

The Impact of Artificial Intelligence on Decision-Making Quality: Toward a Hybrid and Augmented Decision Framework Based on Simon's Model

أثر الذكاء الاصطناعي على جودة اتخاذ القرار: نحو إطار عمل هجين ومُعزز لاتخاذ
القرار قائم على نموذج سيمون

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Abstract:

This study examines the transformative role of artificial intelligence (AI) in enhancing decision-making quality within contemporary organizations. Drawing on Herbert Simon's decision-making model, the study develops a conceptual framework that links AI applications—such as intelligent decision support systems, big data analytics, and machine learning—to decision quality dimensions, including accuracy, objectivity, and predictability. The findings suggest that AI shifts decision-making from intuition-based processes to data-driven and proactive approaches. However, critical challenges related to algorithmic bias and lack of transparency remain significant barriers. The study contributes to the literature by integrating technological, managerial, and ethical perspectives into a unified framework and proposes the concept of augmented decision-making as a balanced model combining machine intelligence and human judgment.

Keywords: Artificial Intelligence, Decision-Making Quality, Data-Driven Management, Herbert Simon's Model, Hybrid Decision-Making, Predictive Analytics.

الملخص :

تتناول هذه الدراسة الدور التحويلي للذكاء الاصطناعي في تحسين جودة اتخاذ القرار داخل المؤسسات المعاصرة، من خلال توظيف نموذج هربرت سيمون لمراحل صنع القرار (الاستخبار، التصميم، الاختيار) كإطار تحليلي مرجعي. وتطوّر الدراسة إطارًا مفاهيميًا يربط بين تطبيقات الذكاء

الاصطناعي — مثل نظم دعم القرار الذكية، وتحليلات البيانات الضخمة، وخوارزميات تعلم الآلة — وأبعاد جودة القرار التي تشمل الدقة، والموضوعية، والقدرة على التنبؤ، إلى جانب البعد الأخلاقي المرتبط بالشفافية والعدالة. وتشير النتائج إلى أن الذكاء الاصطناعي يساهم في نقل عملية اتخاذ القرار من نمط تقليدي قائم على الحدس وردود الفعل إلى نمط استباقي قائم على تحليل البيانات، بما يعزز من كفاءة وموثوقية القرارات. غير أن الدراسة تكشف في المقابل عن تحديات جوهرية، أبرزها التحيز الخوارزمي وضعف القابلية للتفسير، مما قد يؤثر على جودة القرار ومشروعيته. وتتمثل مساهمة الدراسة في تقديم إطار تحليلي تكاملي يدمج بين الأبعاد التكنولوجية والإدارية والأخلاقية، مع اقتراح نموذج "القرار المعزز" بوصفه مقارنة متوازنة تجمع بين كفاءة الذكاء الاصطناعي وحكمة الحكم البشري في البيئات التنظيمية المعاصرة.

الكلمات المفتاحية : الذكاء الاصطناعي، جودة اتخاذ القرار، الإدارة القائمة على البيانات، نموذج هيربرت سايمون، القرار الهجين، التحليلات التنبؤية.

1. INTRODUCTION

The rapid advancement of information and communication technologies (ICT) has generated profound and structural transformations, leading to a genuine revolution in the production, circulation, and processing of information flows. This evolution has fostered the emergence of an integrated digital environment characterized by massive data volumes and continuous information streams, which has directly reshaped economic, administrative, social, and political domains. Within this context, information has become a strategic resource, whereby actors capable of producing, managing, and securing it gain a competitive advantage that strengthens digital sovereignty and enhances organizational decision-making processes.

In this framework, Artificial Intelligence (AI) has emerged as one of the most prominent outcomes of technological development and a fundamental pillar supporting various sectors. AI has evolved from traditional expert systems to more advanced techniques such as Machine Learning and Deep Learning, enabling organizations to process and analyze vast amounts of data with high efficiency. This transformation has reinforced organizational empowerment and supported decision-making by reducing uncertainty, improving decision quality, and enhancing predictive and anticipatory capabilities—thus contributing to what is increasingly conceptualized as Augmented Rationality.

While AI offers significant benefits, its adoption also introduces legal, organizational, and ethical challenges, largely driven by the “interpretability gap” between complex algorithmic outputs and human understanding. Issues

such as algorithmic bias, Algorithmic Opacity, and insufficient digital literacy raise critical concerns regarding accountability and transparency. If left unaddressed, these challenges may undermine decision quality and erode institutional legitimacy, rather than enhance them.

The topic of AI and its impact on administrative decision-making has attracted increasing attention in recent literature. For instance, Górka et al. (2025) highlight the role of AI technologies in enhancing organizational responsiveness and improving decision-making efficiency. Similarly, Badmus et al. (2024) emphasize the importance of predictive analytics in reducing uncertainty-related risks. However, these contributions are not without limitations. Kumar and Kumar (2024) argue that decision quality remains contingent upon addressing ethical challenges, particularly algorithmic bias and poor data quality. This perspective is further reinforced by Coeckelbergh (2020), who underscores the issue of transparency in intelligent systems and its implications for decision legitimacy and credibility.

Current literature often examines AI's technical efficiency and ethical implications in isolation, with limited integration into established frameworks like Herbert Simon's model. Furthermore, a comprehensive link between AI-driven processes and multidimensional decision quality—specifically governance and transparency—remains underdeveloped. This study addresses these gaps by developing an integrated analytical framework that synthesizes technological, managerial, and ethical dimensions within a Hybrid Decision-Making perspective.

This study is guided by the following central research question:

How do AI applications influence decision-making quality in organizations, and what key challenges affect their effectiveness?

Research Questions

- What is Artificial Intelligence, and what are its main applications within organizations?
- What is meant by decision quality, and what are its key determinants in the organizational environment?
- How do AI technologies support the stages of decision-making (intelligence, design, and choice)?
- What advantages does AI provide in enhancing decision efficiency and accuracy, and what are the main challenges associated with its use in organizational decision-making?

- What requirements are necessary to ensure the effective and responsible use of AI in supporting institutional decisions?

- **Research Hypotheses**

H1: The use of AI applications contributes to improving decision quality by enhancing information accuracy, reducing uncertainty, and accelerating the decision-making process.

H2: Ethical and organizational challenges—such as algorithmic bias and lack of transparency—negatively affect decision quality, thereby limiting the effectiveness of AI applications within organizations.

- **Research Objectives**

This study aims to analyze the role of AI in enhancing decision quality and supporting various decision-making stages. It specifically examines the ethical challenges associated with AI implementation, such as algorithmic bias, while proposing strategic mechanisms to foster the responsible and effective integration of intelligent systems within organizational frameworks.

- **Methodology**

This study employs a descriptive-analytical approach to develop an integrated conceptual framework examining the interaction between AI technologies and decision quality. The methodology synthesizes theoretical literature and contemporary empirical studies (e.g., Kumar & Kumar, 2024; Górka et al., 2025) to link technological efficiency with administrative outcomes. The proposed framework treats AI applications as independent variables, Simon's decision-making stages as mediating mechanisms, and decision quality as the dependent variable, while considering ethical governance and digital literacy as critical moderating factors.

- **Structure of the Study**

The first section establishes the theoretical framework, defining AI as a system for simulating human cognitive functions and tracing its evolution toward Machine Learning. It conceptualizes decision quality through the lenses of accuracy and timeliness, structured around Simon's intelligence, design, and choice stages. The second section analyzes organizational AI applications—specifically IDSS, Big Data Analytics, and Machine Learning—examining how these technologies optimize information processing and knowledge extraction to elevate overall decision-making speed, accuracy, and strategic performance.

2. The Theoretical Framework of Artificial Intelligence and Decision Quality

Artificial Intelligence (AI) and decision quality are pivotal to modern organizational dynamics. While AI provides advanced analytical and predictive capabilities, decision quality serves as a benchmark for administrative effectiveness in complex environments. This section establishes an integrated theoretical framework by defining AI's evolution and typologies, alongside an analysis of decision-making stages and determinants. This conceptual foundation is essential for examining how AI applications strategically enhance organizational decision-making outcomes.

This study makes three key contributions to the literature. First, it theoretically extends Herbert A. Simon's decision-making model by incorporating Artificial Intelligence as a core enabling factor across its intelligence, design, and choice stages. Second, it develops a comprehensive multidimensional conceptualization of decision quality that integrates technical accuracy, algorithmic transparency, and ethical fairness. Third, it advances a governance-oriented framework for AI adoption by introducing the concept of Augmented Decision-Making as a balanced model that combines machine efficiency with human judgment.

2.1 Concept of Artificial Intelligence

2.1.1 Definition of Artificial Intelligence

AI can be defined as a set of theories and techniques used to develop machines capable of mimicking human intelligence—such as learning, reasoning, and decision-making. Simultaneously, it constitutes a scientific field concerned with the design and development of intelligent systems capable of perceiving their environment and acting in ways that maximize their chances of success.

1

AI is also conceptualized as the ability of a system to accurately interpret external data, learn from it, and utilize it to achieve specific goals through adaptive processes². In a similar vein, it is defined as the capability of a programmed machine to think and act in ways that resemble human intelligence.³

From a technical and algorithmic perspective, AI is understood as an integrated system based on the interaction between data, algorithms, and

computational power, aimed at analyzing information and transforming it into value-generating outputs. This occurs through mechanisms such as automation, predictive analytics, and intelligent decision-making⁴ Within this framework, AI encompasses advanced technologies such as Machine Learning and Computer Vision, which enable systems to interpret and analyze visual data beyond simple recognition or classification. These technologies rely on sensors and learning algorithms to extract complex contextual information.

The outputs generated by such systems are subsequently employed in automation processes, allowing systems to operate autonomously with minimal or no direct human intervention⁵. This evolution reflects a transition toward more sophisticated models of Hybrid Decision-Making, where human judgment and machine intelligence interact to produce more informed and context-aware decisions, while simultaneously raising concerns related to Algorithmic Opacity and accountability

Artificial Intelligence (AI) is defined as a computational and academic field concerned with the design and development of systems and software capable of simulating human cognitive functions, such as learning, thinking, reasoning, and autonomous decision-making. This field relies on advanced algorithms to analyze large-scale data, enabling these systems to adapt to their environments and improve their performance in order to achieve specific objectives. AI also refers to the intelligence exhibited by machines through behaviors and patterns that mimic human intelligence, whether in responding to programmed situations or interacting intelligently with various inputs.⁶

From another perspective, the returns of artificial intelligence will remain contingent upon two key conditions. The first is that states and governments adopt sustainable development strategies supported by artificial intelligence—an outcome that is not guaranteed across all countries. The second condition is that artificial intelligence aligns with the needs of states and societies, contributing to equipping them with AI-driven technologies that support sustainable development without imposing excessive burdens or prohibitive costs.⁷

Within the field of business administration, AI has emerged as a transformative tool that enables organizations to analyze big data and provide effective solutions to complex problems that traditional systems are unable to address⁸. It is commonly defined as “the study and design of intelligent

systems that perceive their environment and take actions that maximize their chances of success,” while John McCarthy—who introduced the term in 1955—defined it as “the science and engineering of making intelligent machines⁹” From an operational perspective in computer science, this field seeks to develop systems capable of performing tasks that require human intelligence, primarily through Machine Learning techniques that allow systems to improve their performance autonomously.

Moreover, the “intelligent agents” perspective represents one of the most influential contemporary conceptual frameworks in defining AI. From this viewpoint, AI is regarded as a field concerned with designing systems capable of perceiving their environment and interacting with it through rational decision-making processes that maximize the achievement of objectives under conditions of uncertainty¹⁰. This perspective aligns closely with the notion of Augmented Rationality, where machine intelligence enhances—rather than replaces—human decision-making capacities within complex organizational contexts.

Conversely, the philosophical and ethical dimension of AI conceptualizes it as a complex socio-technical system that raises fundamental challenges related to accountability and the attribution of responsibility, particularly in situations where decision-making authority is delegated to intelligent systems. This leads to difficulties in identifying responsibility for decision outcomes, especially when decision-making mechanisms are not easily interpretable, as in the case of the so-called “black box” phenomenon, which reflects a form of Algorithmic Opacity.¹¹

The conceptual foundations of AI are rooted in classical logic and philosophical inquiries into the mechanization of thought. From Aristotle’s formal logic to the computational views of Hobbes and Leibniz, these cumulative perspectives shaped the trajectory of cognitive automation. This philosophical evolution established the framework for modern AI as a scientific field dedicated to simulating human intelligence through computational systems.¹²

Based on the foregoing, the present study operationally defines Artificial Intelligence as an intelligent information system grounded in algorithms and Machine Learning techniques, designed to analyze big data and extract predictive patterns that support administrative decision-making. This, in turn, contributes to enhancing organizational efficiency and improving the quality

of outputs within a framework that emphasizes algorithmic transparency and ethical accountability—ultimately reinforcing a model of Hybrid Decision-Making that integrates human judgment with machine intelligence.

2.1.2 Historical Evolution of Artificial Intelligence

a) Historical Trajectory: From Logic to Support Systems

The evolution of AI began with the 1950s Foundational Phase, where the Dartmouth Conference established the ambition of simulating human intelligence through symbolic logic¹³. During the 1960s and 1970s, defense-supported research (DARPA) shifted the focus toward automated reasoning, laying the technical groundwork for modern Decision Support Systems (DSS) and digital assistants like Siri and Alexa¹⁴

b) The Deep Learning Revolution and Big Data

The 21st century marked a qualitative leap driven by the convergence of Big Data, high-performance computing (GPUs), and advanced neural architectures. Deep Learning emerged as the dominant paradigm, enabling systems to autonomously identify complex patterns and improve performance without direct intervention¹⁵. This era replaced traditional interfaces with intuitive modalities (voice and gesture) and streamlined administrative processes by reducing the need for manual data engineering (SAS, n.d).¹⁶

c) Current Strategic Role and Ethical Governance

Today, AI has transitioned from experimental scenarios to a central operational tool in public administration and healthcare. While AI enhances predictive capabilities and supports structured decision-making¹⁷, However, the expansion of these systems introduces significant challenges. The “black box” nature of deep learning raises concerns related to algorithmic opacity, potential bias, and issues of accountability and responsibility. Given the inability of humans to fully explain how AI systems arrive at specific decisions, it becomes necessary to adopt a “human-in-the-loop” approach, ensuring continuous human oversight of decision-making processes and reinforcing ethical governance as well as the legitimacy of decisions¹⁸.

2.1.3 Types of Artificial Intelligence

Artificial Intelligence (AI) can be classified, based on its capabilities, into three main categories as follows:

a. Artificial Narrow Intelligence (ANI)

Artificial Narrow Intelligence (ANI), also referred to as Weak AI, represents systems designed to simulate specific aspects of human

intelligence within a limited domain. These systems are specialized in performing a single task—or a narrow set of tasks—with high efficiency and precision. However, they operate under significantly greater constraints compared to human intelligence, as they lack general cognitive flexibility.

ANI is currently the most prevalent form of AI, encompassing applications such as autonomous vehicles, speech and image recognition systems, and chess-playing programs embedded in smart devices. In practical organizational contexts, Ashritha and Reddy (2023, pp. 11–12) note that the majority of AI applications adopted by contemporary institutions fall within this category, particularly in areas such as data analytics and decision support systems.

Leveraging specialized algorithms, Artificial Narrow Intelligence (ANI) optimizes operational performance and decision quality in structured tasks. This alignment fosters Augmented Rationality, where machine intelligence extends human analytical capacity rather than replacing it.

b. Artificial General Intelligence (AGI)

Artificial General Intelligence (AGI), also known as Strong AI, refers to systems that possess generalized cognitive abilities comparable to those of humans. Such systems would be capable of understanding, learning, and applying knowledge across a wide range of tasks, enabling them to solve diverse and unfamiliar problems autonomously.

AGI is often associated with advanced robotic systems capable of performing multiple functions and making context-sensitive decisions. However, achieving this level of intelligence remains highly challenging, as it requires the development of complex neural architectures comparable to the human brain.

In this regard, Mark Coeckelbergh (2020) argues that reaching advanced levels of AI—particularly AGI—remains problematic both theoretically and practically. This limitation stems not only from current technological constraints but also from unresolved philosophical questions related to the nature of human consciousness and understanding. Consequently, the full simulation of human cognitive capacities remains a distant objective.

c. Artificial Superintelligence (ASI)

Artificial Superintelligence (ASI) represents a hypothetical form of AI that surpasses human intelligence across all domains, including reasoning, learning, planning, communication, and decision-making. Such systems

would outperform even the most highly skilled human experts.

Despite its conceptual significance, ASI remains purely theoretical and has not yet been realized in practice. It continues to be explored primarily within speculative and future-oriented research, raising profound ethical and governance concerns.

2.2 Decision Quality

2.2.1. The Concept of Quality

Armand V. Feigenbaum defines quality as the process of identifying and meeting customer needs and expectations, rather than being determined solely by markets or managerial perspectives within organizations. In this sense, quality is fundamentally grounded in the customer's experience of the product or service relative to their expectations and requirements.

Accordingly, Feigenbaum outlines several fundamental principles: (Damas, 2011, p. 147)¹⁹

- Quality must be defined in relation to the boundaries of customer requirements and expectations.
- Quality is multidimensional and should be understood holistically.
- Since customer needs and expectations evolve over time, quality management strategies must remain adaptive and responsive to anticipated changes.

The concept of decision quality has evolved significantly in the context of integrating Artificial Intelligence technologies. It is no longer confined to the accuracy of the final output; rather, it encompasses the efficiency of the technological process and its ethical integrity. The main conceptual perspectives can be outlined as follows:

a. From the Perspective of Accuracy and Predictive Efficiency

Decision quality is defined by the organization's ability to reduce reliance on error-prone human intuition and replace it with data-driven insights generated through the analysis of large-scale datasets (Big Data). This transformation enables faster and more effective outcomes, while enhancing the capacity to predict future patterns and trends. Consequently, it strengthens organizational performance and reduces uncertainty within decision-making environments²⁰—reflecting the operationalization of Augmented Rationality.

b. From the Perspective of Transparency and Explainability

Within algorithmic environments, decision quality is closely linked to the principle of Explainability. A high-quality decision is one that allows

managers to understand the logical reasoning process through which the system arrives at its conclusions. This transparency is essential to mitigate the risks associated with Algorithmic Opacity, commonly referred to as the “black box” problem, which undermines trust and accountability in AI-driven decisions.²¹

c. From the Perspective of Fairness and Ethical Considerations

From an ethical standpoint, decision quality is defined by the extent to which algorithmic outputs are free from Algorithmic Bias. High-quality decisions are grounded in comprehensive, balanced, and non-discriminatory datasets. This ensures fairness and integrity toward all stakeholders and prevents the reproduction of historical or social biases through technological systems—particularly those embedded in institutional data and algorithmic design²².

d. From the Perspective of Competitive Advantage and Organizational Value

Strategically, decision quality functions as a 'Decision Advantage' that fosters sustainable competitive superiority. By transforming data into proactive actions through robust governance and continuous learning, organizations can mitigate risks and drive growth within complex, uncertain environments.²³

2.2.2. Rational Decision-Making in Herbert Simon's Perspective

Rational decision-making, in the perspective of Herbert A. Simon, is the outcome of achieving a practical balance between organizational rationality and individual rationality within the framework of bounded rationality. Given that managers occupy formal positions within organizational structures, they are required to establish a careful alignment between their personal objectives and the strategic goals of the organization in order to ensure its continuity and sustainability.

This perspective is consistent with the concept of Organizational Equilibrium, which assumes that individuals operate within a collective system, and that their decisions are influenced by the extent of their effective participation in the decision-making process. Such participation is driven by their perception that involvement contributes to the satisfaction of their needs. This equilibrium is based on a reciprocal relationship between individual contributions and the rewards received, thereby ensuring alignment between individual interests and organizational objectives²⁴

While Simon emphasized the cognitive limitations that prevent individuals from achieving full rationality, the emergence of Artificial Intelligence represents a technological attempt to extend the boundaries of this bounded rationality. However, this expansion must remain governed by the principles of organizational equilibrium, ensuring that decision automation does not undermine individual participation or disrupt the reciprocal relationships upon which organizational stability depends.

Decision-Making Process According to Simon

Within the field of decision engineering, Simon argues that:

“Decision-making involves intelligence, design, and choice. Each stage is essential, and the effectiveness of decisions depends not only on the quality of choice but also on the quality of execution”.²⁵

Accordingly, the decision-making process is structured into three sequential stages:²⁶

1. Intelligence Stage

This stage involves scanning the environment and identifying problems or opportunities facing the organization. Decision-makers collect relevant data, diagnose the current situation, and seek to understand the root causes of issues in order to prepare for appropriate interventions. In contemporary contexts, this stage is significantly enhanced by AI-driven data analytics, which enable early detection of patterns and anomalies.

2. Design Stage

At this stage, alternative solutions and strategic options are developed and analyzed. It includes a systematic evaluation of the advantages and disadvantages of each alternative, as well as the simulation of potential outcomes associated with different courses of action. AI systems contribute here by rapidly generating and assessing multiple strategic scenarios.

3. Choice Stage

This stage involves selecting the most appropriate—or most satisfactory—alternative based on both quantitative and qualitative analyses. It requires a high degree of human judgment, intuition, and creativity to ensure the quality of the final decision. Despite technological support, human oversight remains essential, particularly in complex and ambiguous contexts.

Simon's model gains renewed relevance in the digital era as AI extends the boundaries of bounded rationality. By addressing psychological and

behavioral constraints like stress and uncertainty, AI acts as a critical enabler across all decision stages: in Intelligence, it leverages Big Data to detect patterns and anticipate emerging issues; in Design, algorithms rapidly generate and evaluate strategic alternatives; and in Choice, predictive analytics reduce uncertainty to optimize outcomes. This synergy fosters Augmented Rationality and Hybrid Decision-Making, where human expertise and machine intelligence interact to produce informed, adaptive, and high-quality organizational decisions.

3. Applications of Artificial Intelligence and Their Impact on the Quality of Organizational Decision-Making Stages

This section moves from theoretical frameworks to practical applications by examining key AI technologies, including AI-driven analytics and Machine Learning. It highlights how these technologies reshape managerial mechanisms, shifting decision-making from intuitive and reactive approaches to a proactive, data-driven paradigm characterized by greater accuracy and predictive reliability.

3.1 Key Applications and Technologies of Artificial Intelligence in Supporting Administrative Decision-Making

The business environment has undergone a fundamental transformation in how information is processed, as organizations have moved beyond reliance on traditional statistical methods toward adopting integrated intelligent systems. These applications can be classified, according to their role in supporting decision-makers, as follows:

a) Intelligent Decision Support Systems (IDSS)

Intelligent Decision Support Systems (IDSS) are defined as the integration of information systems with expert knowledge to support managers in the decision-making process. These systems are particularly effective in addressing complex problems faced by top management, enhancing decision accuracy, effectiveness, efficiency, and flexibility. Additionally, they are characterized by user-friendly interactive interfaces that facilitate human–system dialogue²⁷.

Historically, decision support systems evolved from simple databases and traditional Expert Systems—which relied on explicitly encoded human knowledge and fixed inference rules (If–Then logic)—to advanced intelligent systems based on Machine Learning, capable of self-learning from data. This

transformation explains their superior ability to detect complex patterns and respond dynamically to environmental changes in real time, thereby providing organizations with greater strategic agility and anticipatory capacity.

A recent study by Górka et al. (2025) indicates that AI is widely adopted across organizations, particularly in data analytics and decision support. The findings demonstrate that AI enhances decision-making processes by increasing speed, accuracy, and managerial effectiveness. However, despite these advantages, several challenges persist, including employee resistance and high implementation costs. These dynamics contribute to redefining the limits of Bounded Rationality, transitioning toward a model of Algorithmically Augmented Rationality, where human cognition is systematically enhanced by algorithmic capabilities.

b) Big Data Analytics

Artificial Intelligence (AI) represents one of the most disruptive technological transformations reshaping organizational operations and decision-making processes. It provides advanced capabilities in data collection, analysis, and trend prediction, thereby facilitating the transition toward Data-Driven Decision-Making. This shift enhances efficiency, accuracy, and overall managerial effectiveness. It is primarily enabled by Machine Learning and Deep Learning techniques, which allow systems to iteratively learn from data and continuously improve their performance over time.

Within this context, Big Data Analytics constitutes one of the most critical AI applications, enabling the extraction of strategic insights from vast volumes of structured and unstructured data characterized by the well-known dimensions of Volume, Velocity, and Variety. These capabilities directly support the stages of decision-making according to Herbert A. Simon's model (intelligence, design, and choice) by improving problem diagnosis, enhancing the development of alternatives, and strengthening the quality of final decisions.

Moreover, these technologies empower organizations to address complex problems that exceed the capabilities of traditional systems, while enhancing strategic responsiveness and enabling sustainable competitive advantage. Empirical evidence suggests that AI facilitates the rapid and efficient analysis of massive datasets, resulting in more accurate and effective decisions (Prasanth, 2023, p. 1)²⁸.

However, the adoption of Big Data Analytics also raises several challenges, including data privacy concerns, information security risks, ethical considerations, and workforce implications. Furthermore, the quality of decisions remains inherently dependent on the quality of the underlying data. This necessitates the adoption of responsible and balanced governance approaches to ensure the optimal realization of value from these technologies.

c) Machine Learning and Predictive Analytics

Machine Learning represents a foundational pillar of predictive analytics and plays a transformative role in business analytics and organizational decision-making. Through AI-driven capabilities, organizations can analyze historical data and develop predictive models that anticipate future trends and support the formulation of proactive and more accurate strategies within the framework of Bounded Rationality, as conceptualized by Herbert A. Simon.

These predictive models provide real-time insights that accelerate responses to market changes and reduce uncertainty in dynamic environments. This transformation significantly reduces reliance on intuitive human judgment by automating data-driven decisions, thereby enhancing operational efficiency and predictive accuracy.

In this context, AI increasingly integrates with Business Intelligence (BI) tools to extract deeper insights from complex datasets in real time. This integration enables organizations to optimize resource management, improve supply chain performance, and achieve operational excellence²⁹.

Consequently, Machine Learning and Predictive Analytics represent a paradigm shift from reactive management to proactive management, significantly enhancing decision quality and supporting the development of sustainable competitive advantage.

d) Robotic Process Automation (RPA) and Virtual Agents

Artificial Intelligence (AI), through Machine Learning and Deep Learning techniques, enables organizations to extract actionable insights from data and support a wide range of administrative functions, including marketing, financial management, risk management, and supply chain operations. Supervised and unsupervised learning algorithms are employed to analyze customer behavior, identify market patterns, and optimize pricing strategies, while Deep Learning techniques facilitate the processing of unstructured data—such as text and images—to support sentiment analysis

and trend forecasting.

Furthermore, AI's predictive capabilities extend to various financial domains, including fraud detection, risk assessment, and cash flow forecasting, as well as strategic planning and decision-making through regression-based predictive models. In this context, the automation of routine processes through Robotic Process Automation (RPA) and intelligent virtual agents powered by Natural Language Processing (NLP) enables real-time operational decision-making with high efficiency and continuous availability.

This transformation reduces reliance on human judgment in routine tasks while enhancing operational efficiency and minimizing errors. Consequently, it allows top management to focus on more complex strategic decisions within a framework of Hybrid Intelligence, where human cognition and machine capabilities are integrated. Moreover, these technologies contribute to redistributing managerial effort by transferring programmed decisions to intelligent systems, thereby enabling executives to concentrate on non-programmed, strategic decisions—reflecting a fundamental shift in the role of decision-makers in line with Herbert A. Simon's model.

As a result, these applications enhance organizational performance, reduce operational costs, improve customer experience, and support innovation and sustainability in modern business environments³⁰. This directly impacts decision quality in terms of speed, accuracy, and consistency. However, such automation also raises challenges related to transparency and algorithmic accountability, particularly due to the difficulty of interpreting certain algorithmic decisions—commonly referred to as Algorithmic Opacity. This underscores the need for robust governance frameworks to regulate AI-driven decision-making processes.

3.2 The Impact of Artificial Intelligence on Decision-Making Stages (Simon's Model)

Artificial Intelligence (AI) has not merely introduced new technological tools into organizations; it has fundamentally transformed the dynamics through which decisions are made. Drawing on the classical model of Herbert A. Simon, this transformative impact can be traced across the three core stages of the decision-making process as follows:

a) Impact on the Intelligence Phase: Proactive Environmental Scanning

In traditional approaches, this phase relies primarily on managers' ability to search for problems or opportunities within the organizational environment. However, with the integration of AI, this stage has evolved into a process of continuous and automated environmental scanning. Through Big Data Analytics, intelligent systems can process millions of records and detect hidden patterns that exceed human cognitive capabilities (Pattern Recognition).

Kumar and Kumar (2024) emphasize that AI algorithms possess the ability to identify patterns that are not perceptible to humans, thereby generating proactive insights that enable organizations to detect problems—or opportunities—before they fully emerge. This significantly enhances the quality and effectiveness of the intelligence phase.

b) Impact on the Design Phase: Algorithmic Generation of Alternatives

Traditionally, the design phase has been constrained by the concept of Bounded Rationality, as formulated by Herbert A. Simon, where decision-makers generate a limited set of “satisficing” alternatives rather than seeking optimal solutions, due to cognitive and informational limitations.

However, advancements in AI—particularly in Predictive and Prescriptive Analytics—have fundamentally transformed this phase through what can be termed Algorithmic Alternative Generation. AI systems are no longer limited to proposing conventional solutions; instead, they can simulate thousands of potential scenarios for each alternative and analyze their future implications with high precision.

This transformation leads to a significant expansion of the decision space (Decision Space Expansion) and reduces reliance on intuitive human judgment. Empirical studies confirm that AI enables organizations to leverage historical data in developing more accurate and forward-looking strategies, thereby enhancing the quality of proposed alternatives and facilitating a shift toward Augmented Rationality³¹

Consequently, the design phase evolves from a constrained process of limited alternative generation into a systematic exploration of a broad strategic landscape based on modeling and simulation rather than intuition and trial-and-error.

c) Impact on the Choice Phase: Reducing Uncertainty and

Enhancing Decision Trade-offs

The choice phase represents the most complex stage in the decision-making process, as it is inherently associated with high levels of uncertainty and risk. Traditionally, it relies heavily on human judgment, which is often influenced by cognitive biases and perceptual limitations.

In this context, Artificial Intelligence (AI) emerges as a strategic partner, whose role extends beyond merely supporting decisions to fundamentally reshaping the logic of evaluation and selection. Through expert systems and Machine Learning applications, decision-makers are provided with precise probabilistic assessments (Probabilistic Scoring) for each alternative. These include estimations of success and failure probabilities, risk levels, and confidence intervals (Confidence Levels), thereby reducing uncertainty and transforming decision-making from an intuitive process into an evidence-based analytical procedure.

Furthermore, AI contributes to mitigating human cognitive biases, such as confirmation bias and availability bias, by offering objective evaluations grounded in large-scale data analysis. However, this role is not without challenges. Algorithmic models—particularly those based on Deep Learning—introduce the “black box” problem, which limits the interpretability of decisions and creates a tension between predictive accuracy and decision transparency, commonly referred to as Algorithmic Opacity.

Shrestha et al. (2019) highlight Hybrid Human–AI Decision-Making as an integrative model that combines machine speed, scalability, and consistency with human contextual and ethical judgment. In this framework, AI functions as a filter, evaluator, or partner, improving decision trade-offs and reducing cognitive biases. Consequently, the choice phase shifts from intuition-based selection to a probabilistic, data-driven process, while human oversight ensures transparency and accountability.

3.3 Strategic Challenges of AI Adoption in Decision-Making

a) Data Quality and Technical Integrity

The effectiveness of AI-driven decision-making is fundamentally contingent upon the quality, reliability, and integrity of input data. Inaccurate, incomplete, or biased datasets can significantly distort analytical outputs, leading to misleading conclusions—a phenomenon commonly referred to as “Garbage In, Garbage Out.” This limitation directly undermines the intelligence phase of decision-making, where problem identification and

environmental scanning rely heavily on accurate and comprehensive data inputs. Consequently, poor data quality compromises the foundational validity upon which subsequent decision stages are constructed, thereby weakening overall decision quality.

b) Algorithmic Opacity (The Black Box Problem)

The increasing reliance on complex Machine Learning and Deep Learning models introduces a critical challenge related to algorithmic opacity. The “black box” nature of these systems limits the interpretability of decision processes, making it difficult for managers to understand, justify, or challenge AI-generated recommendations. This lack of explainability weakens the choice phase, where transparency and accountability are essential for validating decisions. As a result, reduced interpretability may erode trust in AI systems and negatively affect decision legitimacy within organizational contexts.

c) Organizational Resistance and AI Literacy

Human and organizational factors represent significant barriers to the effective adoption of AI systems. Resistance to technological change—often driven by concerns over job displacement—and insufficient levels of AI literacy among decision-makers can hinder the successful integration of intelligent systems into managerial processes. These constraints particularly affect the design and choice phases, where effective human–AI interaction is essential for evaluating alternatives and making informed decisions. Consequently, the strategic potential of AI may remain underutilized due to limited organizational readiness.

d) Ethical and Legal Accountability

The delegation of decision-making authority to autonomous or semi-autonomous systems raises complex ethical and legal challenges. The difficulty of assigning responsibility for AI-driven outcomes—particularly in cases involving bias, discrimination, or unintended harm—creates ambiguity in accountability frameworks. This issue affects all stages of decision-making but is especially critical in the choice phase, where ethical considerations and fairness are central to decision quality. In the absence of clear governance mechanisms, these challenges may undermine both organizational trust and institutional legitimacy.

4. Discussion

4.1. The Impact of AI on Decision Quality (Support for H1)

The analysis confirms that Artificial Intelligence (AI) has evolved from a supportive tool into a strategic enabler that reshapes the logic of organizational decision-making. These findings provide strong support for H1, demonstrating that AI-driven analytics and simulations enhance effectiveness across all stages: improving accuracy in the intelligence phase, expanding the decision space in the design phase, and mitigating cognitive biases in the choice phase. This qualitative transition from reactive to proactive, data-driven models significantly strengthens organizational adaptability in complex environments.

4.2. Ethical and Organizational Constraints (Validation of H2)

Simultaneously, the study validates H2, highlighting that the impact of AI on decision quality is not inherently positive but contingent upon critical determinants. Technical issues (low data quality), governance challenges (algorithmic opacity), and organizational barriers (resistance to change and literacy gaps) can undermine the legitimacy of AI-driven outcomes. These findings emphasize that without robust governance and transparency mechanisms, AI may introduce new risks, demonstrating that technological efficiency must be balanced with ethical oversight to ensure high-quality decisions.

4.3. Implications for Augmented Rationality

Ultimately, the study demonstrates that decision quality in the digital era is best understood through the lens of Augmented Rationality. This hybrid paradigm integrates machine computational precision with human ethical judgment and strategic reasoning. In this framework, AI enhances predictive capacity while human oversight ensures accountability and contextual understanding. Consequently, achieving organizational excellence requires an integrative model grounded in the interaction between data quality, algorithmic transparency, and effective human leadership.

5. CONCLUSION

This study contributes to the growing literature on Artificial Intelligence and decision-making by proposing an integrated framework that explains how AI enhances decision quality through the lens of augmented rationality.

The findings demonstrate that Artificial Intelligence (AI) has evolved beyond a supportive technological tool into a strategic and integrated system that combines analytical, predictive, ethical, and strategic dimensions, thereby

fundamentally reshaping the logic of decision-making within contemporary organizations. This transformation enhances organizations' ability to operate effectively in complex and uncertain environments. Within the framework of Herbert A. Simon's decision-making model, AI extends the limits of bounded rationality by improving decision quality across all stages of the decision-making process.

Specifically, AI applications—including Intelligent Decision Support Systems, Big Data Analytics, Machine Learning algorithms, and intelligent automation—play a critical role in enhancing problem identification in the intelligence stage, expanding the range of alternatives in the design stage, and supporting more precise evaluations in the choice stage by reducing uncertainty and mitigating cognitive biases. Importantly, the study emphasizes that the true value of AI lies not in replacing human decision-makers, but in fostering a model of Augmented Decision-Making based on the integration of machine computational capabilities with human strategic and ethical judgment. This integration enables organizations to shift from reactive and intuition-based decision-making toward proactive, data-driven approaches that enhance both efficiency and effectiveness.

However, achieving high-quality decision-making in the digital era remains contingent upon several critical determinants, particularly data quality, algorithmic transparency, and organizational readiness. Decision quality, therefore, cannot be understood as a purely technological outcome, but rather as an integrative construct emerging from the interaction between technological capabilities, human judgment, and governance structures.

Ultimately, this study underscores that the future of organizational decision-making lies in balancing technological advancement with ethical responsibility, positioning human–AI collaboration as a central pillar for achieving sustainable and high-quality decisions in increasingly complex environments.

Based on these findings, several strategic recommendations can be formulated to enhance the effective and responsible adoption of AI in organizational decision-making.

First, organizations should adopt comprehensive AI and data governance frameworks by establishing clear regulatory and ethical guidelines that ensure algorithmic transparency, mitigate bias, protect data privacy, and define legal accountability for AI-supported decisions.

Second, there is a need to transition toward hybrid decision-making structures by developing integrative organizational models that combine technical expertise with managerial judgment, ensuring that algorithmic recommendations are critically evaluated in light of human, ethical, and organizational considerations.

Third, AI should be strategically leveraged in public policy design and evaluation through the use of predictive analytics to support evidence-based economic and social policies, particularly in areas such as economic empowerment, thereby enhancing resource allocation efficiency and ensuring the sustainability of development programs.

Finally, enhancing AI literacy and human capital development is essential, which requires continuous training programs that enable decision-makers to effectively understand, interpret, and utilize AI-generated outputs.

This study opens new research avenues toward empirically validating augmented decision-making models in real organizational contexts.

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