

AI-Driven Decision Intelligence in Strategic Business Decision-Making: A Narrative Review Integrating Predictive Analytics, Generative AI, and Prescriptive Optimization

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Abstract

Artificial Intelligence is becoming increasingly important for strategic decision-making, but the research literature on predictive analytics, generative AI, and prescriptive optimization is scattered. They have evolved independently and there are limited studies on how they can operate in concert in an integrated decision architecture. This paper aims to fill that gap in the literature in a narrative review of the 34 peer-reviewed sources. The review identifies that the interfaces between the three streams are real but weak, and each interface poses a translation challenge that cannot be addressed through technical solutions. The effort of integrating was met with three tensions: epistemic authority, governance and accountability, and organizational capability. To address this, the paper suggests a decision intelligence framework that aligns the three streams to be complementary capabilities in a sequenced decision journey. The framework treats governance and the organizational setting as operating together as one, separating this model from already existing models that operate on the separation of technical from organizational matters.

Keywords: Decision intelligence; predictive analytics; generative AI; prescriptive optimization; strategic decision-making; narrative review

1. Introduction

Strategic decision-making ability has always been identified as one of the crucial attributes of successful organisations. However, the circumstances surrounding the making of such decisions have markedly altered over the last 20 years. Three developments have converged to transform the information available to decision-makers, how quickly they can access it, and what they can do with it: the explosion of digital data, the evolution of machine learning algorithms, and the rise of generative AI (Davenport, 2006; Chen et al., 2022). Organizations are now surrounded by data, capable of computational resources, and expecting evidence-based decision-making. But having more sophisticated analytical tools does not ensure that strategic results are better. Rather than generating insights, the challenge is incorporating them into coherent decision processes that account for uncertainty, complexity, and organizational context (Mikalef & Gupta, 2021; Csaszar et al., 2024).

To address different aspects of this challenge, there are three different streams of AI research and practice. Predictive analytics is used to predict future states by recognizing patterns in past data and in doing so, can anticipate customer behavior, market changes, and operational risks (Bertsimas & Kallus, 2020; Gupta et al., 2025). While generative AI, including large language models, can be used to recognize patterns, they also have the power to generate new content, simulate scenarios, and aid in creative problem-solving

(Kanbach et al., 2023; Doshi et al., 2025). Prescriptive optimization, on the other hand, aims to suggest specific actions by addressing intricate constrained optimization issues, converting predictions into actionable strategies (Bertsimas & Kim, 2023; Moesmann & Pedersen, 2025).

Although a number of developments have taken place, the available literature is still scattered. Most studies focus on each stream individually and there are limited efforts to articulate how they could work together within a single framework: the decision architecture (Wissuchek & Zschech, 2024; López-Solís et al., 2025). A new idea that is proposed to address this imbalance is the concept of decision intelligence, but existing frameworks are either too generic to support practice or too technology-specific (Pratt et al., 2023; Redek & Godnov, 2024).

This paper fills that gap by performing a narrative review of the literature on predictive analytics, generative AI, and prescriptive optimization for strategic business decision-making. The following three research questions will be used to guide the review:

RQ1: What are the current perspectives and applications of predictive analytics, generative AI, and prescriptive optimization in business settings?

RQ2: Where are the points of integration, tension, and complementarity in these three AI streams?

RQ3: What concept would be appropriate to run these capabilities together to provide a meaningful basis for strategic decision-making?

The paper contributes in two ways to answering these questions. First, it provides a comprehensive summary of current knowledge regarding AI-informed decision-making in a synthesized manner. Second, it suggests a framework of integration: decision intelligence as a unifying logic for strategic decision-making, both as a theoretical lens for research and a reference for organisations to connect predictive, generative and prescriptive capabilities (Pratt et al., 2023; Mikalef et al., 2022).

2. Methodology

2.1 Review Design

The approach used in this study is a narrative review. A narrative review may be suitable when the purpose is not to answer a specific empirical question but rather to report across multiple, unrelated fields, reveal theme similarities, and to make conceptual advances (Baumeister & Leary, 1997; Snyder, 2019). While systematic reviews are typically focused on ensuring that the material covered is as comprehensive as possible and that the results can be replicated via a standardised methodology, a narrative review is an interpretation-based approach where connections can be made between the work that may not always be evident through the process of aggregating it in a strict procedure (Grant & Booth, 2009). Such flexibility is critical for a topic that covers predictive analytics, generative AI, and prescriptive optimization, three areas of research with different names, traditions and publications. The review follows an integrative narrative synthesis, selecting and interpreting literature to develop a conceptual framework (Cronin & George, 2020).

2.2 Search Strategy

Literature was searched on Scopus, Web of Science, IEEE Xplore, and Google Scholar. The search included keywords from the three AI streams and keywords related to strategic decision-making. Boolean strings were used to combine multiple search terms, such as "predictive analytics" OR "predictive modeling" AND "strategic decision," "generative AI" OR "large language model" AND "business strategy," and "prescriptive analytics" OR "optimization" AND "decision intelligence". The main window of search was 2018-2026, when generative AI became a substantive area of business research, and

prescriptive analytics was emerging as a new field. Studies published prior to 2018 were included if they presented basic concepts or methods that are still used (Tranfield et al., 2003).

2.3 Eligibility Criteria

Sources were included if they were considered to be peer-reviewed, written in English, and focused on one or more of the three AI streams in a business or organizational context. Studies that did not discuss business nor involved in technical algorithm development, and editorials, opinion pieces, and non-peer-reviewed preprints were excluded. Sources also needed to have a clear relevance to decision-making processes, at both strategic and tactical and operational levels, as well as provide either theoretical framing or empirical evidence that could inform the synthesis. The final corpus consisted of 34 sources, with an equal distribution of the three streams and methodological and contextual works.

2.4 Synthesis Process

Thematic analysis of the selected literature was carried out. All of the sources were read and coded for their central claims, the AI stream to which they were directed, the decision context(s) to which they referred, and explicit and implicit linkages to other streams. The codes were then clustered into themes, and these were further developed as patterns were identified throughout the corpus. Particular focus was on where assumptions or outputs of one stream clashed with the others, and where integration seemed possible or underway. This thematic approach is similar to the process of narrative synthesis, in which the aim is to go beyond summarizing to conceptual integration (Hakala et al., 2019).

2.5 Methodological Limitations

This review is not systematic and is not intended to be comprehensive. Formal quality appraisal is not present, so included sources include a range of methodological quality, and the interpretive nature of thematic synthesis means there is a degree of subjectivity. These limitations align with the conceptual goals of the review. The review should not be a comprehensive record of the field, but should be interpreted as a reasoned synthesis, leading to a research agenda for further empirical testing.

3. Conceptual Foundations

3.1 Predictive Analytics in Business

Predictive Analytics is the use of statistical models, machine learning algorithms, and data mining techniques to predict future outcomes based on past patterns (Chen et al., 2022). In the business environment, predictive analytics is essential in fields such as forecasting demand, preventing customers from churning, assessing risk, and planning the supply chain (Davenport, 2006; De La Llave Montiel & López, 2020). Predictive insights are considered a strategic asset by Gupta et al. (2025), which means that companies that can predict accurately have a clear edge over businesses that use intuition or lagging indicators to make their decisions. The COVID-19 pandemic showed the potential and the boundaries of forecasting models, highlighting that organisations faced the challenge of adapting forecasting models to unprecedented conditions (Sheng et al., 2020). The value of predictive analytics is also dependent on the ability of those who are interpreting its outputs and making decisions, and Feng et al. (2022) identified that cognitive style, experience and organizational support all influence the way in which people translate the analytics into action. Predictive analytics is thus the information basis on which strategic decisions are made, but it does not tell you what to do.

3.2 Generative AI in Business

Generative AI, specifically large language models and diffusion models, is a newer addition to the business analytics space. Generative systems, in contrast to predictive models that classify or predict, generate new

content, scenarios and combinations of ideas (Kanbach et al., 2023). These techniques have been used to develop strategic documents, analyse competition and support scenario planning in strategic contexts (Doshi et al., 2025; Mondal et al., 2023). Rather than creating content, Nguyen and Tulabandhula (2023) show how foundation models can be leveraged to provide tools for business strategy, such as option generation and analysis. As mentioned by López-Solís et al. (2025), generative AI can be used as a tool to increase the number of alternatives considered and to structure counterfactuals to counteract cognitive biases in entrepreneurial decision-making. Bernardi et al. (2024) show conversational decision support using LLMs with business process management systems. But there are also risks linked to the use of generative AI, such as hallucination, inconsistencies, and the potential of reinforcing pre-existing biases (Bukar et al., 2024; Mikalef et al., 2022). Generative AI extends the repertoire of decision-making beyond prediction, but it needs to be carefully governed to be effective in practice (Li et al., 2026).

3.3 Prescriptive Optimization in Business

The last step in the analytics journey is prescriptive optimization. Predictive analytics predicts, while generative AI creates; prescriptive optimization recommends action through solutions to constrained optimization problems (Bertsimas & Kallus, 2020). These methods involve operations research, mathematical programming, and, more recently, machine learning techniques to determine the best or near-best possible choices when resources are scarce, regulations are limiting, or competing goals exist (Bertsimas & Kim, 2023). Prescriptive models are employed in business for pricing, inventory management, scheduling and portfolio allocation (Moesmann & Pedersen, 2025; Relich, 2023). Wissuchek and Zschech (2024) note that prescriptive analytics is emerging as a separate category of information systems with increasing focus on user interfaces, explainability, and embedding it in the existing decision-making process. But the problem is that prescriptive models run on the premise that they are given the right objectives and fed the right data. The results of the recommendations may be technically optimal but strategically incorrect if the objective function does not reflect strategic priorities, or if the input predictions are inaccurate. Compared to predictive and generative systems, prescriptive optimization provides the needed orientation to act, but relies on the quality of the input it receives.

These three streams are found at separate but overlapping spaces in the decision-making process. They are summarized in Table 1, which serves as a basis for a comparative foundation for their synthesis.

Table 1. The Three AI Streams in Business Decision-Making

Dimension	Predictive Analytics	Generative AI	Prescriptive Optimization
Primary function	Forecast future states	Create novel content and scenarios	Recommend optimal actions
Core methods	Regression, classification, time-series	Large language models, diffusion models	Mathematical programming, heuristics
Typical outputs	Probabilities, scores, trends	Text, images, synthetic data	Action recommendations, schedules
Decision role	Informs	Explores	Prescribes
Key limitation	Assumes historical continuity	Risk of hallucination and bias	Depends on objective alignment

Representative studies	Chen et al. (2022); Gupta et al. (2025); Sheng et al. (2020)	Kanbach et al. (2023); Doshi et al. (2025); Bernardi et al. (2024)	Bertsimas and Kallus (2020); Moesmann and Pedersen (2025); Relich (2023)
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4. Thematic Synthesis

4.1 From Prediction to Generation

The connection between predictive analytics and generative AI is the most mature of the three interrelationships, but still unbalanced. Predictive models generate a structured output like probabilities, scores, and forecasts. Generative models generate unstructured outputs like text, scenarios, and stories. Doshi et al. (2025) found that LLMs are useful for evaluating strategic decisions alongside quantitative forecasts, especially when the decision context is one that is ambiguous and cannot be resolved by a numerical model. Likewise, Kanbach et al. (2023) contend that generative AI can expand predictive analysis capabilities by presenting alternative visions based on the same data, which allows for a range of possible futures to be considered instead of just one projection. In process-aware systems, where predictive signals are converted into natural language explanations for managers to act upon, Bernardi et al. (2024) show this integration. Predictive models rely on the assumption of historical continuity, and generative models can produce outputs that are completely different from the historical record (Mondal et al., 2023). Generative systems can embellish or tell stories about predictive output, which can make scenarios feel more authoritative than they are. The prediction-to-generation connection is thus encouraging but needs safeguards that ensure that generation is kept in relation to the evidential grounding provided by predictive models.

4.2 From Generation to Optimization

The relationship of generative AI to prescriptive optimization is not as well developed, but nonetheless conceptually important. Well-defined objective functions, constraints and input parameters are necessary for prescriptive models. Generative models can help shape these elements by suggesting potential objectives, uncovering overlooked constraints, and modelling the impacts of other choices (Bertsimas & Kim, 2023; Moesmann & Pedersen, 2025). In this context, generative AI is a front-end to optimization, and it increases the range of options that is then evaluated by the prescriptive models. This shift from optimization in the existing frame to optimization in a new frame has special significance in strategic decision-making scenarios in which the optimization objective is also an issue of debate, as outlined by López-Solís et al. (2025). Similarly, Pratt et al. (2023) advance the idea that generative capabilities can serve as a bridge between data science products and decision processes by the executive. However, there are unanswered questions regarding the integration. Optimization makes an assumption that preferences and constraints are known in advance, while generative models assume that preferences are malleable and can be learned from interactions. To reconcile these assumptions, a decision architecture is needed in which the outcomes of generative exploration feed into the parameters of the prescriptive evaluation, and the outcomes of the prescriptive evaluation feed into the generative exploration. Wissuchek and Zschech (2024) point out that the current systems of prescription do not generally include this feedback, implying that the link between generation and optimization is more theoretical than practical.

Both pairwise integrations involve information transfer from one stream to another, and there is some resistance at the translation point. These intersections and related tensions are summarized in Table 2 for purposes of having a structured overview.

Table 2. Intersections and Tensions Across the Three AI Streams

Integration Point	Nature of Connection	Key Tension	Representative Studies
Prediction to Generation	Generative systems analyze and broaden predictive outcomes	Scenarios may lack links to data	Doshi et al. (2025); Bernardi et al. (2024); Mondal et al. (2023); Kanbach et al. (2023)
Generation to Optimization	Generative exploration provides the framework for objectives and constraints in optimization	Changing preferences face static objectives	López-Solís et al. (2025); Pratt et al. (2023)
Prediction to Optimization	Forecasting supports prescriptive models as input parameters	Uncertainty is challenging to transmit in the process of optimization	Bertsimas and Kallus (2020); Bertsimas and Kim (2023)

4.3 Tensions, Gaps, and Unresolved Issues

There are three tensions between predictive, generative and prescriptive capabilities. The first is related to epistemic authority. Statistical models are credible because the statistics are rigorous; Generative models are credible because they are plausible; Prescriptive models are credible because they are optimal. When all three sources of power clash, the other decision makers do not have any recourse, having only arguments (Csaszar et al. 2024; Marewski et al. 2024). It is not clear from the literature how to deal with the competing claims.

A second tension is in terms of governance and accountability. The increased engagement of generative systems in strategic decisions raises questions of transparency, bias, and responsibility, as shown by Mikalef et al. (2022) and Rai (2019). Predictive models can be audited; generative models are less easy to audit, and prescriptive models can be traced, typically by locating the black-box parts. Integrating all three streams compounds these difficulties rather than resolving them. While there are not many models that include explicit governance mechanisms in their decision frameworks, Bukar et al. (2024) suggest that the framework should include such mechanisms.

The third tension is related to the organization's ability. Previous studies of AI adoption have consistently shown that capability is not enough; complementary abilities, processes, and cultures are needed to turn analytics into decisions (Mikalef & Gupta, 2021; Luchian et al., 2025). Combining three streams of AI requires even more of the organization than deploying any one of them. Not only is the challenge of integrating AI technical, but it can also be an organizational challenge, as Pu et al. (2025) demonstrate that the strategic management abilities of the company are more influential on the ROI of AI investment.

However, the lack of a unified structure in which predictive, generative, and prescriptive are embedded in a unified decision-making architecture. In the literature, they are addressed as independent tools, sometimes indicating complementarity, but rarely in a detailed description of how they can be used together (Redek & Godnov, 2024; Wissuchek & Zschech, 2024). This fragmented landscape is shown in Figure 1, where the three streams are mostly isolated from each other and have few nodes of interaction. The framework outlined in Section 5 addresses this gap by outlining the connections, steps and feedback between the three streams to enable a unified decision intelligence capability.

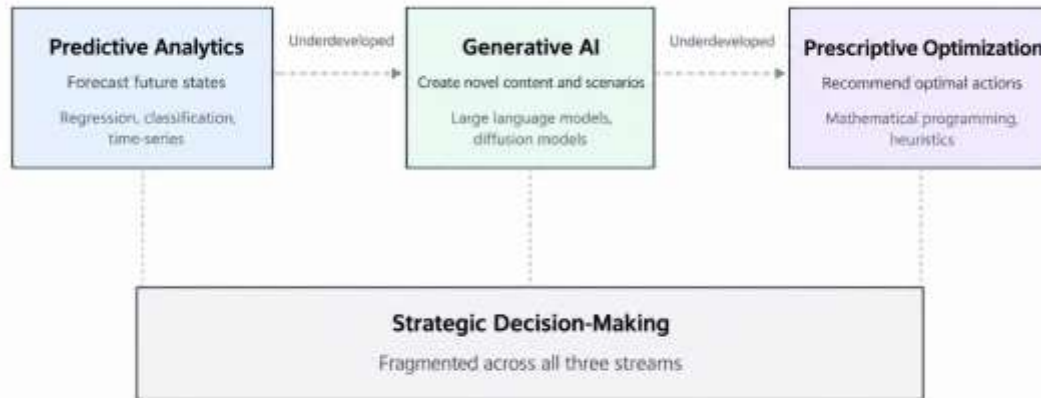


Figure 1. The Current Fragmented Landscape of AI-Driven Decision-Making.

Note. Dashed arrows show underdeveloped integration between streams.

Source: Author's own compilation.

5. Proposed Framework

5.1 Framework Overview

The framework proposed here responds to the fragmentation noted in Section 4 by outlining how the capabilities of predictive analytics, generative AI and prescriptive optimization can integrate to form an overall decision intelligence capability. The three principles are the basis of the framework. Firstly, the three streams are not mutually exclusive but complementary; each reacts to a different aspect of the decision-making process. Second, there is a need for deliberate sequencing for integration; prediction leads to generation, generation leads to optimization, and optimization leads to prediction through outcome data. Third, governance and organizational capability are not a separate system, but are part of the system. The structure consists of three working layers. The three streams of AI and the related methods are in the analytical layer. The integration layer provides interfaces, transformation means and feedback between interfaces. There are also three streams with governance frameworks in place to provide oversight, transparency, and accountability. These layers are placed in an organizational context where the capability can be developed and successfully implemented. Table 3 below lists the properties and purpose of each layer.

Table 3. Components of the Proposed Decision Intelligence Framework

Layer	Component	Function	Source Basis
Analytical	Predictive models	Create forecasts, probabilities, and uncertainties to drive decision-making	Chen et al. (2022); Gupta et al. (2025)
Analytical	Generative exploration	Create scenarios, identify alternative meanings, and provide possible goals	Doshi et al. (2025); Kanbach et al. (2023)
Analytical	Prescriptive evaluation	Solve constrained problems to recommend actions under resource and strategic limitations	Bertsimas and Kallus (2020); Moesmann and Pedersen (2025)

Integration	Forecast-to-scenario translation	Transform structured predictions into narrative scenarios with specific assumptions and contrafactuals	Bernardi et al. (2024); Mondal et al. (2023)
Integration	Objective formalization	Express studied goals and constraints in a form compatible with optimization models	Pratt et al. (2023); López-Solís et al. (2025)
Integration	Outcome feedback	Provide post-implementation data in the models for future prediction updates and refine generative prompts	Wissuchek and Zschech (2024)
Governance	Explainability requirements	Document model inputs, assumptions, and known limitations to support scrutiny	Rai (2019); Mikalef et al. (2022)
Governance	Bias oversight	Detect and address systematic errors that are going throughout processes	Bukar et al. (2024); Mikalef et al. (2022)
Organizational	Decision process alignment	Take integrated results into established management systems and not just develop new systems	Mikalef and Gupta (2021); Luchian et al. (2025)
Organizational	Strategic capability	Develop necessary analytical skills to interpret model outputs and decide between competing claims	Csaszar et al. (2024); Pu et al. (2025)

5.2 Component Interactions

The unique element in the framework is the integration layer. The prediction-to-generation interface takes the prediction and converts it to structured inputs for the generative systems. This is a complex form of translation. This translation requires making clear the meaning of the prediction, the assumptions on which the prediction is based, and the alternative interpretations that may be possible. Generative models then give rise to scenarios that are used to explain the forecast; that is, what the other scenarios would have to be like for them to be possible (Doshi et al., 2025; Kanbach et al., 2023).

This interface between the generation and optimization is more complex. Objectives, constraints and decision frames are candidate results of generative exploration. Such needs to be formalized first, before they can be evaluated by prescriptive models. Strategic judgment is directly involved in the choice of the form of the formalisation itself. If the objective is not in line with strategic priorities, optimization may make technically optimal recommendations, which are not strategically relevant (Bertsimas & Kim, 2023; Pratt et al., 2023). The framework thus does not make human decision-makers the recipients of the outputs of optimizations, but rather players in the framing process.

The feedback loop closes the system. Prescriptive recommendations are followed, outcomes are checked and these checks are used to update predictive models and to improve generative prompts. Current prescriptive systems do not provide much support for this iteration, which is made evident by the framework (Wissuchek and Zschech 2024).

5.3 Strategic Decision Flow

The framework operates as a series of decision phases in practice. Predictive analysis is a strategic question that leads to predictions and estimates of uncertainty. The results end up in the generative exploration, where scenarios are developed and objectives considered. This framing is then encoded and captured as

an optimization problem and solved to return candidate actions. These actions are assessed by decision makers based on governance criteria such as transparency and bias and considerations for accountability. Outcome data is fed back into the predictive layer, and another cycle is started.

This process is not based on linear relationships. Decision-makers may regress from optimization to the generation stage if they find the framing inadequate, while scenario generation can be repeated if it is believed that the predictions are too uncertain. The iterations in the framework are possible in a clearly structured manner. The proposed framework is presented in Figure 2 below, which shows a continuous cycle of three layers that work together by way of analytical streams, integration interfaces, and governance and organizational aspects working together throughout the entire decision-making process.

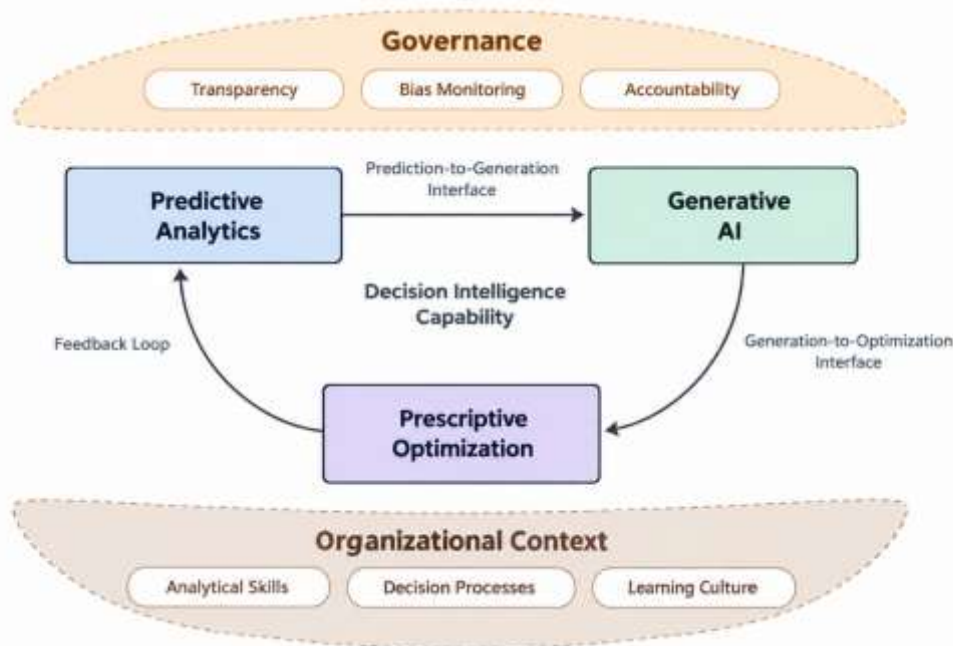


Figure 2. Integrated Decision Intelligence Framework

Source: Author's own compilation.

6. Discussion

6.1 Theoretical Contributions

The review aimed to address three questions. In response to the first, the three streams are currently understood as three separate analytical capacities, with each having its own analytical techniques, products, and decision functions, and are largely conceptualized as self-contained entities. In response to the second, the integration points that exist between the two are present but not fully realized; all interfaces create a problem of translation that cannot be resolved technically alone. To address the third, the framework provided in Section 5 suggests one approach for incorporating these capabilities, focusing on decision intelligence as a capability, and on governance and organizational context as constitutive, not external.

This review contributes in two ways. The first is conceptual integration. The paper outlines the interfaces between predictive analytics, generative AI, and prescriptive optimization and demonstrates that it's not a technical problem, but rather an interpretive issue. Forecasts must be translated into scenarios without losing their foundation in evidence and scenarios must be translated into objectives without foreclosing

the strategic debate that is the source of those objectives. Most previous studies have taken the perspective that the primary challenge is interoperability; the analysis presented in this paper indicates that the more difficult problem is translation, and that human judgment needs to be applied at all stages of the translation process (Pratt et al., 2023).

The second is a diagnostic contribution. Despite the fact that the basic models are often correct, the paper names three tensions that can account for the lack of integration. The first is epistemic: while predictive models are authoritative based on statistical regularity, generative models rely on their plausibility, and prescriptive models are based on optimality; there is no obvious basis for adjudication when these three kinds of authority come into conflict (Csaszar et al., 2024; Marewski et al., 2024). The second relates to governance, as incorporating more streams increases the complexity of determining who is responsible for the decision when it becomes an issue in a partially opaque decision-making process (Mikalef et al., 2022). The third is organizational because companies already having difficulty converting analytics to decisions will find it even more difficult if the three streams are required to be synchronized (Pu et al., 2025).

6.2 Positioning Against Existing Frameworks

The proposed framework is different from the existing decision intelligence models in three ways. The first relates to governance. Pratt et al. (2023) see decision intelligence as an intersection between data science and executive decision-making, but governance as an external condition. Governance is a part of the framework presented here. What the models can do and what they can be used for is determined by explainability, bias monitoring, and accountability mechanisms.

The second difference relates to scope. Wissuchek and Zschech (2024) review prescriptive systems in isolation and do not address how generative exploration might frame objectives. Redek and Godnov (2024) take a step toward integration by extracting decision intelligence from user-generated content, but they are still focused on using a single data source. The contribution here is to describe the interactions between the three streams and also to elucidate the translation challenges that exist at every interface.

The third difference is in the decision-maker. Most of the current literature treats the human as a consumer of products of analysis; a person to read suggestions and accept or reject them. The formulation of the framework developed here puts the decision-maker into the process of framing. Formalizing objectives is a strategic act and not a technical one and the frame puts it at the centre of the action, not at the side.

6.3 Practical Implications

The framework has consequences for the decision-making process in which organisations order their investments in AI capability. Generative tools need to be evidence-based and predictive infrastructure needs to be in place. This implies that data pipelines and model validation procedures, and uncertainty quantification methods need to be defined in advance before generative systems produce scenarios for informing strategic decisions. Governance mechanisms, such as explainability requirements and bias monitoring, should be put in place beforehand, prior to the use of prescriptive models for consequential decisions. Any companies that put the generative tools in place without predictive tools will be creating scenarios that sound authoritative but have no basis in evidence. Without governance, companies that use optimization models risk making decisions on their own that should involve human decision-making (Bukar et al., 2024).

The framework also suggests that decisions are not something that should be automated, although more of the analytical work is becoming automated. If generative exploration generates possible objectives, a human has to determine which objectives are important and why, and this cannot be left to a model without

compromising the legitimacy of the process (Pratt et al., 2023). Interpretive skills need to be cultivated along with technical skills for organizations to invest. Interpretation is not solely about training; research into analytical capability indicates that this skill can be acquired through practice, and organizations that integrate these are going to have a learning curve that cannot be easily bypassed using improved tools (Mikalef & Gupta, 2021; Luchian et al., 2025).

6.4 Future Research Directions and Limitations

Future work should be carried out in three directions. First of all, there is a need for empirical attention to the governance design. The framework is not prescriptive about how explainability, bias monitoring, and accountability mechanisms can be designed or integrated into a business. Comparative studies of different firms that have integrated two or more of the three streams would help to understand which integration arrangement is right to avoid failure (Mikalef et al., 2022; Rai, 2019). Secondly, the feedback loop has not been tested. Longitudinal studies should be conducted to investigate whether outcome data provide meaningful feedback to decision-making in the following cycle or create instability in the absence of generative models being involved in the framing of objectives (Wissuchek & Zschech, 2024). Thirdly, there must be a closer investigation of the role of the human component. The framework places the decision-makers in the role of interpreter and adjudicator, but what skills are required and what conditions are necessary to develop these skills are not clearly understood. Studies conducted here would provide organizations with a more solid foundation on which to construct an augmented human aspect of decision intelligence, instead of assuming it will materialize automatically (Mikalef & Gupta, 2021).

The following limitations are related to the approach used in this review. The aim of a narrative review is to be thorough rather than comprehensive, and the process used to select the literature is based on judgment rather than on a method that could be followed exactly by any other researcher. It is a conceptual framework that has not been empirically tested and it is not meant to prove, but rather to make visible. The body of literature surrounding generative AI in business is rapidly evolving as well and some of the referenced literature in this report may be outdated in the next few years. The limitations do not detract from the contribution of this paper, but they do define the bounds of the claims made by the paper, and point to where empirical investigation should start.

7. Conclusion

The aim of this paper was to explore the potential of combining the capabilities of predictive analytics, generative AI, and prescriptive optimization to assist strategic business decision-making. These three streams have evolved largely independently, and the relationships between them, both in theory and practice, are underdeveloped. Each interface creates translation problems that cannot be resolved technically. Turning a forecast into a scenario involves making judgments about the implications of the forecast and the underlying assumptions.

The framework proposed in this review aims to address the gap by establishing decision intelligence as a capability that builds upon the use of analytical methods, mechanisms for integration, and governance. Governance and organizational capability are considered as internal constraints of the system instead of external constraints. This is different from the existing models that have been developed, where the technical and the organizational aspects are separated, and the reason why integration can fail even if the underlying models work. The tensions in Section 4, related to epistemic authority, accountability and organizational capability, are not a one-time problem to solve. These are conditions that need to be treated on an ongoing basis. The framework should be tested in an empirical way in the future, especially the

governance layer, and the experience of the different organizations in the various sectoral levels should be studied in further detail.

References

1. Baumeister, R. F., & Leary, M. R. (1997). Writing narrative literature reviews. *Review of General Psychology*, 1(3), 311–320. <https://doi.org/10.1037/1089-2680.1.3.311>
2. Bernardi, M. L., Casciani, A., Cimitile, M., & Marrella, A. (2024). Conversing with business process-aware large language models: the BPLLM framework. *Journal of Intelligent Information Systems*, 62(6), 1607–1629. <https://doi.org/10.1007/s10844-024-00898-1>
3. Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. *Management Science*, 66(3), 1025–1044. <https://doi.org/10.1287/mnsc.2018.3253>
4. Bertsimas, D., & Kim, C. W. (2023). A prescriptive machine learning approach to Mixed-Integer Convex optimization. *INFORMS Journal on Computing*, 35(6), 1225–1241. <https://doi.org/10.1287/ijoc.2022.0188>
5. Bukar, U. A., Sayeed, M. S., Razak, S. F. A., Yogarayan, S., & Sneesl, R. (2024). Decision-Making Framework for the utilization of Generative Artificial Intelligence in Education: a case study of CHATGPT. *IEEE Access*, 12, 95368–95389. <https://doi.org/10.1109/access.2024.3425172>
6. Chen, Y., Li, C., & Wang, H. (2022). Big Data and Predictive Analytics for Business intelligence: A bibliographic Study (2000–2021). *Forecasting*, 4(4), 767–786. <https://doi.org/10.3390/forecast4040042>
7. Cronin, M. A., & George, E. (2020). The why and how of the integrative review. *Organizational Research Methods*, 26(1), 168–192. <https://doi.org/10.1177/1094428120935507>
8. Csaszar, F. A., Ketkar, H., & Kim, H. (2024). Artificial Intelligence and Strategic Decision-Making: Evidence from Entrepreneurs and Investors. *Strategy Science*, 9(4), 322–345. <https://doi.org/10.1287/stsc.2024.0190>
9. Davenport, T. H. (2006). Competing on analytics. *Harvard Business Review*, 84(1), 98–107. <https://pubmed.ncbi.nlm.nih.gov/16447373/>
10. De La Llave Montiel, M. A., & López, F. (2020). Spatial models for online retail churn: Evidence from an online grocery delivery service in Madrid. *Papers of the Regional Science Association*, 99(6), 1643–1666. <https://doi.org/10.1111/pirs.12552>
11. Doshi, A. R., Bell, J. J., Mirzayev, E., & Vanneste, B. S. (2025). Generative artificial intelligence and evaluating strategic decisions. *Strategic Management Journal*, 46(3), 583–610. <https://doi.org/10.1002/smj.3677>
12. Feng, J., Han, P., Zheng, W., & Kamran, A. (2022). Identifying the factors affecting strategic decision-making ability to boost the entrepreneurial performance: A hybrid structural equation modeling – artificial neural network approach. *Frontiers in Psychology*, 13, 1038604. <https://doi.org/10.3389/fpsyg.2022.1038604>
13. Grant, M. J., & Booth, A. (2009). A typology of reviews: an analysis of 14 review types and associated methodologies. *Health Information & Libraries Journal*, 26(2), 91–108. <https://doi.org/10.1111/j.1471-1842.2009.00848.x>
14. Gupta, N., Adawadkar, M., Asim, I., Verma, S., & Dubey, B. (2025). Predictive insights: Leveraging artificial intelligence for strategic business decision-making. *Advances in Consumer Research*, 2(5),

- 98–105. <https://acr-journal.com/article/predictive-insights-leveraging-artificial-intelligence-for-strategic-business-decision-making-1659/>
15. Hakala, H., O'Shea, G., Farny, S., & Luoto, S. (2019). Re-storying the Business, Innovation and Entrepreneurial Ecosystem Concepts: the Model-Narrative Review Method. *International Journal of Management Reviews*, 22(1), 10–32. <https://doi.org/10.1111/ijmr.12212>
16. Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M., & Lahmann, A. (2023). The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective. *Review of Managerial Science*, 18(4), 1189–1220. <https://doi.org/10.1007/s11846-023-00696-z>
17. Li, S., Qu, X., & Divekar, R. (2026, August 21). How generative AI reshapes business models: A review through the Business Model Canvas. *California Management Review*. <https://cmr.berkeley.edu/2026/08/how-generative-ai-reshapes-business-models-a-review-through-the-business-model-canvas/>
18. López-Solís, O., Luzuriaga-Jaramillo, A., Bedoya-Jara, M., Naranjo-Santamaría, J., Bonilla-Jurado, D., & Acosta-Vargas, P. (2025). Effect of Generative Artificial Intelligence on Strategic Decision-Making in entrepreneurial Business Initiatives: A Systematic Literature review. *Administrative Sciences*, 15(2), 66. <https://doi.org/10.3390/admsci15020066>
19. Luchian, A. C., Strat, V. A., Jianu, O., & Dragoicea, M. (2025). From Insights to Trust: A review of AI-Driven Business Analytics literature. *Proceedings of the International Conference on Business Excellence*, 19(1), 184–200. <https://doi.org/10.2478/picbe-2025-0017>
20. Marewski, J. N., Katsikopoulos, K. V., & Guercini, S. (2024). Simon's scissors: meta-heuristics for decision-makers. *Management Decision*, 62(13), 283–308. <https://doi.org/10.1108/md-06-2023-1073>
21. Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), 103434. <https://doi.org/10.1016/j.im.2021.103434>
22. Mikalef, P., Conboy, K., Lundström, J. E., & Popovič, A. (2022). Thinking responsibly about responsible AI and 'the dark side' of AI. *European Journal of Information Systems*, 31(3), 257–268. <https://doi.org/10.1080/0960085x.2022.2026621>
23. Moesmann, M., & Pedersen, T. B. (2025). Data-driven prescriptive analytics applications: A comprehensive survey. *Information Systems*, 134, 102576. <https://doi.org/10.1016/j.is.2025.102576>
24. Mondal, S., Das, S., & Vrana, V. G. (2023). How to Bell the Cat? A Theoretical Review of Generative Artificial Intelligence towards Digital Disruption in All Walks of Life. *Technologies*, 11(2), 44. <https://doi.org/10.3390/technologies11020044>
25. Nguyen, S., & Tulabandhula, T. (2023). *Generative AI for business strategy: Using foundation models to create business strategy tools* [Preprint]. arXiv. <https://doi.org/10.48550/arxiv.2308.14182>
26. Pratt, L., Bisson, C., & Warin, T. (2023). Bringing advanced technology to strategic decision-making: The Decision Intelligence/Data Science (DI/DS) Integration framework. *Futures*, 152, 103217. <https://doi.org/10.1016/j.futures.2023.103217>
27. Pu, Y., Li, H., Hou, W., & Pan, X. (2025). The analysis of strategic management decisions and corporate competitiveness based on artificial intelligence. *Scientific Reports*, 15(1), 17942. <https://doi.org/10.1038/s41598-025-02842-x>
28. Rai, A. (2019). Explainable AI: from black box to glass box. *Journal of the Academy of Marketing Science*, 48(1), 137–141. <https://doi.org/10.1007/s11747-019-00710-5>

29. Redek, T., & Godnov, U. (2024). From data to decision: distilling decision intelligence from user-generated content. *Kybernetes*, 53(13), 1–23. <https://doi.org/10.1108/k-08-2023-1447>
30. Relich, M. (2023). Predictive and prescriptive analytics in identifying opportunities for improving sustainable manufacturing. *Sustainability*, 15(9), 7667. <https://doi.org/10.3390/su15097667>
31. Sheng, J., Amankwah-Amoah, J., Khan, Z., & Wang, X. (2020). COVID-19 Pandemic in the new Era of Big Data Analytics: Methodological Innovations and future research Directions. *British Journal of Management*, 32(4), 1164–1183. <https://doi.org/10.1111/1467-8551.12441>
32. Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, 104, 333–339. <https://doi.org/10.1016/j.jbusres.2019.07.039>
33. Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing Evidence-Informed management knowledge by means of systematic review. *British Journal of Management*, 14(3), 207–222. <https://doi.org/10.1111/1467-8551.00375>
34. Wissuchek, C., & Zschech, P. (2024). Prescriptive analytics systems revised: a systematic literature review from an information systems perspective. *Information Systems and e-Business Management*, 23(2), 279–353. <https://doi.org/10.1007/s10257-024-00688-w>