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Bridging Prediction and Prescription: Explainable AI for Managerial Decision Analytics under Uncertainty

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ABSTRACT

The increasing adoption of artificial intelligence in business environments has significantly enhanced predictive capabilities; however, a persistent gap remains between prediction and actionable decision-making. This study addresses this limitation by developing a conceptual framework that integrates predictive analytics, explainable artificial intelligence, and prescriptive decision-making within managerial contexts. The proposed framework is structured around three interconnected layers: predictive, explainability, and decision, where predictive models generate insights, explainability interprets these outputs, and the decision layer translates them into actionable strategies. Explainability is positioned as a central mechanism that bridges predictive outputs and decision logic, enhancing transparency, interpretability, and usability. The study further examines decision-making under uncertainty, emphasizing the role of explainability in improving decision quality, reducing ambiguity, and enabling adaptive decision processes. Theoretical propositions are developed to guide future empirical research, and conceptual insights demonstrate the framework's value in strengthening decision effectiveness. Overall, the study contributes by offering an integrated perspective that connects prediction and prescription through explainability, with implications for improving managerial decision-making in complex and uncertain environments.

1. Introduction

The increasing reliance on artificial intelligence (AI) in organizational contexts has fundamentally transformed how decisions are made in modern business environments. Advances in machine learning and data analytics have enabled organizations to process large volumes of data and generate highly accurate predictions regarding market trends, customer behavior, and operational performance. These predictive capabilities have become essential components of competitive strategy, allowing firms to anticipate future developments and respond proactively. However, despite the growing sophistication of predictive models, their direct contribution to actionable

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decision-making remains limited, as accurate forecasts do not automatically translate into effective managerial actions [1].

In practice, decision-making requires more than predictive accuracy; it involves selecting optimal actions under constraints, uncertainty, and competing objectives. This need has led to the development of prescriptive analytics, which aims to recommend decisions based on analytical outputs. Nevertheless, the integration between predictive and prescriptive analytics remains insufficient in many organizational settings. As a result, decision processes often rely on fragmented analytical approaches that fail to fully exploit the potential of data-driven insights. This disconnect highlights a critical gap in decision analytics, where predictive insights are not effectively transformed into actionable strategies [2].

A key challenge in bridging this gap is the limited interpretability of advanced AI models. Many machine learning techniques operate as "black-box" systems, producing outputs that are difficult for managers to interpret or justify. This lack of transparency undermines trust and restricts the use of AI in high-stakes decision-making contexts. Explainable Artificial Intelligence (XAI) has emerged as a promising approach to address this issue by providing methods that enhance the interpretability of model outputs. Beyond improving transparency, XAI enables decision-makers to understand the reasoning behind predictions, thereby supporting more informed and accountable decisions [3].

The importance of explainability becomes particularly evident in environments characterized by uncertainty. Organizations today face increasing levels of uncertainty driven by rapid technological change, global competition, and economic volatility. Under such conditions, decision-makers must evaluate multiple scenarios and manage risks while operating with incomplete information. The ability to interpret predictive outputs and assess their implications is therefore essential for improving decision quality. Integrating explainability into decision analytics can enhance both the robustness and transparency of managerial decisions in uncertain environments [4].

Despite the growing body of research on AI, predictive analytics, and decision support systems, these domains are often treated as separate streams of inquiry. This fragmentation limits the development of comprehensive frameworks capable of supporting the full decision-making process—from prediction to action. Addressing this limitation requires a unified approach that integrates predictive modeling, explainability, and prescriptive decision-making within a coherent analytical framework. Such integration is essential for advancing both theoretical and practical aspects of managerial decision analytics [5].

1.1 Background and Research Context

The contemporary business environment is increasingly shaped by digital transformation and the integration of advanced analytical technologies into organizational processes. Artificial intelligence has become a central driver of this transformation, enabling organizations to enhance efficiency, improve forecasting accuracy, and support strategic decision-making. As firms seek to leverage data as a strategic asset, predictive analytics has emerged as a key tool for identifying patterns, trends, and relationships within complex datasets. These capabilities allow organizations to anticipate future developments and make proactive decisions, thereby strengthening their competitive position in dynamic markets [6].

However, the growing reliance on predictive analytics has also revealed important limitations, particularly in relation to its practical application in decision-making. While predictive models can generate accurate forecasts, they often do not provide clear guidance on how these insights should be translated into specific actions. This limitation becomes more pronounced in complex organizational settings, where decisions must consider multiple objectives, constraints, and

uncertainties. As emphasized in recent research, effective decision-making requires not only accurate predictions but also structured approaches that connect analytical outputs to strategic actions [7].

In response to these challenges, there has been increasing interest in integrating predictive and prescriptive analytics within unified decision frameworks. Prescriptive analytics focuses on recommending optimal actions based on predictive insights, thereby addressing the gap between forecasting and decision-making. However, the successful implementation of such integration depends on the ability of decision-makers to understand and trust the underlying analytical models. Without sufficient transparency, the adoption of advanced analytics in managerial contexts remains limited, particularly in situations involving high levels of risk and uncertainty [8].

Explainable Artificial Intelligence plays a critical role in addressing this challenge by enhancing the interpretability of complex models and facilitating their integration into decision processes. By providing insights into the factors influencing model predictions, XAI enables managers to evaluate alternative scenarios, assess risks, and justify their decisions. This capability is particularly important in uncertain environments, where decision-makers must rely on incomplete information and probabilistic outcomes. As organizations increasingly operate in such environments, the demand for explainable and actionable analytics continues to grow [9].

Furthermore, the strategic importance of integrating analytics into decision-making is closely linked to broader organizational objectives, including sustainability, governance, and long-term competitiveness. Recent studies highlight the need for decision frameworks that align analytical capabilities with strategic goals, particularly in the context of sustainable development and digital transformation. In this regard, AI-driven decision-making is not only a technical tool but also a strategic enabler that supports organizational resilience and adaptability in the face of uncertainty [10].

1.2 Literature Review

The literature on data-driven decision-making has expanded significantly over the past decade, reflecting the growing importance of analytics in organizational contexts. A substantial body of research has focused on predictive analytics, emphasizing its ability to generate accurate forecasts by identifying patterns within large datasets. Predictive models have been widely applied across business functions, including marketing, finance, and operations, where they support forecasting and performance optimization. However, despite their analytical power, predictive approaches are often limited in their ability to directly inform decision-making, as they primarily focus on “what is likely to happen” rather than “what should be done” [11].

To address this limitation, prescriptive analytics has emerged as a complementary approach aimed at recommending optimal actions based on predictive insights. Prescriptive models integrate optimization techniques, simulation, and decision rules to guide managerial actions under specific constraints. Research in this area highlights the potential of prescriptive analytics to enhance decision quality by translating analytical outputs into actionable strategies. Nevertheless, the integration of predictive and prescriptive analytics remains an ongoing challenge, as many existing systems treat these processes separately, resulting in fragmented decision support frameworks [12].

Parallel to these developments, the field of Explainable Artificial Intelligence (XAI) has gained increasing attention as a response to the lack of transparency in complex machine learning models. XAI techniques aim to make model outputs more interpretable by providing insights into the relationships between input variables and predicted outcomes. Studies have shown that explainability improves trust, accountability, and user acceptance of AI systems, particularly in high-stakes decision-making environments. However, much of the existing literature treats explainability

as a tool for model interpretation rather than as an integral component of decision-making processes, limiting its practical impact on managerial decisions [13].

In addition to challenges related to integration and interpretability, decision-making in business contexts is inherently influenced by uncertainty. Uncertainty arises from various sources, including incomplete information, dynamic market conditions, and external disruptions. Research on decision-making under uncertainty emphasizes the need for flexible and adaptive frameworks that allow decision-makers to evaluate multiple scenarios and manage risks effectively. While predictive models can provide probabilistic forecasts, they often lack mechanisms to support decision-making in uncertain environments, particularly when the underlying assumptions are not fully transparent or interpretable [14].

Recent studies have begun to explore the convergence of predictive analytics, prescriptive analytics, and explainability within unified decision frameworks. These efforts aim to bridge the gap between data-driven insights and actionable decision-making by integrating analytical capabilities with decision logic. In the context of business administration, such integration is increasingly viewed as essential for achieving strategic objectives, enhancing organizational performance, and supporting sustainable development. As highlighted in contemporary management research, aligning analytical tools with organizational goals is critical for ensuring that data-driven approaches contribute effectively to long-term competitiveness and resilience [15].

Despite these advances, literature still lacks a comprehensive conceptual framework that explicitly connects prediction, explanation, and prescription within a unified structure. Existing approaches tend to focus on individual components rather than their interaction, limiting their ability to support end-to-end decision-making processes. This gap underscores the need for further research that integrates these domains and positions explainability as a central mechanism for transforming predictive outputs into actionable decisions, particularly in uncertain and complex managerial environments [16].

1.3 Research Gap and Problem Statement

Despite the significant advancements in data-driven analytics, a critical gap remains in the integration of predictive and prescriptive approaches within managerial decision-making. While predictive analytics has achieved considerable success in forecasting future outcomes, it primarily focuses on generating insights rather than guiding concrete actions. Conversely, prescriptive analytics aims to recommend decisions but often operates independently from predictive models, resulting in a fragmented analytical process. This separation limits the ability of organizations to fully leverage data-driven insights in a coherent and actionable manner.

A central issue underlying this gap is the lack of effective mechanisms to translate predictive outputs into decision-oriented frameworks. In many cases, predictive models produce results that are technically accurate but lack practical relevance for decision-makers. This disconnect becomes more pronounced in complex organizational environments, where decisions must consider multiple objectives, constraints, and trade-offs. As a result, managers are often required to rely on intuition or simplified decision rules, reducing the overall effectiveness of advanced analytical tools.

Another critical limitation is the insufficient integration of explainability into decision-making processes. Although Explainable Artificial Intelligence has been developed to improve the interpretability of complex models, its application is frequently confined to enhancing model transparency rather than supporting decision logic. This restricts its potential to influence managerial decisions, as explanations are not systematically linked to actionable recommendations. Without a

clear connection between explanation and action, the practical value of explainability remains underutilized in organizational contexts.

The challenge is further intensified by the presence of uncertainty in modern business environments. Decision-makers must operate under conditions characterized by incomplete information, dynamic changes, and unpredictable external factors. In such settings, the absence of interpretable and integrated analytical frameworks makes it difficult to assess risks, evaluate alternatives, and justify decisions. Consequently, organizations face limitations in their ability to make informed and robust decisions, even when advanced analytical tools are available.

Given these limitations, there is a clear need for a unified conceptual framework that bridges the gap between prediction and prescription by incorporating explainability as a core component of decision analytics. Such a framework should enable the transformation of predictive insights into actionable decisions while maintaining transparency and adaptability under uncertainty. Addressing this gap is essential for enhancing the effectiveness of managerial decision-making and ensuring that analytical capabilities are aligned with organizational objectives and strategic priorities.

1.4 Research Objectives

This study aims to address the disconnect between predictive analytics and actionable decision-making by developing a comprehensive conceptual framework that integrates prediction, explanation, and prescription within managerial contexts. The primary objective is to enhance the effectiveness of decision analytics by transforming predictive outputs into interpretable and actionable insights that support strategic and operational decisions under conditions of uncertainty.

Specifically, the study seeks to achieve the following objectives:

i. To examine the limitations of existing approaches to predictive and prescriptive analytics in managerial decision-making environments.
ii. To analyze the role of explainability in improving the usability and interpretability of analytical models for decision-makers.
iii. To develop a conceptual framework that integrates predictive analytics, explainable artificial intelligence, and prescriptive decision-making processes.
iv. To explore how explainability can act as a linking mechanism between predictive insights and decision logic.
v. To assess the implications of integrating explainability into decision analytics for improving decision quality under uncertainty.
vi. To provide theoretical and managerial insights that support the adoption of integrated analytics frameworks in business organizations.

Through these objectives, the study aims to contribute to advancing the understanding of how explainable AI can be effectively utilized to bridge the gap between prediction and prescription, thereby supporting more transparent, robust, and informed managerial decision-making processes.

2. Methodology

This study adopts a conceptual research design aimed at developing an integrated framework that links predictive analytics, explainable artificial intelligence, and prescriptive decision-making within managerial contexts. The methodology is grounded in the synthesis of existing literature and the structured integration of key analytical components into a unified model.

Rather than relying on empirical data, the study focuses on theoretical development to address the disconnect between predictive outputs and actionable decisions. The methodological approach

emphasizes identifying core constructs, clarifying their roles, and defining the relationships that enable effective decision-making under uncertainty. This ensures that the proposed framework is both logically coherent and relevant to real-world managerial challenges.

2.1 Research Design and Approach

The research follows a theory-building approach that integrates insights from multiple domains, including predictive analytics, decision support systems, explainable AI, and decision-making under uncertainty. A systematic and critical review of relevant literature is conducted to identify key concepts, recurring limitations, and gaps in existing approaches.

An iterative development process is employed to refine the framework. Initial conceptual relationships are established based on the literature and subsequently adjusted to ensure alignment with managerial decision requirements. This process enhances both theoretical consistency and practical applicability.

In addition, the study adopts a managerial perspective by focusing on how analytical outputs can be interpreted and used in decision-making contexts. The framework is therefore designed to support decision-makers operating under constraints such as uncertainty, limited information, and organizational complexity. This perspective ensures that the model goes beyond theoretical abstraction to provide meaningful insights for practice.

2.2 Conceptual Framework Development

The conceptual framework is structured around three interconnected layers: prediction, explainability, and decision-making. The predictive layer generates forecasts and probabilistic insights based on data-driven models. The explainability layer interprets these outputs by identifying key drivers and relationships, enhancing transparency and understanding. The decision layer utilizes these interpreted insights to support structured managerial actions.

Explainability plays a central role as a linking mechanism between prediction and decision-making. By transforming complex model outputs into interpretable information, it enables decision-makers to evaluate alternatives, assess risks, and justify their choices. This integration ensures that predictive insights are not only accurate but also actionable.

To illustrate this integration, the proposed framework is presented in Figure 1. The figure highlights the sequential flow from data input to managerial action, emphasizing the role of explainability in connecting predictive outputs with decision logic. This representation clarifies how each component contributes to the overall decision-making process and how information is transformed across stages.

As shown in Figure 1, the framework operates as a structured yet dynamic process in which predictive outputs are first generated, then interpreted through explainability mechanisms, and finally translated into actionable decisions. The inclusion of explainability as an intermediate layer ensures that decision-makers can understand the rationale behind predictions, thereby improving both the transparency and reliability of decisions.

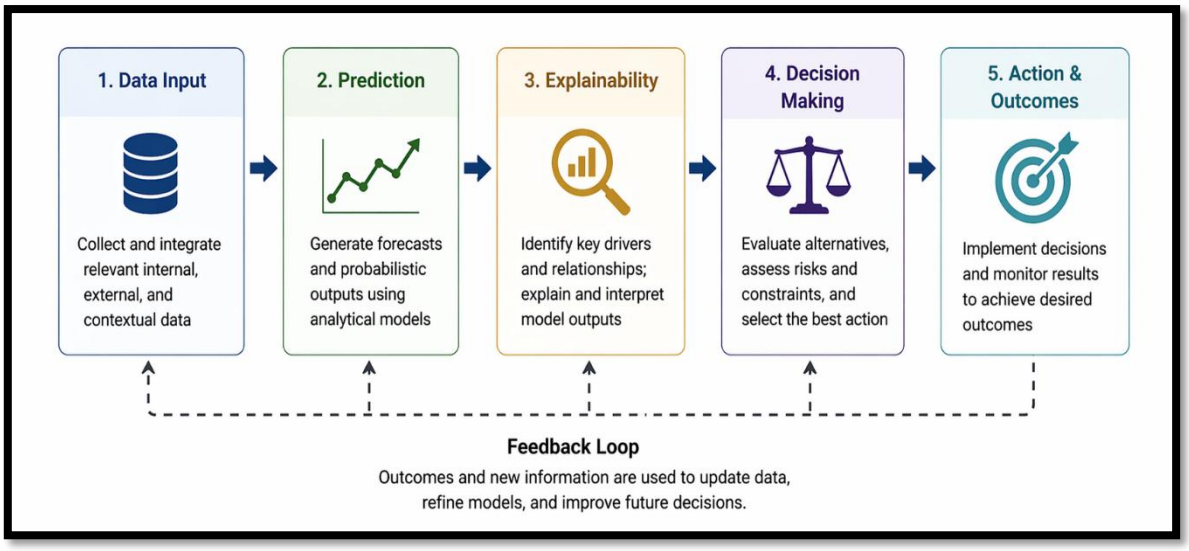

Fig. 1. Conceptual Framework: Bridging Prediction and Prescription

In addition, the framework allows for feedback loops, where outcomes from the decision stage can inform future predictions and adjustments. This iterative capability reflects real-world managerial environments, where decisions are continuously refined based on new data and evolving conditions. Overall, the framework provides a clear and practical structure for integrating predictive analytics and prescriptive decision-making under uncertainty.

3. Conceptual Foundations of the Predictive–Prescriptive Gap

The increasing reliance on data-driven analytics has highlighted a fundamental distinction between predicting future outcomes and making effective decisions. While predictive analytics enhances the ability of organizations to anticipate events, prescriptive approaches focus on determining appropriate actions. However, these two domains often operate independently, creating a gap that limits the practical value of analytical insights in managerial contexts. Understanding the conceptual foundations of this gap is essential for developing integrated frameworks that connect predictive outputs with decision-making processes [17].

3.1 Predictive Analytics in Managerial Contexts

Predictive analytics plays a critical role in modern organizations by enabling managers to forecast future trends, behaviors, and outcomes based on historical and real-time data. It utilizes statistical models, machine learning algorithms, and data mining techniques to identify patterns and generate probabilistic insights. These capabilities support a wide range of managerial functions, including demand forecasting, risk assessment, customer segmentation, and performance optimization [18].

In managerial contexts, predictive analytics enhances decision-making by providing evidence-based insights that reduce uncertainty and improve planning accuracy. For example, organizations can anticipate market demand fluctuations, detect potential risks, and optimize resource allocation. This predictive capability allows managers to move from reactive to proactive decision-making, improving operational efficiency and strategic alignment [19].

Despite its advantages, predictive analytics is inherently limited in its ability to guide decisions directly. It answers the question of “what is likely to happen” but does not provide clear guidance on “what should be done.” As a result, decision-makers must interpret predictive outputs and translate

them into actions, often relying on experience or intuition. This limitation highlights the need for complementary approaches that extend beyond prediction to support actionable decision-making [20].

3.2 Prescriptive Analytics and Decision Logic

Prescriptive analytics addresses the limitations of predictive models by focusing on recommending optimal actions based on analytical insights. It combines predictive outputs with optimization techniques, simulation models, and decision rules to evaluate alternative courses of action and identify the most effective solutions. This approach supports decision-making under constraints such as limited resources, competing objectives, and risk considerations [21].

In managerial settings, prescriptive analytics provides structured decision support by integrating analytical insights with organizational goals and constraints. It enables managers to assess trade-offs, evaluate potential outcomes, and select strategies that maximize value. For instance, prescriptive models can optimize pricing strategies, inventory management, and resource allocation, thereby improving both efficiency and effectiveness [22].

However, the effectiveness of prescriptive analytics depends heavily on the quality and interpretability of the inputs derived from predictive models. When predictive outputs are complex or opaque, their integration into decision models becomes challenging. This creates a dependency on interpretability, highlighting the importance of explainability in ensuring that prescriptive recommendations are both reliable and understandable [23].

To better clarify the conceptual differences between predictive and prescriptive analytics, a structured comparison is presented in Table 1. This comparison highlights the distinct roles, capabilities, and limitations of each approach within managerial decision-making contexts.

Table 1
Comparison between Predictive and Prescriptive Analytics

Dimension	Predictive Analytics	Prescriptive Analytics
Objective	Forecast future outcomes	Recommend optimal actions
Key Question	What is likely to happen?	What should be done?
Techniques	Machine learning, statistical models	Optimization, simulation, decision rules
Output Type	Probabilities, forecasts	Actionable decisions, strategies
Role in Decision-Making	Supports understanding	Supports action
Level of Complexity	High (model complexity)	High (decision constraints + models)
Interpretability	Often limited (black-box models)	Depends on input clarity
Dependency	Data-driven patterns	Requires predictive inputs
Limitation	Lacks direct action guidance	Depends on quality of predictions

As shown in Table 1, predictive and prescriptive analytics serve complementary but distinct functions within decision-making processes. While predictive analytics provides valuable insights into future outcomes, it does not directly guide managerial actions. Conversely, prescriptive analytics focuses on decision-making but depends heavily on the quality and interpretability of predictive inputs. This structural separation contributes to the gap between prediction and prescription, which is examined in the following section.

3.3 The Gap between Prediction and Prescription

The gap between prediction and prescription arises from the lack of integration between analytical outputs and decision-making processes. While predictive analytics provides valuable insights into future outcomes, these insights are often not systematically linked to actionable decisions. Similarly, prescriptive models may rely on simplified assumptions or incomplete information when predictive insights are not effectively incorporated. This disconnect limits the overall effectiveness of decision analytics in organizational contexts [24].

A key factor contributing to this gap is the absence of interpretability in advanced analytical models. Without clear explanations, decision-makers may struggle to trust or utilize predictive outputs, leading to underutilization of analytical capabilities. Additionally, organizational factors such as complexity, uncertainty, and time constraints further complicate the translation of predictions into decisions. These challenges highlight the need for frameworks that integrate prediction, explanation, and decision logic into a cohesive process [25].

Addressing this gap requires a shift from isolated analytical approaches to integrated decision frameworks that emphasize usability, transparency, and adaptability. By incorporating explainability as a central component, organizations can enhance the connection between predictive insights and prescriptive actions. This integration is essential for improving decision quality, particularly in environments characterized by uncertainty and dynamic change [26].

4. Role of Explainable Artificial Intelligence in Decision Contexts

Explainable Artificial Intelligence (XAI) has become increasingly important in enabling the practical use of advanced analytical models within managerial decision-making. While machine learning models offer strong predictive capabilities, their complexity often limits their transparency and usability. Decision-makers require not only accurate predictions but also clear and understandable explanations that support evaluation and action. XAI addresses this challenge by translating complex model outputs into interpretable insights, thereby enhancing trust and facilitating informed decision-making in organizational contexts [27].

4.1 Model Interpretability vs Decision Interpretability

Model interpretability refers to the ability to understand how a model generates its output, including the relationships between inputs and predictions. This form of interpretability is primarily technical, focusing on transparency at the algorithmic level. It allows analysts to examine model behavior and validate its performance, but it does not necessarily ensure that the outputs are useful for decision-making [28].

In contrast, decision interpretability focuses on how analytical outputs are understood and applied by decision-makers. It emphasizes the translation of technical explanations into actionable insights that support managerial decisions. Even when a model is technically interpretable, its output may still be difficult to use in practice if they are not aligned with decision requirements. Therefore, decision interpretability extends beyond model transparency to include relevance, clarity, and usability in real-world contexts [29].

The distinction between these two concepts highlights a key limitation in current AI applications. Many approaches prioritize explaining models rather than enabling decisions, resulting in explanations that lack practical value. Addressing this issue requires shifting toward decision-oriented interpretability that directly supports managerial actions and strategic choices [30].

To further clarify the distinction between model interpretability and decision interpretability, Table 2 presents a structured comparison highlighting their different roles and implications in managerial decision-making contexts.

Table 2
Comparison between Model Interpretability and Decision Interpretability

Dimension	Model Interpretability	Decision Interpretability
Primary Focus	Understanding how the model works	Understanding how to use outputs in decisions
Perspective	Technical / algorithmic	Managerial / practical
Key Question	How does the model produce results?	What do these results mean for action?
Target Users	Data scientists, analysts	Managers, decision-makers
Output Type	Feature importance, model logic	Actionable insights, decision guidance
Level of Abstraction	High (mathematical/technical)	Moderate (contextual and applied)
Role in Decision-Making	Supports model validation	Supports decision execution
Dependency	Model structure and data	Organizational context and objectives
Limitation	May lack practical relevance	Depends on clarity of explanations

As shown in Table 2, model interpretability and decision interpretability serve different but complementary purposes. While model interpretability focuses on explaining how analytical outputs are generated, decision interpretability emphasizes how these outputs can be translated into meaningful actions. This distinction highlights the need for explainability approaches that go beyond technical transparency to actively support managerial decision-making, which is further discussed in the following section.

4.2 Explainability as a Decision Support Mechanism

Explainability enhances decision support by improving the transparency and usability of analytical outputs. By identifying key drivers and relationships within predictive models, XAI enables decision-makers to better understand the factors influencing outcomes. This understanding allows managers to evaluate alternatives, assess risks, and justify their decisions in complex environments [31].

As a decision support mechanism, explainability contributes to several important functions. It improves trust in analytical systems by clarifying how results are generated, reduces uncertainty by highlighting influential factors, and supports scenario analysis by enabling the evaluation of potential changes in inputs. These capabilities enhance the overall quality and reliability of managerial decisions [32].

Moreover, explainability plays a crucial role in connecting predictive analytics with prescriptive decision-making. When predictive outputs are interpretable, they can be more effectively incorporated into decision models, enabling the development of actionable strategies. This integration strengthens the link between insight generation and decision execution, particularly in dynamic and uncertain environments [33].

To further illustrate how explainability supports the transformation of analytical outputs into actionable decisions, the interpretability flow is presented in Figure 2. This figure provides a simplified representation of the transition from data-driven predictions to managerial decision-making, emphasizing the role of explainability as a connecting layer.

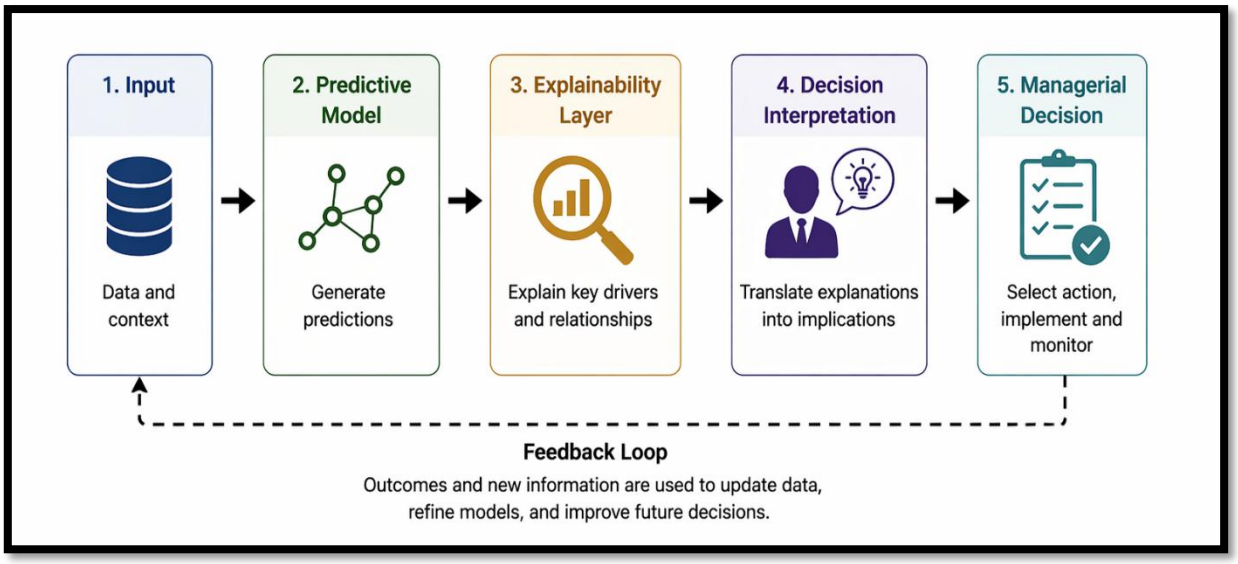

Fig. 2. Interpretability Flow: From Model Output to Managerial Decision

As shown in Figure 2, the interpretability process begins with data inputs and predictive modeling, followed by an explainability layer that translates model outputs into understandable insights. These insights are then interpreted within a decision context to support managerial actions. The inclusion of a feedback loop highlights the iterative nature of decision-making, where outcomes continuously inform future predictions and improvements.

This flow demonstrates that explainability is not merely a technical feature but a critical mechanism that enables the practical use of analytical models in decision-making environments. However, despite its advantages, the application of explainability in real-world contexts remains subject to several limitations, which are discussed in the following section.

4.3 Limitations of Current XAI Approaches

Despite its advantages, XAI faces several limitations that constrain its effectiveness in decision-making contexts. One major limitation is that many explainability techniques are designed for technical audiences, making them difficult for non-expert decision-makers to interpret and apply. This reduces their practical usability in managerial environments [34].

Another challenge is the inherent trade-off between model complexity and interpretability. Highly accurate models often lack transparency, while more interpretable models may offer lower predictive performance. This tension complicates the selection of appropriate models for decision-making purposes [35].

In addition, many XAI approaches lack contextual awareness, focusing primarily on model outputs without considering organizational constraints, strategic objectives, or environmental factors. This limits their ability to support real-world decision-making, where context plays a critical role. Addressing these limitations requires the development of integrated frameworks that align explainability with decision processes and managerial needs [36].

5. Decision-Making under Uncertainty

Uncertainty is a defining characteristic of contemporary managerial environments, where decision-makers must operate under conditions of incomplete information, dynamic changes, and

increasing complexity [37]. The growing integration of artificial intelligence in organizational processes has improved predictive capabilities; however, these predictions often remain probabilistic and subject to variability. As a result, managerial decisions require continuous evaluation of alternative scenarios and strategic adaptation. Understanding uncertainty is therefore essential for developing decision frameworks that are both flexible and robust in complex environments [38].

5.1 Types of Uncertainty in Managerial Environments

Uncertainty in managerial contexts can be categorized into several interconnected forms. **Environmental uncertainty** arises from external factors such as market volatility, technological disruption, and global economic changes, which limit the predictability of future outcomes and complicate strategic planning [39].

Informational uncertainty reflects limitations in data availability, quality, or timeliness. Even with advanced analytics, organizations often face incomplete or imperfect data, which affects the reliability of predictive insights and increases decision complexity. This challenge is particularly relevant in digital transformation contexts, where large volumes of data must be processed and interpreted effectively [40].

Model uncertainty stems from the assumptions and limitations embedded in analytical models. Predictive models may not fully capture real-world complexity, leading to variability in outputs and potential misinterpretation. This creates challenges for decision-makers who rely on these models to guide strategic actions [41].

Finally, **behavioral uncertainty** arises from human factors such as cognitive biases, leadership styles, and organizational dynamics. Decision-makers may interpret the same analytical outputs differently, resulting in variability in decisions. This highlights the need to consider both analytical and managerial dimensions in decision frameworks [42].

5.2 Implications for Decision Quality

Uncertainty significantly affects the quality and consistency of managerial decisions. Under uncertain conditions, decision-makers must evaluate multiple possible outcomes, consider trade-offs, and manage risks, which increases the complexity of decision-making processes [43].

One major challenge is the interpretation of probabilistic predictions. While predictive models provide valuable insights, they do not offer definitive answers, requiring managers to translate probabilities into actionable decisions. Without clear interpretation, this may lead to misjudgment or over-reliance on certain outcomes.

Additionally, uncertainty impacts the robustness of decisions. Strategies that are effective under specific conditions may become ineffective as environments change. This necessitates adaptive decision-making approaches that allow continuous adjustment based on new information. As emphasized in sustainability-oriented management research, the ability to manage uncertainty effectively is a key factor in achieving long-term organizational performance and resilience [44].

5.3 The Need for Explainability under Uncertainty

Explainability plays a critical role in enhancing decision-making under uncertainty by improving the interpretability of analytical outputs. By clarifying the factors driving predictions, explainable AI enables decision-makers to better understand the assumptions and limitations of models, supporting more informed evaluation of risks and alternatives [45].

Furthermore, explainability strengthens trust in analytical systems by making results transparent and justifiable. In uncertain environments, trust is essential for adopting data-driven approaches,

particularly in strategic decision-making. When managers understand how predictions are generated, they are more likely to rely on analytical insights and integrate them into decision processes.

Explainability also supports adaptive decision-making by enabling continuous learning. As new data becomes available, decision-makers can reassess previous decisions and refine their strategies accordingly. This iterative process enhances decision quality and organizational adaptability in dynamic environments [46].

Overall, integrating explainability into decision-making under uncertainty strengthens the connection between predictive insights and actionable decisions. It ensures that analytical outputs are not only accurate but also interpretable and usable, thereby improving the effectiveness of managerial decision-making in complex and uncertain contexts.

6. Theoretical Integration: Bridging Prediction and Prescription

Bridging the gap between predictive analytics and prescriptive decision-making requires an integrated framework that connects data-driven insights with actionable decisions. This section develops a theoretical structure composed of three core layers—predictive, explainability, and decision—linked through a coherent integration mechanism. The objective is to transform predictive outputs into interpretable and actionable knowledge that supports managerial decision-making under uncertainty. By embedding explainability within this process, the framework enhances transparency, usability, and strategic alignment of analytical outputs [47].

6.1 Predictive Layer

The predictive layer represents the foundation of the framework, focusing on generating forecasts and probabilistic insights based on data-driven models. It utilizes statistical methods and machine learning algorithms to identify patterns, trends, and relationships within data, enabling organizations to anticipate future outcomes. These predictions provide valuable inputs for decision-making by reducing uncertainty and supporting proactive strategies [48].

However, predictive outputs are often complex and may lack direct interpretability, particularly when derived from advanced models. As a result, while this layer enhances analytical capability, it does not by itself provide clear guidance for action. This limitation highlights the need for additional layers that translate predictive insights into decision-relevant knowledge.

6.2 Explainability Layer

The explainability layer acts as a critical intermediary that interprets predictive outputs and transforms them into understandable insights. It focuses on identifying the key drivers of predictions, clarifying relationships between variables, and providing transparency into model behavior. This layer enhances the usability of predictive analytics by enabling decision-makers to understand the rationale behind analytical results [49].

By converting complex outputs into interpretable information, explainability reduces ambiguity and supports informed evaluation of alternatives. It also plays a central role in building trust in analytical systems, particularly in environments characterized by uncertainty and risk. Through this function, the explainability layer bridges the gap between technical analysis and managerial understanding [50].

6.3 Decision Layer

The decision layer represents the stage where interpreted insights are translated into actionable managerial decisions. This layer incorporates decision logic, organizational objectives, and contextual constraints to determine appropriate courses of action. It enables managers to evaluate alternatives, assess risks, and select strategies that align with both short-term and long-term goals [51].

The effectiveness of this layer depends on the clarity and reliability of the inputs provided by the predictive and explainability layers. When insights are both accurate and interpretable, decision-makers can make more informed and consistent choices. This enhances decision quality and supports organizational performance in complex environments.

6.4 Integration Mechanism

The integration mechanism connects the three layers into a unified framework, ensuring a seamless transition from prediction to decision. Explainability serves as the central linking component, transforming predictive outputs into decision-relevant knowledge. This integration enables organizations to move beyond isolated analytical processes toward a coherent decision system.

The framework operates as a sequential yet dynamic process, where outputs flow from prediction to explanation and then to decision-making. Feedback loops allow continuous refinement, enabling the system to adapt to new data and changing conditions. This iterative capability reflects real-world managerial environments, where decisions are continuously updated based on evolving information [52].

To illustrate the integration between predictive analytics, explainability, and decision-making, the proposed framework is presented in Figure 3. The figure provides a simplified representation of how predictive insights are transformed into actionable managerial decisions through an explainability-driven process.

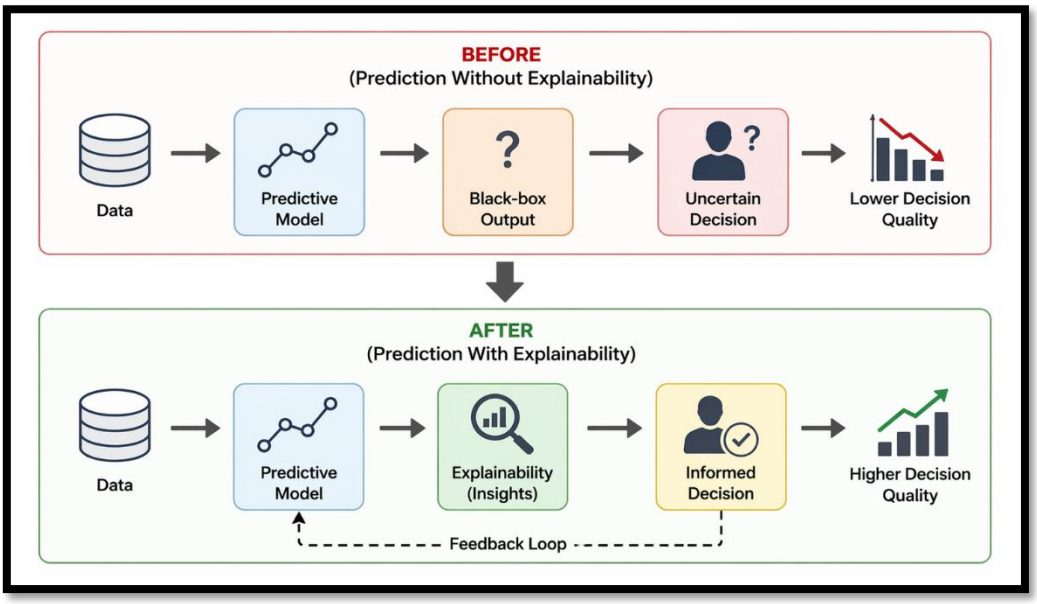

Fig. 3. Integrated Framework: Bridging Prediction and Prescription

As shown in Figure 3, the framework follows a sequential flow starting from data inputs and predictive modeling, followed by an explainability stage that interprets model outputs. These interpreted insights are then utilized within a decision context to support managerial actions. The feedback loop reflects the iterative nature of decision-making, where outcomes continuously inform future predictions and adjustments.

This simplified representation highlights the central role of explainability in bridging the gap between prediction and prescription. By ensuring that predictive outputs are interpretable and actionable, the framework enhances the effectiveness and transparency of decision-making processes in uncertain environments.

7. Integration into Decision Processes

The effectiveness of decision analytics depends on the ability to integrate predictive insights with prescriptive actions within a coherent decision process. While predictive analytics provides forecasts and probabilistic insights, and prescriptive analytics recommends actions, their practical value is realized only when these components are systematically connected. This integration requires mechanisms that ensure analytical outputs are interpretable, contextually relevant, and directly applicable to decision-making. In this regard, explainable artificial intelligence plays a central role in facilitating the transition from data-driven insights to actionable managerial decisions [53].

7.1 Integration of Predictive and Prescriptive Layers

The integration of predictive and prescriptive analytics is essential for transforming analytical capabilities into effective decision support systems. Predictive models generate insights about future outcomes, while prescriptive approaches determine optimal actions based on these insights. However, in many organizational contexts, these layers operate independently, leading to fragmented decision processes [54].

A key challenge in integration lies in aligning predictive outputs with decision logic. Predictive models often produce probabilistic results that require interpretation before they can be used in decision-making. Prescriptive models, on the other hand, depend on structured inputs that define objectives, constraints, and trade-offs. Without effective integration, the transition from prediction to action remains incomplete.

To address this challenge, integrated frameworks must ensure that predictive insights are directly embedded within decision models. This involves linking forecasting outputs with optimization techniques and decision rules, enabling managers to evaluate alternatives and select appropriate strategies. Such integration enhances decision consistency, improves resource allocation, and supports strategic alignment in complex environments [55].

7.2 Role of Explainability in Decision Processes

Explainability plays a critical role in enabling the integration of predictive and prescriptive layers by transforming analytical outputs into interpretable and actionable insights. By clarifying the factors driving predictions, explainable AI allows decision-makers to understand the underlying logic of analytical models and assess their relevance within specific decision contexts [56].

In decision processes, explainability supports several key functions. First, it enhances transparency by making model outputs understandable, thereby increasing trust in analytical systems. Second, it facilitates decision evaluation by enabling managers to explore alternative

scenarios and assess potential outcomes. Third, it improves accountability by providing justifications for decisions, which is particularly important in strategic and high-stakes contexts.

Furthermore, explainability enables a more dynamic and adaptive decision process. As new data becomes available, decision-makers can reinterpret predictive outputs, refine their understanding, and adjust their strategies accordingly. This iterative capability strengthens organizational responsiveness and supports continuous improvement in decision-making.

By integrating explainability into decision processes, organizations can bridge the gap between prediction and prescription more effectively. This integration ensures that analytical insights are not only technically accurate but also practically relevant, thereby enhancing decision quality and organizational performance in uncertain environments [57].

8. Theoretical Propositions

Building on the proposed framework, this section formulates theoretical propositions that articulate the relationships between predictive analytics, explainability, and decision-making outcomes. The aim is to translate conceptual integration into testable statements that can guide future empirical research. The propositions focus on how explainability functions as a linking mechanism that enhances the transformation of predictive insights into effective managerial decisions under uncertainty.

8.1 Proposition Development

The first set of propositions addresses the structural relationships between the three layers of the framework. Predictive analytics provides probabilistic insights that improve the understanding of future outcomes; however, its impact on decision-making depends on how these insights are interpreted and utilized.

Proposition 1: The effectiveness of predictive analytics in managerial decision-making is positively influenced by the level of interpretability of its outputs.

This proposition suggests that predictive accuracy alone is insufficient. When outputs are interpretable, decision-makers can better understand underlying patterns and incorporate them into decision processes, thereby enhancing their practical value [58].

Proposition 2: Explainability mediates the relationship between predictive analytics and prescriptive decision-making.

This proposition highlights the central role of explainability as a bridging mechanism. By translating complex model outputs into understandable insights, explainability enables the integration of predictive results into decision logic and supports actionable outcomes.

Proposition 3: Higher levels of integration between predictive and prescriptive layers lead to improved decision consistency and alignment with organizational objectives.

This proposition reflects the importance of combining analytical capabilities within a unified framework. Integrated systems reduce fragmentation and enable more coherent and structured decision-making processes.

8.2 Linking Explainability to Decision Effectiveness

The second set of propositions focuses on the impact of explainability on decision quality and effectiveness. In uncertain environments, decision-makers must evaluate risks, justify actions, and

adapt to changing conditions. Explainability enhances these capabilities by improving transparency and understanding.

Proposition 4: Explainability positively influences decision quality by enhancing transparency and reducing ambiguity in analytical outputs.

When decision-makers understand the reasoning behind predictions, they are better equipped to assess alternatives and make informed choices. This reduces the likelihood of misinterpretation and improves overall decision quality.

Proposition 5: Explainability strengthens trust in analytical systems, which in turn increases the adoption of data-driven decision-making approaches.

Trust is a critical factor in the use of advanced analytics. Transparent and interpretable models are more likely to be accepted by managers, particularly in high-stakes decision contexts.

Proposition 6: The impact of explainability on decision effectiveness is stronger under conditions of high uncertainty.

Under uncertain conditions, the need for clarity and justification becomes more pronounced. Explainability provides the necessary insights to evaluate risks and adapt strategies, thereby enhancing decision effectiveness in dynamic environments [59].

9. Results and Discussion

This section presents the conceptual outcomes derived from the proposed framework, focusing on how the integration of predictive analytics, explainable artificial intelligence, and prescriptive decision-making enhances managerial decision processes. Rather than empirical findings, the results are interpreted as theoretical insights that demonstrate the value of the framework in improving decision quality, transparency, and adaptability under uncertainty.

9.1 Framework Outcomes

The proposed framework generates several key outcomes that address the limitations of traditional analytics approaches. First, it enables the transformation of predictive outputs into actionable insights by incorporating explainability as a central mechanism. This ensures that analytical results are not only accurate but also interpretable and relevant for decision-making.

Second, the framework promotes a structured decision process by linking prediction, explanation, and action within a unified system. This integration reduces fragmentation in decision-making and supports more consistent and aligned outcomes across organizational levels.

Third, the framework enhances organizational adaptability by incorporating feedback loops that allow continuous refinement of decisions based on new data. This dynamic capability is particularly valuable in environments characterized by rapid change and uncertainty.

9.2 Decision Quality Impact

The integration of predictive and prescriptive layers, supported by explainability, significantly improves decision quality. Decision-makers are better equipped to evaluate alternatives, assess risks, and select strategies that align with organizational objectives. The availability of interpretable insights reduces ambiguity and enhances the reliability of decisions.

Moreover, the framework supports consistency in decision-making by providing a structured approach that minimizes reliance on intuition or ad hoc judgments. This leads to more rational and

evidence-based decisions, improving both short-term performance and long-term strategic outcomes.

In addition, the framework facilitates accountability by enabling decision-makers to justify their choices based on transparent analytical processes. This is particularly important in complex organizational environments where decisions must be communicated and validated across multiple stakeholders.

9.3 Explainability under Uncertainty

Explainability plays a critical role in enhancing decision-making under conditions of uncertainty. By clarifying the factors driving predictive outputs, it enables decision-makers to better understand the assumptions and limitations of analytical models. This understanding supports more informed evaluation of risks and alternative scenarios.

Under uncertain conditions, the ability to interpret probabilistic insights becomes essential. Explainability reduces the cognitive burden associated with complex models and provides a clearer basis for decision-making. It also enhances trust in analytical systems, encouraging greater adoption of data-driven approaches.

Furthermore, explainability supports adaptive decision-making by enabling continuous learning. As new information becomes available, decision-makers can reassess previous decisions and refine their strategies. This iterative process strengthens organizational resilience and improves responsiveness to changing conditions.

9.4 Comparison with Traditional Approaches

Compared to traditional decision-making approaches, the proposed framework offers significant advantages in terms of transparency, consistency, and adaptability. Traditional approaches often rely on intuition or isolated analytical tools, which may lead to inconsistent and less reliable decisions. In contrast, the integrated framework provides a systematic and transparent process that aligns analytical insights with decision logic.

The framework also enhances the ability to manage uncertainty by combining predictive capabilities with explainability and structured decision-making. This contrasts with traditional methods, which may struggle to effectively incorporate uncertainty into decision processes is presented in Table 3.

Table 3
Comparison between Traditional and Proposed Decision Approaches

Dimension	Traditional Approach	Proposed Framework
Decision Basis	Intuition / partial analysis	Data-driven + explainable
Transparency	Limited	High
Decision Consistency	Variable	Structured and consistent
Risk Handling	Reactive	Proactive and analytical
Adaptability	Low	Dynamic with feedback loops

Overall, the results demonstrate that the proposed framework provides a comprehensive and effective approach for integrating predictive analytics, explainability, and decision-making. By addressing the gap between prediction and prescription, the framework enhances the quality, transparency, and adaptability of managerial decisions in complex and uncertain environments.

10. Managerial Implications

The proposed framework offers practical implications for managers seeking to enhance decision-making through the integration of predictive analytics, explainable artificial intelligence, and prescriptive approaches. By structuring the transition from prediction to action, the framework supports more transparent, consistent, and adaptive decision processes. These implications extend across individual decision-makers, organizational systems, and risk management practices, highlighting the value of explainability as a core component of data-driven management.

10.1 Implications for Decision-Makers

For decision-makers, the framework provides a structured approach to interpreting and utilizing analytical outputs. Instead of relying solely on predictive accuracy, managers are encouraged to consider how insights are generated and how they can be translated into actionable strategies. The inclusion of explainability enables decision-makers to better understand the factors influencing predictions, improving their ability to evaluate alternatives and making informed choices.

Furthermore, the framework reduces reliance on intuition by supporting evidence-based decision-making. By integrating predictive and prescriptive layers, managers can systematically assess options and align decisions with organizational objectives. This enhances both the consistency and reliability of decisions, particularly in complex and uncertain environments.

In addition, the ability to justify decisions through transparent analytical processes strengthens managerial accountability. Decision-makers can communicate the rationale behind their choices more effectively, facilitating alignment with stakeholders and improving organizational trust in data-driven approaches.

10.2 Organizational Applications

At the organizational level, the framework supports the development of integrated decision systems that connect analytics with strategic and operational processes. Organizations can leverage the framework to align predictive models with decision logic, ensuring that analytical outputs are directly linked to actionable outcomes.

The framework is applicable across various functional areas, including operations, marketing, finance, and strategic planning. For example, organizations can use predictive insights to anticipate demand while applying prescriptive models to optimize resource allocation. The inclusion of explainability ensures that these processes remain transparent and understandable, supporting effective implementation across departments.

Moreover, the framework enhances organizational adaptability by incorporating feedback mechanisms that allow continuous learning and improvement. As new data becomes available, organizations can update their models and refine their decision strategies, enabling more responsive and resilient operations in dynamic environments.

10.3 Risk and Transparency Considerations

The integration of explainability within decision processes has important implications for risk management and transparency. By providing clear insights into how predictions are generated, explainable AI enables organizations to better assess risks and understand potential uncertainties associated with analytical outputs.

Transparency also plays a critical role in building trust in analytical systems. When decision processes are interpretable, stakeholders are more likely to accept and support data-driven decisions. This is particularly important in high-stakes contexts where decisions must be justified and aligned with regulatory or ethical standards.

In addition, the framework supports proactive risk management by enabling decision-makers to identify key drivers of uncertainty and evaluate alternative scenarios. This improves the ability of organizations to anticipate potential challenges and respond effectively.

Overall, the managerial implications of the proposed framework demonstrate its practical value in enhancing decision-making processes. By integrating predictive analytics, explainability, and prescriptive approaches, organizations can achieve greater transparency, improved decision quality, and stronger alignment with strategic objectives in uncertain environments.

11. Contributions, Limitations, and Future Research

This section consolidates the study's academic contributions, acknowledges its constraints, and outlines directions for subsequent inquiry. Given the conceptual nature of the work, the emphasis is on theoretical advancement, boundary conditions, and testable avenues for future research.

11.1 Theoretical Contributions

This study makes several important theoretical contributions to the literature on decision analytics and artificial intelligence in management. First, it develops an integrated conceptual framework that connects predictive analytics, explainable artificial intelligence, and prescriptive decision-making within a unified structure. By addressing the fragmentation that typically characterizes these domains, the study provides a more comprehensive understanding of how analytical capabilities can support managerial decision-making.

Second, the study redefines the role of explainability by positioning it as a central mediating mechanism rather than merely a tool for model transparency. In this context, explainability facilitates the transformation of predictive outputs into decision-relevant knowledge, thereby enhancing the practical applicability of analytical models. This perspective extends existing research by emphasizing the importance of decision-oriented interpretability in managerial contexts.

Third, the study contributes by establishing a structured pathway that links prediction to action through sequential analytical stages. This pathway clarifies how data-driven insights can be systematically translated into actionable decisions, improving both the consistency and effectiveness of decision-making processes. Additionally, the development of theoretical propositions provides a foundation for future empirical research, enabling the validation and refinement of the proposed framework.

11.2 Limitations

Despite its contributions, this study has several limitations that should be acknowledged. The primary limitation is its conceptual nature, as the proposed framework has not been empirically tested. Consequently, the findings are based on theoretical reasoning rather than observed data, which may limit the ability to generalize the results across different contexts.

Another limitation is the broad scope of the framework, which is designed to be applicable across various managerial settings. While this enhances its general relevance, it may overlook industry-specific factors that influence decision-making processes. Additionally, the framework abstracts

technical details related to specific analytical models and explainability techniques, which may restrict its direct implementation in practice.

Furthermore, the study does not explicitly incorporate organizational and behavioral factors such as culture, leadership, and decision-maker expertise. These elements can significantly influence how analytical insights are interpreted and applied, suggesting that future research should consider these dimensions more explicitly.

11.3 Future Research

Future research can build on this study by empirically testing the proposed framework and its underlying propositions. Quantitative and qualitative studies can be conducted to examine how the integration of predictive analytics, explainability, and decision-making affects organizational performance and decision quality. Such research would provide valuable evidence to support or refine the theoretical relationships identified in this study.

In addition, future studies can explore the application of the framework in specific domains such as finance, supply chain management, healthcare, and public policy. Domain-specific analysis would help identify contextual factors that influence the effectiveness of the framework and provide more practical insights for implementation.

Further research is also needed to examine the role of different explainability techniques in supporting decision-making. Comparative studies can evaluate the effectiveness of various approaches in enhancing interpretability and decision outcomes. Moreover, incorporating behavioral and organizational perspectives, including cognitive biases and trust in AI systems, would provide a more comprehensive understanding of how explainability influences managerial decisions.

Finally, future research can focus on developing dynamic and adaptive decision systems that incorporate real-time data and feedback mechanisms. Such systems would enhance the ability of organizations to respond to changing conditions and improve decision-making under uncertainty.

12. Conclusion

This study sets out to address a central limitation in contemporary decision analytics: the disconnect between predictive insights and actionable managerial decisions. While advances in artificial intelligence have significantly improved the ability of organizations to generate accurate forecasts, the translation of these predictions into effective decisions remains a persistent challenge. By developing a conceptual framework that integrates predictive analytics, explainable artificial intelligence, and prescriptive decision-making, the study provides a structured approach for bridging this gap.

The proposed framework highlights the importance of explainability as a core mechanism that connects analytical outputs with decision processes. By transforming complex model results into interpretable and decision-relevant insights, explainability enhances transparency, supports informed evaluation of alternatives, and strengthens trust in data-driven systems. This integration enables decision-makers to move beyond isolated predictions toward more structured, consistent, and accountable decision-making practices.

In addition, the study emphasizes the role of uncertainty in shaping managerial decisions. In dynamic and complex environments, the ability to interpret probabilistic information and adapt to changing conditions is critical. The framework addresses this challenge by incorporating feedback mechanisms and promoting adaptive decision processes that improve over time. This contributes to enhancing organizational resilience and long-term performance.

Overall, the study advances theoretical understanding of decision analytics by offering an integrated perspective that aligns predictive, explanatory, and prescriptive components within a unified structure. It also provides practical insights for managers seeking to leverage artificial intelligence in decision-making contexts. By emphasizing transparency, interpretability, and integration, the framework contributes to improving the effectiveness of managerial decisions in uncertain environments.

Future research is encouraged to empirically validate the proposed framework and explore its application across different industries and organizational settings. Such efforts will further strengthen the link between theory and practice, supporting the development of more robust and actionable decision analytics systems.

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Conflicts of Interest
The authors declare no conflicts of interest.

Declaration of Generative AI and AI-Assisted Technologies in the Manuscript Preparation Process
During the preparation of this work, the authors used AI-assisted tools (e.g., ChatGPT) to enhance language clarity, improve structure, and support the organization of the manuscript. These tools were not used to generate scientific content, analyses, or conclusions. All intellectual contributions, conceptual development, and interpretations remain the responsibility of the authors.
The authors take full responsibility for the final content of the manuscript.

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