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# Developing a Conceptual Framework for the Role of Artificial Intelligence in Strategic Decision-Making Cycle: A Systems Approach

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## Abstract

Recent research indicated that despite extensive investments in artificial intelligence (AI), many organizations have yet to fully leverage its potential in strategic decision-making. This study integrated fragmented evidence on the role of AI across the stages of strategic decision-making and developed a conceptual framework based on the systems approach encompassing input, process, and output stages. Using a structured literature review, 55 articles published between 2019 and 2025 were retrieved from Scopus, Web of Science, and Google Scholar and analyzed using Braun and Clarke's (2006) six-phase thematic analysis, supported by MAXQDA 2024. The findings indicated that, at the input stage, AI enhanced the quality of decision-making inputs through predictive analysis, data processing, strategic intelligence enhancement, and key stakeholder analysis. At the process stage, automation, risk identification, scenario modeling, enhanced decision rationality, and resource optimization improved decision-making efficiency and agility. At the output stage, improved business performance, adaptive and innovative strategy execution, strategic performance evaluation, and data-driven competitive advantages were identified. In addition, organizational, human, ethical, legal, data-related, privacy, security, and transparency-related challenges emerged as cross-cutting conditions that may influence all three levels of the decision-making cycle. The study's contribution lies in developing an integrated systems framework that links inputs, processes, and outputs while accounting for feedback among these levels.

## Keywords

Artificial Intelligence, Strategic Decision-Making, Systems Approach, Thematic Analysis, Structured Review

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## Introduction

Digital transformation and the increasing complexity of business environments have confronted organizations with growing volumes of data, uncertainty, and the need to respond rapidly to environmental changes. Under these conditions, strategic decision-making, as one of the most critical organizational processes, increasingly requires analytical and informational capabilities. With its ability to process large volumes of data, identify patterns, and provide predictive analyses, AI has become an important technology for supporting organizational and strategic decision-making (Berente et al., 2021; Trunk et al., 2020). This relevance has continued to grow in the most recent literature. The emerging work explicitly frames AI not merely as an analytical add-on but as a structural driver reshaping how organizations sense opportunities, evaluate alternatives, and commit resources under uncertainty (Saura et al., 2026) , while the topic has simultaneously gained prominence in leading practitioner-oriented outlets, underscoring its immediacy for both scholars and managers (Csaszar, 2026). However, the value of AI in decision-making is not limited solely to its computational capabilities; rather, combining the analytical capabilities of AI with human judgment, experience, and contextual understanding can improve the quality and speed of decision-making under complex and uncertain conditions (Jarrahi, 2018; Shrestha et al., 2019).

Despite these capabilities, the integration of AI into strategic decision-making continues to face significant challenges. Overreliance on algorithms, ethical issues, interpretability limitations, and human resistance to technology are among the factors that can constrain the effectiveness of AI in organizational decision-making (Keding & Meissner, 2021). Moreover, despite increasing investments in AI, many organizations continue to face barriers such as insufficient understanding of the capabilities of this technology, incompatibility between the existing structures and intelligent tools, and difficulties in integrating AI into decision-making processes (Bean, 2021; Enholm et al., 2022). A recent systematic review of managerial decision-making literature reinforced this concern, showing that the strategic value of AI lies not in full automation but in augmenting human judgment—an orientation that introduces new governance and responsibility challenges that organizations have yet to resolve (García López & Nájera Ochoa, 2026). Consistent with this pattern, a recent multiple case study of manufacturing SMEs found that, despite AI's potential to improve the quality, speed, and decentralization of international strategic decisions, the firm-level adoption remains cautious and incremental rather than systematic (Aiudi et al., 2026). From this perspective, the fundamental issue is not simply what capabilities AI possesses, but rather which parts of the strategic decision-making cycle these capabilities are applied to, through what mechanisms, and with what consequences.

Strategic decision-making is particularly important in this regard because it is not a single or linear process; rather, it is a complex and iterative process in which information, analysis, choice, implementation, and the consequences of decisions influence one another (Mintzberg, 1972; Moreira & Tjahjono, 2016). The existing literature has examined various dimensions of the role of AI in decision-making, ranging

from information processing and data analysis to supporting cognitive activities and designing human–AI structures (Jarrahi, 2018; Shrestha et al., 2019; Trunk et al., 2020). However, these streams of research have predominantly focused on specific capabilities, stages, or applications, while the conceptual position and interrelationships of AI roles across the strategic decision-making cycle have received less integrated attention. This fragmentation persists even in the most recent literature. Reviews published as recently as 2026 continue to describe the evidence based on AI and strategic decision-making as dispersed across management, information systems, and organizational studies, without a coherent structure connecting the informational, procedural, and outcome-related roles of AI within a single decision cycle (Saura et al., 2026). Recent quantitative studies illustrated this pattern as well. For instance, a 2026 survey-based analysis using PLS-SEM demonstrated that strategic AI influences decision-making quality and, through it, business performance, but examined this relationship as a set of discrete constructs rather than as a structured input–process–output cycle (Riya & Mukherji, 2026). Consequently, there is still no coherent picture of how AI enters the decision-making processes by enhancing informational inputs and how these processes are associated with different outcomes. Addressing this issue requires a framework capable of organizing fragmented evidence according to its position within the decision-making cycle. The input–process–output logic provides such an opportunity. A similar logic was employed by Akbari Emami et al. (2023) to organize applications of AI in human resource management, and the present study extends this logic to the domain of strategic decision-making by considering the three levels of input, process, and output as its analytical structure.

In this context, a systems approach can provide an appropriate framework for integrating this body of literature. In the present study, strategic decision-making is conceptualized as a set of interdependent and interacting elements that constitute a dynamic system characterized by interrelationships, dependencies, and feedback loops among its components (Koch et al., 2009; Senge, 2006). Accordingly, the application of AI in strategic decision-making can be examined through the relationships among inputs, decision-making processes, and outputs, while decision outcomes and the learning derived from them may influence the information and conditions underlying subsequent decisions. Such a perspective makes it possible to analyze the role of AI not as an isolated tool operating at a single point in decision-making, but as part of a dynamic and interconnected cycle.

Accordingly, the present study sought to identify and organize the applications of AI throughout the strategic decision-making cycle from a systems perspective by conducting a structured literature review and thematic analysis of the existing studies. The objective of the study was to integrate the fragmented evidence concerning the role of AI across the three levels of input, process, and output in strategic decision-making and to develop a conceptual framework for organizing and explaining the relationships among these levels. Accordingly, the main research question is: How is the role of AI across different levels of the strategic decision-making cycle conceptualized? Three

subsidiary questions are also addressed: (1) What themes and applications of AI are identified in the inputs of the strategic decision-making cycle? (2) What themes and applications of AI are identified in strategic decision-making processes? and (3) What themes and applications of AI are identified in the outputs of strategic decision-making?

## Literature Review

### Artificial Intelligence (AI)

AI has been defined in the literature from several complementary perspectives. From a capability-based perspective, AI is described as a set of computational methods and systems that provide learning from data, pattern recognition, prediction, language processing, optimization, and decision support (Chong et al., 2022; Mikalef & Gupta, 2021). A closely related, task-oriented definition characterizes AI as machines' ability to learn from experience, adapt to new inputs, and perform tasks that would otherwise require human intelligence (Duan et al., 2019; Manyika et al., 2017). A third stream of definitions emphasizes imitation of human cognitive behavior, describing AI as technologies capable of mimicking intelligent human behavior and decision-making (Clifton et al., 2020; Ma & Sun, 2020). Earlier foundational work framed AI even more broadly, as systems that exhibit intelligence or as techniques enabling machines to perform tasks normally requiring human intelligence (Bolander, 2019; Huang et al., 2019; Piscopo & Birattari, 2008; Simon, 1995 ).

Across these perspectives, two elements recur: (a) the algorithmic processing of data to generate insight, and (b) the capacity to support or partially substitute human cognitive and decision-related tasks. In the present study, AI is defined, consistent with the capability-based and task-oriented streams above, as a set of algorithmic systems that process large volumes of structured and unstructured data to learn patterns, generate predictions, and support or automate specific components of human decision-making (Chong et al., 2022; Duan et al., 2019; Russell & Norvig, 2016). This definition was adopted because it is broad enough to encompass the heterogeneous AI applications reported in the reviewed literature—ranging from predictive analytics to generative language models—while remaining specific enough to distinguish AI from generic information technology or automation tools that do not involve learning or pattern-based inference.

### Strategic Decision-Making

Strategic decision-making has similarly been conceptualized in different, though overlapping, ways. The process-oriented definitions describe it as a multistage sequence involving the identification of opportunities and threats, generation and evaluation of alternatives, choice, implementation, and monitoring (Elbanna, 2006; Mintizberg & Quinn, 1998). The outcome-oriented definitions instead emphasize the consequences of such decisions, characterizing strategic decisions as those that are important in terms of the actions taken, the resources committed, or the precedents set, and that are difficult to reverse once implemented (Eisenhardt, 1997; Papadakis et al., 2010). A third,

comparative perspective distinguishes strategic decisions from tactical and operational ones on the basis of the scope of their consequences, the level of uncertainty involved, and their long-term, organization-wide impact (Elbanna & Child, 2007; Mintzberg, 1972; Shafie et al., 2017).

For the purposes of this study, strategic decision-making is defined, following the process-oriented tradition, as a multistage and iterative organizational process through which information is gathered and interpreted, alternatives are generated and evaluated, a course of action is selected and implemented, and outcomes are monitored and fed back into subsequent decisions (Elbanna, 2006; Mintzberg, 1972; Papadakis et al., 2010). This process-based definition was adopted, rather than a purely outcome-based one, because it aligns directly with the input–process–output logic used to structure the present review and makes it possible to situate specific AI applications at identifiable stages of the decision cycle rather than treating strategic decision-making as a single undifferentiated event.

Within this process, AI can support the identification of opportunities and threats, the processing of large volumes of information, the generation and evaluation of alternatives, and the monitoring of outcomes. However, strategic decision-making remains subject to uncertainty, managerial judgment, conflicting stakeholder interests, and cognitive biases (Elbanna, 2006; Kahneman et al., 2016). Accordingly, the role of AI should be examined in relation to the different stages and activities through which strategic decisions are developed, implemented, and evaluated.

### Prior Research Streams on AI and Strategic Decision-Making

Previous research on AI and strategic decision-making can be organized into six complementary streams. Although these streams have advanced understanding of specific aspects of AI-supported decision-making, they have generally examined individual capabilities, organizational conditions, or outcomes rather than integrating the entire decision-making cycle.

The first stream focused on human–AI interaction. Shrestha et al. (2019), Schneider and Leyer (2019), and Trunk et al. (2020) examined different forms of human–AI collaboration, while Chernov et al. (2020) and Keding and Meissner (2021) highlighted ethical considerations and managerial reliance on AI advice. More recent research has sought to develop broader typologies of human–AI collaboration, emphasizing the importance of how decision authority and responsibility are distributed between humans and AI (Liu & Shen, 2025; Li & Tian, 2026). To sum up, these studies demonstrated that AI's contribution depends strongly on the configuration of human–AI collaboration.

The second stream examined the organizational frameworks for AI integration. Rajagopal et al. (2022) and Pratt et al. (2023) proposed frameworks for aligning AI and decision intelligence with organizational objectives. Recent studies further emphasized organizational readiness, governance, leadership, data quality, and human oversight as conditions shaping AI adoption and strategic decision-making (Aiudi et al., 2026; Islam Tohfa et al., 2026; Rivero, 2025; Saup et al., 2026 ). These studies indicated that AI

effectiveness depends not only on technical capabilities but also on its organizational embedding.

The third stream addressed sectoral and industrial applications of AI, including marketing, finance, leadership, and business consulting (Al-Bayed et al., 2024; Özemre & Kabadurmus, 2020; Volkmar et al., 2022). While these studies demonstrated the practical value of AI across different contexts, their sector-specific focus provided limited insight into AI's role across the complete strategic decision-making cycle.

The fourth stream concerned adoption barriers and ethical, cultural, and organizational factors. Previous studies have identified challenges such as limited trust, restrictive regulations, cultural resistance, and organizational constraints (Booyse & Scheepers, 2023; Gudigantala et al., 2023; Volkmar et al., 2022). Recent evidence further showed that AI outcomes vary across organizational contexts and that responsible AI requires governance, training, and organizational adaptation (Huang & Lin, 2025; Ruster & Daniell, 2025). Thus, AI-supported decision-making remains influenced by human, organizational, ethical, and contextual conditions.

The fifth stream focused on generative AI and large language models. Csaszar et al. (2024) showed that large language models can support the generation and evaluation of strategic options, while Doshi et al. (2025) examined their use in evaluating strategic decisions. More recently, Csaszar et al. (2026) proposed a framework distinguishing the cognitive hierarchy of strategic tasks from the degree of AI delegation. This literature reflected a shift from AI as an analytical support tool toward more active involvement in generating and evaluating strategic alternatives.

The sixth and most recent stream connected AI with systems thinking in decision-making. Qudrat-Ullah (2025) proposed integrating AI and systems thinking for decision-making in complex environments, while Kumar and Suthar (2026) examined how AI can reconfigure the decision premises underlying organizational decision-making. These studies reinforced the relevance of a systems perspective but remained focused on particular theoretical or organizational contexts rather than systematically connecting AI's role across the input, process, and output stages.

The studies conducted in Iran have also contributed to this field. Riahi et al. (2025) identified four dimensions of data-driven strategic decision-making in the AI era, while Masoumi et al. (2024) proposed a conceptual model for applying AI to strategic decision-making.

Overall, these six streams demonstrated substantial progress in understanding AI–decision-making relationships, but the literature remained fragmented across human–AI interaction, organizational integration, sectoral applications, adoption conditions, generative AI, and systems perspectives. Few studies provided an integrated account of how AI operates across input, process, and output levels and how these levels interact within a recurring strategic decision-making cycle. This gap motivates the systems-based framework developed in the present study.

All in all, these six streams showed that, although the existing literature—including its most recent 2025 and 2026 contributions—addressed diverse dimensions of the AI–

decision-making relationship, individual studies have predominantly focused on one of three areas: input capabilities, process mechanisms, or decision outcomes, or on a single organizational function, theoretical lens, or context, rarely integrating all three within a single structure. Even the most closely related recent work—whether it paired systems thinking with AI (Kumar & Suthar, 2026; Qudrat-Ullah, 2025), proposed multi-layer organizational frameworks for AI-augmented decision-making (Islam Tohfa et al., 2026; Rivero, 2025), or reframed strategy itself as a question of task-level delegation to AI (Csaszar et al., 2026)—stopped short of organizing AI's role in strategic decision-making according to a systems-based input–process–output logic. This gap directly motivates the systems-based, three-level framework adopted in the present study, in which the organization's strategic decision-making system is conceptualized as one where data and information constitute inputs, analytical and cognitive activities constitute the process, and decision outcomes constitute outputs, with AI operating as an intervening capability across all three levels rather than as an isolated tool.

This synthesis indicates that the novelty of the present study lies in the structured integration of the input, process, and output domains of strategic decision-making within a systems framework. Whereas prior studies have typically examined AI's role in decision-making through a specific analytical, empirical, or organizational lens—and even the most recent 2025–2026 contributions remained anchored to a single theoretical perspective, organizational function, or case context—the present study incorporates the interactions and feedback among the three levels of the decision cycle. In doing so, it moves beyond the fragmented examinations of AI applications toward a coherent account of the role of this technology throughout the strategic decision-making cycle, interpreting the diverse applications of AI according to their position within the architecture of strategic decision-making rather than as isolated tools.

## Methodology

### Research Approach and Analytical Framework

Drawing on the logic of the research onion, the methodological design of the study was structured across several distinct layers. From a philosophical perspective, the study adopted an interpretivist approach. In terms of the approach to knowledge development, the analysis followed a deductive–inductive logic. Regarding methodological choice, a qualitative approach was employed. The research strategy consisted of a systematic literature review and thematic analysis of the selected studies. The time horizon was cross-sectional and limited to studies published between 2019 and 2025. At the level of techniques and procedures, the selected studies were coded and analyzed using MAXQDA after the search and screening processes.

A systematic literature review was employed to identify the relevant studies, and the processes of identification, screening, and study selection were reported in accordance with the logic of the PRISMA 2020 framework (Page et al., 2021).

This study adopted a qualitative-analytical design, as it did not test pre-specified hypotheses through statistical inference; rather, it interpreted and synthesized textual

evidence from the literature by combining a predetermined analytical structure (input–process–output) with inductive coding, consistent with directed qualitative content analysis (Hsieh & Shannon, 2005). The analytical framework was informed by a systems perspective, which views organizational processes as interconnected elements whose relationships and feedback can influence the subsequent conditions and actions (Mele et al., 2010; Senge, 2006). Accordingly, the input–process–output structure was used to organize the analysis, with particular attention to the interrelationships among these levels rather than treating them as isolated stages. This systems logic provided the methodological basis for organizing the extracted codes and themes and for interpreting the strategic decision-making cycle as an interconnected process. The selection of these three analytical levels was based on the systems logic of the study and on the study by Akbari Emami et al. (2023), which addressed the design of an AI application framework using an exploratory approach. Accordingly, the input–process–output framework was employed as the organizing structure for the analysis, while the components, codes, and themes associated with each level were extracted and developed from the evidence available in the selected studies. This combination of a predetermined theoretical framework and data-driven thematic extraction enabled the simultaneous use of a coherent conceptual structure and the identification of new components emerging from the research literature (Elo et al., 2014; Vaismoradi et al., 2013).

### Search Strategy and Data Sources

The literature search was conducted on April 20, 2025, using three international databases ofScopus, Web of Science, and Google Scholar. The study population consisted of relevant scholarly articles published in these databases.

The search strategy was designed to identify studies related to the application of AI in strategic decision-making by combining two groups of terms related to “artificial intelligence” and “strategic decision-making”. The basic search string was as follows and was adapted to the search structure and rules of each database:

("Artificial Intelligence" OR "Machine Learning" OR "Natural Language Processing" OR "Deep Learning" OR "Neural Network" OR "ChatGPT") AND ("Strategic Decision-Making" OR "Strategic Decision Making")

At the identification stage, the retrieved records were examined based on the study's inclusion criteria. These criteria included document type (scholarly article), publication language (English), publication period (2019–2025), and relevance to the management and business domain. To avoid the premature exclusion of potentially relevant studies, the final assessment of the content relevance of the sources was conducted during the screening and full-text review stages.

The initial search retrieved 1,252 records from Scopus, 1,608 from Web of Science, and 1,099 from Google Scholar, yielding a total of 3,959 initial records. Following the consolidation of the results from the three databases, the records entered the screening process based on the specified criteria. The details of the exclusion, screening, and study-selection stages are presented in the following section.

## Study Selection and Screening Process

The study selection process was conducted in several stages to obtain a set of articles relevant to the research problem and objectives. In the first stage, the retrieved records were examined with respect to the specified publication period. Of the 3,959 initial records, 303 records were excluded because they fell outside the specified period, namely 2019–2025, leaving 3,656 records.

In the second stage, the titles and abstracts of the remaining studies were examined for relevance to the subject area of the research. A study was deemed relevant if it examined one or more AI capabilities or applications in direct relation to the formulation, analysis, selection, implementation, or outcomes of a decision that was explicitly strategic in nature. At this stage, 3,461 records were excluded because they lacked sufficient thematic relevance to the research domain, leaving 195 articles for further examination.

In the third stage, the remaining records were examined for duplication. As a result, 41 duplicate articles were removed, leaving 154 unique articles for content evaluation.

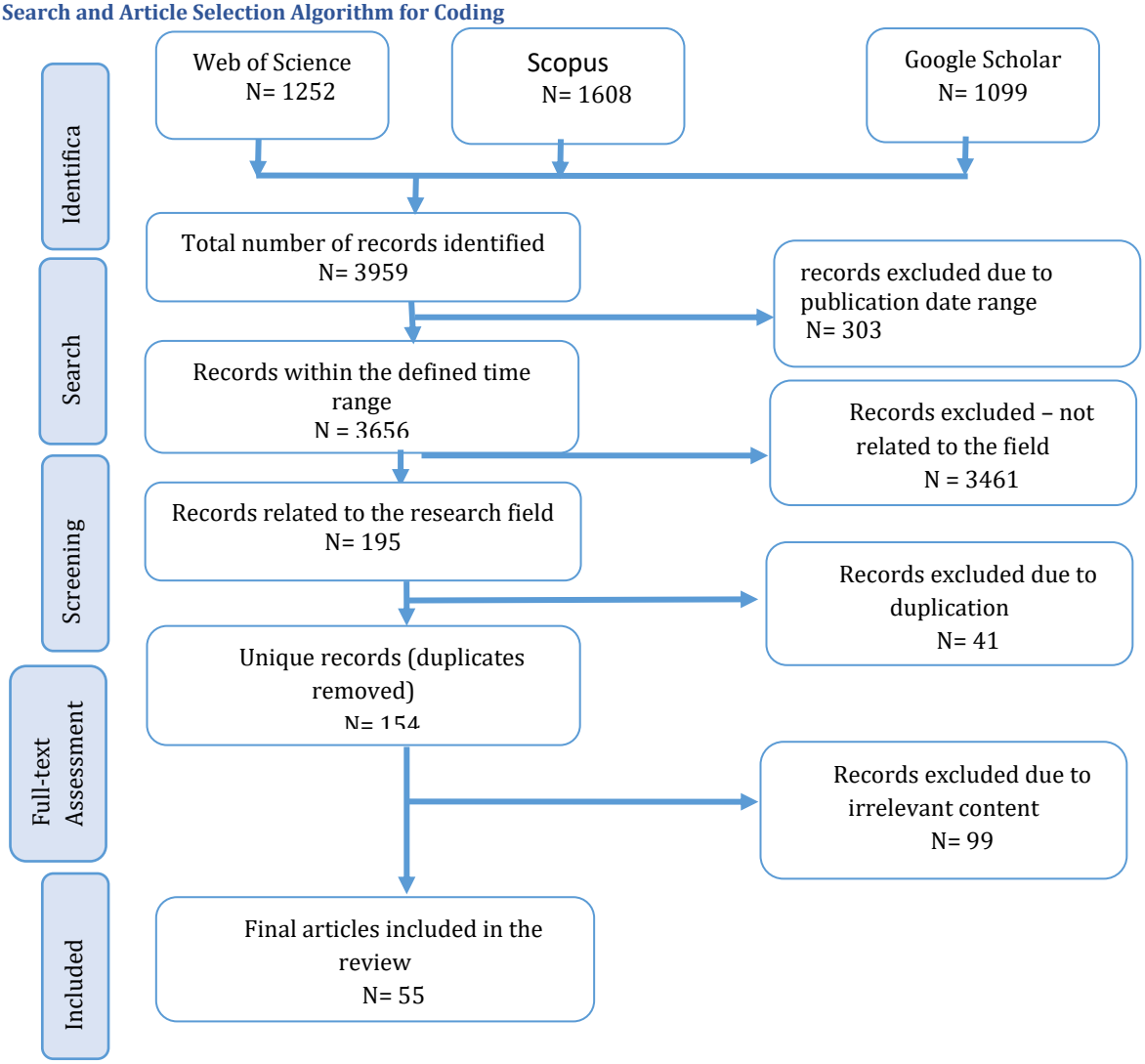
In the fourth stage, the full texts of the remaining studies were examined for their content alignment with the research problem and objectives. At this stage, 99 articles were excluded because their content was not relevant to the main research topic. Ultimately, 55 articles meeting the eligibility criteria were selected for analysis and coding. Thus, the study-selection process began with 3,959 initial records and, following the screening stages, resulted in 55 final studies.

**Table 1.**
**A Summary of the Source Screening Process**

| Stage | Process Description | Number (N) |
|---|---|---|
| Identification | Identification of records from the Scopus, Web of Science, and Google Scholar databases | 3,959 |
| Temporal Screening | Application of publication-year restrictions (2019–2025), English language, scholarly article document type, and the management and business subject area | 3,656 |
| Title and Abstract Screening | Examination of article titles, abstracts, and content, and assessment of their theoretical and conceptual alignment with the research objectives | 195 |
| Removal of Duplicate Articles | Number of unique articles | 154 |
| Final Selection | Selection of valid and relevant articles for inclusion in the analysis; coding and organization of data in MAXQDA 2024 | 55 |

**(Source: The Researcher's Findings)**

**Figure 1.**
**Search and Article Selection Algorithm for Coding**




**(Source: The Researcher's Findings and PRISMA 2020 (Page et al., 2021))**

## Thematic Analysis and Coding Process

At the initial stage, three overarching categories—input, process, and output—were considered as the initial deductive framework. Subsequently, within each category, codes and subthemes were inductively extracted from the findings of the studies. During the thematic analysis, challenges associated with the application of AI were identified across the different levels of the decision-making cycle rather than as a stage-specific category. Accordingly, the challenges were treated as a cross-cutting conceptual dimension that can arise at, and influence, the input, process, and output levels. This distinction was maintained in the subsequent organization and interpretation of the findings so that the challenges were not treated as a separate stage of the decision-making cycle. Data were analyzed using the six-phase thematic analysis model of Braun and Clarke (2006), supported by MAXQDA 2024. The six phases consisted of: familiarizing with the data through in-depth and repeated reading of the texts; extracting initial codes through the coding of salient meaning units; identifying and organizing themes by grouping similar codes into subthemes and main themes;

reviewing and refining the themes in terms of semantic coverage and internal coherence; defining and naming the themes based on their conceptual nature; and, finally, producing the final report. The data analysis was organized across three levels—input, process, and output—to maintain alignment with the systems framework of the study and to facilitate the identification and organization of the conceptual relationships and feedback patterns reported in the literature across these three levels. Challenges identified in the reviewed studies were not assigned to a specific stage because their nature and implications could extend across multiple levels of the decision-making cycle. They were therefore interpreted as a cross-cutting dimension that may affect the quality of inputs, shape decision-making processes, and influence strategic outcomes. This distinction allowed the three-stage structure to remain conceptually focused while incorporating challenges as conditions that can interact with and affect the entire cycle.

In this study, an initial coding occurrence represented an independently coded meaning unit concerning the role, application, process, or outcome of AI in strategic decision-making. Whenever a relevant meaning unit was identified in the text of a reviewed article, it was coded as a separate occurrence. Therefore, the same or a conceptually similar idea could generate multiple coding occurrences when it appeared repeatedly within or across the reviewed articles. These initial coding occurrences were subsequently compared and grouped based on semantic similarity and conceptual coherence. Conceptually related occurrences were consolidated into secondary codes, and related secondary codes were further organized into main themes within the three predefined levels of input, process, and output.

This analytical procedure was used to move from the detailed evidence reported in individual studies toward a more coherent conceptual structure. Accordingly, the analysis focused on identifying recurring concepts, their conceptual relationships, and their position within the input–process–output framework rather than treating individual coding instances as independent quantitative observations.

During this consolidation process, redundant or conceptually overlapping codes were reviewed and merged where appropriate, while codes that did not contribute meaningfully to the emerging conceptual structure were excluded.

To complement the occurrence-based coding frequency, article-level frequency was also calculated. The article frequency represents the number of reviewed articles in which a given code or theme was identified at least once, regardless of how many coding occurrences were recorded within that article. Thus, a single article could contribute multiple coding occurrences to a theme but only one count to its article-level frequency.

### Reliability and Trustworthiness of the Study

To assess the consistency of the coding process, 20% of studies included in the analysis (11 articles out of a total of 55 studies) were randomly selected and independently coded by two coders. The first coder extracted 1885 coding occurrences, while the second coder extracted 1793 coding occurrences, of which 1644 coding occurrences were agreed upon by both coders. The level of agreement was calculated using the Holsti

coefficient[1]. The resulting agreement coefficient indicated an appropriate level of agreement between the two coders in the examined sample. The resulting agreement coefficient was 89.3%, indicating an appropriate level of agreement between the two coders in the examined sample. Given that the reliability coefficient exceeds the 70% threshold, this level of agreement can be considered acceptable (Holsti, 1969).

To enhance the transparency and rigor of the analytical process, the search strategy, study-selection criteria, and screening stages were explicitly defined and documented. In addition, the codes and themes were reviewed over several stages, and analytical memos were used throughout the coding process to document the rationale underlying the formation, merging, and separation of codes and themes. During the analysis, the conceptual adequacy of the themes was also progressively assessed; that is, newly identified codes and themes were compared with the existing structure, and the analysis continued until the examination of subsequent studies no longer resulted in the emergence of a distinct new conceptual theme (Lincoln & Guba, 1985).

Throughout all stages of the study, ethical considerations were addressed through accurate citation of sources, respect for the intellectual property rights of authors, transparent reporting of the study-selection and analysis processes, and avoidance of the omission, alteration, or distortion of evidence for the purpose of supporting the conceptual framework.

## Findings

### Descriptive Characteristics of the Studies

Among the studies reviewed, 55 articles met the eligibility criteria for inclusion in the final analysis after completing the search, screening, and selection stages. The highest number of publications was recorded in 2024, with 26 articles, followed by 2025, with 15 articles, indicating a notable concentration of research on the application of AI in strategic decision-making in recent years. In contrast, no article published in 2019 met the criteria for inclusion in the final analysis. It should be noted that the count for 2025 reflects a partial year, as the literature search was conducted on April 20, 2025 (see Method section), and therefore does not represent a complete annual total; consequently, this figure should not be interpreted as a decline in research interest relative to 2024. In terms of geographical distribution, the United States, with 12 articles, and Germany, with 6 articles, accounted for the largest shares among the selected studies.

The thematic analysis of the selected studies resulted in a set of main themes organized across the three levels of strategic decision-making: input, process, and output. The input level comprised four main themes, the process level comprised five main themes, and the output level comprised four main themes. In addition to these stage-specific themes, the

1. $CR = 2A/(N_1 + N_2)$
A: Number of agreements
$N_1$: Number of coding occurrences identified by the first coder
$N_2$: Number of coding occurrences identified by the second coder

analysis identified a set of challenges whose implications were not confined to a particular level. These challenges were therefore interpreted as a cross-cutting conceptual dimension rather than as a main theme belonging to the output level.

To provide an additional indicator of the breadth of evidence, the article-level frequency is reported, representing the number of reviewed articles in which each theme was identified at least once.

**Table 2.**
**The Distribution of the Main Themes within the Three-Stage Framework (Inputs, Processes, and Outputs)**

| Stage | Main Theme | Articles Frequency |
|---|---|---|
| Input | Predictive analysis & forecasting | 44 |
| | Data processing & access | 42 |
| | Enhancing strategic intelligence & environmental awareness | 51 |
| | Analyzing & predicting key stakeholders | 49 |
| Processes | Automation & autonomous systems | 45 |
| | Risk identification & anomaly detection | 39 |
| | Modeling & simulating strategic scenarios | 53 |
| | Increasing rationality & reducing bias in decision process | 54 |
| | Optimization of processes & resources | 41 |
| Outputs | Business performance & customer experience enhancement | 49 |
| | Adaptive strategy execution & innovation | 43 |
| | Evaluating outcomes & enhancing strategic performance | 47 |
| | Achieving data-driven competitive advantages | 40 |

**(Source: Researcher's Findings)**

## Inputs to Strategic Decision-Making

At the input level, the coding occurrences were identified across four main themes: Predictive Analysis and Forecasting, Data Processing and Access, Strategic Intelligence Enhancing and Environmental Awareness, and Analyzing and Predicting Key Stakeholders. These themes focus on the capacity of AI to collect, process, and interpret diverse data and transform them into information and insights that can be used in strategic decision-making.

**Table 3.**
**The Main Themes and Sample Subthemes of the Input Level**

| Main Theme | Secondary Code Examples | Supporting Studies |
|---|---|---|
| Predictive analysis & forecasting | Improving & enhancing predictive analysis, enhancing predictive capability, enabling more accurate prediction | (Anastasios & Maria, 2024; Mundlos, 2024; Neiroukh et al., 2024; Onari et al., 2024; Potwora et al., 2024) |
| Data processing & access | Data preprocessing, learning from data, classification, extracting valuable information | (Trunk et al., 2020; Geurts et al., 2022; Pratt et al., 2023; Mas & Puspita, 2024) |
| Enhancing strategic intelligence & environmental awareness | Real-time big data analytics, enhancing data management, identifying opportunities | (Özemre & Kabadurmus, 2020; Keding & Meissner, 2021; Trunk et al., 2020; Pérez-Campuzano et al., 2022; Pratt et al., 2023) |
| Analyzing & predicting key stakeholders | Customer data/behavior & preferences, demand and supply forecasting, pattern recognition in data | (Biloslavo et al., 2024; Kim & Seo, 2023; Menzies et al., 2024; Rosa et al., 2024; Zhao et al., 2024) |

**(Source: The Researcher's Findings)**

**Table 4.**
**The Sample of Coding Subthemes of the Input Level**

| Secondary Code Examples | Sample Literature Text |
|---|---|
| Improving & enhancing predictive analysis | AI-powered tools such as predictive analytics (Büber & Seven, 2025) |
| Data preprocessing | This section delves into key AI-driven models in business analytics, encompassing data collection and preprocessing (Rimon, 2024) |
| Real-time big data analytics | Additionally, the role of AI in strategic decision-making is crucial, offering unparalleled abilities to analyze vast datasets (Jaboob et al., 2025) |
| pattern recognition in data | By analyzing vast amounts of historical data, predictive AI models identify patterns (Anastasios & Maria, 2024) |

**(Source: The Researcher's Findings)**

### Predictive Analysis and Forecasting

The Predictive Analysis and Forecasting theme comprised coding occurrences and focused on improving and enhancing forecasting models through the use of machine learning and deep learning algorithms to analyze historical patterns and predict future scenarios. Within this theme, "improving and enhancing predictive analysis" and "enhancing predictive capability" were the most frequent secondary codes, while "enabling more accurate prediction" was also identified as a secondary code. The reviewed studies reported the application of these capabilities to analyze historical patterns and support future forecasting and data-driven decision-making (Büber & Seven, 2025; Siddiqui, 2025).

### Data Processing and Access

The Data Processing and Access theme comprised several coding occurrences. The most important secondary codes were data preprocessing, learning from data, classification, and extracting valuable information. The studies highlighted the ability of AI to collect, organize, classify, and process structured and unstructured data (Pratt et al., 2023; Trunk et al., 2020). Using data from various sources, including customer feedback, market research, and social media, to identify new trends and opportunities was also reported (Biloslavo et al., 2024). In the area of customer behavior, deep learning algorithms have also been used to extract information related to customers' behaviors, preferences, and interactions (Modak et al., 2024).

### Strategic Intelligence Enhancing and Environmental Awareness

This theme was the most frequent theme at the input level. "Real-time big data analytics", "enhancing data management", and "identifying opportunities" were among the prominent secondary codes. The findings showed that AI contributes to enhancing organizational awareness of the surrounding environment by scanning large volumes of data and identifying trends, opportunities, and environmental signals. In this regard, real-time data analysis and the rapid identification of environmental changes were emphasized in the reviewed studies (Biloslavo et al., 2024; Geurts et al., 2022).

### Analyzing and Predicting Key Stakeholders

The fourth theme at the input level, concerning Analyzing and Predicting Key Stakeholders, was one of the prominent themes identified in the reviewed studies.

Within this theme, particular emphasis was placed on customer behavior and preferences, demand and supply forecasting, and pattern recognition in data, alongside the related areas such as market trend forecasting, customer segmentation, market conditions, and targeted marketing. The reviewed studies emphasized the use of customer data and the analysis of behavioral and demand patterns to improve understanding of markets and stakeholders (Modak et al., 2024; Rimon, 2024).

Overall, the four input themes indicated that applications of AI at this level primarily revolve around information preparation and enrichment, forecasting, enhancing environmental awareness, and understanding stakeholders.

## Strategic Decision-Making Processes

At the process level, coding occurrences were identified across five main themes: Automation and Autonomous Systems, Risk Identification and Anomaly Detection, Modeling and Simulating Strategic Scenarios, Increasing Rationality and Reducing Bias in the Decision Process, and Optimization of Processes and Resources. This level primarily focused on the direct use of AI capabilities in task execution, decision support, testing different options, and resource management.

**Table 5.**
**The Main Themes and Sample Subthemes of the Process Level**

| Main Theme | Secondary Code Examples | Supporting Studies |
|---|---|---|
| Automation & autonomous systems | Process and repetitive decision automation, automated data collection, organizational process improvement | (Büber & Seven, 2025; Garg et al., 2025; Jaboob et al., 2025; Doshi et al., 2025; Boozary et al., 2025) |
| Risk identification & anomaly detection | Fraud detection, anomaly detection, risk reduction, reduction of financial losses | (Menzies et al., 2024; Onari et al., 2024; Pratt et al., 2023; Rosa et al., 2024; Zhao et al., 2024) |
| Modeling & simulating strategic scenarios | Scenario modeling, enhancing strategic planning, scenario simulation | (Biloslavo et al., 2024; Doshi et al., 2025; Onari et al., 2024; Özemre & Kabadurmus, 2020; Trunk et al., 2020) |
| Increasing rationality & reducing bias in decision process | Improving the decision-making process, improving strategic decision-making, increasing decision accuracy | (Büber & Seven, 2025; Jaboob et al., 2025; Kim & Seo, 2023; Onari et al., 2024; Pratt et al., 2023) |
| Optimization of processes & resources | Enhancing human resource management, improving resource allocation, knowledge management | (Biloslavo et al., 2024; Geurts et al., 2022; Koliousis et al., 2024; Menzies et al., 2024; Trunk et al., 2020) |

**(Source: The Researcher's Findings)**

**Table 6.**
**The Sample of Coding Subthemes of the Process Level**

| Secondary Code Examples | Sample Literature Text |
|---|---|
| Process and repetitive decision automation | Clara is designed to automate a wide range of accounting tasks (Türegün, 2025) |
| risk reduction | and reduce risk (e.g. AI applied to financial data analysis and risk prediction (Biloslavo et al., 2024) |
| Scenario modeling | Artificial intelligence (AI) applications enable entrepreneurs in small and medium-sized enterprises (SMEs) to make strategic decisions based on more accurate predictions and modeling scenarios (Jaboob et al., 2025) |
| Enhancing human resource management | AI excels in real-time data processing, optimization, and adaptive decision execution (Garg et al., 2025) |
| improving resource allocation | AI-driven hiring tools identify skills gaps and talent trends, enhancing firms' ability to retain high-value employees while reducing inefficiencies in workforce management (Büber & Seven, 2025) |

**(Source: The Researcher's Findings)**

### Automation and Autonomous Systems

The Automation and Autonomous Systems theme comprised several coding occurrences. Automating processes and tasks and automated data collection were the prominent secondary codes. The findings showed that AI has been used in some studies to automate repetitive tasks and processes and reduce manual intervention. These applications were reported in association with freeing employees' capacity for more complex and strategic activities (Türegün, 2025).

### Risk Identification and Anomaly Detection

This theme comprised coding occurrences, with fraud detection and anomaly detection representing the most important secondary codes. The reviewed studies reported the use of AI algorithms for fraud detection, early identification of operational and financial anomalies, and data analysis to predict and mitigate risks (Nwoke, 2025; Nweke & Owusu-Berko, 2025). Other examples included the use of AI for disease detection, reducing financial losses, and decreasing downtime or operational disruptions.

### Modeling and Simulating Strategic Scenarios

The Modeling and Simulating Strategic Scenarios theme was one of the major themes at the process level. The studies showed that AI can model and simulate different strategic options in virtual environments, enabling their comparison and testing before actual implementation. This capability was reported in connection with predictive analysis and strategic planning in the reviewed studies (Csaszar et al., 2024; Nweke & Owusu-Berko, 2025).

### Increasing Rationality and Reducing Bias in the Decision Process

This theme indicated that the role of AI in strategic decision-making cannot be understood solely in terms of speed or automation. Part of its value was associated with increasing the capacity to process information, compare alternatives, and identify patterns that may exceed the cognitive capacity of human decision-makers. However, this effect depended on data quality and the way systems are designed and used (Garg et al., 2025; Neiroukh et al., 2024).

### Optimization of Processes and Resources

The Optimization of Processes and Resources theme comprised coding occurrences. Enhancing human resource management and improving resource allocation were the prominent secondary codes. Other reported applications included knowledge management, supply chain and logistics optimization, and improving resource utilization. In the reviewed studies, these applications were associated with improved resource allocation, potentially reduced waste, and increased organizational flexibility (Nweke & Owusu-Berko, 2025; Wang & Dai, 2025).

## Strategic Decision-Making Outputs

At the output level, four main themes were identified: Business Performance and Customer Experience Enhancement, Adaptive Strategy Execution and Innovation, Evaluating Outcomes and Enhancing Strategic Performance, and Achieving Data-Driven

Competitive Advantages. This level primarily focused on the organizational and strategic consequences associated with AI-supported decision-making, including improvements in business and operational performance, enhanced customer experiences, adaptive strategy implementation, innovation, outcome evaluation, and the development of data-driven competitive advantages.

**Table 7.**
**The Prominent Subthemes of the Outputs**

| Main Theme | Secondary Code Examples | Supporting Studies |
|---|---|---|
| Business performance & customer experience enhancement | Enhancing financial management, improving customer satisfaction & loyalty, improving operational efficiency | (Boozary et al., 2025; Mundlos, 2024; Rosa et al., 2024; Tang, 2025; Türegün, 2025) |
| Adaptive strategy execution & innovation | Improving marketing, personalized marketing, improving supply chain management | (Boozary et al., 2025; Garg et al., 2025; Jaboob et al., 2025; Menzies et al., 2024; Patro et al., 2025) |
| Evaluating outcomes & enhancing strategic performance | Improving risk assessment, proactive threat identification, outcome evaluation | (Biloslavo et al., 2024; Onari et al., 2024; Pérez-Campuzano et al., 2022; Pratt et al., 2023; Trunk et al., 2020) |
| Achieving data-driven competitive advantages | Enhancing competitive advantages, increasing competitiveness, strengthening innovation | (Jaboob et al., 2025; Koliousis et al., 2024; Menzies et al., 2024; Rosa et al., 2024; Türegün, 2025) |

**(Source: The Researcher's Findings)**

**Table 8.**
**The Sample of Coding Subthemes of the Outputs Level**

| Secondary Code Examples | Sample Literature Text |
|---|---|
| Enhancing financial management | AI through AppZen's expense audit platform significantly enhances operational efficiency within finance departments (Türegün, 2025) |
| Improving supply chain management | Google's AI-powered search algorithms and Netflix's recommendation engine leverage proprietary data-driven models to create personalized experiences (Büber & Seven, 2025) |
| Outcome evaluation | AI's ability to evaluate strategic decisions (Doshi et al., 2025) |
| Strengthening innovation | , these technologies automate processes and provide innovative solutions (Garg et al., 2025) |

**(Source: The Researcher's Findings)**

### Business Performance and Customer Experience Enhancement

Prominent aspects within this theme included enhancing financial management, improving customer satisfaction and loyalty, and improving operational efficiency. These findings demonstrated the breadth of AI applications in improving financial and operational performance and customer experience (Mohammed & Madhumithaa, 2024).

### The Adaptive Strategy Execution and Innovation

This theme included improving marketing, personalized marketing, and improving supply chain management. The reviewed studies reported the use of data-driven insights to respond to market changes, personalize marketing activities, and manage supply chains intelligently (Büber & Seven, 2025).

### Evaluating Outcomes and Enhancing Strategic Performance

This theme was another prominent theme. Key aspects within this theme included improving risk assessment, proactive identification of threats, and evaluating outcomes.

In the reviewed studies, real-time monitoring, outcome evaluation, and the continuous refinement of actions and strategies were reported in association with AI applications (Nweke & Owusu-Berko, 2025).

### Achieving Data-Driven Competitive Advantages

Finally, this theme was identified as an important theme. Its prominent aspects included enhancing competitive advantages, increasing competitiveness, and strengthening innovation. Various studies reported the use of data analytics, identification of emerging trends, and enhancement of innovation in relation to organizational competitiveness and competitive advantages (Arumugam & Manida, 2024; Mohammed & Madhumithaa, 2024; Neiroukh et al., 2024).

## Cross-Cutting Challenges Across the Strategic Decision-Making Cycle

The thematic analysis also identified a set of challenges associated with the application of AI in strategic decision-making. Rather than being confined to the output level, these challenges were found to have implications across the different levels of the decision-making cycle. They included organizational changes, the continuing need for human oversight, ethical and legal issues, data quality and bias, privacy and security, rapid AI developments and innovations, and transparency of AI logic.

These challenges can affect the quality and reliability of decision-making inputs, constrain or shape decision-making processes, and influence the conditions under which strategic outcomes are achieved. For example, data quality and bias may affect the informational basis of subsequent decisions, while human oversight, ethical and legal considerations, and transparency may shape how AI-supported analyses are interpreted and used during decision-making (Geurts et al., 2022; Keding & Meissner, 2021; Neiroukh et al., 2024; Trunk et al., 2020 ). Organizational changes, privacy and security, and rapid technological developments may likewise influence the organizational conditions under which AI is integrated throughout the decision-making cycle (Geurts et al., 2022; Trunk et al., 2020).

Accordingly, the challenges identified in the reviewed literature are conceptualized in this study as a cross-cutting dimension rather than as a stage-specific category. Their position is therefore not equivalent to the input, process, or output levels; instead, they represent conditions that may arise within and influence any of these levels. This interpretation is consistent with the systems perspective adopted in the study, in which the effectiveness of one component of the decision-making system may be affected by conditions operating across the broader system.

## An Integrated Pattern of the Findings in the Strategic Decision-Making Cycle

Overall, the findings showed that the identified applications of AI across the three levels of input, process, and output constitute a set of interrelated capabilities. At the input level, the main focus was on Data Processing and Access, Predictive Analysis and Forecasting, Strategic Intelligence and Environmental Awareness, and Analyzing and Predicting Key Stakeholders. At the process level, these capabilities were accompanied by Automation and Autonomous Systems, Risk Identification and Anomaly Detection,

Modeling and Simulating Strategic Scenarios, Increasing Rationality and Reducing Bias in the Decision Process, and Optimization of Processes and Resources. At the output level, the identified themes concerned Business Performance and Customer Experience Enhancement, Adaptive Strategy Execution and Innovation, Evaluating Outcomes and Enhancing Strategic Performance, and Achieving Data-Driven Competitive Advantages.

In addition to these stage-specific themes, the analysis identified challenges that were not conceptually confined to any single level. These challenges may influence the quality of inputs, shape decision-making processes, and affect the conditions under which the strategic outcomes are achieved. They therefore constitute a cross-cutting dimension of the decision-making system rather than an additional stage within the input–process–output structure.

The key point of this pattern lies not in the three components themselves, but in their interdependence and in the conditions that may affect their functioning. The quality of inputs provides a foundation for subsequent analytical and decision-making processes, while evaluated outputs and organizational learning can generate information that feeds into subsequent decision cycles. At the same time, cross-cutting challenges may influence any of these levels by affecting the quality of information, the conduct of decision-making activities, or the realization of strategic outcomes. Therefore, the proposed framework should be interpreted not merely as a linear input–process–output sequence, but as a recurring cycle in which the three levels are connected through feedback and are simultaneously subject to cross-cutting conditions and challenges.

## Discussion and Conclusion

The findings of this study provided an integrated picture of the role of AI in the strategic decision-making cycle by organizing the available evidence across three levels: input, process, and output. In response to the main research question, the synthesis showed that AI is not limited to a single technological application; rather, its role extends from enriching decision-making information to supporting analytical and cognitive processes and shaping organizational and competitive outcomes. This interpretation is consistent with studies emphasizing the facilitating role of AI and the importance of complementary human–AI interaction (Jarrahi, 2018; Shrestha et al., 2019; Trunk et al., 2020). It also corresponds with more recent research emphasizing human–AI collaboration, organizational embedding, and the strategic use of AI beyond isolated analytical tasks (Liu & Shen, 2025; Li & Tian, 2026; Saura et al., 2026). By placing these roles within a three-level structure, the present study further interpreted them as interconnected components of a strategic decision-making cycle.

In response to the first research question, the findings showed that at the input level, AI contributes to enriching the informational basis of decision-making through Predictive Analysis and Forecasting, Data Processing and Access, Strategic Intelligence and Environmental Awareness, and Analyzing and Predicting Key Stakeholders. The prominence of Strategic Intelligence and Environmental Awareness is consistent with studies emphasizing the AI's capacity to process large volumes of data, identify patterns,

and analyze the environment in real time (Biloslavo et al., 2024; Jaboob et al., 2025). Recent research similarly emphasizes the importance of AI-enabled environmental sensing and data-driven strategic decision-making (Riya & Mukherji, 2026; Saura et al., 2026). The significance of this finding lies not merely in increasing the volume or speed of data access; rather, AI can transform dispersed data into information and insights that broaden managers' attention from current conditions toward trends, environmental changes, stakeholders, and possible future conditions. Thus, part of the AI's strategic value is generated before the decision-selection stage, through the way the environment is observed and the informational basis of decisions is formed. This also reinforces the interdependence of the framework, because the quality of subsequent activities such as scenario modeling, risk identification, and decision support depends partly on the quality of the inputs.

In response to the second research question, the findings showed that at the process level, Increasing Rationality and Reducing Bias in the Decision Process was the most prominent theme. This finding is consistent with Shrestha et al. (2019) regarding human–AI hybrid structures and with Keding and Meissner (2021), who highlighted the potential role of AI in reducing certain cognitive limitations and biases. The coexistence of Automation and Autonomous Systems, Risk Identification and Anomaly Detection, Modeling and Simulating Strategic Scenarios, and Optimization of Processes and Resources further indicated that AI can support both structured activities and more complex analytical tasks. This pattern is also consistent with recent research that conceptualizes AI–human collaboration in terms of differentiated roles, decision authority, and degrees of delegation rather than complete substitution (Csaszar et al., 2026; Li & Tian, 2026). From the perspective of bounded rationality, AI can expand the capacity to process information, compare alternatives, and identify patterns. However, this does not imply the elimination of bias or the replacement of managerial judgment. Data quality, algorithmic design, and interpretation may themselves introduce new limitations. Therefore, the findings support a complementary human–AI logic in which AI enhances analytical capacity while human judgment remains important for contextual interpretation, ambiguity, value considerations, and responsibility.

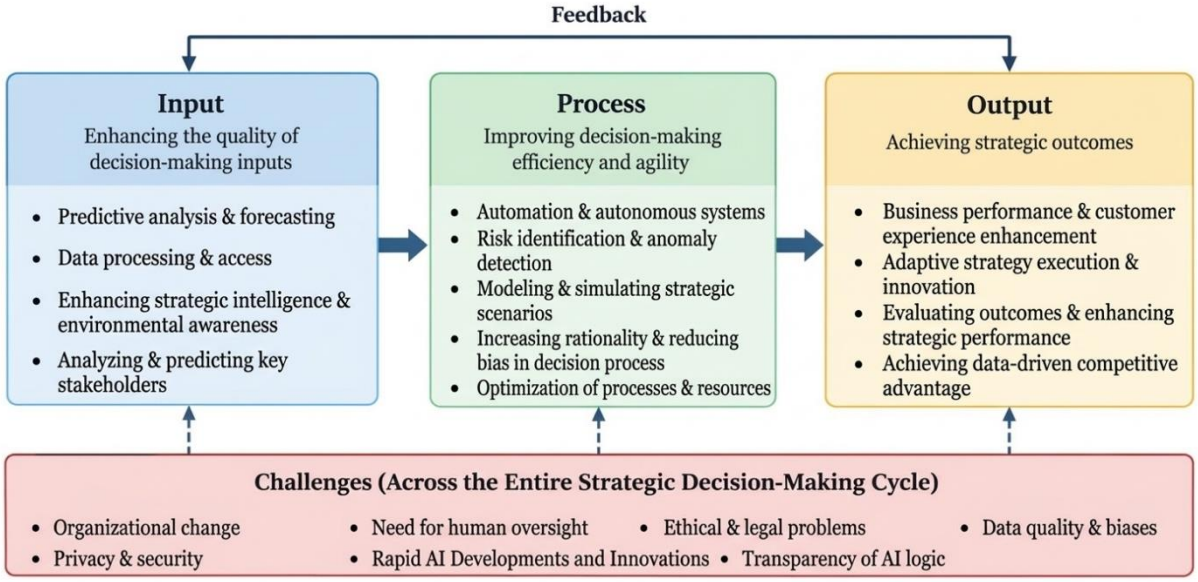
In response to the third research question, the findings at the output level identified four main themes: Business Performance and Customer Experience Enhancement, Adaptive Strategy Execution and Innovation, Evaluating Outcomes and Enhancing Strategic Performance, and Achieving Data-Driven Competitive Advantages. These themes indicated that AI-supported strategic decision-making can be associated with improvements in organizational performance, adaptive strategy execution, strategic performance evaluation, and data-driven competitive positioning. The analysis also identified a distinct set of challenges associated with AI-supported strategic decision-making. Importantly, these challenges were not treated as output-level outcomes because their implications extend beyond the realization of strategic results. Instead, they were interpreted as cross-cutting conditions that may affect inputs, shape decision-making processes, and influence the achievement of outputs. This interpretation helps

distinguish between what the decision-making system produces and the conditions that may constrain or shape how the system operates. This interpretation is consistent with Booyse and Scheepers (2023) and Enholm et al. (2022), while recent research further emphasizes governance, organizational adaptation, and human oversight as conditions shaping responsible and effective AI use (García López & Nájera Ochoa, 2026; Huang & Lin, 2025; Ruster & Daniell, 2025). The findings therefore reinforce the view that strategic AI adoption involves organizational and managerial changes in addition to technological implementation, as also illustrated by recent evidence from SMEs (Aiudi et al., 2026).

From a systems perspective, the significance of the findings lies in the interdependence among the three levels. The themes identified at the input and process levels provided the informational and analytical foundations for AI-supported strategic decisions. At the output level, the themes of Business Performance and Customer Experience Enhancement, Adaptive Strategy Execution and Innovation, Evaluating Outcomes and Enhancing Strategic Performance, and Achieving Data-Driven Competitive Advantages indicated that AI-supported decisions can generate outcomes that inform subsequent strategic activities. In particular, codes related to outcome evaluation, continuous improvement, and strategy refinement suggested that decision outcomes can generate information and organizational learning that may influence the subsequent decision cycles. Csaszar et al. (2024) showed that feedback from AI can improve business plans, while Büber and Seven (2025) highlighted the AI's role in continuous learning and strategic refinement. This interpretation extends the emerging literature linking AI with systems thinking and AI-mediated decision premises (Kumar & Suthar, 2026; Qudrat-Ullah, 2025). Thus, the findings suggested that the decision-making cycle is not a one-directional input–process–output sequence. Rather, evaluated outcomes and organizational learning can feed back into subsequent inputs, analytical activities, and strategic choices. Consistent with the systems perspective of Senge (2006) and Koch et al. (2009), feedback is therefore conceptualized as a cross-level mechanism that connects outcomes with subsequent decision-making and strategic adaptation. Figure 2 illustrates this recurring relationship among AI-supported inputs, processes, outputs, and feedback. Importantly, this feedback relationship represents a conceptual synthesis of evidence across the reviewed studies rather than an empirically tested longitudinal mechanism within a single organizational setting. It should therefore be interpreted as a conceptual inference from the reviewed literature rather than as an empirically verified feedback loop.

The challenges presented in the figure are not confined to a specific stage; rather, they can influence and arise across all stages of the strategic decision-making cycle (input, process, and output). These challenges may affect the quality of decision-making inputs, constrain or shape decision-making processes, and ultimately influence the achievement of strategic outcomes, highlighting the need to consider them as cross-cutting issues throughout the entire cycle.

**Figure 2.**
**The Conceptual Framework of the Role of Artificial Intelligence in the Strategic Decision-Making Cycle: A Systems Approach**




**(Source: The Researcher's Findings)**

This study examined how the role of AI can be conceptualized across the strategic decision-making cycle from a systems perspective. The synthesis of 55 studies identified a set of AI applications spanning three interconnected levels. At the input level, AI supported predictive analysis and forecasting, data processing and access, strategic intelligence and environmental awareness, and the analysis and prediction of key stakeholders. At the process level, its roles included automation and autonomous systems, risk identification and anomaly detection, strategic scenario modeling and simulation, increasing rationality and reducing bias, and optimizing processes and resources. At the output level, the reviewed literature indicated outcomes related to business performance and customer experience, adaptive strategy execution and innovation, evaluation of outcomes and strategic performance, and data-driven competitive advantages. In addition, a set of cross-cutting challenges was identified that may influence the functioning of the input, process, and output levels rather than constituting a separate stage of the cycle. Taken together, these findings answered the main research question by showing that AI is not confined to a particular stage or application within strategic decision-making; rather, its role extends across the decision cycle and can be understood as a distributed capability connecting information, analytical processes, and decision outcomes.

The theoretical contribution of the study lies not simply in identifying themes of AI application, but in integrating these previously dispersed roles within an input–process–output systems framework. The proposed framework positioned AI as a capability operating across the different levels of strategic decision-making rather than as an isolated technological tool. More importantly, it conceptualized these levels as interdependent rather than sequential. The quality of information and intelligence generated at the input level provides a foundation for subsequent analytical and

decision-making processes, while evaluated outcomes and organizational learning may feed back into subsequent data collection, analytical activities, and strategic choices. Alongside this recurring feedback relationship, the identified challenges were conceptualized as cross-cutting conditions that may influence the functioning of all three levels. In this sense, the study provided a conceptual structure in which inputs, processes, outputs, feedback, and cross-cutting challenges are distinguished but interconnected elements of a recurring decision-making system.

From a managerial perspective, the findings suggested that realizing the potential of AI in strategic decision-making depends on more than the adoption of AI technologies. Organizations need to ensure the quality and relevance of the data used as decision inputs, establish appropriate mechanisms for human oversight and managerial judgment, and align AI-supported analyses with organizational contexts and strategic objectives. AI can support environmental analysis, forecasting, risk identification, scenario modeling, and other decision-related activities, but its outputs should be interpreted alongside human experience and contextual understanding, particularly when decisions involve uncertainty, competing objectives, ethical considerations, or long-term consequences. Equally important, organizations should evaluate the outcomes of AI-supported decisions and use the resulting information to improve data, analytical models, and subsequent decision processes. Thus, the managerial value of AI emerges not from technology alone, but from the quality of the broader decision-making system in which data, AI capabilities, human judgment, oversight, and organizational learning operate together.

## Practical Implications and Recommendations

The findings of this study have several practical implications for managers and organizations. First, the effective use of AI in strategic decision-making requires simultaneous attention to all three levels of the decision-making cycle. Accordingly, investment in AI tools alone may not be sufficient to realize their full potential without ensuring high-quality data and appropriate mechanisms for integrating AI-generated analytical outputs into decision-making processes.

Second, organizations should establish appropriate mechanisms for human oversight of AI-generated analyses and recommendations, particularly in strategic decisions characterized by uncertainty, long-term consequences, or ethical considerations. Third, managers can use AI capabilities to support environmental analysis, risk assessment, and scenario modeling. However, AI-supported insights should be considered alongside managerial judgment and an understanding of the organizational context when making final strategic decisions.

Fourth, organizations should continuously monitor the outcomes of AI-supported decisions and use the resulting information to improve data quality, analytical models, and subsequent decision-making processes. Such feedback mechanisms can help transform the proposed framework from a purely analytical structure into a basis for continuous learning and improvement in strategic decision-making.

## Limitations and Future Research Directions

Future research can first examine and test the proposed framework and the conceptual relationships among the input, process, and output levels, the feedback mechanism, and the cross-cutting challenges through empirical studies in organizations. Comparing the framework across different industries, such as banking, healthcare, manufacturing, and technology, could also reveal the extent to which the importance and interaction of these three levels depend on the industrial context. Another avenue for future research is to examine the factors influencing the effectiveness of human–AI interaction, including the role of managerial judgment, trust in AI, decision-makers' degree of reliance on algorithmic outputs, and organizational culture. Longitudinal studies could also examine how the outcomes of AI use in strategic decision-making change over time and whether learning from previous decisions actually leads to improvements in the inputs and processes of subsequent decisions.

The present study has several limitations. First, the findings were based on a secondary analysis of published studies, and the proposed framework has not yet been tested in real organizational settings. Second, although part of the coding process was examined through independent coding by two coders and calculation of an agreement coefficient, the potential influence of researcher judgment on the interpretation and organization of the data cannot be completely eliminated. Third, restricting the review to studies published between 2019 and 2025 may have resulted in the exclusion of some relevant studies outside this period. Fourth, the search strategy was based on a specified set of keywords; therefore, some studies using different or emerging terminology may not have been identified. Finally, the frequency of extracted codes merely indicated the presence of themes within the set of studies reviewed and should not be interpreted as an effect size, the strength of relationships among variables, or the relative importance of themes.

## Conflict of Interest Disclosure

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