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AI-Driven Strategic Planning and Decision-Making in Management

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Abstract

Artificial intelligence systems have enabled the formulation of multiple strategic frameworks with considerable operational, financial, and organizational benefits. Advances on data-driven modeling are challenging traditional conceptions of management and decision-making, and in the process, opening up windows of opportunity for strengthening the analytical capabilities associated with strategic planning. As little is known about where AI-based decision support is gaining momentum beyond predictive analytics and optimization models, the purpose of this study is to map in what domains of management it is perceived to gain traction. Drawing on data from Analytic Hierarchy Process and regression–correlation analysis in organizational case studies, we identify a long tail of decision areas and planning processes in which a total of 47 unique managerial applications operate, including contexts such as investment evaluation, resource allocation, and performance monitoring. Our findings reveal a strong, positive correlation coefficient ($r = 0.82$) between regression-based forecasting and AHP-derived prioritization. However, managers do not passively comply. Rather, their preferences and judgments are integrated into the architecture of decision-making. The article concludes by identifying methodological implications, reflecting on the application of AI-driven planning in the field of management, and proposing suggestions for future organizational adoption. The empirical insights enrich understandings of the workings of artificial intelligence in experiences of strategy and governance.

Keywords: *AI-Driven Strategic Planning, Decision Support Systems, Analytic Hierarchy Process (AHP), Regression–Correlation Analysis, Managerial Competence, Organizational Adaptability, Predictive Analytics in Management*

Introduction

According to Rivero (2025), artificial intelligence in management is characterized as a transformative paradigm that is adaptive and dynamic by design and aims to keep operational efficiency, financial performance, and organizational agility at their highest effectiveness and reliability at all times, distinguishing between strategic and operational cycles (Rivero, 2025; Büber, 2025).

Learning from the past, a multi-layered model was proposed to help guide managerial responses, which integrates the classical, adaptive, and resource-based aspects of strategy, while accepting the complexity and non-linearity of organizational dynamics (Büber, 2025; Murugesan, 2023).

Despite their promise, though, there is limited knowledge as to how predictive analytics and optimization algorithms can be leveraged to support the transition to AI-driven strategic planning. Recent contributions have highlighted that the adoption of AI may be perceived both optimistically and cautiously (Zein, 2025; Jowarder, 2025), and described the phenomenon as currently in a state of experimentation and transition (Csaszar, 2024; Ramachandran, 2023), particularly between entrepreneurial contexts and established enterprises (Csaszar, 2024; Egwuatu, 2025). Despite this general agreement, little attention has been paid to how managerial judgment may be used to overcome adoption challenges.

One can draw multiple similarities between AI adoption and strategic foresight. Both advocate the focus on fulfilling the evolving needs of the organization in an effort to radically lower uncertainty impacts (Kim, 2023; Chandra, 2023). Indeed, recent studies advocate that the application of AI-enabled decision frameworks may increase organizational adaptability by about 30%, bringing to a net benefit of about 20% higher return on strategic investments by mid-decade without compromising governance (Vudugula, 2023; Strategic Data Management and Innovation, 2025).

In this regard, Rainy (2023) suggests that "AI-enhanced decision support tools provide a great opportunity to integrate foresight and planning through the judicious selection of indicators relevant to enterprise performance, the prioritization for resource allocation, and the supporting analytics… risks can be managed to protect competitiveness, and indirectly, reduce inefficiencies." Though more consensus remains to be achieved, technological readiness, managerial competence, and overall integration into business models are reported to be at the roots of successful applications such as investment evaluation and resource allocation (Badmus, 2024; Miller, 2023).

Thus, contributing to past inadequate analytical and organizational responses to strategic challenges. At the same time, though, overreliance on automation might lead to rigid practices and less adaptive models, most notably through black-box effects (Ramachandran, 2023; Jowarder, 2025).

While not entirely the same, the commonalities between AI-driven foresight and classical strategic management invite a deeper investigation into strategic planning from a computational perspective.

This study attempts to close this gap by conducting regression–correlation analysis and Analytic Hierarchy Process, in order to evaluate the application of AI-driven decision support to support the transition to strategic planning. The purpose of this paper is therefore to map in what domains the AI-based paradigm is currently perceived to be effective, while also discussing the associated methodological implications with regard to increased organizational adoption.

Therefore, it poses the following research question:

RQ: How can AI-driven decision support systems support the transition to strategic planning in management?

We do so by systematically assessing ways in which managers in organizational case studies, as well as practitioners in applied research, perceive that the AI-based paradigm is being integrated into different decision domains.

We organize the rest of this paper as follows: In Section 2, we briefly review the artificial intelligence literature underpinning strategic decision-making, and the management literature guiding our conceptual framework; in Section 3, we describe the methodology followed to meet research objectives, by first presenting the dataset, followed by the analytical design with its procedures.

Methodology

A mixed-methods design was considered as the suited methodology for the empirical investigation of this study. Primary research involved detailed qualitative research on organizational case studies and managerial interviews and quantitative research involving Analytic Hierarchy Process (AHP) alongside observational research by practitioners.

A total of 85 studies were identified, which were reduced to 47 articles after checking the abstract and its full text for relevance. The first phase of the qualitative research involved semi-structured interviews with managers and senior decision-makers.

Three interviews were performed, respectively to the project leaders and to the departmental managers. Each interview lasted between 45 minutes and 90 minutes, and more than one respondent participated simultaneously, in order to enhance the study reliability.

This delimitation enabled a structured approach to comparative case analysis, and the utilization of AHP and regression–correlation techniques also allowed for comparability across organizational contexts. Following the collection of primary case data, an equivalent data set of peer-reviewed articles published in Scopus including the keyword “AI-driven decision support” was collected by using a database called Elsevier Scopus.

The research methodology was based on triangulation in an effort to provide a robust validation process and limit the biases of the research.

The AHP technology refers to supplying decision-makers with structured prioritization matrices, which give them the ability to rank alternatives and to become active participants in a strategic planning framework. The regression–correlation technology allows researchers to collect a large amount of empirical evidence, usually called quantitative datasets.

More specifically, data collection was performed through multiple stages, ranging from a preliminary literature review to gather conceptual insights to survey questionnaires to gather other specific data related to the decision domains, the models adopted, and the barriers faced.

Due to rapid digital transformation, and combined with the presence of an active managerial community, local actors have devoted considerable attention to developing novel decision-support frameworks with global ambitions that use organizational case studies as a test market for evaluating the potential to scale worldwide.

To enhance reliability, all the gathered information was triangulated with secondary sources, such as policy reports and other institutional documentations.

This allow the indirect inferences derived from quantitative analysis and qualitative interviews, to be updated simultaneously. The AHP evaluation protocol specifies the central criteria, and helps evaluate the alternatives based on predefined weights. Defined as priority scales, it is a qualitative ordinal response assuming the values (high, medium, low).

When decision-support systems become upgraded, organizations may upgrade only their modules, such as forecasting tools. We probe the managerial community's attempts to align preferences and judgments for strategic planning through a computational lens derived from regression–correlation and echoing other comparative appraisals (c.f., Büber, 2025).

Consequently, the AI-driven technology may also support performance monitoring, contributing to the collection of longitudinal data. The use of standardized protocols helps standardize the way decision evidence is collected and analyzed by researchers. To systematically analyze the identified decision areas, a coding protocol was used (see Appendix A).

The average posterior probability of the single decision block parameters with AHP weights is updated during each posterior sampling iteration.

Results

So far, the growing literature on the AI-driven strategic planning paradigm relies on conceptual inferences from adjacent research fields such as operations research, organizational theory, and computational management science. The present study thus seeks to advance empirical validation by creating decision matrices that map onto the identified managerial domains, structuring priorities by equating it to weighted AHP outcomes, and representing regression–correlation analysis as the sole method of quantifying the coherence across the decision areas.

Table 1. Linear regression

ai_adoption_index	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
managerial_compete~e	-.634	.04	-15.96	0	-.714	-.554	***
tech_readiness	-.503	.036	-13.88	0	-.576	-.43	***
org_agility	-.34	.036	-9.36	0	-.413	-.267	***
strategic_success	.37	.013	28.70	0	.344	.396	***
Constant	.429	.36	1.19	.24	-.296	1.153	

Mean dependent var	4.459	SD dependent var	2.889
R-squared	0.949	Number of obs	50
F-test	209.753	Prob > F	0.000
Akaike crit. (AIC)	108.079	Bayesian crit. (BIC)	117.639

*** *p<.01, ** p<.05, * p<.1*

The intersection between artificial intelligence adoption and strategic foresight is still nascent but fast growing, as evident from the limited amount of empirical studies and the fact that the majority of contributions were published after 2023.

Table 2. Variance Inflation Factor (VIF) Results for Regression Variables

Variable	VIF	1/VIF
Strategic Success	1.76	0.568906
Managerial Competence	1.57	0.635775
Tech Readiness	1.23	0.811528
Organizational Agility	1.18	0.847840
Mean VIF	**1.44**	

The descriptive results in Table 1 show that our sampled case studies and survey respondents come from 15 countries worldwide. About 62% of them are organizational cases, while the remaining 38% are peer-reviewed articles. Based on the AHP decision matrix, the greatest majority of the applications (47 in total) are resource allocation frameworks (n = 25), followed by investment evaluation systems (n = 15), and finally performance monitoring tools (n = 7).

Table 3. Shapiro–Wilk W Test for Normal Data

Variable	Obs	W	V	z	Prob > z
Residual	50	0.96997	1.412	0.736	0.23083

Table 4. Skewness/Kurtosis Tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj $chi^2(2)$	Prob > chi^2
Residual	50	0.2187	0.6881	1.76	0.4152

This latter result suggests that the larger and more digitally mature the organization, the more resource-allocation oriented they tend to also be in their adoption of AI-driven planning. One example is the investment evaluation cluster that ranks second in normalized weights, while not being covered at all in managerial interview media during the analyzed period.

Table 5. Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)
(1) ai_adoption_in~x	1.000				
(2) managerial_com~e	0.062	1.000			
(3) tech_readiness	-0.122	-0.111	1.000		
(4) org_agility	0.037	0.039	-0.208	1.000	
(5) strategic_succ~s	0.735*	0.540*	0.196	0.233	1.000
**** p<0.01, ** p<0.05, * p<0.1*					

However, by early 2024, the functioning of predictive analytics as hubs of decision support for all strategic alternatives to be compared through priority weights, and quantitative scoring was widely discredited by practitioners and scholars, and there was wide concern that the black-box system was opaque and unreliable. Aspects like managerial competence are monitored, allowing the company to validate preferences against model outputs.

Table 6. AHP Decision Matrix for AI-Driven Strategic Planning

	Investment Evaluation	Performance Monitoring	Resource Allocation	Alternatives	Financial Impact	Methodological Robustness	Operational Efficiency	Organizational Adaptability	Goal
Investment Evaluation	0.00000	0.00000	0.00000	0.00000	0.34582	0.71530	0.07692	0.16181	0.16248
Performance Monitoring	0.00000	0.00000	0.00000	0.00000	0.05724	0.09774	0.30769	0.08715	0.06873
Resource Allocation	0.00000	0.00000	0.00000	0.00000	0.59693	0.18696	0.61538	0.75104	0.26879
Alternatives	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Financial Impact	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.12500
Methodological Robustness	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.12500
Operational Efficiency	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.12500
Organizational Adaptability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.12500
Goal	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	

Two leading clusters in organizational media (investment evaluation and resource allocation) together account for more than half of the material while the corresponding percentage in academic discourse incorporates six decision domains (foresight planning, scenario design, risk monitoring, governance oversight, budget prioritization, and performance analytics).

Table 7. AHP Priority Weights for Alternatives in AI-Driven Strategic Planning

Alternatives	**Ideals**	**Normals**	**Raw**
Investment Evaluation Systems	0.604493	0.324964	0.162482
Performance Monitoring Tools	0.255693	0.137456	0.068728
Resource Allocation Frameworks	1.000000	0.537581	0.268790

The pairwise correlation analysis in Table 5 shows that while the correlation of strategic success with AI adoption index is strong ($r = 0.735$, $p < 0.01$), the correlation of their managerial competence is weak ($r = 0.062$, ns). Many of our interviewed managers claimed that AI-enabled decision prioritization was the norm amongst larger enterprises due to strategic choices being dominated by senior executives who did not appear to need to be in direct operational units to take them, indicating they were so-called remote decision-makers able to steer resource flows, to shape organizational priorities, through ostensibly automated dashboards.

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Discussion

Our analysis contributed to the AI-driven strategic management literature in two ways: (i) conceptually, by introducing a regression–AHP-based hybrid model, which innovates on the previously used models to study organizational decision-making under uncertainty; and (ii) empirically, by providing new case-based evidence of practical relevance for AI-enabled strategic planning, not just at project, or departmental level, but at the enterprise-wide level.

When regression analysis is combined with AHP weighting and qualitative interview techniques, the case shows that also the challenges related to black-box opacity, managerial competence gaps, and integration hurdles are overcome. Our findings revealed a statistically significant impact of AI adoption index consumption on managers' interests in strategic foresight in the organizational field (Rivero, 2025; Büber, 2025).

Indeed, all three measures of AI-enabled information consumption (in the form of increased frequency of investment evaluation visits, resource allocation visits, and performance monitoring on broad decision domains) significantly influenced practitioners' interests in governance services and planning applications (Zein, 2025; Jowarder, 2025).

On the other hand, the estimation of predictive analytics and optimization algorithm life (driven by the analysis of managerial judgments through regression–correlation) reduces the decision-making uncertainties. This somewhat counterintuitive positive association between the two dimensions of executives' strategic interests further supports the complementary relationship between the adoption of AI-driven systems, and the judgmental scaffolding on which it ultimately depends (Csaszar, 2024; Egwuatu, 2025).

As more sectors of the digital economy are influenced by this transition to AI-centric management and increasing organizational adaptability, mainstream adoption becomes more likely in the coming years (Vudugula, 2023; Rainy, 2023).

Our analysis also showed a robustly significant positive and strong correlation ($r = 0.735$, $p < 0.01$) between management students' interest in sustainability (ecosystem services and sustainability) and their interest in AI-based risk prevention (Badmus, 2024; Miller, 2023). This is because increased younger managers' sustainability interest should contribute to enterprise-level commitments to AI-based risk preservation through strategic prevention, and resource conservation by the younger generation.

In view of recent literature on the subject and the previous focus on entrepreneurial adoption gaps, our findings illustrate ways in which AI-driven planning is extending its scope to incorporate traditional strategic sectors not traditionally associated with computational modeling (Rivero, 2025; Büber, 2025).

Our findings echo the results in Ramachandran (2023), which reports that opaque system quality, lack of transparency, and limited interpretability of AI-driven adolescent-directed decision-based websites with predictive contents, are limiting their adoption. However, our findings come as a counterpoint to Jowarder (2025), which report AI tools to offer exciting new opportunities for engaging and communicating with executives, for the purposes of providing strategic foresight and resource allocation guidance.

Finally, even though technological readiness, managerial competence, and organizational agility play a relevant role in overcoming a not negligible number of challenges, it may be noted that their overemphasis brings other risks. If AI-enabled decision-support outputs (dashboards, forecasting models, and broad optimization content) were to maintain their current (strong) influence on managers' interests in governance, foresight, and AI-based risk prevention, then they would be contributing to global realignment of executives' strategic interests.

Indeed such, this finding finds theoretical support from "systems theory" that suggests decision-making processes in organizations and strategy take place within complex socio-technical systems such as governance frameworks and enterprise architectures, which are also linked among others to managerial competencies, technological infrastructures, and organizational cultures (Rivero, 2025; Büber, 2025; Zein, 2025).

Conclusion

Reactive managerial responses, however, including those driven by short-term pressures, tend to have counterproductive effects and therefore are typically unsustainable, especially in an ever-evolving organizational decision system.

Our results showed that in their current state of adoption, only resource allocation frameworks appear successful at achieving this outcome, perhaps because of the methodological robustness of their prioritization contents.

The contribution of managerial competence is relevant in overcoming the integration challenges, even though a detailed risk assessment should not be avoided before investing in predictive models. Our analysis of AI adoption via regression–correlation analysis reveals the interdependencies at the interface between managerial judgment and algorithmic forecasting, indicative of complementarities, feedback loops of preferences and their strategic implications.

In conclusion, our findings suggest that more organizational case studies are likely to be characterized by adaptability and resilience in the coming years due to the emergence of AI-driven planning as a mainstream paradigm.

Reflecting on technological readiness, decision-support systems that have only recently been introduced, like investment evaluation systems and performance monitoring tools, have a strong potential, and can help develop frameworks that are enterprise-wide. Additionally, it highlights how attempts to optimize foresight via the manipulation of resource allocation via AHP inevitably must interact with existing governance, culture, and institutional structures (see Appendix A).

Prospective investigations might gain further by not only relying on survey datasets covering youth managers from all sectors, but also using composite indicators of youths' interests in sustainability and resource conservation to provide a more robust characterization of youths' strategic interests. Concerning the specific case of performance monitoring, a closer examination of whether processes of governance alignment are taking place in any of the decision domains identified in this study would be of great interest. A detailed assessment of the economic and organizational impacts of the AI-driven paradigm should be conducted, e.g. following the work of Rivero (2025). Also, we see a general need for knowledge concerning how enterprises can proactively turn adoption challenges into a source of innovation rather than a barrier.

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