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Factors of Managerial Decision-Making in the Age of Artificial Intelligence

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Factors of Managerial Decision-Making in the Age of Artificial Intelligence

Suman Raja Bajracharya*

Abstract

Managerial decision-making has long been a central concern in management research due to its critical influence on organizational performance and competitive advantage. The rapid advancement of Artificial Intelligence (AI) has fundamentally transformed traditional decision-making processes by enabling data-driven, automated, and predictive capabilities that augment managerial judgment. This study examines the key factors influencing managerial decision-making in the age of Artificial Intelligence, drawing on classical, behavioral, and contemporary management theories. Through an extensive review of literature indexed in Scopus, Web of Science, and TCI databases, the study identifies and categorizes influencing factors at the individual, organizational, technological, and environmental levels. Individual factors include managerial experience, cognitive style, risk tolerance, and ethical values, while organizational factors encompass culture, structure, power dynamics, and information systems. Technological factors such as data quality, algorithm transparency, and levels of automation, along with external environmental factors including market competition, technological change, and regulatory pressures, are also examined. The findings highlight that managerial decision-making in the AI era is best understood as a socio-technical process shaped by dynamic interactions between human judgment and machine intelligence. The study contributes to the growing body of knowledge on AI-enabled management by providing an integrative framework for understanding decision-making complexity and offers practical insights for managers seeking to balance analytical rigor with ethical responsibility and strategic oversight in AI-driven organizational contexts.

Keywords: Managerial Decision-Making, Artificial Intelligence, Human–AI Collaboration, Decision-Making Models

Introduction

Managerial decision-making has long been recognized as a core function of management and a critical determinant of organizational performance and competitive advantage (Simon, 1977; Mintzberg, Raisinghani, & Théorêt, 1976). Traditionally, managerial decisions were largely grounded in human experience, intuition, judgment, and limited historical data. Managers operated under conditions of bounded rationality, where cognitive limitations and information constraints shaped decision outcomes (Simon, 1955). While such approaches allowed flexibility and contextual understanding, they were often susceptible to bias, uncertainty, and inefficiencies, particularly in complex and dynamic business environments.

The rapid advancement of Artificial Intelligence (AI) has fundamentally transformed the nature of managerial decision-making. AI technologies—including machine learning, big data analytics, natural language processing, and predictive modeling—enable organizations to process vast volumes of structured and unstructured data with unprecedented speed and accuracy (Davenport & Ronanki, 2018). These technologies support managers in identifying patterns, forecasting trends, optimizing operations, and evaluating decision alternatives that would be difficult or impossible through purely human analysis (Shrestha, Ben-Menahem, & von Krogh, 2019). As a result, decision-making processes are increasingly data-driven, automated, and augmented by intelligent systems.

In the age of Artificial Intelligence, managerial decision-making is no longer solely a human-centered activity but rather a collaborative process between human intelligence and machine intelligence. This human–AI collaboration reshapes traditional decision roles, where AI systems provide analytical insights and recommendations while managers retain responsibility for interpretation, judgment, and final decision authority (Raisch & Krakowski, 2021). Studies suggest that AI enhances decision quality by reducing uncertainty and cognitive bias; however, it also introduces new challenges related to trust, transparency, and accountability (Glikson & Woolley, 2020).

Moreover, the integration of AI into managerial decision-making alters how managers perceive problems, evaluate alternatives, and implement decisions. Algorithmic recommendations can influence managerial cognition, potentially reshaping strategic thinking and organizational learning processes (Faraj, Pachidi, & Sayegh, 2018). At the same time, excessive reliance on AI may lead to automation bias, reduced critical thinking, and ethical concerns such as discrimination, data privacy violations, and lack of explainability in algorithmic decisions (Martin, 2019; Mittelstadt et al., 2016). These issues highlight the importance of understanding the contextual and organizational factors that shape AI-enabled decision-making.

From an organizational perspective, factors such as data quality, technological infrastructure, managerial competencies, organizational culture, ethical governance, and regulatory frameworks significantly influence the effectiveness of AI-supported decisions (Kiron et al., 2014; Tarafdar, Beath, & Ross, 2019). Managers must not only possess technical awareness but also develop new skills in critical evaluation, ethical reasoning, and strategic oversight to effectively leverage AI systems (Jarrahi, 2018). Consequently, managerial decision-making in the AI era extends beyond technical adoption and requires a holistic understanding of socio-technical interactions within organizations.

Understanding the factors influencing managerial decision-making in the age of Artificial Intelligence is therefore essential for effective leadership and sustainable organizational performance. As organizations increasingly rely on AI to support strategic, tactical, and operational decisions, examining these factors provides valuable insights into how managers can balance technological capabilities with human judgment. This study aims to contribute to the growing body of literature by analyzing the key factors that shape managerial decision-making in AI-driven organizational contexts.

Objective

To study the key factors influencing managerial decision-making in the age of Artificial Intelligence (AI).

Theoretical Foundations of Managerial Decision-Making

Classical View of Decision-Making

Early management theories viewed decision-making as a rational and objective process. The classical model assumes that managers are fully informed, capable of identifying all possible alternatives, and able to select the optimal solution that maximizes organizational outcomes (Taylor, 1911). This rational decision-making model emphasizes logical analysis, clear objectives, and systematic evaluation of alternatives. Under this approach, decision-making follows a linear sequence: problem identification, data collection, alternative evaluation, and choice of the best solution. While this model provides a useful normative framework, critics argue that it oversimplifies real-world managerial contexts, where information is incomplete, time is limited, and organizational politics influence outcomes (March & Simon, 1958).

Bounded Rationality

Herbert Simon’s concept of bounded rationality significantly reshaped decision-making theory by acknowledging human cognitive limitations (Simon, 1955). According to this perspective, managers cannot process all available information or evaluate every possible alternative. Instead of optimizing, managers often “satisfice” by selecting solutions that are good enough under existing constraints. Bounded rationality highlights the role of heuristics, rules of thumb, and experience in managerial decision-making. This perspective remains highly influential, particularly in explaining decision-making under uncertainty and complexity. Even with advanced analytical tools, managers continue to face cognitive and organizational constraints that shape their decisions.

Behavioral and Psychological Perspectives

Behavioral decision-making research emphasizes the psychological factors that influence managerial choices. Studies in this tradition demonstrate that decisions are often affected by cognitive biases such as overconfidence, anchoring, confirmation bias, and loss aversion (Kahneman & Tversky, 1979). These biases can lead managers to deviate from rational decision-making, sometimes resulting in suboptimal outcomes. Emotions also play a critical role in decision-making. Research suggests that affective states influence risk perception, judgment, and choice behavior, particularly in high-stakes or uncertain situations (Lerner et al., 2015). Consequently, managerial decision-making is not purely analytical but is deeply intertwined with psychological and emotional factors.

Decision-Making as a Managerial Function

Decision-making is not a separate managerial activity but an integral part of all management functions. Planning involves decisions about goals, strategies, and resource allocation. Organizing requires decisions about structure, roles, and authority. Leading involves decisions related to motivation, communication, and conflict resolution. Controlling requires decisions regarding performance evaluation and corrective actions (Koontz et al., 2010). Managers at different levels make decisions with varying scopes and impacts. Top-level managers focus on strategic decisions, middle-level managers handle tactical decisions, and lower-level managers are primarily responsible for operational decisions. Each level requires distinct decision-making skills and perspectives.

Types of Managerial Decisions

1. Strategic Decisions Strategic decisions are long-term, non-routine decisions that determine the overall direction of the organization. These decisions involve significant resource commitments and have far-reaching consequences (Eisenhardt & Zbaracki, 1992). Examples include market entry, mergers and acquisitions, innovation strategies, and competitive positioning. Strategic decision-making is characterized by high uncertainty, complexity, and ambiguity. Managers must consider external environmental factors such as competition, technological change, and regulatory conditions, making strategic decisions particularly challenging.

2. Tactical Decisions Tactical decisions translate strategic objectives into specific plans and actions. These decisions are typically made by middle-level managers and focus on resource

utilization, departmental goals, and performance improvement. Tactical decisions are less complex than strategic decisions but still require analytical and coordination skills.

3. Operational Decisions Operational decisions are routine, short-term decisions that ensure the efficient functioning of daily activities. These decisions are often standardized and guided by established procedures. Examples include scheduling, inventory management, and employee task assignments. Advances in automation and AI have increasingly supported or replaced human involvement in operational decision-making (Davenport & Ronanki, 2018).

Decision-Making Models in Management

Decision-making is a central activity in management and a key determinant of organizational effectiveness. Managers continuously make decisions related to strategy formulation, resource allocation, problem-solving, and performance improvement. To understand how managers make decisions, scholars have developed various decision-making models that explain the cognitive, behavioral, and organizational processes underlying managerial choices. These models provide conceptual frameworks that help explain why decisions differ across individuals, organizations, and contexts (March, 1994).

Decision-making models in management range from highly structured and analytical approaches to more flexible and experience-based perspectives. No single model fully captures the complexity of real-world managerial decision-making. Instead, each model highlights particular assumptions, strengths, and limitations. In contemporary organizations—especially those influenced by digital technologies and Artificial Intelligence (AI)—managers often combine multiple decision-making models rather than relying on a single approach (Jarrahi, 2018). This section discusses four major decision-making models in management: the rational decision-making model, incremental decision-making, intuitive decision-making, and evidence-based decision-making. Each model is examined in terms of its theoretical foundations, key characteristics, applications, and limitations.

Rational Decision-Making Model

The rational decision-making model is one of the earliest and most influential models in management theory. It assumes that decision-makers are fully rational and capable of identifying clear objectives, gathering complete and accurate information, generating all possible alternatives, and selecting the option that maximizes organizational outcomes (Simon, 1977). Under this model, decision-making is viewed as a logical, systematic, and objective process.

The rational model typically follows a linear sequence of steps: problem identification, information collection, evaluation of alternatives, selection of the optimal solution, implementation, and evaluation. This approach provides a normative benchmark for decision quality and is widely used in strategic planning, policy analysis, and operations management. One of the main strengths of the rational decision-making model is its clarity and structure. By emphasizing systematic analysis and objective evaluation, the model reduces ambiguity and provides a clear framework for complex decisions (Bazerman & Moore, 2013). It is particularly useful in stable environments where goals are clear, data is reliable, and decision outcomes can be reasonably predicted. The rational model also aligns well with analytical tools, quantitative methods, and AI-based decision-support systems. Optimization models, forecasting algorithms, and cost–benefit analyses reflect the logic of rational decision-making and support managers in making data-driven choices (Davenport & Harris, 2007).

Limitations of the Rational Model

Despite its theoretical appeal, the rational decision-making model has been widely criticized for its unrealistic assumptions. In practice, managers rarely have access to complete information or unlimited cognitive capacity. Time constraints, uncertainty, political pressures, and emotional factors often prevent fully rational decision-making (March & Simon, 1958). Herbert Simon's concept of bounded rationality highlights these limitations, arguing that managers satisfice rather than optimize by selecting solutions that are acceptable rather than optimal (Simon, 1955). As a result, the rational model is best viewed as an idealized benchmark rather than a realistic description of managerial behavior. Incrementalism suggests that managers make decisions through small, gradual adjustments rather than comprehensive analysis (Lindblom, 1959). This approach is common in public administration and complex organizations where consensus-building and political considerations are important. Intuitive decision-making relies on experience-based pattern recognition rather than conscious analysis (Dane & Pratt, 2007). Experienced managers often use intuition in time-pressured or uncertain situations. While intuition can enhance speed and creativity, it may also increase susceptibility to bias. Evidence-based management emphasizes the use of empirical research, organizational data, and systematic analysis in decision-making (Rousseau, 2006). This approach has gained prominence with the rise of analytics and AI, promoting more objective and transparent decisions.

Incremental Decision-Making Model

Incremental decision-making, also known as incrementalism, challenges the comprehensive analysis assumed in the rational model. Lindblom (1959) argued that managers and policymakers often make decisions through small, gradual adjustments rather than radical changes. Instead of evaluating all alternatives, decision-makers focus on options that differ only marginally from existing practices. Incrementalism reflects the reality of complex organizations where decision-making is constrained by limited information, competing interests, and the need for consensus. This model is particularly common in public administration, large bureaucracies, and politically sensitive environments.

Incremental decision-making emphasizes continuity, negotiation, and compromise. Managers rely on past decisions as reference points and make adjustments based on feedback and experience. This approach reduces risk by avoiding drastic changes and allows organizations to adapt gradually to environmental shifts (Quinn, 1980). Incrementalism also acknowledges the political nature of decision-making. By focusing on small changes, managers can minimize resistance and maintain organizational stability. This makes the model especially relevant in organizations with strong stakeholder involvement and power dynamics.

The strength of incremental decision-making lies in its practicality and adaptability. It allows managers to cope with uncertainty and complexity without requiring comprehensive analysis. Incremental decisions are often easier to implement and less disruptive to organizational routines. However, incrementalism can also limit innovation and strategic renewal. By emphasizing small adjustments, organizations may fail to respond effectively to major environmental changes or disruptive technologies (Mintzberg, 1994). In rapidly changing environments, incremental decision-making may lead to strategic inertia.

Intuitive Decision-Making Model

Intuitive decision-making relies on experience-based pattern recognition rather than deliberate analytical reasoning. According to Dane and Pratt (2007), intuition is a rapid, non-conscious process grounded in accumulated knowledge and expertise. Experienced managers often use intuition when facing time pressure, uncertainty, or ambiguous information.

Intuitive decision-making does not imply irrationality; rather, it reflects a different mode of cognition that complements analytical thinking. Research in cognitive psychology suggests that intuition can be highly effective in familiar contexts where decision-makers have deep domain expertise (Kahneman, 2011).

Experience is a critical factor in intuitive decision-making. Expert managers develop mental models that allow them to recognize patterns and anticipate outcomes quickly. This enables fast decision-making in dynamic environments such as crisis management, entrepreneurship, and innovation (Eisenhardt, 1989). In the age of AI, intuition remains relevant because not all decisions can be fully captured by data or algorithms. Strategic judgment, leadership decisions, and ethical dilemmas often require human insight beyond analytical outputs.

While intuition can enhance speed and creativity, it also increases susceptibility to cognitive biases such as overconfidence, availability bias, and confirmation bias (Kahneman & Tversky, 1979). Intuitive decisions may be influenced by emotions and personal preferences, potentially reducing objectivity. Therefore, intuitive decision-making is most effective when balanced with analytical validation and evidence-based approaches.

Evidence-Based Decision-Making Model

Evidence-based decision-making, also known as evidence-based management (EBM), emphasizes the systematic use of the best available evidence from multiple sources, including scientific research, organizational data, professional expertise, and stakeholder input (Rousseau, 2006). This model seeks to improve decision quality by reducing reliance on intuition, tradition, and personal opinion. EBM has gained prominence with the rise of big data, analytics, and AI technologies, which enable organizations to collect and analyze large volumes of information in real time (Davenport, 2014).

Evidence-based decision-making supports transparency, accountability, and learning. Managers using this model critically evaluate data sources, assess the validity of evidence, and integrate quantitative and qualitative insights. This approach is particularly valuable in areas such as human resource management, healthcare administration, and strategic planning.

AI-driven analytics enhance evidence-based decision-making by providing predictive insights and scenario analysis. However, managers must still interpret evidence within organizational and ethical contexts. Despite its advantages, evidence-based decision-making faces practical challenges. Managers may lack access to high-quality evidence, analytical skills, or time to conduct systematic evaluations. Organizational cultures resistant to data-driven approaches may also limit EBM adoption (Kiron et al., 2014).

Additionally, evidence does not eliminate uncertainty or value-based judgments. Managers must still make decisions under incomplete information and competing stakeholder interests.

In practice, managerial decision-making rarely follows a single model. Managers often combine rational analysis, incremental adjustments, intuitive judgment, and evidence-based insights depending on the context. For example, strategic decisions may begin with evidence-based analysis, incorporate intuitive judgment, and be implemented incrementally. The integration of AI further reinforces the need for hybrid decision-making models that balance analytical rigor with human judgment and ethical responsibility (Raisch & Krakowski, 2021).

Organizational-Level Factors Influencing Decision-Making

Organizational culture shapes shared values, norms, and assumptions that guide managerial behavior. A culture that emphasizes innovation, learning, and experimentation encourages managers to adopt AI tools and integrate them into decision processes (Schein, 2010). Conversely, risk-averse or hierarchical cultures may discourage AI adoption and limit decision autonomy. Culture also influences trust in AI. Organizations that promote data-driven decision-making are more likely to accept algorithmic insights, whereas cultures emphasizing intuition and authority may resist machine-generated recommendations (Kiron et al., 2014). Therefore, culture plays a foundational role in shaping AI-enabled managerial decisions.

Organizational Structure and Decision Authority

Organizational structure determines how decision authority is distributed across levels and functions. Centralized structures concentrate decision-making power at the top, while decentralized structures empower lower-level managers (Mintzberg, 1979). AI can both reinforce and disrupt existing structures by enabling real-time information sharing and automated decision-making. For example, AI-driven dashboards may empower frontline managers by providing actionable insights, while centralized AI systems may shift decision authority upward or toward technical specialists. Structural alignment is therefore essential for effective AI-supported decision-making (Shrestha et al., 2019). Decision-making is inherently political, as managers pursue competing interests and negotiate power relationships (Pfeffer, 1992). AI does not eliminate organizational politics; instead, it can reshape power dynamics by privileging those who control data, algorithms, or technological expertise. Managers may selectively use AI outputs to legitimize predetermined decisions or strengthen their influence within the organization. Consequently, political behavior remains a significant factor influencing how AI is used in managerial decision-making. The quality of organizational information systems strongly influences decision effectiveness. Reliable data infrastructure, integration capabilities, and governance mechanisms are prerequisites for meaningful AI-driven insights (Davenport & Harris, 2007). Poor data quality can lead to misleading recommendations and undermine trust in AI systems. Data governance policies regarding ownership, access, privacy, and security also shape managerial decisions. Managers must navigate regulatory and ethical constraints when using AI-generated information, making information systems a central organizational factor in decision-making.

Technological Factors in AI-Enabled Decision-Making

AI systems rely heavily on data quality, volume, and relevance. Inaccurate, incomplete, or biased data can distort AI outputs and negatively influence managerial decisions (Mittelstadt et al., 2016). Managers must assess data credibility before relying on AI-generated recommendations. Access to real-time data enhances responsiveness but also increases cognitive and operational demands on managers. Thus, data availability both enables and complicates decision-making in AI-driven environments. Algorithmic transparency refers to the extent to which AI decision processes can be understood and explained. Lack of explainability can reduce trust and hinder managerial accountability (Glikson & Woolley, 2020). Managers are more likely to accept AI recommendations when they understand how conclusions are generated. Explainable AI (XAI) has therefore emerged as a critical factor influencing managerial reliance on AI-supported decisions, particularly in regulated industries. The degree of automation determines how much control managers retain over decisions. Fully automated systems may improve efficiency but reduce managerial involvement and situational awareness. Augmented systems, by contrast, support human judgment rather than replacing it (Raisch & Krakowski, 2021). Decisions about automation level are themselves managerial decisions influenced by trust, risk perception, and organizational norms. Maintaining appropriate human oversight is essential for balancing efficiency and responsibility.

External Environmental Factors Influencing Decision-Making

Competitive pressure influences managerial decision-making by increasing the need for speed, accuracy, and innovation. AI enables rapid analysis of market trends and competitor behavior, shaping strategic and tactical decisions (Eisenhardt, 1989). In highly competitive environments, managers may rely more heavily on AI to gain strategic advantage, while in stable environments, traditional decision approaches may persist. Rapid technological change creates uncertainty and complexity, influencing managerial risk perception and strategic choices. AI both contributes to and helps manage technological disruption. Managers must decide how aggressively to adopt AI technologies while balancing organizational readiness and long-term sustainability. Regulatory frameworks governing data protection, algorithmic accountability, and AI ethics significantly influence managerial decision-making (European Commission, 2020). Compliance requirements may constrain data usage or algorithm deployment, shaping how managers integrate AI into decisions. Institutional norms and industry standards also influence managerial behavior, particularly in highly regulated sectors such as finance and healthcare.

Interaction of Factors and Decision Complexity

Managerial decision-making in the AI era is best understood as a socio-technical process shaped by interacting individual, organizational, technological, and environmental factors. These factors do not operate independently; rather, they dynamically influence one another, creating unique decision contexts (Papadakis et al., 1998). For example, a manager's cognitive style interacts with organizational culture and AI transparency to shape trust in algorithmic recommendations. Similarly, regulatory pressures interact with ethical values and data governance structures to influence decision outcomes. This interactional complexity explains why AI adoption does not automatically improve decision quality and why managerial judgment remains essential. Understanding the factors influencing managerial decision-making in the age of AI has important practical implications. Managers must develop AI literacy, ethical awareness, and adaptive leadership skills. Organizations must align culture, structure, and governance mechanisms to support effective human–AI collaboration. Rather than viewing AI as a replacement for managerial decision-making, organizations should adopt an augmentation perspective that leverages both human judgment and machine intelligence.

Conclusion

Managerial decision-making in the age of Artificial Intelligence is characterized by increasing complexity arising from the interaction of human judgment and machine intelligence. This study examined the key factors influencing managerial decision-making by integrating insights from classical, behavioral, and contemporary management theories with emerging research on AI-enabled decision processes. Through a comprehensive review of the literature, the study identified individual, organizational, technological, and environmental factors as critical determinants shaping how managers interpret information, evaluate alternatives, and exercise judgment in AI-driven contexts.

The findings suggest that while Artificial Intelligence significantly enhances analytical capacity, speed, and predictive accuracy, it does not replace the need for managerial experience, ethical reasoning, and contextual understanding. Instead, managerial decision-making in the AI era functions as a socio-technical process in which human cognition and organizational context interact dynamically with algorithmic systems. Factors such as cognitive style, risk tolerance, organizational culture, data quality, algorithm transparency, and regulatory pressures collectively influence the extent to which AI-supported decisions are trusted, adopted, and effectively implemented.

Moreover, the study highlights that effective managerial decision-making requires the integration of multiple decision-making models. Rational and evidence-based approaches are strengthened by AI-driven analytics, while intuitive and incremental decision-making remain essential in situations characterized by ambiguity, uncertainty, and ethical considerations. Consequently, organizations that adopt an augmentation perspective—leveraging AI to support rather than replace managerial judgment—are better positioned to improve decision quality and achieve sustainable performance.

Overall, this study contributes to the body of knowledge on managerial decision-making by offering an integrative framework that captures the multidimensional nature of decision-making in AI-enabled organizational environments. It underscores the importance of balancing analytical rigor with human judgment, innovation with accountability, and technological advancement with ethical responsibility.

Body of Knowledge

The body of knowledge on managerial decision-making has evolved significantly over time, reflecting changes in organizational environments, technological capabilities, and theoretical perspectives. Early management research conceptualized decision-making as a rational and objective process, emphasizing optimization, clear objectives, and systematic analysis. This classical perspective provided foundational models that continue to influence strategic planning and analytical decision-support systems. Subsequent theoretical developments challenged the assumptions of full rationality by introducing the concept of bounded rationality, which recognizes the cognitive and informational limitations faced by managers. Behavioral and psychological research further expanded the body of knowledge by demonstrating the influence of cognitive biases, emotions, and heuristics on managerial decisions. These perspectives shifted the focus from idealized decision-making toward more realistic explanations of managerial behavior under uncertainty and complexity. The literature also distinguishes among different types of managerial decisions, strategic, tactical, and operational, each characterized by varying levels of uncertainty, time horizons, and organizational impact. Decision-making models such as rational, incremental, intuitive, and evidence-based approaches have been developed to explain how managers navigate these decision contexts. Contemporary research emphasizes that managers rarely rely on a single model, instead adopting hybrid approaches tailored to situational demands. With the advent of Artificial Intelligence, the body of knowledge on managerial decision-making has expanded to incorporate socio-technical perspectives. AI technologies enhance analytical capacity, reduce information-processing constraints, and support evidence-based decision-making through predictive analytics and real-time data processing. At the same time, scholars highlight that AI reshapes managerial roles by shifting decision-making from purely human-centered processes toward human–AI collaboration.

1. Decision-making models in management include:
    - Rational decision-making model
    - Incremental decision-making model
    - Intuitive decision-making model
    - Evidence-based decision-making model
2. Contemporary research emphasizes that:
    - Managers rarely rely on a single decision-making model
    - Hybrid decision-making approaches are commonly used
    - Decision models are adapted based on context, uncertainty, and time pressure
3. The emergence of Artificial Intelligence has expanded the body of knowledge by:
    - Introducing socio-technical perspectives on decision-making
    - Enhancing analytical capacity and data-processing speed
    - Supporting evidence-based and predictive decision-making
4. AI has reshaped managerial decision-making by:
    - Reducing information-processing constraints
    - Enabling real-time data analysis and forecasting
    - Shifting decision-making from human-centered to human–AI collaboration

Overall, the existing body of knowledge suggests that managerial decision-making in the age of Artificial Intelligence cannot be understood through a purely technical or rational lens. Instead, it represents a dynamic, context-dependent process shaped by the interaction of human cognition, organizational systems, and intelligent technologies. This study builds on and integrates these theoretical streams by providing a comprehensive framework of factors influencing managerial decision-making in AI-driven organizational environments.

Suggestions

Suggestions for Implementation

Based on the findings of this study, several practical suggestions can be offered for organizations seeking to enhance managerial decision-making in the age of Artificial Intelligence. First, organizations should invest in developing managerial AI literacy. Managers need not become technical experts, but they should possess sufficient understanding of AI capabilities, limitations, and assumptions to critically evaluate algorithmic recommendations and avoid overreliance on automated outputs.

Second, organizations should foster a data-driven yet ethically grounded decision-making culture. Establishing clear data governance policies, ethical guidelines, and accountability mechanisms can help ensure responsible use of AI in managerial decisions. Emphasis on transparency and explainable AI systems can further enhance managerial trust and facilitate informed judgment, particularly in high-stakes or regulated decision contexts.

Third, organizational structures and decision authority should be aligned with AI-supported processes. Clear delineation of roles between human decision-makers and AI systems is essential to maintain accountability and prevent ambiguity in responsibility. AI should be designed to augment managerial judgment by providing insights and alternatives, while final decision authority remains with managers.

Finally, continuous learning and feedback mechanisms should be incorporated into AI-enabled decision systems. By systematically evaluating decision outcomes and refining both human and algorithmic inputs, organizations can enhance organizational learning and improve long-term decision quality.

Suggestions for Future Research

Future research could further advance understanding of managerial decision-making in the age of Artificial Intelligence in several ways. First, empirical studies are needed to examine how individual differences—such as cognitive style, AI literacy, managerial experience, and ethical orientation—moderate reliance on and interpretation of AI-generated recommendations. Such research would provide deeper insight into effective human–AI collaboration.

Second, future studies should investigate organizational-level factors through comparative and cross-industry research designs. Examining how different organizational cultures, governance structures, and leadership styles influence AI-enabled decision-making would help identify best practices and contextual contingencies.

Third, further research is warranted on the role of explainable Artificial Intelligence (XAI) in managerial decision-making. Empirical evidence is needed to assess how algorithm transparency affects managerial trust, accountability, decision quality, and ethical judgment, particularly in complex and uncertain environments.

Finally, longitudinal research designs would be valuable in capturing how managerial decision-making evolves as organizations gain experience with AI technologies. Such studies could reveal learning effects, shifts in decision authority, and long-term implications for organizational performance and strategy.

Declaration of Interests

The author declares that there is no competing financial, professional, or personal interests that could have influenced the research reported in this article.

Ethical Considerations

This study is based entirely on a review and synthesis of previously published literature. No primary data were collected from human participants, and no experiments or interventions were conducted. As such, ethical approval was not required. Nevertheless, the study adheres to established academic standards of integrity, transparency, and proper citation, ensuring that all sources are appropriately acknowledged and represented accurately.

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Definition of Conflicts of Interest

A conflict of interest refers to any situation in which an author's financial, professional, or personal relationships could inappropriately influence, or be perceived to influence, the objectivity, integrity, or interpretation of the research findings. In the context of this study, no such conflicts of interest were identified or reported by the author.

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