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A Structured Decision Intelligence Framework for Context-Aware Decision Making

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ABSTRACT

Decision Intelligence (DI) has emerged as an integrative paradigm that combines data, analytics, and artificial intelligence to enhance organizational decision-making. Despite this growing interest, many existing DI approaches place disproportionate emphasis on predictive intelligence while providing limited methodological guidance on how predictions are transformed into actionable and accountable decisions. Machine learning models are highly effective at forecasting and classification; however, they do not inherently incorporate organizational constraints, human preferences, or decision trade-offs. This study proposes a structured, end-to-end Decision Intelligence framework that explicitly integrates machine learning–based prediction with Decision Support System (DSS) modelling. The framework positions DSS as the core decision logic by employing the Analytic Hierarchy Process (AHP) to formalize contextual and human preferences and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to execute alternative ranking. Furthermore, contextual intelligence and outcome intelligence are embedded to ensure decision relevance, transparency, and continuous improvement. Using a Design Science Research approach, this study develops and demonstrates the proposed framework as a systematic solution for bridging the gap between predictive analytics and decision execution. The framework contributes to Decision Intelligence research by clarifying the role of DSS in AI-driven decision environments and by providing a replicable structure for integrating prediction, decision modelling, and outcome evaluation.

1. Introduction

Organizations increasingly rely on data-driven and artificial intelligence (AI) technologies to support complex decision-making processes. Advances in data science and machine learning have enabled accurate forecasting, classification, and risk estimation across various domains, including finance, education, healthcare, and public administration (Du et al., 2023). These predictive capabilities have significantly enhanced organizations’ ability to anticipate future conditions and identify latent patterns in large-scale data.

Despite these advances, a growing body of research emphasizes that high predictive accuracy does not necessarily lead to high-quality decisions (Kovári, 2024). Machine learning models are primarily optimized for prediction tasks and do not inherently prescribe actions that account for organizational objectives, policy constraints, human preferences, or ethical considerations. As a result, decision-makers often face a gap between *what is predicted* and *what should be decided*.

Decision Support Systems (DSS) were originally developed to address this gap by providing structured decision logic through mathematical modelling, optimization techniques, and multi-criteria decision-making (MCDM) methods (Power, 2007). Model-driven DSS approaches enable decision-makers to explicitly evaluate trade-offs, incorporate subjective preferences, and justify decisions in a transparent and explainable manner (Saaty, 2008). However, many classical DSS implementations were designed for relatively static environments and remain loosely integrated with modern machine learning pipelines (Pratt, 2020).

Decision Intelligence (DI) has recently emerged as a paradigm that integrates data, analytics, AI, and decision-making into a unified decision lifecycle (Gartner, 2022). Unlike traditional analytics-centric approaches, DI emphasizes problem framing, contextual awareness, decision execution, and outcome evaluation. Nevertheless, existing DI frameworks often remain abstract and provide limited methodological guidance on how predictive outputs are transformed into executable decisions through formal decision models (O'Callaghan et al., 2023).

Motivated by these limitations, this study develops a structured Decision Intelligence framework that explicitly integrates machine learning–based prediction with DSS-based decision modelling. The proposed framework positions DSS as the core decision logic, incorporates contextual intelligence to capture human and organizational considerations, and embeds outcome intelligence to support continuous learning. This study contributes to the literature by strengthening the theoretical and methodological foundations of Decision Intelligence in AI-driven decision environments.

2. Literatur Review

2.1 Decision Support Systems and Multi-Criteria Decision Making

Decision Support Systems have been extensively studied as tools for supporting semi-structured and unstructured decision-making problems (Power, 2007). Among the various DSS paradigms, model-driven DSS has played a central role in formalizing decision logic through mathematical modelling and optimization. In particular, multi-criteria decision-making (MCDM) methods have been widely applied to problems involving conflicting criteria and subjective preferences, such as supplier selection, project prioritization, and policy evaluation.

The Analytic Hierarchy Process (AHP) is one of the most established MCDM techniques and is widely recognized for its ability to translate qualitative human judgments into quantitative weights (Saaty, 2008). Similarly, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) provides a systematic approach for ranking alternatives based on their relative closeness to ideal and anti-ideal solutions. These methods are valued for their transparency, interpretability, and suitability for explainable decision-making.

However, most MCDM-based DSS studies assume that decision criteria values are static and known with certainty. In contemporary decision environments characterized by uncertainty and rapidly changing conditions, this assumption is increasingly unrealistic. As noted by Pratt (2020), the lack of integration between DSS and predictive analytics limits the ability of decision systems to respond adaptively to emerging patterns and risks.

2.2 Machine Learning in Decision-Making Systems

Machine learning has become a dominant approach for predictive analytics, enabling accurate forecasting, classification, and risk estimation from large-scale data. Numerous empirical studies demonstrate the effectiveness of machine learning in predicting outcomes such as disease progression, financial market movements, and student dropout risks (Du et al., 2023; Susanto et al., 2023). These advances have led to widespread adoption of AI-based decision support tools across various sectors.

Nevertheless, several researchers caution against equating predictive accuracy with decision quality. Kovári (2024) argues that machine learning models often lack transparency and fail to capture organizational priorities, leading to decision recommendations that are difficult to justify or operationalize. Moreover, over-reliance on AI predictions without structured decision logic may increase the risk of bias amplification and inappropriate automation of decision-making processes.

These limitations highlight the need for frameworks that integrate machine learning with formal decision models. Rather than replacing human judgment or DSS logic, machine learning should be positioned as a complementary component that enhances decision-making by providing probabilistic and predictive information.

2.3 Decision Intelligence Frameworks

Decision Intelligence has been proposed as a holistic approach that combines data, analytics, AI, and decision-making processes into a unified framework (Gartner, 2022). Existing DI frameworks emphasize the alignment of analytics with business objectives and the integration of AI into operational workflows. Some studies also highlight the importance of human-in-the-loop mechanisms to maintain trust, accountability, and ethical oversight in AI-assisted decisions (O'Callaghan et al., 2023).

Despite these contributions, the majority of DI frameworks remain high-level and conceptual. The mechanisms through which predictive outputs are transformed into executable decisions are often not formally specified. In particular, the role of DSS modelling within DI frameworks is frequently underdeveloped, resulting in ambiguity regarding how decisions are actually produced (Kovári, 2024). Furthermore, outcome evaluation is rarely treated as a core component of DI, limiting the ability of such frameworks to support continuous learning and improvement (Susanto et al., 2023).

2.4 Research Gap

Based on the reviewed literature, three major research gaps can be identified. First, there is a lack of structured Decision Intelligence frameworks that explicitly bridge machine learning–based prediction and DSS-based decision execution. Second, contextual intelligence—encompassing human preferences, organizational policies, and resource constraints—remains insufficiently formalized in existing DI models. Third, outcome intelligence as a systematic mechanism for evaluating decision impacts and enabling learning loops is largely absent from current frameworks. These gaps motivate the development of the proposed Decision Intelligence framework, which aims to provide a rigorous and replicable structure for integrating prediction, decision logic, and outcome evaluation in complex decision environments.

3. Research Method

This study adopts a Design Science Research (DSR) methodology to develop and evaluate the proposed Decision Intelligence (DI) framework. DSR is particularly suitable for this research because the primary objective is not merely to analyze existing phenomena, but to design, develop, and justify a structured solution to a practical and complex decision-making problem. In the context of Decision Intelligence, such a solution must integrate predictive analytics, decision logic, and organizational context within a coherent and replicable framework. Design Science Research has been widely recognized as an appropriate methodology for research in Information Systems and Decision Support Systems, especially when the research outcome is a prescriptive model or framework intended to improve decision-making practices (Hevner et al., 2004). By employing DSR, this study ensures that the proposed framework is grounded in both theoretical rigor and practical relevance.

Design Science Research Process

The DSR process in this study follows the six-stage framework proposed by Hevner et al. (2004), consisting of:
(1) problem identification,
(2) objective definition,
(3) framework design and development,
(4) demonstration,
(5) evaluation, and
(6) communication.

Each stage is explicitly mapped to the development of the proposed Decision Intelligence framework to ensure methodological transparency and replicability.

A. Problem Identification

The first stage of the DSR process focuses on identifying and clearly articulating the research problem. Based on an extensive review of the literature, this study identifies a persistent gap between predictive intelligence generated by machine learning models and decision execution supported by Decision Support Systems. While machine learning models provide accurate predictions, they often lack mechanisms for incorporating contextual factors, human preferences, and organizational constraints into the decision-making process. In contrast, traditional DSS approaches provide structured decision logic but are frequently disconnected from modern predictive analytics. This fragmentation results in decision systems that are either data-rich but decision-poor, or decision-structured but prediction-poor. Addressing this gap constitutes the core problem motivating this research.

B. Objective Definition

Based on the identified problem, the objective of this study is to develop a structured and integrated Decision Intelligence framework that bridges predictive analytics and decision execution. Specifically, the framework aims to: 1) Integrate machine learning outputs as decision inputs rather than final decisions, 2) Position DSS modelling as the core mechanism for decision execution, 3) Incorporate contextual intelligence to represent human and organizational considerations, and 4) Embed outcome intelligence to support evaluation and continuous improvement. These objectives guide the design and development of the proposed framework.

C. Framework Design and Development

The design and development stage focuses on constructing the proposed Decision Intelligence framework as a modular and end-to-end architecture. The framework is designed to consist of multiple layers, including contextual intelligence, data intelligence, machine learning, DSS modelling, decision engine, decision delivery interface, and outcome intelligence. At this stage, multi-criteria decision-making techniques are selected as the core decision models. The Analytic Hierarchy Process (AHP) is employed to model contextual and human preferences through criteria weighting, while the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is used to rank decision alternatives. Machine learning models are integrated to provide predictive indicators that serve as quantitative inputs to the DSS modelling layer. This design explicitly separates prediction from decision execution, while ensuring their systematic integration.

D. Demonstration

The demonstration stage aims to illustrate the applicability and internal consistency of the proposed framework. Rather than focusing on domain-specific performance metrics, the framework is demonstrated through a conceptual decision scenario that shows how data, predictions, contextual information, and decision logic interact across the framework layers. This demonstration serves as a proof-of-concept, highlighting the end-to-end decision flow from contextual intelligence and predictive analytics to decision recommendation and outcome evaluation.

E. Evaluation

The evaluation stage assesses the quality and validity of the proposed framework. Given the conceptual nature of this study, evaluation is conducted through logical and structural assessment, focusing on the coherence of the framework, the consistency between its components, and its alignment with established principles of Decision Intelligence and DSS research. In addition, expert-based evaluation may be employed to assess the clarity, relevance, and practical applicability of the framework. Such evaluation provides qualitative evidence that the proposed framework addresses the identified problem and meets the research objectives.

F. Communication

The final stage of the DSR process involves communicating the research results to the academic community. In this study, the proposed framework and its methodological foundation are communicated through a peer-reviewed journal article. Clear documentation of the framework design, methodological steps, and theoretical positioning ensures that the research can be critically evaluated and extended by future studies.

4. Result and Discussions

Proposed Decision Intelligence Framework

This study proposes a structured Decision Intelligence (DI) framework that integrates predictive analytics and Decision Support Systems (DSS) within an end-to-end decision-making lifecycle. As illustrated in Figure 1, the framework consists of seven tightly connected layers: contextual intelligence, data intelligence, machine learning, DSS modelling, decision engine, decision delivery interface, and outcome intelligence. The framework is designed to ensure that predictions generated by machine learning models are transformed into context-aware, explainable, and actionable decisions.

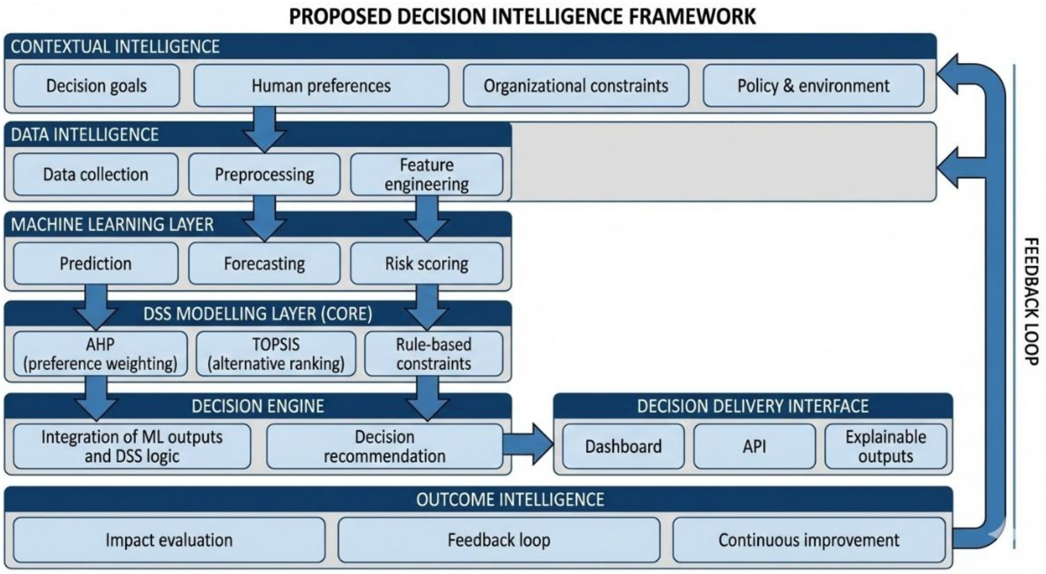

Fig. 1. Decision Intelligence Framework

Contextual Intelligence

Contextual intelligence constitutes the foundational layer of the proposed framework. This layer captures the decision context prior to any data processing or model execution. As shown in the framework, contextual intelligence includes decision goals, human preferences, organizational constraints, and policy or environmental factors.

The primary role of this layer is to ensure that decision-making is aligned with real-world organizational conditions rather than being driven solely by data patterns. Prior research has emphasized that decisions derived from purely data-driven models often fail when contextual constraints are ignored. In the proposed framework, contextual intelligence explicitly informs the selection of decision criteria and influences their relative importance, thereby embedding human and organizational considerations into the decision process from the outset.

Data Intelligence

The data intelligence layer is responsible for transforming raw data into decision-ready information. As depicted in the framework, this layer encompasses data collection, preprocessing, and feature engineering. Data may originate from heterogeneous sources, including operational systems, transactional databases, or external data providers.

By separating data intelligence from predictive and decision layers, the framework promotes modularity and scalability. This design allows data pipelines to evolve independently of decision logic, while ensuring that machine learning and DSS components receive consistent and high-quality inputs.

Machine Learning Layer

The machine learning layer provides predictive intelligence within the framework. This layer includes prediction, forecasting, and risk scoring tasks, depending on the nature of the decision problem. Machine learning models are trained to estimate future states, probabilities, or risk levels associated with decision alternatives.

Importantly, the proposed framework deliberately limits the role of machine learning to prediction rather than decision execution. Machine learning outputs are treated as decision indicators that inform subsequent decision modelling, rather than as autonomous decision-makers. This design choice addresses concerns raised in the literature regarding over-reliance on black-box AI systems and the conflation of prediction with decision-making.

DSS Modelling Layer (Core)

The DSS modelling layer represents the core of the proposed Decision Intelligence framework, as explicitly highlighted in the diagram. This layer is responsible for transforming predictive outputs and contextual information into structured decisions using formal decision models.

In this study, the DSS modelling layer employs multi-criteria decision-making (MCDM) techniques. The Analytic Hierarchy Process (AHP) is used to derive criteria weights based on contextual intelligence and human preferences, while the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is used to rank decision alternatives. In addition, rule-based constraints are incorporated to ensure compliance with organizational policies and regulatory requirements. By positioning DSS modelling at the core, the framework reinforces the role of transparent and explainable decision logic in AI-driven decision environments.

Decision Engine

The decision engine integrates outputs from the machine learning layer and the DSS modelling layer. As shown in the framework, this component combines predictive indicators with weighted decision criteria and applies decision rules to generate final decision recommendations.

The decision engine ensures that decision recommendations are not solely based on predicted values, but also reflect trade-offs among multiple criteria, contextual priorities, and predefined constraints. This integration addresses a key limitation of many existing Decision Intelligence approaches, which often lack a clear mechanism for operationalizing predictive analytics into executable decisions.

Decision Delivery Interface

The decision delivery interface serves as the communication layer between the decision system and its users or external systems. As illustrated in the framework, this layer may include dashboards, application programming interfaces (APIs), and explainable outputs.

The inclusion of explainable outputs is particularly important for supporting transparency, trust, and accountability. Decision-makers are not only presented with recommendations, but also with explanations of how decisions were derived, including the influence of predictive indicators and decision criteria.

Outcome Intelligence and Feedback Loop

Outcome intelligence represents the final stage of the decision lifecycle and distinguishes the proposed framework from many existing DI models. This layer evaluates the real-world impact of implemented decisions and captures performance outcomes using predefined metrics.

As shown by the feedback loop in the framework, outcome intelligence provides feedback to earlier layers, enabling continuous improvement. Evaluation results may be used to refine decision criteria, adjust weights, update decision rules, or improve machine learning models. This feedback mechanism transforms the framework from a static decision system into a learning-oriented decision intelligence system.

Framework Significance

Overall, the proposed Decision Intelligence framework establishes a clear separation between prediction and decision execution while ensuring their systematic integration. By embedding contextual intelligence, DSS modelling, and outcome intelligence within a unified architecture, the framework provides a comprehensive foundation for context-aware, explainable, and adaptive decision-making.

5. Conclusion

This study developed a structured Decision Intelligence framework that integrates machine learning–based prediction with DSS-based decision modelling. By positioning DSS as the core decision logic and embedding contextual and outcome intelligence, the framework addresses key limitations in existing AI-driven decision systems. The proposed framework contributes theoretically by clarifying the role of DSS within Decision Intelligence and practically by providing a systematic guide for organizations seeking to operationalize AI-assisted decision-making. Future research should empirically validate the framework across diverse domains and explore automated mechanisms for adapting decision models based on outcome feedback.

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