce transitions deliberately by identifying roles at risk, investing in reskilling and creating new roles that exploit the complementarity between human and machine capabilities. This is the role of the change management mechanism in the model: without it, the efficiency gains of AI may be purchased at the cost of employee morale, institutional knowledge and social legitimacy.

Finance, Risk and Compliance

Financial services and corporate finance functions were early adopters of machine learning, using it for credit scoring, fraud detection and algorithmic trading (Ngai et al., 2011). These applications highlight the importance of the governance component of the model. Credit and insurance decisions affect individuals' life chances, and regulators increasingly require that such decisions be explainable and non-discriminatory. The opacity of complex models (Burrell, 2016) therefore creates direct compliance risks and strengthens the case for explainable AI techniques (Adadi & Berrada, 2018; Arrieta et al., 2020). Model risk, the possibility that a model is wrong, misapplied or manipulated, therefore requires continuous monitoring, validation and documentation across the model life cycle.

Ethical, Social and Governance Challenges

Across all functions, ethical and governance issues emerge as cross-cutting concerns. The convergence of ethics guidelines identified by Jobin et al. (2019) suggests a growing consensus on principles, but also exposes a gap between principle and practice. Organisations frequently adopt statements of values without establishing the processes, roles and incentives required to implement them. Effective governance requires clearly assigned accountability for AI systems, impact assessments before deployment, mechanisms for contesting algorithmic decisions, and independent auditing. It also requires technical measures, including bias testing, documentation of data provenance and explainability tools. Mittelstadt et al. (2016) emphasise that responsibility for algorithmic outcomes is distributed across designers, deployers and users, which makes it essential for organisations to specify who is answerable at each stage.

Implementation and Organisational Capability

The discussion of implementation underscores the importance of the enabler component. Many AI initiatives fail to progress beyond the pilot stage because organisations underestimate the data, process and cultural changes required (Brock & von Wangenheim, 2019; Fountaine et al., 2019). Benbya et al. (2020) suggest that organisations should approach AI as a long-term organisational learning agenda, not as a series of discrete technology projects. Practically, this means building cross-functional teams that combine technical and domain expertise, investing in data governance, adopting incremental deployment strategies that allow learning and adjustment, and aligning AI initiatives explicitly with business strategy. Davenport and Ronanki (2018) recommend beginning with applications that have clear business value and moderate risk and then progressing to more ambitious projects as capabilities mature, advice that is consistent with the dynamic capabilities logic of the model.

Implications for Practice and Policy

For managers, the model has four main implications. First, AI strategy should be treated as an integral part of business strategy and not as a separate technological programme. Second, investment in enablers, particularly data foundations, skills and leadership, should precede or accompany investment in algorithms. Third, governance should be built into AI initiatives from the outset, with explicit attention to fairness, transparency, accountability and privacy. Fourth, organisations should redesign work around human–AI collaboration and invest in reskilling so that employees participate in, rather than merely experience, the transformation. For policymakers, the model highlights the importance of regulatory frameworks that protect individuals without stifling innovation, of education and training systems that prepare workers for evolving task structures, and of support for small and medium-sized enterprises and for organisations in emerging economies, which may lack the resources to build AI capabilities independently.

Conclusion

This paper set out to examine the role of artificial intelligence in modern business management and to develop an integrative conceptual model of its opportunities and challenges. The review of the literature showed that AI is reshaping management across strategy, operations, marketing, human resources and finance, offering significant gains in efficiency, decision quality and innovation, while simultaneously raising serious concerns about bias, opacity, privacy, employment and trust. It also showed that research on these themes has remained fragmented and that few frameworks integrate benefits and risks within a single explanatory structure.

The conceptual model proposed in this paper responds to these gaps. By linking adoption enablers, functional applications, dual effects, organisational outcomes and moderating governance mechanisms, the model explains why organisations that deploy similar technologies may achieve very different results. Its central argument is that the value of AI is not determined by the technology itself but by the organisational and governance context in which it is embedded. Organisations that invest in data and skills, design decision processes around human–AI collaboration, institutionalise responsible governance and manage workforce transition are more likely to realise the opportunities of AI while containing its risks. Those that do not may find that efficiency gains are offset by reputational, legal and human costs.

The study makes three contributions. Theoretically, it integrates the TOE framework, the resource-based view, dynamic capabilities theory and the automation–augmentation perspective within a single model and derives four testable propositions. Conceptually, it treats opportunities and challenges as coupled effects rather than as separate literatures. Practically, it offers managers a structured way to think about AI adoption as an organisation-wide capability-building and governance undertaking.

The study also has limitations. As a conceptual paper, it is based on the synthesis of existing literature and has not been tested empirically; the propositions therefore require validation. The literature reviewed is selective, and the rapid pace of technological change, including the diffusion of generative AI systems, means that new evidence will continue to emerge. The model is also general, and its application may need to be refined for particular industries, firm sizes and national contexts. Future research could test the propositions using quantitative and mixed-methods designs, examine the moderating role of specific governance practices, investigate the experience of small firms and organisations in emerging economies, and explore how generative and autonomous AI systems alter the balance of opportunities and challenges identified here. Longitudinal studies would be especially valuable in tracing the feedback processes through which the outcomes of AI adoption reshape organisational capabilities over time.

In conclusion, AI is neither a panacea nor an inevitable threat. It is a powerful general-purpose capability whose consequences are shaped by managerial choices. By adopting an integrative and responsible approach, organisations can position AI as a means of enhancing human judgement, creating durable value and sustaining trust among their stakeholders.

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