

# AI-Driven Decision Intelligence in Managerial Economics: Leveraging Predictive Analytics and Intelligent Technologies for Strategic Decision-Making

Disha Grover<sup>1</sup>, Shivani Vats<sup>2</sup>

Associate Professor, Jagan Institute of Management Studies, [disha.grover@jimsindia.org](mailto:disha.grover@jimsindia.org)<sup>1</sup>

Assistant Professor, Jagan Institute of Management Studies, [drshivanivats@gmail.com](mailto:drshivanivats@gmail.com)<sup>2</sup>

## Abstract

Managerial economics applies economic reasoning to decisions concerning demand, pricing, cost, production, resource allocation, investment, risk and competition. The growth of digital business has expanded the information available for these decisions, while artificial intelligence (AI), predictive analytics and business intelligence have increased the ability to process that information. This paper develops a conceptual framework for AI-driven decision intelligence in managerial economics. It connects established economic tools with predictive and intelligent technologies so that managers can move from historical information to forecasts, alternatives and economically justified actions. The paper reviews literature on data-driven decision-making, business intelligence, predictive analytics, AI-enabled strategy, digital transformation, big data capabilities, risk management and responsible AI. It then considers applications in demand forecasting, pricing, production, resource allocation, investment, marketing, supply chains and competitive strategy. The paper argues that the value of AI depends not simply on prediction accuracy but on the quality of the economic objective, data, managerial interpretation and implementation. It proposes an integrated decision cycle in which managerial economics defines the decision problem, analytics estimates future conditions, intelligent technologies support evaluation of alternatives, and managerial judgment remains responsible for the final choice. Data quality, organizational capability, explainability and ethical governance are identified as important conditions for sustained value.

**Keywords:** Managerial economics; artificial intelligence; decision intelligence; predictive analytics; business intelligence; big data analytics; strategic decision-making; demand forecasting; pricing; risk management

## Introduction

Managerial economics provides an important link between economic theory and practical business decision-making. It enables managers to apply concepts such as demand analysis, price elasticity, marginal cost and revenue, production theory, opportunity cost, market structure, and risk analysis to evaluate alternative courses of action. In practice, however, managerial decisions are rarely made under conditions of complete information. Demand may change because of variations in consumer preferences, income, market conditions, and competitor behaviour, while production costs may fluctuate with input prices, resource availability, and capacity constraints. Similarly, investment and strategic decisions are influenced by uncertainty and rapidly changing market conditions. Consequently, the availability of timely, relevant, and reliable information has become an increasingly important complement to traditional economic reasoning.

The rapid growth of digital technologies has significantly increased both the volume and velocity of information available to organizations. Business intelligence (BI), business analytics, big data analytics, predictive analytics, and artificial intelligence (AI) have created new opportunities for organizations to transform large and complex datasets into actionable information. Chen, Chiang and Storey (2012) describe the evolution of business intelligence and analytics as an important development in organizational information management, while Brynjolfsson and McElheran (2019) provide evidence of the increasing adoption of data-driven decision-making within firms. Davenport and Harris (2017) further emphasize the strategic importance of analytics, demonstrating how systematic use of organizational data can support competitive decision-making. These developments suggest that managerial economics can increasingly be strengthened by analytical approaches that provide forward-

looking insights rather than relying primarily on historical information, conventional assumptions, or managerial intuition.

Predictive analytics represents an important step in this transformation because it enables organizations to move beyond understanding what has happened toward estimating what is likely to happen in the future. Shmueli and Koppius (2011) distinguish predictive analysis from explanatory modelling and highlight the importance of prediction in decision-oriented contexts. Ghosh and Scott (2018) similarly present predictive analytics as a structured business approach for generating useful predictions from organizational data. Within managerial economics, such capabilities can be particularly valuable because many economic decisions require managers to anticipate future demand, costs, revenues, customer responses, market conditions, and risks before selecting an appropriate course of action.

Artificial intelligence further extends analytical capabilities by enabling systems to identify complex relationships, learn from data, automate analytical activities, and support decisions in dynamic environments. Brynjolfsson and McAfee (2017) discuss the broader transformation associated with machine intelligence and digital technologies, while Ransbotham et al. (2017) highlight how organizations are reshaping business activities around artificial intelligence. Sin and Kathiarayan (2023) identify both opportunities and challenges associated with the use of AI in strategic decision-making, emphasizing its growing relevance to managerial practice. Accenture (2023) similarly argues that AI can contribute to competitive advantage when its adoption is connected with organizational strategy and business objectives.

Despite these developments, the integration of AI into managerial decision-making raises an important conceptual issue. **Prediction and economic decision-making are not the same activity.** An AI system may generate a highly accurate prediction of future demand, but the prediction alone does not determine whether increasing production is economically desirable. The manager must still consider marginal cost, marginal revenue, available capacity, opportunity cost, expected profitability, and competitive responses. Similarly, an AI system may identify customers who are likely to respond to a price change, but the resulting pricing decision must also consider price elasticity, competitor behaviour, customer lifetime value, and broader strategic objectives. Thus, the value of AI in managerial economics depends not only on predictive accuracy but also on the extent to which analytical outputs are interpreted within an appropriate economic decision framework.

This distinction becomes increasingly important as organizations adopt AI-enabled systems across pricing, demand forecasting, production, resource allocation, investment, marketing, supply-chain management, and competitive strategy. While AI can improve the availability and processing of information, economic decisions continue to involve trade-offs among scarce resources, uncertain outcomes, costs, benefits, and competing objectives. Therefore, AI should not be viewed as a replacement for managerial-economic reasoning. Rather, it can be positioned as an analytical and decision-support layer that enhances the information available to managers while leaving the evaluation of economic consequences and accountability for final decisions with human decision-makers.

The organizational context in which AI is implemented is also important. Ransbotham et al. (2017) emphasize that successful AI adoption involves changes in organizational activities and capabilities, while Wamba et al. (2017) demonstrate the relationship between big data analytics, dynamic capabilities, and firm performance. Zhou and Li (2012) further highlight the importance of knowledge acquisition and internal knowledge sharing for organizational innovation. These findings indicate that technological capability alone may not be sufficient to generate economic value. Organizations also require appropriate data, analytical skills, knowledge-sharing mechanisms, managerial expertise, and the ability to translate analytical insights into effective actions.

At the same time, the growing use of AI in economically significant decisions creates concerns relating to data quality, explainability, fairness, accountability, and governance. Poor-quality or incomplete data can undermine the reliability of analytical outputs, while opaque models may make it difficult for managers to understand the basis and limitations of AI-generated recommendations. Forbes (2020) highlights data-related challenges in AI integration, while Binns (2018) discusses important issues surrounding fairness in machine learning. IBM (2023), Harvard Business Review (2022), and the World Economic Forum (2022) similarly emphasize the importance of

responsible approaches to AI deployment. These concerns are particularly relevant when AI-supported decisions affect customers, employees, prices, credit, resource access, or other stakeholders.

Although existing research provides substantial insights into business intelligence, predictive analytics, artificial intelligence, digital transformation, big data capabilities, and responsible AI, these research streams are frequently examined independently. Managerial economics, in contrast, provides an established decision logic based on marginal analysis, demand, cost, opportunity cost, competition, resource constraints, and uncertainty. A conceptual opportunity therefore exists to integrate these perspectives into a unified decision-intelligence process in which economic reasoning defines the decision problem, data and analytics provide evidence about future conditions, AI supports the generation and comparison of alternatives, and managerial judgment evaluates and authorizes the final decision.

The present study addresses this opportunity by developing a conceptual framework for **AI-driven decision intelligence in managerial economics**. The framework positions the economic objective at the beginning of the decision process rather than treating the AI algorithm as the starting point. It subsequently connects data, business intelligence, predictive analytics, AI-supported alternatives, economic evaluation, managerial decision-making, outcome measurement, and organizational learning. In this way, the study seeks to explain how AI-enabled analytical capabilities can complement rather than substitute for established principles of managerial economics.

The study has four primary objectives: (1) to examine how predictive analytics, AI, and business intelligence can support major managerial-economic decisions; (2) to integrate economic reasoning with an AI-driven decision process; (3) to identify organizational, data, and ethical conditions that influence the usefulness of AI-supported decisions; and (4) to develop a conceptual framework and propositions that can guide future empirical research.

Accordingly, the study addresses the following research questions:

**RQ1:** How can AI and predictive analytics strengthen decision-making in managerial economics?

**RQ2:** Which managerial-economic decisions can benefit most from intelligent technologies?

**RQ3:** What organizational and data conditions influence the usefulness of AI-supported decisions?

**RQ4:** How should managers address uncertainty, explainability, fairness, and governance when using AI?

By addressing these questions, the study contributes to the emerging discussion on decision intelligence by emphasizing a fundamental principle: **AI can improve prediction and analytical capability, but economic reasoning is required to convert predictions into economically meaningful decisions**. The proposed perspective therefore seeks to bridge the technological capabilities of AI and predictive analytics with the established logic of managerial economics, while recognizing the importance of organizational capability, responsible governance, and human accountability.

## Review of Literature

The increasing integration of artificial intelligence (AI), predictive analytics, business intelligence (BI), and big data analytics into organizational decision-making has created new opportunities for improving the quality, timeliness, and scope of managerial decisions. However, the contribution of these technologies depends not only on their technical capabilities but also on the organizational context in which they are implemented and the extent to which their outputs are connected with managerial objectives and decision processes. Business intelligence and analytics provide an important information foundation for organizational decision-making. Chen, Chiang and Storey (2012) describe the development of business intelligence and analytics from traditional information systems toward more advanced approaches capable of generating insights from increasingly large and complex datasets. Davenport and Harris (2017) further emphasize the strategic importance of analytics, presenting systematic analytical use of organizational data as a basis for improving business performance and competitive decision-making. The increasing adoption of data-driven decision-making also supports this transformation, with Brynjolfsson and McElheran (2019) documenting the growing use of data-driven approaches within firms. Marr (2016) similarly demonstrates the practical application of big data analytics across multiple business functions.

These developments have direct relevance to managerial economics because decisions concerning demand, pricing, production, resource allocation, investment, and competition require information about both internal and external economic conditions. Business intelligence can provide managers with timely descriptive and diagnostic information, while advanced analytical technologies can extend this capability toward prediction and alternative evaluation. Nevertheless, the availability of analytical information does not by itself ensure economically optimal decisions. Analytical outputs must be interpreted in relation to economic objectives, constraints, costs, benefits, and uncertainty. This indicates that data-driven decision-making should complement rather than replace the economic reasoning used by managers.

Predictive analytics extends traditional business intelligence by focusing on future events and conditions. Shmueli and Koppius (2011) distinguish predictive analysis from explanatory modelling and emphasize the distinctive role of prediction in decision-oriented contexts. This distinction is particularly relevant to managerial economics because many managerial decisions require estimates of future demand, sales, costs, risks, and market responses. Ghosh and Scott (2018) present predictive analytics as a structured business framework through which organizational data can be transformed into useful predictions. Such capabilities can assist managers in anticipating potential outcomes and evaluating alternative courses of action before resources are committed.

Within managerial economics, predictive analytics can therefore support decisions by reducing informational uncertainty. Demand forecasts can inform production and inventory decisions, while estimates of customer responses can support pricing and marketing decisions. However, a prediction represents an estimate of a future condition rather than a decision regarding what an organization should do. A highly accurate prediction may not necessarily lead to a better economic outcome. For example, a forecast of increased demand does not automatically imply that production should be increased. Managers must also consider marginal costs, production capacity, expected revenues, opportunity costs, and competitive responses. Predictive analytics therefore strengthens the information component of managerial economics but does not replace economic analysis.

Artificial intelligence further extends analytical capabilities by enabling systems to identify patterns, process large and complex datasets, support automation, and generate predictions or recommendations. Brynjolfsson and McAfee (2017) discuss the broader transformation associated with machine intelligence and digital technologies and their implications for organizations and economic activity. Ransbotham et al. (2017) emphasize that AI is reshaping business activities and organizational processes. The strategic implications of AI have also received increasing attention. Sin and Kathiarayan (2023) discuss opportunities and challenges associated with AI in strategic decision-making, while Accenture (2023) emphasizes the potential of AI to generate competitive advantage when its adoption is aligned with organizational strategy. AI-supported pricing can therefore incorporate consumer behaviour and sustainability-related considerations alongside traditional economic variables such as marginal revenue, marginal cost, and price elasticity. Sharma and Vats (2025) highlight the relevance of consumer behaviour in shaping sustainable pricing decisions, suggesting that pricing strategies need to consider not only immediate economic outcomes but also changing consumer expectations and sustainability-related preferences.

The literature suggests that AI can contribute to managerial decision-making through capabilities such as pattern recognition, customer analysis, forecasting, scenario generation, and process automation. However, AI-supported recommendations remain dependent on the objectives, data, assumptions, and constraints incorporated into the analytical system. Consequently, AI should be understood as an enabling technology within the decision process rather than as an independent substitute for managerial reasoning. For managerial economics, this distinction is particularly significant because economic decisions involve trade-offs among scarce resources and competing objectives. AI may identify a potentially attractive alternative, but managers must evaluate whether that alternative is economically feasible and consistent with organizational objectives.

The effectiveness of AI and analytics also depends on organizational capability. Technological implementation alone may not generate improved performance if organizations lack the skills, processes, knowledge, and capabilities required to interpret and act upon analytical outputs. Workforce training and the development of human capabilities are particularly important as organizations move from automation toward augmentation in the digital era of Industry 5.0 (Ragaur et al., 2025). Wamba et al. (2017) examine the relationship between big data

analytics and firm performance through the perspective of dynamic capabilities and indicate that analytical resources can contribute to performance when organizations possess the capabilities required to integrate and exploit them. Zhou and Li (2012) demonstrate the importance of knowledge acquisition and internal knowledge sharing for innovation. Kumar et al. (2020) examine digital transformation in business-to-business marketing and highlight the changing role of data and technology in organizational processes. These studies collectively suggest that organizations require not only technological resources but also analytical capabilities, knowledge-sharing mechanisms, and managerial expertise to translate analytical insights into effective actions.

Risk and uncertainty are also important considerations in managerial-economic decision-making. Investment decisions, production planning, supply-chain management, resource allocation, and strategic choices are frequently made under uncertain future conditions. AI and predictive analytics can assist organizations by identifying patterns, estimating potential risks, and supporting the evaluation of alternative scenarios. McKinsey (2021) highlights the potential application of AI in risk management, particularly in relation to the identification and assessment of organizational risks. However, AI does not eliminate uncertainty. Model outputs remain dependent on the quality and completeness of available data and on the assumptions and relationships represented within the analytical model. Changes in market conditions may also reduce the reliability of historical relationships. From a managerial-economic perspective, risk assessment should therefore be integrated with opportunity cost, expected benefits, resource constraints, and the organization's tolerance for risk.

The increasing use of AI in organizational decision-making has also highlighted the importance of data quality, explainability, fairness, accountability, and responsible governance. Since AI systems rely on data to generate predictions and recommendations, incomplete, inaccurate, outdated, or inappropriate data can reduce the reliability of their outputs. Forbes (2020) highlights data-related challenges associated with AI integration, reinforcing the importance of data readiness and quality in AI-enabled decision processes. Explainability is particularly important when AI recommendations influence economically significant decisions because managers need to understand the basis and limitations of such recommendations. Fairness and accountability are also relevant when AI-supported decisions affect customers, employees, or other stakeholders. Binns (2018) examines fairness in machine learning and highlights the challenges associated with fair algorithmic decision-making. Sharma et al. (2025) further discuss the challenges associated with AI bias, its mitigation, and the ethical implications of AI-supported systems, highlighting the need for responsible approaches to AI deployment. IBM (2023), Harvard Business Review (2022), and the World Economic Forum (2022) similarly emphasize the importance of ethical considerations and responsible governance in AI adoption.

These concerns are particularly relevant to managerial economics because AI may influence decisions relating to prices, credit, employment, customer treatment, resource allocation, and access to services. Economic efficiency therefore cannot be considered independently of responsible decision-making. Data quality, explainability, fairness, and governance can influence the reliability and acceptability of AI-supported decisions and should therefore be considered as important conditions for their effective implementation.

Overall, the reviewed literature demonstrates that business intelligence and analytics provide mechanisms for transforming data into useful information (Chen et al., 2012; Davenport & Harris, 2017), while predictive analytics extends these capabilities by providing estimates of future conditions (Shmueli & Koppius, 2011; Ghosh & Scott, 2018). AI further contributes capabilities related to pattern recognition, learning, automation, and strategic decision support (Brynjolfsson & McAfee, 2017; Ransbotham et al., 2017; Sin & Kathiarayan, 2023). At the same time, organizational capabilities, dynamic capabilities, knowledge acquisition, and knowledge sharing influence the ability of firms to convert analytical resources into meaningful outcomes (Wamba et al., 2017; Zhou & Li, 2012). Data quality, explainability, fairness, and governance are also increasingly important considerations in AI-supported decision-making (Forbes, 2020; Binns, 2018; IBM, 2023; Harvard Business Review, 2022; World Economic Forum, 2022).

Despite these developments, the literature provides limited integration of these technological and organizational capabilities with the established economic logic used by managers to evaluate alternatives under conditions of scarcity and uncertainty. Managerial economics provides concepts such as demand, elasticity, marginal analysis, opportunity cost, competition, resource constraints, and risk that are essential for evaluating the economic

consequences of alternative decisions. The present study therefore builds on the existing literature by positioning AI and predictive analytics as analytical capabilities within a broader managerial-economic decision process. This integrated perspective provides the foundation for the research gap and conceptual framework developed in the following sections.

### Research Gap

The review of existing literature indicates that substantial research has examined business intelligence, predictive analytics, artificial intelligence, digital transformation, big data capabilities, strategic decision-making, risk management, and responsible AI. However, these streams of research have largely developed around different analytical and managerial concerns. Business intelligence and analytics research has primarily emphasized the transformation of organizational data into actionable information (Chen et al., 2012; Davenport & Harris, 2017), while research on predictive analytics has focused on forecasting and estimating future outcomes (Shmueli & Koppius, 2011; Ghosh & Scott, 2018). Research on artificial intelligence has increasingly examined its implications for organizational activities and strategic decision-making (Brynjolfsson & McAfee, 2017; Ransbotham et al., 2017; Sin & Kathiaryan, 2023), whereas research on organizational capabilities has emphasized the conditions under which analytical resources can generate business value (Wamba et al., 2017; Zhou & Li, 2012).

Although these streams provide important insights, they do not sufficiently explain how AI-generated predictions and analytical recommendations should be incorporated into the established economic logic of managerial decision-making. Managerial economics is fundamentally concerned with selecting among alternative uses of scarce resources under conditions of uncertainty. Its decision logic incorporates demand, elasticity, marginal cost and revenue, opportunity cost, production constraints, competition, risk, and expected economic outcomes. Existing discussions of AI-enabled decision-making frequently emphasize technological capability, prediction, automation, or strategic benefits, but comparatively less attention is given to the process through which AI outputs are subjected to explicit economic evaluation before managerial action is taken.

A particularly important conceptual gap therefore exists between **prediction and economic decision-making**. Predictive analytics can estimate what may happen, and AI can identify patterns or generate potential alternatives, but neither capability alone establishes what an organization should do. For example, an AI system may forecast an increase in demand, but the resulting production decision requires consideration of marginal costs, available capacity, expected revenue, opportunity cost, and competitive responses. Similarly, an AI-enabled pricing system may identify customer response patterns, but an economically appropriate price requires consideration of elasticity, marginal revenue, competitor behaviour, and long-term customer value. This indicates that prediction quality and decision quality should not be treated as equivalent constructs.

A second gap concerns the **role of the economic objective in AI-enabled decision processes**. Many technology-oriented decision frameworks implicitly begin with available data, analytical models, or technological capabilities. In contrast, managerial economics suggests that the decision objective should precede the selection and interpretation of analytical tools. Whether the objective is revenue maximization, cost reduction, profit improvement, risk control, resource optimization, or sustainable growth determines what information is relevant and how alternative outcomes should be evaluated. The absence of an explicit economic objective at the beginning of an AI decision process can therefore result in technically sophisticated analyses that are not necessarily aligned with managerial priorities.

A third gap relates to the **integration of managerial interpretation into AI-supported decision-making**. Existing research recognizes the importance of organizational capability, knowledge processes, and managerial involvement in realizing value from analytics (Wamba et al., 2017; Zhou & Li, 2012). However, the specific role of managerial interpretation between AI-generated analytical outputs and economic decision outcomes requires further conceptual attention. Managers do not merely receive AI recommendations; they interpret them in light of organizational objectives, market conditions, resource constraints, uncertainty, and domain knowledge. This suggests that managerial interpretation may represent an important mechanism through which predictive and AI capabilities influence actual economic decisions.

A fourth gap concerns the integration of **responsible AI with economic decision quality**. Existing literature increasingly emphasizes data quality, fairness, explainability, accountability, and governance (Binns, 2018; IBM, 2023; Harvard Business Review, 2022; World Economic Forum, 2022). However, responsible AI is often discussed as an ethical or governance issue separately from economic decision-making. In practice, these dimensions can interact. An AI-supported decision that appears economically efficient may create unacceptable risks if it is based on poor-quality data, cannot be adequately explained, or produces unfair outcomes for affected stakeholders. Consequently, responsible governance should be considered as an integral condition of sustainable AI-supported managerial decision-making rather than as an external constraint added after the analytical process.

Based on these gaps, there is a need for a conceptual perspective that brings together **managerial economics, business intelligence, predictive analytics, artificial intelligence, organizational capability, and responsible AI** within a single decision process. The present study addresses this need by proposing an AI-driven decision-intelligence framework in which the economic objective constitutes the starting point of the decision process. Data and business intelligence provide the evidence base, predictive analytics estimates future conditions, AI-supported technologies generate or compare alternatives, and managerial-economic analysis evaluates those alternatives in relation to costs, benefits, constraints, risks, and strategic objectives. The manager subsequently makes the final decision and evaluates its outcome, creating a feedback mechanism for organizational learning.

The proposed perspective therefore differs from a technology-centred view of AI adoption. Rather than asking only whether AI can predict accurately or automate a particular activity, the framework asks how AI-generated insights can be converted into **economically justified decisions**. This shifts the emphasis from AI as an autonomous decision-maker toward AI as an analytical and decision-support capability embedded within managerial-economic reasoning.

The study consequently makes three principal conceptual contributions. First, it **integrates technological and economic decision perspectives** by positioning AI and predictive analytics within the established logic of managerial economics. Second, it **distinguishes predictive capability from decision capability**, emphasizing that forecasts and AI-generated recommendations require economic evaluation before managerial action. Third, it incorporates **organizational capability and responsible AI conditions**—including data quality, managerial interpretation, explainability, fairness, and governance—into the proposed decision-intelligence process.

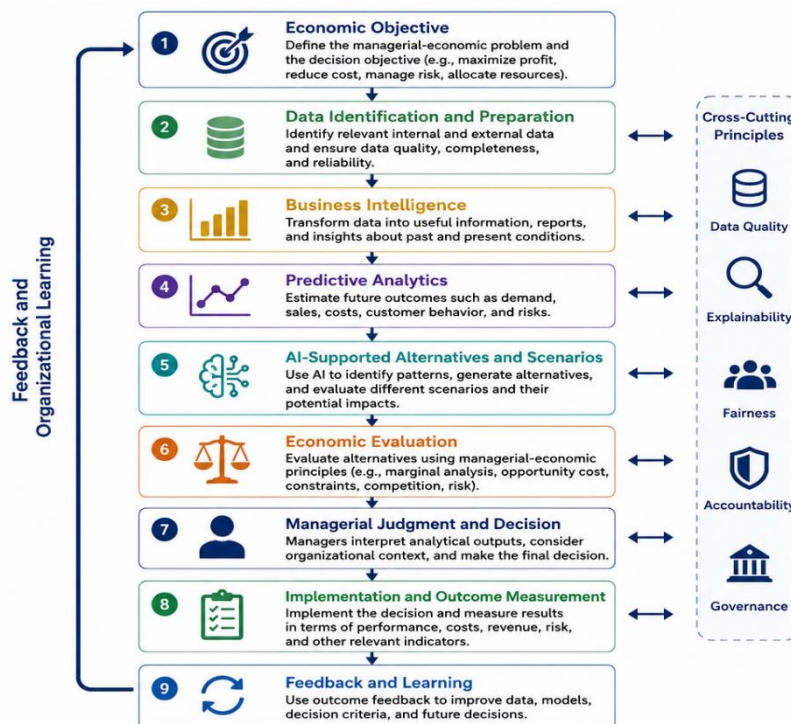
### Conceptual Framework

The proposed conceptual framework integrates artificial intelligence (AI), business intelligence, predictive analytics, and managerial economics into a structured decision-making process. The framework is based on the view that AI should support managerial decision-making rather than replace economic reasoning and managerial judgment. Managerial economics provides the basis for defining the decision objective and evaluating alternatives, while AI and analytics improve the availability, processing, and interpretation of information. This approach is consistent with the literature showing the growing importance of analytics and organizational capabilities in data-driven decision-making (Chen et al., 2012; Davenport & Harris, 2017; Wamba et al., 2017).

The framework begins with the identification of an economic objective or managerial problem. This may involve increasing revenue, reducing costs, improving resource utilization, managing risk, or allocating scarce resources efficiently. Once the objective is defined, relevant internal and external data are identified and prepared for analysis. Business intelligence can then be used to organize and interpret historical and current information, while predictive analytics can provide estimates of future demand, sales, costs, customer behaviour, or risks (Shmueli & Koppius, 2011; Ghosh & Scott, 2018).

AI-enabled technologies can further support the process by identifying patterns, generating alternatives, and examining possible scenarios. AI can therefore help managers understand different possible outcomes and provide additional information for decision-making (Brynjolfsson & McAfee, 2017; Ransbotham et al., 2017). However, the output of an AI system should not automatically be treated as the final decision. The alternatives generated through analytics and AI need to be evaluated using managerial-economic principles such as marginal cost, marginal revenue, elasticity, opportunity cost, resource constraints, competition, and risk.

For example, an AI system may predict an increase in demand and suggest higher production. However, the manager must determine whether the additional production is economically beneficial after considering marginal cost, production capacity, expected revenue, and opportunity cost. Similarly, an AI system may identify a suitable price based on customer behaviour, but the final pricing decision should also consider elasticity, competitor behaviour, marginal revenue, and long-term customer value. This demonstrates the important distinction between prediction and decision-making. Predictive analytics can indicate what may happen, while managerial economics helps determine what should be done.



**Figure 1. AI-Driven Decision-Intelligence Framework in Managerial Economics**

As illustrated in Figure 1, the proposed framework connects economic objectives with data, analytics, AI-supported alternatives, economic evaluation, managerial decision-making, and outcome-based learning. The final stage provides feedback from actual outcomes to future analysis and decision-making. In this way, the framework represents a continuous process rather than a one-time technological intervention. The organizational capabilities required to convert analytical information into useful actions are supported by research on dynamic capabilities, knowledge acquisition, and knowledge sharing (Wamba et al., 2017; Zhou & Li, 2012).

Data quality, explainability, fairness, and governance are considered important conditions throughout the framework. Poor-quality data can affect the reliability of AI outputs, while explainability can help managers understand the basis and limitations of recommendations. Fairness and accountability are also important when AI-supported decisions affect customers, employees, or other stakeholders (Binns, 2018; IBM, 2023; Harvard Business Review, 2022; World Economic Forum, 2022). Thus, responsible AI should be considered alongside economic efficiency when implementing AI-supported managerial decisions.

Overall, the proposed framework positions managerial economics at the centre of the decision process and AI as an enabling analytical layer. It emphasizes that the value of AI does not depend only on prediction accuracy but also on the quality of data, clarity of economic objectives, organizational capability, managerial interpretation, and responsible governance. The framework provides the conceptual foundation for examining how AI and predictive analytics can contribute to improved managerial-economic decision-making.

### **AI Applications in Managerial Economics**

The proposed framework shown in Figure 1 can be applied to several important areas of managerial economics. These applications demonstrate how artificial intelligence (AI), predictive analytics, and business intelligence can support managers in making decisions involving demand, pricing, production, resources, investment, marketing, supply chains, and competition. The role of AI in these applications is primarily to improve information processing, prediction, pattern identification, and scenario analysis, while managerial economics provides the basis for evaluating the economic consequences of alternative decisions.

Demand forecasting is one of the important applications of predictive analytics in managerial economics. Historical sales, customer behaviour, market indicators, and external variables can be analyzed to estimate future demand. Predictive analytics can therefore support short-term sales planning as well as longer-term production and capacity decisions (Ghosh & Scott, 2018; Shmueli & Koppius, 2011). However, demand forecasts need to be considered together with factors such as price elasticity, income effects, market conditions, and competitor behaviour. The forecast provides an estimate of expected demand, while economic analysis helps managers determine the appropriate response to that forecast.

AI can also support pricing and revenue decisions by analyzing transaction data, customer behaviour, demand patterns, and market conditions. Intelligent systems can identify different customer responses and generate alternative pricing scenarios. However, a pricing decision should not be based only on an AI-generated recommendation. Managers need to consider marginal revenue, marginal cost, price elasticity, competitor reactions, and customer value before implementing a pricing strategy. Thus, AI can improve the analytical basis of pricing decisions, while managerial economics provides the principles for determining whether a proposed price is economically appropriate.

In cost and production decisions, predictive models can assist managers in estimating input requirements, operating costs, equipment maintenance needs, and production conditions. These insights can support more efficient allocation of resources and help managers identify activities where the expected benefits are greater than the associated costs. The value of such analytical capabilities is influenced by the organization's ability to integrate data and analytical insights into its decision processes, consistent with the findings of Wamba et al. (2017).

Investment and risk-related decisions can also benefit from AI-supported analysis. AI and predictive analytics can be used to examine different assumptions relating to sales, costs, cash flows, market conditions, and potential risks. McKinsey (2021) highlights the relevance of AI to risk management. However, investment decisions involve uncertainty and opportunity costs, and managers must consider the organization's risk tolerance before selecting an alternative. AI can therefore support scenario analysis and risk identification, but the final investment decision requires managerial evaluation of expected returns, risks, and available resources.

Marketing and customer-related decisions represent another important application. Digital transformation has increased the amount of information available about customers and markets, creating opportunities for AI-supported segmentation, customer analysis, and prediction of customer responses. Kumar et al. (2020) discuss the transformation of business-to-business marketing through digital technologies and the changing role of data in organizational decision-making. AI-supported customer analysis can help managers identify potential customer segments and estimate customer responses, while managerial economics can be used to assess customer acquisition costs, expected revenues, and customer lifetime value.

AI can also contribute to supply-chain management and competitive decision-making. Predictive analytics can support inventory forecasting, supplier analysis, logistics planning, and identification of potential disruptions. Big data analytics can provide organizations with information that supports operational and strategic decisions across different business functions (Marr, 2016). At the strategic level, however, analytical information needs to be converted into organizational knowledge and action. Knowledge acquisition and internal knowledge sharing are therefore important for enabling organizations to use analytical insights effectively (Zhou & Li, 2012).

Across these applications, the same basic decision logic applies. The manager first identifies the economic objective, relevant data are then collected and analyzed, predictive methods estimate possible future conditions,

and AI can support the generation or comparison of alternative scenarios. The alternatives are subsequently evaluated using economic principles and organizational constraints before a final decision is made. Outcomes are then measured and used as feedback for future decisions, as illustrated in Figure 1.

The applications also demonstrate why AI should be viewed as an enabling capability rather than an independent decision-maker. AI can improve the speed and scale of analysis and can provide managers with information that may not be easily obtained through traditional approaches. Nevertheless, economic decisions involve objectives, trade-offs, uncertainty, and organizational constraints that require managerial interpretation. The effectiveness of AI-driven decision intelligence therefore depends on the integration of technological capabilities with economic reasoning, organizational knowledge, reliable data, and responsible managerial judgment.

### **Research Propositions**

The proposed framework suggests that the effectiveness of AI-driven decision intelligence depends on the integration of technological capabilities with managerial-economic reasoning. AI and predictive analytics can improve the availability of information and support the identification of future conditions and alternative actions. However, the resulting value depends on the quality of data, organizational capabilities, managerial interpretation, and responsible use of AI. Based on the reviewed literature and the conceptual framework presented in Figure 1, the following propositions are developed.

**P1: Greater integration of predictive analytics with managerial-economic analysis is associated with improved decision quality.**

Predictive analytics can provide managers with forward-looking information regarding demand, costs, customer behaviour, and risks (Shmueli & Koppius, 2011; Ghosh & Scott, 2018). However, predictions become more useful when they are evaluated using managerial-economic principles. Integrating predictive outputs with considerations such as marginal costs, expected benefits, opportunity costs, and resource constraints can therefore improve the quality of managerial decisions.

**P2: Data quality strengthens the relationship between AI use and decision usefulness.**

AI-supported decisions depend on the availability of relevant, accurate, complete, and reliable data. Poor-quality or incomplete data can reduce the reliability of analytical outputs and consequently affect managerial decisions (Forbes, 2020). Therefore, higher data quality is expected to strengthen the usefulness of AI-supported decision-making.

**P3: Organizational analytical capability strengthens the effect of AI-supported decision-making on strategic performance.**

The availability of AI technology alone may not be sufficient to generate improved organizational outcomes. Organizations require appropriate analytical capabilities, knowledge processes, and the ability to integrate analytical insights into managerial activities. Wamba et al. (2017) highlight the relationship between big data analytics, dynamic capabilities, and firm performance, while Zhou and Li (2012) emphasize knowledge acquisition and internal knowledge sharing. Therefore, organizations with stronger analytical capabilities are expected to obtain greater strategic value from AI-supported decision-making.

**P4: Managerial interpretation mediates the relationship between predictive analytics and economic decision outcomes.**

Predictive analytics provides estimates of possible future conditions, but managers must interpret these outputs in relation to organizational objectives, economic conditions, constraints, and uncertainty. The proposed framework therefore considers managerial interpretation as an important mechanism through which predictive information can influence economic decision outcomes. AI-generated predictions are expected to contribute more effectively to decision outcomes when managers are able to understand, evaluate, and appropriately apply the analytical information.

**P5: Responsible AI practices, including fairness and governance, positively influence the sustainability of AI-supported managerial decisions.**

AI-supported decisions may affect customers, employees, and other stakeholders, making fairness, accountability, explainability, and governance important considerations. Binns (2018) discusses fairness in machine learning, while IBM (2023), Harvard Business Review (2022), and the World Economic Forum (2022) emphasize responsible approaches to AI. Accordingly, responsible AI practices are expected to contribute to the sustainability, acceptability, and long-term usefulness of AI-supported managerial decisions.

The five propositions collectively suggest that AI-driven decision intelligence is influenced by both technological and managerial factors. The framework does not assume that greater AI adoption automatically produces better economic outcomes. Instead, it proposes that the benefits of AI are more likely to emerge when predictive capabilities are integrated with economic analysis, supported by high-quality data and organizational analytical capabilities, interpreted by managers, and implemented within appropriate governance structures. These propositions provide a basis for future empirical studies using organizational surveys, case studies, experiments, or quantitative performance data.

**Discussion and Managerial Implications**

The conceptual analysis indicates that AI-driven decision intelligence can strengthen managerial economics by improving the quality, speed, and availability of information used in decision-making. The proposed framework positions AI and predictive analytics as supporting capabilities within the managerial-economic decision process rather than as replacements for economic reasoning. This distinction is important because managerial decisions involve scarce resources, competing alternatives, costs and benefits, and uncertain future conditions. AI can improve the analytical basis of these decisions, but managers remain responsible for evaluating alternatives and selecting actions that are consistent with organizational objectives.

A major implication of the framework is that organizations should define the economic objective before selecting an AI technology or analytical approach. Different objectives require different information and analytical methods. For example, a firm seeking revenue growth may focus on demand and customer behaviour, while a firm seeking cost reduction may require greater emphasis on production, resource utilization, and operating costs. Similarly, organizations focused on risk management may require scenario analysis and risk prediction. Therefore, AI adoption should be driven by the decision problem rather than by the availability of a particular technology.

The framework also highlights the importance of integrating analytical capability with managerial capability. AI systems can process large amounts of information and identify patterns that may be difficult to detect through traditional approaches, but managers need sufficient knowledge to interpret these outputs and understand their limitations. The importance of organizational capabilities and knowledge processes is consistent with Wamba et al. (2017) and Zhou and Li (2012). Organizations should therefore develop both technical analytical capabilities and managerial capacity to use analytical information effectively.

Another important implication concerns the evaluation of AI-supported decisions. Organizations should assess AI initiatives according to their contribution to actual business and economic outcomes rather than focusing only on technological deployment or prediction accuracy. Accenture (2023) and Gartner (2022) emphasize the strategic importance of aligning AI adoption with organizational objectives. In the context of managerial economics, this means evaluating whether AI-supported decisions contribute to relevant outcomes such as revenue improvement, cost reduction, resource efficiency, risk control, or other defined economic objectives.

The proposed framework further suggests that managers should consider multiple scenarios rather than relying on a single AI-generated recommendation. AI can support the identification of patterns and alternative courses of action, but economic evaluation is necessary to determine the consequences of those alternatives. This approach can be particularly useful in pricing, production, investment, resource allocation, and supply-chain decisions, where managers must balance expected benefits against costs, risks, constraints, and opportunity costs.

Responsible AI is also an important managerial consideration. When AI influences decisions relating to prices, credit, employment, customer treatment, or resource access, organizations need appropriate mechanisms for

explainability, fairness, accountability, and governance. Binns (2018), IBM (2023), Harvard Business Review (2022), and the World Economic Forum (2022) highlight the importance of responsible approaches to AI. From a managerial-economic perspective, responsible AI should therefore be considered part of sustainable decision quality rather than as a separate technical or ethical issue.

Overall, the framework suggests that effective AI-driven decision intelligence requires a combination of **economic reasoning, reliable data, analytical capability, AI technologies, managerial interpretation, and responsible governance**. The central managerial implication is that organizations should not adopt AI simply to automate decisions. Instead, they should use AI to improve the information and analytical foundation of decisions while retaining human responsibility for evaluating economic consequences and making significant managerial choices.

### **Limitations and Future Research**

This study is conceptual in nature and does not present primary survey, experimental, or organizational performance data. The proposed framework and research propositions are developed from the reviewed literature and therefore provide a basis for future empirical investigation rather than statistically validated relationships. In addition, the literature considered in the study includes both peer-reviewed research and practitioner or institutional publications. While these sources provide useful perspectives on the practical development of AI, greater reliance on peer-reviewed empirical research can further strengthen future studies.

Future research can empirically examine the propositions developed in this study across different industries and organizational contexts. Survey-based studies can investigate the relationships among AI adoption, data quality, analytical capability, managerial interpretation, and decision quality. Case studies can provide deeper understanding of how organizations integrate AI with managerial-economic decisions, while quantitative studies can compare traditional decision-making with AI-supported approaches. Future research can also examine whether improvements in predictive accuracy actually translate into better economic outcomes and how managerial expertise, explainability, organizational readiness, and responsible AI practices influence this relationship. Sector-specific studies in areas such as finance, healthcare, manufacturing, retail, pricing, and supply-chain management can further test the applicability of the proposed framework.

### **Conclusion**

Artificial intelligence, predictive analytics, and business intelligence provide organizations with increasing opportunities to improve decision-making under conditions of uncertainty. These technologies can support the prediction of demand, costs, customer behaviour, market conditions, and risks, while AI can assist in identifying patterns and evaluating alternative scenarios. However, the analysis presented in this study emphasizes that technological capability alone does not guarantee better economic decisions.

The proposed AI-driven decision-intelligence framework places managerial economics at the centre of the decision process. It begins with the economic objective, followed by data identification, business intelligence, predictive analytics, AI-supported alternatives, economic evaluation, managerial decision-making, outcome measurement, and feedback for learning. As illustrated in Figure 1, data quality, explainability, fairness, accountability, and governance provide important supporting conditions throughout the process.

The framework highlights the fundamental distinction between prediction and decision-making. AI and predictive analytics can provide information about what may happen and can support managers in identifying possible courses of action. Managerial economics is then required to evaluate the costs, benefits, opportunity costs, constraints, competition, and risks associated with those alternatives. Managerial judgment remains important for interpreting analytical outputs and making the final decision.

The study therefore contributes a conceptual perspective that connects AI-enabled analytical capabilities with established managerial-economic reasoning. Its central implication is that organizations should not adopt AI simply to automate decisions. Instead, AI should be integrated with clearly defined economic objectives, reliable data, organizational analytical capabilities, managerial interpretation, and responsible governance. Such integration can provide a more structured and informed basis for managerial decision-making while retaining human accountability for economically significant choices.

**References**

- [1] Accenture. (2023). Strategic AI: Unlocking competitive advantage. Accenture Insights.
- [2] Binns, R. (2018). Fairness in machine learning: Lessons from political philosophy. *Proceedings of Machine Learning Research*, 81, 149–159. <https://proceedings.mlr.press/v81/binns18a.html>
- [3] Brynjolfsson, E., & McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future*. W.W. Norton & Company.
- [4] Forbes. (2020). Data challenges in AI integration.
- [5] Gartner. (2022). AI adoption in business strategies. Gartner Research.
- [6] Harvard Business Review. (2022). Ethical implications of AI in strategic management.
- [7] IBM. (2023). Building Ethical AI: Guidelines and Practices. IBM Research.
- [8] McKinsey. (2021). AI and the future of risk management. McKinsey & Company.
- [9] Sin, J. C., & Kathiarayan, V. (2023). The role of artificial intelligence in strategic decision-making: Opportunities, challenges, and implications for managers in the digital age. <https://www.researchgate.net/publication/370865760>
- [10] World Economic Forum. (2022). Artificial intelligence for a better future. WEF Reports.
- [11] Brynjolfsson E, McElheran K. The rapid adoption of data-driven decision-making. *Am Econ Rev*. 2019;109(5):133-139. doi:10.1257/aer.p20191080.
- [12] Chen H, Chiang RHL, Storey VC. Business intelligence and analytics: From big data to big impact. *MIS Q*. 2012;36(4):1165-1188. doi:10.2307/41703503.
- [13] Davenport TH, Harris JG. *Competing on analytics: The new science of winning*. Rev ed. Boston (MA): Harvard Business Review Press; 2017.
- [14] Ghosh R, Scott J. Predictive analytics in business: A framework and a case study application. *Bus Horiz*. 2018;61(6):857-869. doi:10.1016/j.bushor.2018.07.005.
- [15] Kumar V, Dixit A, Javalgi R, Dass M, Schroeder J. Digital transformation of business-to-business marketing: Frameworks, evolution, and research directions. *J Bus Res*. 2020;122:325-337 doi:10.1016/j.jbusres.2020.09.056.
- [16] Marr B. *Big data in practice: How 45 successful companies used big data analytics to deliver extraordinary results*. Chichester (UK): Wiley; 2016.
- [17] Ransbotham S, Kiron D, Gerbert P, Reeves M. Reshaping business with artificial intelligence. *MIT Sloan Manag Rev*. 2017;59(1):1-17.
- [18] Ragaur, S., Kaur, B., & Sharma, S. (2025). From automation to augmentation: Workforce training transformations in the digital era of Industry 5.0. *Korea Review of International Studies*, 18(73).
- [19] Shmueli G, Koppius OR. Predictive analytics in information systems research. *MIS Q*. 2011;35(3):553-572. doi:10.2307/23042796.
- [20] Sharma, M., & Vats, S. (2025). Balancing price and purpose: How consumer behaviour shapes sustainable pricing decisions. *European Economic Letters*, 15(4), 169.
- [21] Sharma, R., Bajaj, K., Singh, A. R., Narang, V., & Singh, A. (2025). Navigating AI bias: Challenges, mitigation, and ethical implications. *ES*, 21(5(S)), 207–217. <https://doi.org/10.69889/tt8vsa10>
- [22] Wamba SF, Gunasekaran A, Akter S, Ren SJ, Dubey R, Childe SJ. Big data analytics and firm performance: Effects of dynamic capabilities. *J Bus Res*. 2017;70:356-365. doi:10.1016/j.jbusres.2016.08.009.
- [23] Zhou KZ, Li CB. How knowledge affects radical innovation: Knowledge base, market knowledge acquisition, and internal knowledge sharing. *Strat Manag J*. 2012;33(9):1090-1102. doi:10.1002/smj.1959.