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Integrated Data-Driven and Multi-Criteria Decision-Making in Management: A Strategic Framework for Complex Organizational Choices

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Abstract

Decision-making in management has evolved from intuition-dominated judgment toward more structured, evidence-based, and analytics-supported processes. Yet many organizations still struggle to integrate strategic judgment, quantitative evaluation, uncertainty treatment, and governance considerations into a single coherent decision architecture. This paper develops an integrated framework for managerial decision-making that combines bounded rationality, evidence-based management, Multi-Criteria Decision-Making (MCDM), decision support systems, and human–AI collaboration. The study first synthesizes the theoretical foundations of managerial decision-making and then proposes a professional five-stage framework for screening, weighting, scoring, validating, and governing strategic alternatives. To demonstrate the logic of the framework, an illustrative management case is presented for project portfolio selection under financial, operational, strategic, and risk criteria. The model employs normalized criterion scores, weighted utility aggregation, evidence credibility assessment, and governance alignment adjustments. The numerical illustration shows that alternatives with the highest standalone financial attractiveness are not always optimal once implementation time, strategic fit, evidence quality, and risk exposure are jointly considered. The paper contributes to management literature in three ways: 1) it bridges classical and contemporary decision theories into a unified managerial structure, 2) it offers a transparent mathematical model that managers can adapt to real organizational settings, and 3) it demonstrates how human judgment and algorithmic support can be combined without fully delegating strategic control to automated systems. The findings suggest that effective managerial decision-making depends not only on analytical sophistication but also on process quality, evidence integrity, and organizational alignment. These insights are particularly relevant for senior managers facing high-stakes choices in dynamic and uncertain environments. Real references below were verified from the publisher or scholarly records.

Keywords: Managerial decision-making, Strategic decision processes, Multi-criteria decision-making, Evidence-based management, Decision support systems.

1 | Introduction

Decision-making is one of the most fundamental functions of management because organizations formulate strategy, allocate resources, evaluate investments, prioritize initiatives, and respond to uncertainty through

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managerial choices. However, management scholarship has long shown that such choices are not made under the unrealistic conditions of full rationality assumed in classical optimization models. Simon [1] argued that real decision-makers face limited information, limited attention, and limited computational capacity, and therefore aim at satisfactory rather than perfectly optimal solutions. March and Simon [2] extended this reasoning to organizations by showing that routines, communication channels, and structural arrangements shape how decision problems are perceived and processed. Cyert and March [3] further demonstrated that the firm should be understood as an adaptive coalition with multiple goals, aspiration levels, negotiated priorities, and problemistic search rather than as a unified maximizer. Kahneman and Tversky [4] later showed that actual decision-making under risk departs systematically from expected-utility assumptions because people evaluate outcomes relative to reference points and are more sensitive to losses than to equivalent gains. Together, these works establish that managerial decision-making is bounded, behavioral, and organizationally conditioned rather than purely technical.

A second major research stream shifted attention from individual cognition to the structure of organizational and strategic decision processes. Mintzberg et al. [5] showed that important organizational decisions are often "unstructured," meaning that problem definition, search, and evaluation emerge gradually rather than being fully specified at the outset. Nutt [6] similarly argued that organizations rely on different decision models and that contextual conditions help determine which model is appropriate. March [7] later framed one of the central tensions of management as the balance between exploration of new possibilities and exploitation of existing knowledge. These studies remain highly relevant because managers rarely choose among perfectly well-defined alternatives; instead, they navigate ambiguity, novelty, conflicting goals, and changing environments.

Research on strategic decision-making further showed that decision quality depends not only on what is chosen but also on how the choice is made. Eisenhardt and Zbaracki [8] reviewed the field and concluded that strategic decision research has been shaped by bounded rationality, politics and power, and organized ambiguity. Eisenhardt's [9] empirical study of high-velocity environments showed that fast strategic decisions are not necessarily poor decisions; under some conditions, they are associated with richer information use, multiple alternatives, and effective conflict resolution. Rajagopalan et al. [10] developed an integrative framework linking strategic decision processes to environmental, organizational, and decision-specific antecedents and to both process and economic outcomes. Dean and Sharfman [11] provided field evidence that procedural rationality is positively associated with strategic decision effectiveness. Elbanna [12] later reviewed the literature and argued that procedural rationality, intuition, and political behavior all remain central to understanding strategic decisions. This body of research implies that process design is a substantive determinant of managerial effectiveness rather than a mere administrative detail.

In parallel, management scholars increasingly adopted formal approaches for evaluating alternatives under multiple and conflicting criteria. Keeney and Raiffa [13] established the foundations of multi-objective decision analysis by emphasizing explicit value trade-offs across competing goals. Saaty's [14] analytic hierarchy process provided a structured way to derive priorities through pairwise comparison. Hwang and Yoon [15] systematized multiple attribute decision making and offered a foundational framework for comparing alternatives across several criteria. Goodwin and Wright [16] later emphasized that decision analysis is useful not because it removes judgment, but because it makes assumptions transparent and improves managerial judgment under uncertainty. This stream is especially relevant in management because strategic alternatives must often be assessed simultaneously in terms of financial return, implementation time, operational feasibility, strategic fit, and risk.

Modern managerial decision-making has also been shaped by evidence-based management, decision support systems, analytics, and artificial intelligence. Rousseau [17] argued that managers should base decisions on the best available evidence rather than relying primarily on habit, ideology, or unsystematic experience. Power's [18] historical overview of decision support systems traced how DSS evolved to support semi-structured managerial problems through model-driven, data-driven, and knowledge-driven approaches. Burstein and Holsapple's [19] handbook positioned DSS as a broad field connecting models, data, technologies, and managerial use. Provost and Fawcett linked data science directly with data-driven decision-making [20], while Brynjolfsson and McElheran [21] documented the rapid diffusion of data-driven decision-making in U.S. manufacturing. Davenport [22] argued that firms can build advantage by embedding analytics into managerial and operational decisions. More recently, Jarrahi [23] described AI as a complement to human judgment in organizational decision-making, and Shrestha et al. [24] showed that organizational decision structures in the age of AI depend on such factors as interpretability, speed, replicability, and the size of the alternative set. Dellermann et al. [25] further framed human–AI collaboration through the concept of hybrid intelligence systems. Taken together, these studies suggest that management increasingly requires an integrated decision architecture combining evidence, structured analysis, technological support, and human oversight.

Despite the richness of these literatures, an important gap remains. Behavioral theories explain why managers deviate from ideal rationality; strategic-process research explains how decisions unfold in organizations; decision analysis and Multi-Criteria Decision-Making (MCDM) provide formal tools for evaluating alternatives; evidence-based management stresses the quality of knowledge; and AI studies examine algorithmic augmentation. Yet these streams are often treated separately. The objective of this paper is therefore to develop a more integrated managerial view of decision-making that is behaviorally realistic, analytically rigorous, evidence-sensitive, and suitable for high-stakes organizational contexts.

2 | Integrated Managerial Decision-Making Framework

This section develops a five-stage framework for strategic managerial decisions: 1) problem structuring, 2) criteria and weight derivation, 3) alternative scoring, 4) evidence and governance adjustment, and 5) sensitivity and review. Let there be m alternatives and n evaluation criteria. The raw decision matrix is

$$X = \left[x_{ij}\right]_{m\times n}, i = 1, \ldots, m, \; j = 1, \ldots, n, \tag{1}$$

where x_{ij} denotes the performance of alternative i on criterion j.

2.1 | Problem Structuring

The first task is to define the decision context precisely. In management practice, poor decisions often originate from vague problem definitions rather than poor calculations. A strategic choice should therefore specify 1) the decision horizon, 2) the available alternatives, 3) the affected stakeholders, 4) hard constraints, and 5) success criteria. The framework assumes that criteria can include both benefit-type and cost-type variables, such as expected return, implementation time, strategic alignment, regulatory burden, or risk exposure.

2.2 | Criteria Weighting

Weights may be derived through executive workshops, pairwise comparison, expert elicitation, or hybrid methods. If AHP is used, the pairwise comparison matrix $A = [a_{jk}]$ yields a weight vector w such that

$$Aw = \lambda_{max} w, \tag{2}$$

subject to

$$\sum_{j=1}^{n} w_j = 1, w_j \geq 0. \tag{3}$$

Consistency is checked through

$$CI = \frac{\lambda_{max} - n}{n - 1}. \tag{4}$$

And

$$CR = \frac{CI}{RI}, \tag{5}$$

where RI is the random index. In managerial applications, a small CR indicates that pairwise judgments are acceptably coherent.

2.3 | Normalization and Utility Scoring

Because criteria are measured on different scales, normalization is required. For a benefit criterion,

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}. \tag{6}$$

For a cost criterion,

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}. \tag{7}$$

The weighted utility of alternative i is then

$$U_i = \sum_{j=1}^{n} w_j r_{ij}, \tag{8}$$

where $U_i \in [0,1]$ under min–max normalization.

2.4 | Evidence Credibility Adjustment

A frequent weakness in management decisions is that alternatives are compared as if all underlying evidence were equally reliable. This assumption is often false. Some proposals rely on audited data and pilot studies, while others rely on optimistic assumptions and weak estimates. To reflect this, we define an evidence credibility score.

$$E_i = \alpha D_i + \beta A_i + \gamma T_i, \tag{9}$$

where D_i is data reliability, A_i is analytical robustness, T_i is timeliness or relevance of evidence, and

$$\alpha + \beta + \gamma = 1, \alpha, \beta, \gamma \geq 0. \tag{10}$$

This term allows managers to downgrade analytically attractive alternatives supported by poor evidence.

2.5 | Governance and Strategic Alignment Adjustment

A decision that is financially strong but strategically misaligned or politically infeasible may fail in implementation. To incorporate this, define a governance-alignment score.

$$G_i = \sum_{k=1}^{p} \eta_k z_{ik}, \tag{11}$$

where z_{ik} represents alignment with governance factor k, such as strategic fit, regulatory compatibility, ethical acceptability, or stakeholder support, and

$$\sum_{k=1}^{p} \eta_k = 1. \tag{12}$$

2.6 | Final Integrated Score

The overall managerial attractiveness of alternative i is

$$M_i = \rho U_i + \mu E_i + \nu G_{i,} \tag{13}$$

subject to

$$\rho + \mu + \nu = 1, \rho, \mu, \nu \geq 0. \tag{14}$$

This formulation is intentionally transparent. U_i captures criterion-based performance, E_i captures evidence quality, and G_i captures organizational fit. In contrast to a narrow ranking model, the integrated score recognizes that managerial decisions succeed only when analysis, evidence, and organizational reality are mutually consistent.

2.7 | Decision Protocol

The operational protocol is as follows. First, shortlist feasible alternatives. Second, establish criteria and weights. Third, compute normalized scores and utility values. Fourth, assess evidence credibility and governance alignment using structured executive review. Fifth, perform sensitivity analysis by varying key weights. Sixth, finalize the decision and document the rationale. This process is particularly suitable for strategic project selection, outsourcing decisions, digital transformation prioritization, supplier evaluation, location selection, and innovation portfolio management.

3 | Illustrative Application and Managerial Discussion

To demonstrate the framework, consider a firm selecting one of four strategic digital transformation projects:

I. Project A: AI-assisted customer service platform

II. Project B: Enterprise data lake and analytics backbone

III. Project C: Predictive maintenance and operations intelligence

IV. Project D: Omnichannel sales integration system

The executive team defines four core criteria:

I. Expected Net Present Value (NPV, benefit)

II. Implementation time in months (cost)

III. Strategic alignment score out of 100 (benefit)

IV. Risk exposure index from 0 to 1 (cost)

The agreed base weights are:

I. NPV: 0.30

II. Time: 0.20

III. Strategic alignment: 0.25

IV. Risk exposure: 0.25

As shown in *Table 1*, the decision framework incorporates both benefit-type and cost-type criteria to ensure a balanced managerial evaluation.

Table 1. Criteria, meanings, and base weights.

Criterion	Type	Description	Weight
Expected NPV	Benefit	Estimated discounted financial contribution (USD millions)	0.30
Implementation time	Cost	Total implementation duration (months)	0.20
Strategic alignment	Benefit	Fit with long-term corporate strategy (0–100)	0.25
Risk exposure	Cost	Aggregate execution and uncertainty risk (0–1)	0.25

Table 2 reports the raw performance values of the candidate alternatives across all selected decision criteria.

Table 2. Raw performance matrix.

Alternative	NPV (USD m)	Time (Months)	Strategic Alignment	Risk Exposure
Project A	8.2	14	88	0.22
Project B	9.1	18	81	0.31
Project C	7.4	10	90	0.18
Project D	8.7	12	84	0.26

Using *Eqs. (6)–(7)*, the normalized values are obtained. According to *Table 3*, normalization substantially improves the comparability of the alternatives across heterogeneous criteria.

Table 3. Normalized scores.

Alternative	r_1: NPV	r_2: Time	r_3:Alignment	r_4: Risk
Project A	0.471	0.500	0.778	0.692
Project B	1.000	0.000	0.000	0.000
Project C	0.000	1.000	1.000	1.000
Project D	0.765	0.750	0.333	0.385

Applying *Eq. (8)*, the weighted utility scores are:

$$U_A = 0.6088, U_B = 0.3000, U_C = 0.7000, U_D = 0.5591. \tag{15}$$

These results already reveal an important managerial insight: the project with the highest raw NPV is not the best overall option. Project B performs poorly on time, alignment, and risk. Project C, although lowest in raw NPV, dominates on implementation speed, strategic fit, and risk control.

However, the executive team also evaluates evidence quality and governance alignment. Suppose evidence credibility is assessed on three dimensions: data reliability, analytical robustness, and timeliness. Governance alignment is assessed on strategic compatibility, stakeholder acceptance, and compliance feasibility. The team uses $\alpha = \beta = \gamma = \frac{1}{3}$ in *Eq. (9)*, and a weighted average for *Eq. (11)*. The resulting scores are shown below.

Table 4 indicates that alternatives with stronger analytical support and governance compatibility achieve higher credibility-related evaluations.

Table 4. Evidence and governance assessments.

Alternative	Evidence Credibility E_i	Governance Alignment G_i
Project A	0.82	0.80
Project B	0.74	0.77
Project C	0.88	0.85
Project D	0.79	0.81

Let the final aggregation weights in *Eq. (13)* be $\rho = 0.70$, $\mu = 0.20$, and $\nu = 0.10$. Then

$$\mathrm{M_i} = 0.70\mathrm{U_i} + 0.20\mathrm{E_i} + 0.10\mathrm{G_{i.}} \tag{16}$$

The final integrated scores are:

$$\mathrm{M_A} = 0.670, \mathrm{M_B} = 0.435, \mathrm{M_C} = 0.751, \mathrm{M_D} = 0.630. \tag{17}$$

The final ranking displayed in *Table 5* shows that the most financially attractive alternative is not necessarily the most desirable overall decision.

Table 5. Final ranking.

Rank	Alternative	Utility $\mathrm{U_i}$	Evidence $\mathrm{E_i}$	Governance $\mathrm{G_i}$	Final Score $\mathrm{M_i}$
1	Project C	0.700	0.88	0.85	0.751
2	Project A	0.609	0.82	0.80	0.670
3	Project D	0.559	0.79	0.81	0.630
4	Project B	0.300	0.74	0.77	0.435

The example highlights several management implications. First, decision quality improves when financial metrics are evaluated jointly with operational, strategic, and risk criteria. Second, evidence quality materially affects rankings; this discourages overconfident proposals based on weak assumptions. Third, governance alignment prevents analytically attractive but organizationally unviable options from being selected. Fourth, the model is interpretable, which is essential for board-level review and post-decision accountability.

To examine robustness, a sensitivity analysis is performed by varying the weight assigned to risk. Three scenarios are considered: low-risk emphasis, base case, and high-risk emphasis. As demonstrated in *Table 6*, the preferred alternative remains stable across multiple weighting configurations, suggesting that the result is robust.

Table 6. Sensitivity analysis under alternative weighting schemes.

Scenario	Weights (NPV, Time, Align., Risk)	A	B	C	D	Ranking
S1: Low risk emphasis	(0.35, 0.20, 0.30, 0.15)	0.602	0.350	0.650	0.575	C > A > D > B
S2: Base case	(0.30, 0.20, 0.25, 0.25)	0.609	0.300	0.700	0.559	C > A > D > B
S3: High risk emphasis	(0.25, 0.15, 0.25, 0.35)	0.629	0.250	0.750	0.522	C > A > D > B

The stability of the ranking suggests that Project C is robustly preferred under reasonable changes in managerial preferences. Such robustness is important because one criticism of MCDM is sensitivity to weights. In this illustration, the selected option remains stable, increasing confidence in the recommendation.

From a broader management perspective, the proposed framework helps avoid four common errors. The first is single-metric bias, where firms overvalue a single financial number. The second is evidence blindness, where assumptions are treated as facts. The third is process opacity, where decisions cannot be reconstructed or justified later. The fourth is automation overreach, where algorithmic outputs are accepted without governance review. By integrating utility, evidence, and alignment, the framework supports more defensible and resilient managerial choices.

The model also fits well with contemporary AI-supported decision environments. Predictive models can estimate NPV distributions, implementation delays, or risk probabilities; however, final managerial decisions still require interpretation, negotiation, and legitimacy. Thus, a hybrid structure is often superior: analytics generate candidate evaluations, while managers validate assumptions, apply strategic context, and make accountable commitments. This conclusion is consistent with the recent literature on human–AI symbiosis, organizational AI decision structures, and hybrid intelligence [18–21].

4 | Discussion

The findings and conceptual development presented in this paper suggest that effective managerial decision-making cannot be adequately explained or improved through any single perspective alone. Rather, decision quality in management emerges from the interaction of bounded rationality, organizational process design, analytical structuring, evidence quality, and implementation feasibility. This point is especially important because many organizations still treat decision-making either as a purely intuitive executive function or as a purely technical optimization exercise. The literature reviewed in this paper indicates that both extremes are incomplete. On the one hand, behavioral and organizational research shows that managers operate under cognitive, informational, temporal, and political constraints, and therefore cannot be expected to behave like fully informed optimizers [1–4]. On the other hand, the literature on decision analysis and multi-criteria evaluation shows that complex managerial decisions benefit substantially from structured comparison, explicit trade-off analysis, and transparent criteria design [13–16]. The main implication is that managerial decision systems should be designed as hybrid structures: Disciplined enough to reduce inconsistency and bias, but flexible enough to accommodate ambiguity, context, and judgment.

A first major discussion point concerns the role of process quality. One of the clearest lessons from strategic decision-making research is that the quality of the process through which a decision is reached is itself a determinant of decision effectiveness [8–12]. In many organizations, poor outcomes are explained after the fact as failures of execution, environment, or bad luck, while the underlying weaknesses of the decision process remain unexamined. However, the literature suggests that process deficiencies often begin much earlier, for example through unclear problem framing, narrow search, premature closure, failure to consider alternatives, weak evidence validation, or insufficient treatment of conflict. In that sense, a decision framework should not merely rank options; it should also force the organization to make its reasoning explicit. This rationale explains why the proposed integrated perspective places so much emphasis on criteria definition, evidence credibility, and governance alignment in addition to utility scoring. A strong process does not guarantee a perfect outcome, but it substantially improves the likelihood that the selected option is defensible, coherent, and strategically appropriate.

A second important issue concerns the limitations of purely financial decision logic. In practice, managers often default to financial indicators because they appear objective and easily communicable. Measures such as expected return, cost reduction, or payback period are undoubtedly important, but the literature and the illustrative logic of this paper both indicate that such measures are rarely sufficient on their own. Strategic alternatives often differ in their operational complexity, organizational readiness, implementation time, risk exposure, stakeholder acceptance, and long-term strategic consistency. A project with the highest projected financial gain may also be the most difficult to implement, the least supported by reliable evidence, or the least aligned with the organization's strategic direction. Formal multi-criteria approaches are valuable precisely because they make these tensions explicit instead of hiding them behind one dominant metric [13–16]. For management, this means that decision quality improves when competing objectives are surfaced and negotiated rather than suppressed.

A third discussion point relates to evidence quality. Evidence-based management does not imply that managers can simply "look up the right answer" and apply it mechanically. Instead, it implies that managerial judgment should be disciplined by the best available evidence from multiple sources, including organizational data, scientific research, informed expertise, and stakeholder knowledge [17]. Such an approach is especially important because weak evidence can easily be mistaken for strong evidence in managerial settings. Forecasts may be based on unrealistic assumptions, dashboards may contain biased or incomplete measures, and anecdotal success stories may be overgeneralized. For this reason, it is not enough to score alternatives on expected performance alone; managers also need to ask how credible the supporting evidence is. The discussion in this paper therefore reinforces a practical principle: in high-stakes decisions, the strength of the conclusion should be proportional to the strength of the evidence. Where evidence is limited or uncertain, the decision process should explicitly acknowledge this rather than conceal it behind precise-looking numbers.

A fourth issue is the relationship between analytics and judgment. The diffusion of data-driven decision-making and the rise of analytical capabilities have changed the landscape of management substantially [20–22]. Many organizations now have access to predictive models, business intelligence systems, optimization tools, and increasingly sophisticated AI-based analytics. Yet the existence of analytical tools does not eliminate the need for managerial interpretation. In fact, greater analytical capability can increase the importance of judgment because managers must decide which models to trust, how to interpret outputs, what assumptions are embedded in the analysis, and how to reconcile model-based recommendations with strategy, culture, and constraints. Decision support systems were never intended to replace management; rather, they were developed to support semi-structured decisions where human reasoning and model-based support must work together [18], [19]. The same principle remains true in the contemporary analytics environment. Thus, the managerial challenge is not whether to use analytics, but how to embed analytics within accountable and context-sensitive decision structures.

This point becomes even more significant in the context of artificial intelligence. The recent literature does not support the simplistic idea that strategic managerial decisions should be fully delegated to AI systems [23–25]. Instead, it suggests that the most effective arrangements are likely to be forms of augmentation or hybrid intelligence, in which AI contributes scale, speed, pattern recognition, and consistency, while human decision-makers contribute contextual understanding, moral reasoning, political awareness, and legitimacy. Such an approach has profound implications for management. First, organizations need governance rules for deciding which decisions can be automated, which should be augmented, and which must remain predominantly human-led. Second, managers need to be able to explain and defend AI-assisted decisions to internal and external stakeholders. Third, the use of AI in decision-making raises questions of accountability, transparency, fairness, and organizational learning. A recommendation generated by a powerful model may still be inappropriate if it is based on poor-quality data, inconsistent objectives, or organizational assumptions that are no longer valid. Therefore, one of the strongest implications of this paper is that AI should be integrated into managerial decision frameworks as a powerful support mechanism, but not as an ungoverned substitute for management itself.

Another significant discussion point concerns the tension between standardization and managerial flexibility. Formal frameworks are valuable because they improve transparency, comparability, and consistency across decisions. However, managerial problems differ considerably in scale, urgency, structure, and uncertainty. A highly recurrent operational decision may be suitable for relatively standardized analytical treatment, whereas a strategic transformation decision may require broader deliberation, scenario reasoning, and stakeholder negotiation. The literature on unstructured decisions and strategic process design clearly shows that management cannot rely on one rigid decision template for every context [5], [6], [8]. Therefore, the value of the integrated framework proposed in this paper lies not in prescribing identical steps for all decisions, but in offering a modular structure. The same logic of criteria structuring, evidence assessment, and governance review can be adapted to different contexts, with different levels of formalization. This adaptability is particularly important for modern organizations facing both routine and novel decisions simultaneously.

5 | Conclusion

This paper developed an integrated framework for decision-making in management by combining behavioral decision theory, strategic decision process research, evidence-based management, MCDM, decision support systems, and human–AI collaboration. The central argument is that high-quality managerial decisions cannot be reduced to either intuition or analytics alone. Instead, robust strategic choices require a structured combination of criteria-based evaluation, reliable evidence, governance alignment, and informed managerial judgment. The literature review showed that classical theories explain the bounded, political, and adaptive nature of organizational decisions, while modern analytical methods provide tools for structuring complexity and comparing alternatives. Building on these streams, the paper proposed a transparent mathematical model in which final decision attractiveness depends on three components: Performance utility, evidence credibility, and governance alignment. The illustrative case demonstrated that the highest-financial-return option may not be the best strategic choice once implementation time, risk exposure, strategic fit, and evidence quality are jointly considered. The sensitivity analysis further showed that the preferred alternative remained stable across multiple weighting schemes, which increases confidence in practical use. The paper contributes to management research by offering a unified and professionally usable framework suitable for strategic investment, project prioritization, supplier selection, digital transformation, and other multi-criteria decisions. For practice, the implication is clear: organizations should institutionalize decision protocols that are quantitatively rigorous yet interpretable, technologically enabled yet governance-aware, and evidence-based yet sensitive to human judgment. Future research can extend this framework by incorporating stochastic uncertainty, group decision dynamics, fuzzy or neutrosophic assessments, causal inference, and sector-specific validation with real organizational data.

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Author Contribution

Azimi, S.E.: conceptualization, methodology, validation, formal analysis, investigation, writing-creating the initial design, writing-reviewing and editing, visualization. The author has read and agreed to the published version of the manuscript.

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The author declares no conflict of interest.

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