

Artificial Intelligence in Strategic Management: A Quantitative Validation of the Proposed Framework in Iraqi Public Universities

Hassan. Fadhel Saleh Al-Thabhwhee¹, Nasrin. Razi^{1*}, Mohammad. Fariyabi¹

¹ Department of Strategic Management, Faculty of Economics and Management, University of Tabriz, Tabriz, Iran

* Corresponding author email address: n.razi@tabrizu.ac.ir

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ABSTRACT

Objective: This study aimed to empirically examine and validate the impact of artificial intelligence on strategic management, with particular emphasis on strategy formulation, strategy implementation, and strategic control.

Methods and Materials: The study adopted a quantitative, applied-developmental research design grounded in a descriptive-analytical approach. Data were collected using a structured questionnaire administered to senior managers and decision-makers within the target organizational context. The measurement instrument encompassed validated indicators of artificial intelligence capabilities and the three core dimensions of strategic management. Reliability and validity were assessed using Cronbach's alpha, composite reliability, average variance extracted, exploratory factor analysis, and confirmatory factor analysis. Structural relationships among variables were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software, supported by inferential statistical analysis to evaluate correlations and causal paths among constructs.

Findings: The inferential results revealed a statistically significant and positive relationship between artificial intelligence and overall strategic management. Structural model analysis demonstrated that artificial intelligence exerted a significant direct effect on strategic management, explaining a substantial proportion of its variance. At the dimensional level, artificial intelligence showed significant positive effects on strategy formulation, strategy implementation, and strategic control, with the strongest effect observed on strategic control.

Conclusion: The findings confirm that artificial intelligence functions as a critical strategic enabler that strengthens the effectiveness of strategic management by enhancing analytical rigor in formulation, operational efficiency in implementation, and real-time oversight in control.

Keywords: Artificial intelligence · Strategic management, PLS-SEM

1 Introduction

The acceleration of digital transformation has fundamentally altered the foundations of strategic management, positioning artificial intelligence (AI) not merely as a technological tool but as a strategic resource capable of reshaping organizational cognition, decision architectures, and long-term value creation. Contemporary organizations operate in environments characterized by volatility, uncertainty, complexity, and ambiguity (VUCA), where traditional strategic planning models—largely reliant on human judgment and linear forecasting—have become increasingly inadequate. In this context, artificial intelligence has emerged as a pivotal enabler of strategic agility, analytical depth, and adaptive governance, offering unprecedented capabilities for data-driven strategy formulation, implementation, and control (Biloslavov, 2024; Nazari Zadeh et al., 2023; Shaddel, 2023).

Recent scholarship emphasizes that AI-driven systems are no longer confined to operational automation or tactical optimization; rather, they are progressively embedded within core strategic processes such as environmental scanning, scenario analysis, strategic forecasting, and performance evaluation (Gusai & Rani, 2022; Sestino & Mauro, 2021). The strategic relevance of AI stems from its ability to process vast volumes of structured and unstructured data, identify latent patterns, generate predictive insights, and support complex decision-making under uncertainty—capabilities that exceed conventional managerial analytics (Meena et al., 2024; Sulistiani & Bustanul, 2025). Consequently, AI is increasingly recognized as a catalyst for transforming strategic management from an intuition-driven practice into an evidence-based, continuously adaptive system.

The integration of artificial intelligence into strategic management has been examined across multiple organizational domains, including marketing, finance, human resources, supply chain management, and governance. In strategic marketing, AI enables organizations to formulate data-informed market positioning, optimize branding strategies, and enhance customer engagement through predictive personalization and real-time analytics (Anjorin, 2024; Parsakia & Jafari, 2023; Sajan & Giri, 2025; Sundari et al., 2025). In financial management and forecasting, AI-based models improve accuracy, reduce cognitive bias, and support strategic planning under dynamic economic conditions (Mehrabi et al., 2024; Sulistiani & Bustanul, 2025). Similarly, AI-driven decision intelligence

has been shown to strengthen strategic flexibility and resilience in knowledge-based firms operating in turbulent environments (Hosseini & Sadeghi, 2023; Rezaei et al., 2024).

From a strategic human resource management perspective, artificial intelligence contributes to workforce planning, talent analytics, and diversity management, while simultaneously reshaping governance structures and managerial roles (Musthafa, 2024; Varkiani Pour & Sarhadi, 2024; Yamin et al., 2024). These findings collectively suggest that AI acts as an integrative strategic capability—linking organizational resources, human capital, and digital infrastructure to strategic outcomes. However, despite the growing body of empirical and conceptual research, the mechanisms through which AI systematically influences the full cycle of strategic management remain insufficiently theorized and empirically validated.

Strategic management literature increasingly calls for rethinking classical strategy models in light of artificial intelligence. Traditional frameworks often conceptualize strategy as a sequential process involving formulation, implementation, and control, predominantly guided by managerial expertise and static environmental analysis. In contrast, AI-enabled strategy introduces dynamic feedback loops, real-time performance monitoring, and continuous strategic recalibration (Mahmoud El Sayed El Khouly et al., 2022; Nazarian-Jashnabadi et al., 2023). AI-supported systems enhance strategy formulation by integrating predictive analytics, scenario modeling, and SWOT intelligence, enabling organizations to identify opportunities and risks with higher precision (Alizadeh & Foroughi, 2023; Kiakojouri, 2025).

During the implementation phase, AI facilitates automation, resource optimization, and decision support, thereby reducing execution gaps between strategic intent and operational reality (Gusai & Rani, 2022; Mohammadi et al., 2024). In strategic control, AI-powered monitoring systems provide real-time dashboards, anomaly detection, and early-warning signals, allowing organizations to assess strategic performance and intervene proactively (Saadati et al., 2025; Tong et al., 2021). These capabilities fundamentally transform strategic management from a periodic planning exercise into a continuous, learning-oriented process.

Despite these advancements, existing research remains fragmented across disciplines and application domains, often focusing on isolated strategic functions rather than offering an integrated view of AI-driven strategic management. Several studies concentrate on specific

sectors—such as banking, airlines, sports management, or supply chains—without developing a comprehensive framework applicable across organizational contexts (Meena et al., 2024; Nalbant & Aydin, 2022; Pérez-Campuzano et al., 2021; Yamin et al., 2024). Other contributions emphasize conceptual discussions or future-oriented scenarios without empirical validation of AI's strategic impact (Nazari Zadeh et al., 2023; Shaddel, 2023). As a result, the literature lacks a unified model that empirically explains how artificial intelligence affects the interrelated dimensions of strategic management in complex organizational environments.

Furthermore, while recent studies highlight the strategic benefits of AI adoption, they also underscore challenges related to governance, organizational readiness, ethical considerations, and managerial acceptance. AI-driven decision systems require alignment with organizational strategy, transparent governance mechanisms, and adaptive leadership capable of integrating human judgment with algorithmic intelligence (Biloslav, 2024; Kiakouri, 2025). Without such alignment, AI risks becoming a fragmented technological investment rather than a source of strategic value. This concern is particularly salient in public sector and knowledge-intensive organizations, where strategic decisions are embedded within institutional constraints, accountability requirements, and long-term societal objectives.

The growing emphasis on AI-enabled strategic governance reflects a broader shift toward intelligent organizations—entities that leverage digital technologies not only to optimize operations but also to enhance strategic foresight, policy coherence, and organizational learning (Kiakouri, 2025; Nazarian-Jashnabadi et al., 2023). AI contributes to transcendent governance by enabling evidence-based policymaking, strategic simulation, and adaptive control mechanisms that align organizational actions with long-term strategic visions (Saadati et al., 2025). Nevertheless, empirical studies that quantitatively validate AI-based strategic frameworks remain limited, particularly in emerging economies and public sector contexts.

Recent empirical research has begun to address this gap by examining AI's impact on strategic decision-making, organizational innovation, and strategic agility. Evidence suggests that AI enhances strategic outcomes indirectly through mediating mechanisms such as organizational innovation, analytical maturity, and dynamic capabilities (Mehrani et al., 2022; Mohammadi et al., 2024; Rezaei et al.,

2024). Moreover, AI-driven intelligence systems have been shown to improve strategic coordination across organizational units, strengthen resilience under uncertainty, and support long-term competitiveness (Biloslav, 2024; Gusai & Rani, 2022). However, these studies often focus on private-sector organizations, leaving public and educational institutions underexplored.

In addition, methodological limitations persist within the existing literature. Many studies rely on qualitative approaches, conceptual analyses, or case studies, which, while valuable for theory development, offer limited generalizability. Quantitative validation of AI-based strategic management models—particularly using advanced techniques such as structural equation modeling—remains scarce (Hosseini & Sadeghi, 2023; Meena et al., 2024). This methodological gap constrains the ability of scholars and practitioners to assess the magnitude, direction, and robustness of AI's strategic effects across organizational contexts.

Against this backdrop, there is a clear need for integrative, empirically grounded research that systematically examines the role of artificial intelligence across all stages of strategic management. Such research should move beyond fragmented analyses and sector-specific insights to develop and validate comprehensive frameworks that explain how AI capabilities interact with strategic formulation, implementation, and control in complex organizations. Addressing this gap is essential for advancing strategic management theory, informing managerial practice, and guiding policy decisions in an era of accelerating digital transformation.

Accordingly, the aim of this study is to empirically examine and validate the role of artificial intelligence in enhancing strategic management—specifically strategy formulation, strategy implementation, and strategic control—through a quantitative framework grounded in contemporary strategic management and artificial intelligence literature.

2 Methods and Materials

The present study employed a quantitative, applied research design using a descriptive-analytical approach to examine the role of artificial intelligence in strategic management. The research was cross-sectional in nature and focused on testing a theoretically grounded model through empirical data. The statistical population consisted of senior managers, middle managers, and key decision-makers

working in organizations that had experience with, or exposure to, artificial intelligence-based systems in managerial and strategic processes. Participants were selected because of their direct involvement in strategic planning, implementation, or control activities and their familiarity with digital and analytical tools used within their organizations. Sampling was carried out using a purposive and accessibility-based approach to ensure that respondents possessed sufficient knowledge to provide informed evaluations of artificial intelligence and strategic management practices. The final sample size met the minimum requirements for structural equation modeling, ensuring adequate statistical power and model stability.

Data were collected using a researcher-developed structured questionnaire designed in accordance with the theoretical foundations of artificial intelligence and strategic management. The questionnaire comprised two main sections. The first section gathered demographic and professional information, including managerial position, years of experience, and level of familiarity with artificial intelligence technologies. The second section measured the main research constructs, including artificial intelligence capabilities and the three dimensions of strategic management: strategy formulation, strategy implementation, and strategic control. All items were measured using a five-point Likert scale ranging from strongly disagree to strongly agree. Content validity of the instrument was assessed through expert review by academics and practitioners with expertise in strategic management and artificial intelligence. Reliability was evaluated using internal consistency measures, and construct validity was examined through factor analysis procedures prior to hypothesis testing.

Table 1

Frequency distribution of respondents' gender

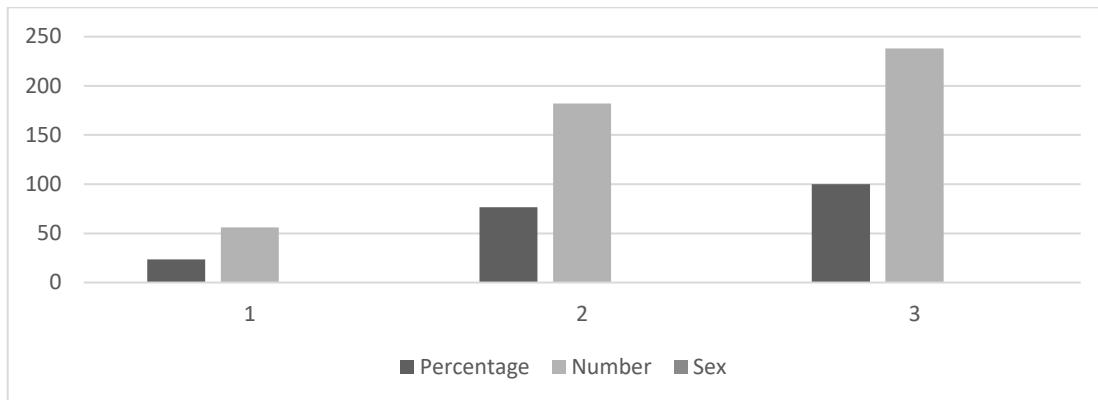
Sex	Number	Percentage
Females	56	23.5
Males	182	76.5
Total	238	100

Data analysis was conducted using a combination of descriptive and inferential statistical techniques. Initially, descriptive statistics were employed to summarize respondents' characteristics and to assess the distributional properties of the data. Measurement model evaluation was performed to assess reliability, convergent validity, and discriminant validity using Cronbach's alpha, composite reliability, and average variance extracted indices. Subsequently, the structural model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. Path coefficients, coefficient of determination values, and predictive relevance indicators were examined to evaluate the strength and significance of hypothesized relationships. Bootstrapping procedures were applied to determine the statistical significance of direct effects, ensuring robust inference regarding the impact of artificial intelligence on strategic management and its dimensions.

3 Findings and Results

To explain and describe the data collected in the second phase of the survey process, descriptive statistics was used first. Tables and graphs are used here to show the status of the research variables and the 238 demographic characteristics of the respondents who were asked at the beginning of the survey questionnaire.

As can be seen in Table above, more than 76% of the respondents, equivalent to 182 people, are men. It is clear that the vast majority of respondents are men. The frequency plot related to the gender of the respondents is shown below.

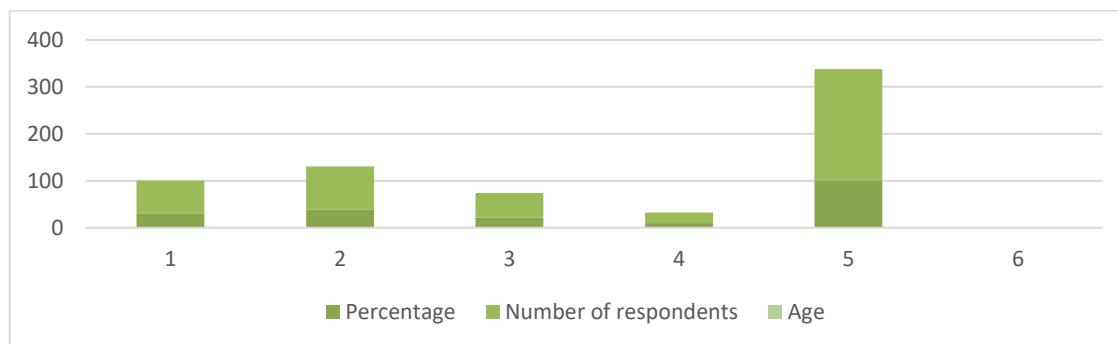
Figure 1*Histogram of respondents' gender*

As can be seen from Table above, the majority of respondents, 92 people, are between 45 and 60 years old, representing about 40% of the study sample. After that, the age group of 30 to 45 years old came next, which includes 71 people, which is about 30% of the total respondents.

Together, these two groups represent 68.5% of the total respondents. The lowest frequency of respondents was among people under the age of 30, who made up less than 5% of the sample. Below is a histogram related to the age of the respondents.

Table 2*The age of the respondents from the research sample*

Age	Number of respondents	Percentage
30-40	71	29.8
41-50	92	38.6
51-60	52	21.8
More than 60	23	9.7
Total	238	100

Figure 2*The ages of the respondents from the research sample*

The majority of the 79 participants, listed in Table 4 to 10, are between 21 and 25 years old. This group represents more than 33% of the total study sample. After that, the professional category of 16 to 20 years comes next with a

frequency of 60 people, which also influenced the research by experience category. The smallest percentage of the statistical sample, out of 25, belongs to jobs of less than 10 years, with 20 participants, less than 9% of the statistical

sample, which also gives a frequency related to experience. The table is attached.

The statistical sample consisted of 238 people, all of whom have a doctoral degree. It should be noted that the Iraqi state has a system that those who hold senior positions must hold a doctorate degree.

In this section, the obtained survey data was first used to validate the factor models. Then, the structural model of the research was estimated to test its hypotheses.

This section focuses on analyzing the normal distribution of the study data for the purpose of identifying whether it is teacher or non-teacher data, to then diagnose the statistical

tools that suit the type of analysis, and then test the hypotheses assumed by the researcher, and this requires several conditions, including identifying the homogeneity of variance, and the extent of the distribution of the data for the population representing the sample, The extent of the distribution of data for the population that represents the sample, as there are many types of samples that have a non-normal distribution, and this leads to the fact that some statistical tests do not give accurate results that can be adopted by the (T test) and (F test), and the normal distribution procedure requires diagnosing the values of the Skewness and Kurtosis.

Table 3

The results of the normal distribution of the artificial intelligence variable

	Std. Error of Kurtosis	Std. Error of Skewness		
	0.319	0.416		
Sample	238	Missing values	0	
Variable	Paragraph	Kurtosis	Skewness	Verdict
Artificial intelligence				
	AI1	0.867	0.813	Acceptable
	AI2	0.711	0.754	Acceptable
	AI3	0.711	0.636	Acceptable
	AI4	0.801	0.813	Acceptable
	AI5	0.763	0.752	Acceptable
	AI6	0.429	-0.735	Acceptable
	AI7	-0.477	-0.606	Acceptable
	AI8	-0.2380	0.505	Acceptable
	AI9	0.801	-0.907	Acceptable
	AI10	0.754	0.654	Acceptable
	AI11	0.777	-0.506	Acceptable
	AI12	-0.609	-0.572	Acceptable
	AI13	0.702	0.031	Acceptable
	AI14	0.862	0.630	Acceptable
	AI15	0.702	0.731	Acceptable
	AI16	0.801	0.807	Acceptable
	AI17	0.808	0.811	Acceptable
	AI18	0.717	0.588	Acceptable
	AI19	0.806	0.811	Acceptable
	AI20	0.842	0.717	Acceptable
	AI21	0.817	0.688	Acceptable
	AI22	0.706	0.611	Acceptable
	AI23	0.842	0.717	Acceptable
	AI24	0.777	0.628	Acceptable
	AI25	0.836	0.711	Acceptable
	AI26	0.872	0.767	Acceptable
	AI27	0.767	0.888	Acceptable
	AI28	0.816	0.731	Acceptable

Items AI1 to AI5 recorded values for torsion between (0.636 - 0.813) and flattening between (0.711 - 0.867), which are all within statistically acceptable limits, indicating that the distribution of responses in these items is normal. Items

AI6 through AI9 had negative values for torsion (e.g. AI6 = -0.735, AI7 = -0.606, AI9 = -0.907), but they are still within the acceptable range. Flattening was slightly lower in AI8 (-0.2380), but it does not exceed the rejected statistical limit,

meaning that all of these are also normal. AI10 to AI15 had values within the acceptable range, with skewness ranging from -0.506 to 0.731 and kurtosis from 0.702 to 0.777, indicating symmetry and moderation in the distribution. AI16 to AI21 recorded positive skewness between 0.588 and 0.811 and moderate kurtosis between 0.717 and 0.842, which are also within acceptable statistical limits. AI22 to AI28 maintained the same acceptable pattern, with values ranging from (skewness = 0.611 to 0.888) and (kurtosis = 0.706 to 0.872), reinforcing that they meet the characteristics

of a normal distribution. III: Summary and Conclusion All scale items (AI1 to AI28) fall within the acceptable limits for torsion and flattening ($= \pm 1.96$) according to (Hair et al., 2014, p. 76), which means that the data do not contain significant statistical deviations. No vertebrae showed anomalous or abnormal distribution, either in terms of skewness or kurtosis. These results reflect the integrity and stability of the distribution and support the use of parametric tests in analyzing these data such as factor analysis and analysis of variance.

Table 4

The results of the normal distribution of the Strategic management variable

Std. Error of Kurtosis		Std. Error of Skewness		
	0.319		0.416	
Sample	238	Missing values	0	
Variable	Paragraph	Kurtosis	Skewness	Verdict
Strategy Formulation	SF29	0.745	0.771	Acceptable
	SF30	0.795	0.785	Acceptable
	SF31	0.663	0.772	Acceptable
	SF32	0.903	0.842	Acceptable
	SF33	0.965	0.861	Acceptable
	SF34	0.791	0.725	Acceptable
	SF35	0.865	0.965	Acceptable
Strategy Implementation	SI36	0.765	0.865	Acceptable
	SI37	0.838	0.707	Acceptable
	SI38	-0.909-	-0.772-	Acceptable
	SI39	0.725	0.567	Acceptable
	SI40	0.695	0.815	Acceptable
	SI41	0.763	0.720	Acceptable
	SI42	0.735	0.631	Acceptable
Strategic Control	SI43	0.755	0.745	Acceptable
	SC44	0.854	0.238	Acceptable
	SC45	0.525	0.321	Acceptable
	SC46	0.791	0.885	Acceptable
	SC47	0.678	0.771	Acceptable
	SC48	0.712	0.732	Acceptable
	SC49	0.793	0.782	Acceptable

First dimension: Strategy Formulation (SF29 - SF35) The skewness values of the paragraphs ranged between (0.663 - 0.965), while the kurtosis values ranged between (0.725 - 0.965), all of which are within the statistically acceptable limits (± 1.96). This indicates that the sample's responses to the paragraphs of this dimension are normally distributed, and there are no outliers or skewed distributions in the data. We note that SF33 recorded the highest value for flattening (0.965), while SF31 was the lowest (0.663), however, all values remain within the acceptable range.

Second dimension: Strategy Implementation (SI36 - SI43) The paragraphs recorded high adherence to the normal

distribution, with skews ranging from (-0.909 to 0.838) and flattening from (-0.772 to 0.865), all of which are within the acceptable range. Paragraph SI38 was characterized by the highest negative score for torsion (-0.909) and flattening (-0.772), but it is still below the unacceptable critical limit. The rest of the paragraphs came with moderate values, reflecting the balance of the data and the absence of excessive centralization or dispersion.

The third dimension: Strategic Control (SC44 - SC49) The items showed values ranging from (0.525 - 0.854) and (0.321 - 0.2382), which are also within the acceptable range. SC45 recorded the lowest values (Skew = 0.525, Kurt =

0.321), while SC44 and SC46 recorded relatively higher values, but still acceptable.

General conclusion: All three dimensional vertebrae were within the acceptable range for torsion and flattening (± 1.96) according to the approved statistical reference. There are no

items that indicate abnormal deviations or issues with the data distribution. These results can be relied upon to apply advanced statistical analyses such as exploratory factor analysis and validation.

Table 5

Cronbach's Alpha coefficient for the message scale

Variable	Dimension	Symbol	Cronbach's Alpha
Artificial Intelligence		AI	0.972
Strategic Management	Strategy Formulation	SF	0.914
	Strategy Implementation	SI	0.902
	Strategic Control	SC	0.901

Artificial Intelligence (AI) is one of the most prominent technological innovations that has fundamentally transformed decision-making systems within contemporary organizations, especially in complex and changing business environments. As organizations increasingly rely on AI tools to improve strategic performance, an in-depth structural analysis is needed to understand the underlying dimensions of this variable and ensure its construct validity within the organizational context. Exploratory Factor Analysis (EFA) is used as an effective statistical tool to reveal the underlying structure of relationships between a set of variables or items, and is a pivotal step in the validation phase of measures used in quantitative research, especially when the goal is to develop an integrated conceptual model. This analysis acquires special importance when applied to the variable "Artificial Intelligence", due to its multidimensionality and the overlap of its applications between technical, administrative and cognitive aspects.

This section aims to conduct an exploratory factor analysis of the AI variable as measured in this research, in order to: Verify the number of factors that make up this variable as reflected in the sample's responses. Measuring the consistency and coherence of the items used with the theoretical dimensions extracted from the previous methodological study. Determine the suitability of the data for analysis using indicators such as KMO and Bartlett's Test. Paving the way for testing the proposed theoretical model in the confirmatory factor analysis later on. This analysis was adopted within the statistical methodology of the research using the SmartPLS after confirming the conditions of its application, based on the importance of building a measurement tool that enjoys reliability and validity in representing the dimensions of artificial intelligence, in preparation for measuring its impact on the components of strategic management in Iraqi educational institutions.

Table 6

The saturation matrix of the paragraphs of the artificial intelligence variable

Variable	Paragraph Code	Component
Artificial Intelligence	AI1	0.617
	AI2	0.790
	AI3	0.793
	AI4	0.806
	AI5	0.756
	AI6	0.716
	AI7	0.603
	AI8	0.773
	AI9	0.629
	AI10	0.709
	AI11	0.838
	AI12	0.668

AI13	0.777
AI14	0.587
AI15	0.767
AI16	0.704
AI17	0.710
AI18	0.736
AI19	0.650
AI20	0.684
AI21	0.866
AI22	0.812
AI23	0.907
AI24	0.812
AI25	0.822
AI26	0.858
AI27	0.777
AI28	0.783

In light of the methodological objectives of the study, which seeks to build an integrated conceptual model to measure the impact of AI on strategic management components, an exploratory factor analysis (Exploratory Factor Analysis - EFA) was conducted using SmartPLS to verify the construct validity of the AI variable. A 28-item scale (AI1-AI28) developed based on a comprehensive systematic review of the scientific literature and the results of the qualitative phase (Delphi) was used in its design. Factor loadings ranged from 0.587 to 0.907, indicating good to excellent correlation between the statements and the overall component of the AI scale. AI23 had the highest factor loadings (0.907), followed by AI21 (0.866) and AI26 (0.858), reflecting the high consistency of these indicators with the conceptual structure of the variable. In contrast, the lowest loading value was observed for AI14 (0.587), yet it remains within scientifically acceptable limits (>0.50) according to Hair et al. (2014), justifying its retention in the analytical model. This relative variation in loading values indicates the existence of internal pluralism in AI dimensions, which is consistent with the complex and

multifaceted nature of this variable, which includes dimensions such as: Machine learning, big data analysis, automation, decision support, and strategic forecasting. This confirms that the designed statements cover a wide range of AI components, which supports the Construct Validity of the scale.

In addition to the factor loadings, the KMO test was calculated to check the suitability of the data for factor analysis, and the value reached (0.921), which is a very high value indicating the adequacy of the sample and the extent to which the variables are correlated. Bartlett's Test of Sphericity also showed a statistically significant result ($p < 0.001$), which enhances the validity of the data to undergo factor analysis. Therefore, it can be said that the exploratory factor analysis resulted in strong indicators of the quality of the factor structure of the AI variable, which qualifies it to move to the next stage of statistical analysis (confirmatory factor analysis - CFA) within the framework of structural equation modeling (SEM), in order to verify the suitability of the proposed theoretical model with field data.

Table 7

KMO and Bartlett test for the artificial intelligence variable

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.921
Bartlett's Test of Sphericity	Approx. Chi-Square	1129.569
	Df	27
	Sig.	0.000

Strategic management is a multidimensional concept that requires accurate and integrated measurement tools that reflect its main components, namely: Strategy Formulation, Strategy Implementation, and Strategy Control. In order to

verify the validity of the strategic management scale adopted in this thesis, an exploratory factor analysis (EFA) was conducted using SmartPLS to analyze the consistency of the scale items with the adopted theoretical structure. This

analysis seeks to test the construct validity of the scale by examining the extent to which each statement is related to the latent factor it represents, and to ensure the adequacy of the sample to apply the factor analysis, as an essential step before moving on to the confirmatory factor analysis. The

results of this analysis are an important indicator of the quality of the content and its suitability to measure the components of strategic management as identified theoretically and practically within the framework of the current study.

Table 8

The saturation matrix of the strategic management items

Variable	Paragraph Code	Component
Strategy Formulation	SF29	0.744
	SF30	0.791
	SF31	0.842
	SF32	0.815
	SF33	0.845
	SF34	0.795
	SF35	0.786
Strategy Implementation	SI36	0.795
	SI37	0.704
	SI38	0.827
	SI39	0.795
	SI40	0.835
	SI41	0.807
	SI42	0.607
Strategic Control	SI43	0.752
	SC44	0.712
	SC45	0.782
	SC46	0.782
	SC47	0.771
	SC48	0.784
	SC49	0.680

In light of the objectives of the study to measure the impact of AI on the components of strategic management, an Exploratory Factor Analysis (EFA) was conducted for the variable "strategic management" to verify the construct validity of the dimensions of the scale adopted in the thesis. The scale included three main dimensions: Strategy Formulation, Strategy Implementation, and Strategic Control, consisting of 21 statements distributed by 7 for each dimension. The results of the analysis showed that factor loadings ranged from 0.607 to 0.845, which are all within the scientifically acceptable range (>0.60), indicating the consistency of the statements with the hypothesized theoretical factors. The highest loading within the strategy formulation dimension was for SF33 (0.845), followed by SF31 (0.842) and SF32 (0.815), reflecting the strength of internal consistency of this dimension. The lowest loading was recorded for SI42 in the strategy implementation dimension with a value of (0.607), which, despite its

relatively low value, is still statistically acceptable and does not require deletion.

For the strategic control dimension, the statements showed strong loadings ranging from 0.680 to 0.784, with SC48 recording the highest value (0.784), indicating the quality of the structural representation of this dimension. It is important to note that the KMO was 0.914, which is a very high value indicating the suitability of the data for factor analysis, while the Bartlett's Test of Sphericity was statistically significant ($p < 0.001$), reinforcing the validity of the model for latent factors.

Taken together, these results indicate that the Strategic Management Scale has a high degree of internal consistency and construct validity, and clearly reflects the theoretical structure adopted in this study. Consequently, this scale is eligible to proceed to the Confirmatory Factor Analysis (CFA) stage within the Structural Equation Model (SEM), to verify the goodness of fit between the theoretical model and the field data.

Table 9*KMO and Bartlett test for the corporate governance variable*

KMO and Bartlett's Test	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.914
Bartlett's Test of Sphericity	Approx. Chi-Square
	Df
	Sig.

Measurement Model Evaluation is the first and basic step in the analysis of structural equation modeling using PLS-SEM, as it aims to verify the validity and reliability of the measurement instruments used to represent the latent variables in the study. This evaluation includes a set of statistical criteria that ensure the accuracy of the relationships between the items (indicators) and the

variables they measure, such as content validity, convergent validity, discriminant validity, and internal consistency of the variables through consistency coefficients such as Cronbach's Alpha and Composite Reliability. This evaluation is a necessary step before moving on to testing the structural model and testing the research hypotheses.

Table 10*Results of testing the measurement tool for the AI variable*

Paragraph Code	Component	Cronbach Alpha	Compound stabilizer	AVE
AI1	0.617	0.973	0.962	0.626
AI2	0.790			
AI3	0.793			
AI4	0.806			
AI5	0.756			
AI6	0.716			
AI7	0.603			
AI8	0.773			
AI9	0.629			
AI10	0.709			
AI11	0.838			
AI12	0.668			
AI13	0.777			
AI14	0.587			
AI15	0.767			
AI16	0.704			
AI17	0.710			
AI18	0.736			
AI19	0.650			
AI20	0.684			
AI21	0.866			
AI22	0.812			
AI23	0.907			
AI24	0.812			
AI25	0.822			
AI26	0.858			
AI27	0.777			
AI28	0.783			

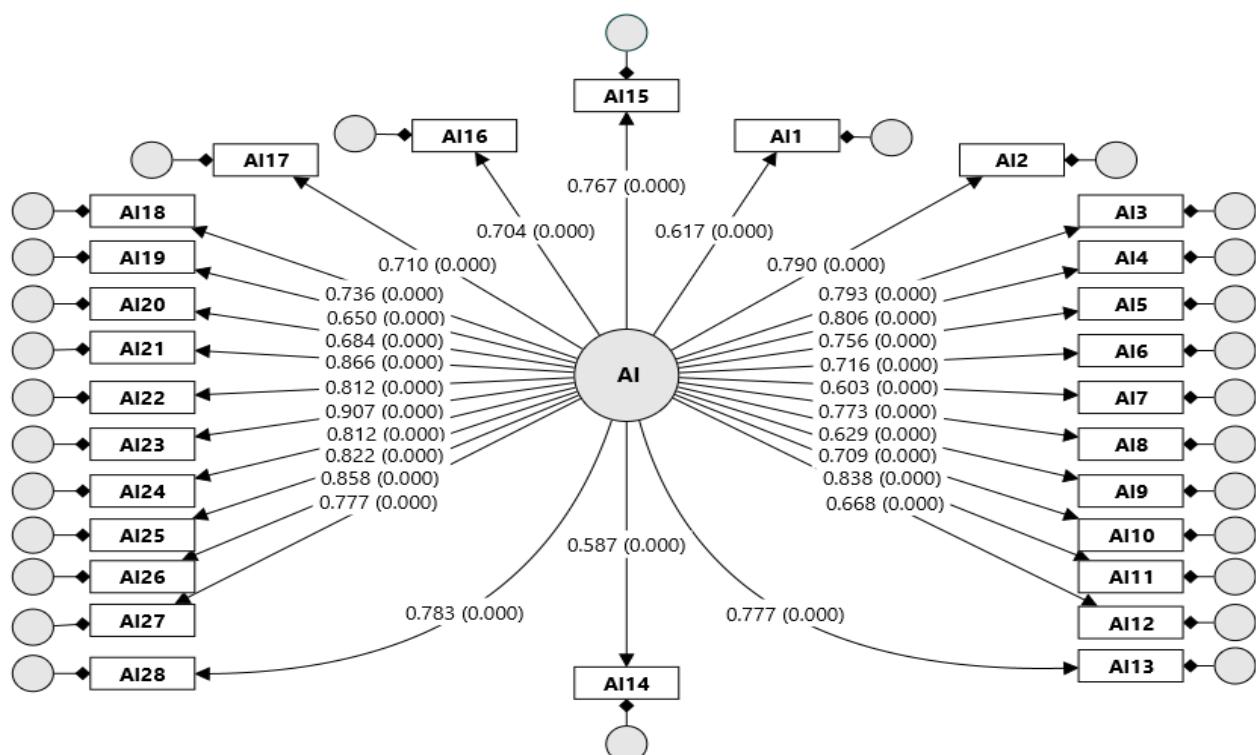
In light of the requirements of structural equation modeling analysis (PLS-SEM), the measurement model was evaluated to verify the quality and validity of the study instrument to measure the latent variables. This evaluation was based on three main criteria: Internal Consistency, Convergent Validity, and Discriminant Validity. Regarding internal consistency, the results of the Cronbach's Alpha coefficient for the AI variable showed a value of (0.962), which exceeds the minimum acceptable value (0.70) according to the recommendations of Nunnally & Bernstein (1994), indicating a very high degree of internal consistency among the scale's paragraphs. The value of the Composite Reliability coefficient of the scale (0.973), which is also above the required limit (0.70), which confirms the excellent reliability of the measurement instrument. As for convergent validity, the average variance extracted (Average Variance Extracted - AVE) was used, which amounted to (0.626), exceeding the minimum acceptable threshold (0.50),

indicating that the items explain a sufficient proportion of the variance of the latent variable.

This value indicates that the AI-related items are sufficiently convergent and reflect the theoretical concept they represent. As for Factor Loadings, the values ranged between (0.587) and (0.907), and the vast majority of items had loadings higher than (0.70), confirming the quality of the construct representation. Paragraph AI23 recorded the highest loading value (0.907), followed by paragraph AI21 (0.866), while paragraph AI14 recorded the lowest loading value (0.587), which is within the scientifically acceptable threshold and does not require deletion at this stage. Based on these results, it can be confirmed that the AI measurement instrument adopted in this study has a high degree of stability and construct validity, which makes it suitable for use in testing the structural model later on and analyzing the causal relationships between AI and strategic management.

Figure 3

Saturation ratios for the AI variable



Factor analysis is an essential step in validating the construct validity of the strategic management measurement instrument, which is a multidimensional concept that encompasses strategy formulation, implementation, and control. This analysis aims to ensure that the items in the questionnaire are statistically significantly related to the

theoretical dimensions they measure, and that each dimension represents a distinct and homogeneous conceptual structure. In addition, the stability of these dimensions was measured using two internal consistency indices: Cronbach's Alpha and Composite Reliability, to check for measurement stability and repeatability across

different samples. These steps are necessary before moving on to modeling the relationships between variables within the framework of structural equation modeling (SEM).

Table 11

The results of testing the measurement tool for the strategic management variable

Paragraph Code	Component	Cronbach Alpha	Compound stabilizer	AVE
SF29	0.744	0.927	0.912	0.645
SF30	0.791			
SF31	0.842			
SF32	0.815			
SF33	0.845			
SF34	0.795			
SF35	0.786			
SI36	0.795	0.902		0.594
SI37	0.704		0.900	
SI38	0.827			
SI39	0.795			
SI40	0.835			
SI41	0.807			
SI42	0.607			
SI43	0.752	0.901	0.897	0.567
SC44	0.712			
SC45	0.782			
SC46	0.782			
SC47	0.771			
SC48	0.784			
SC49	0.680			

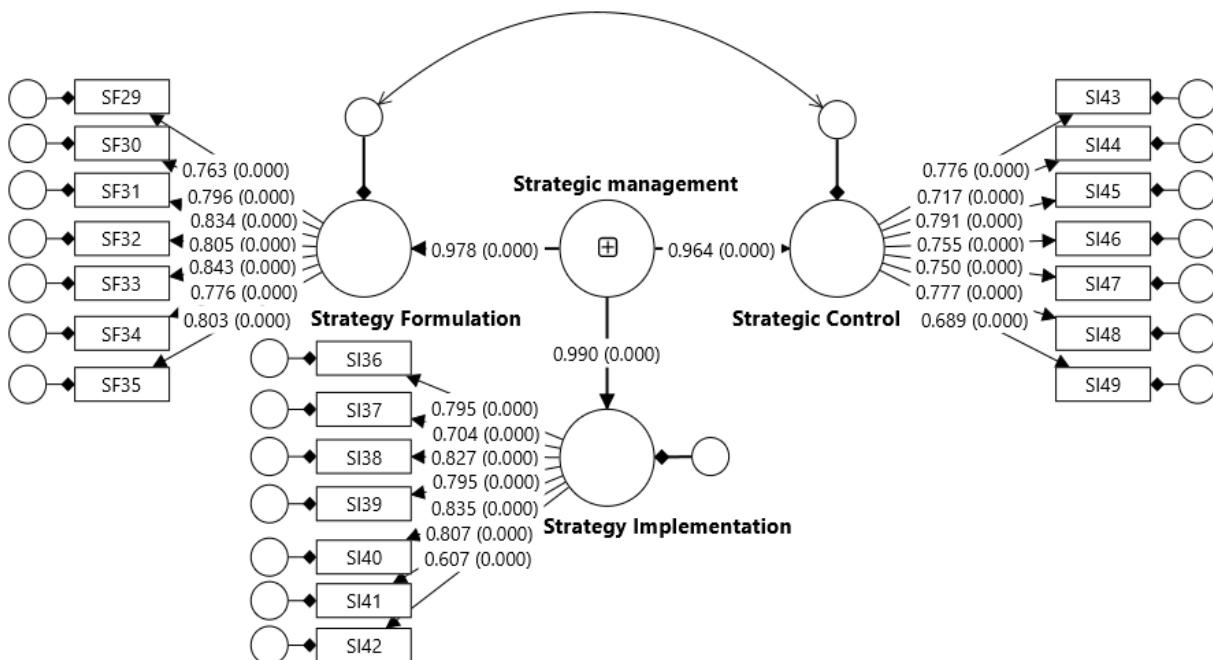
Exploratory and confirmatory factor analysis of the strategic management variable was conducted to verify the construct validity of the measurement instrument used in this study, which included three main dimensions: Strategy Formulation, Strategy Implementation, and Strategic Control. The quality of each dimension was assessed based on factor loadings, Cronbach's alpha, Composite Reliability, and Average Variance Extracted (AVE). First, the items on the Strategy Formulation dimension (SF29-SF35) showed factor loadings ranging from 0.744 to 0.845, all above the minimum acceptable threshold of 0.60, indicating a strong correlation between the items and the factor they represent. Cronbach's alpha for this dimension (0.927) and composite stability (0.912), both of which are above the minimum acceptable level (0.70), indicating a high degree of internal consistency. The AVE value (0.645) is above the minimum required value (0.50), indicating the asymptotic validity of this dimension. Second, the "Strategy Implementation" dimension (SI36-SI42) recorded factor loadings between

0.607 and 0.835, which are also statistically acceptable, although SI42 (0.607) is close to the threshold, which should be monitored later in the confirmatory analysis. Cronbach's alpha (0.902) and composite stability (0.900), reflecting strong internal consistency. The AVE for this dimension was (0.594), confirming that the items explain a sufficient proportion of the variance in the latent variable. Third, the "Strategic Control" dimension (SC43-SC49) recorded factor loadings ranging from 0.680 to 0.784, all within the acceptable range. Cronbach's alpha (0.901), composite stability (0.897), and AVE (0.567). Together, these values indicate that this dimension has strong measurement properties in terms of stability and validity.

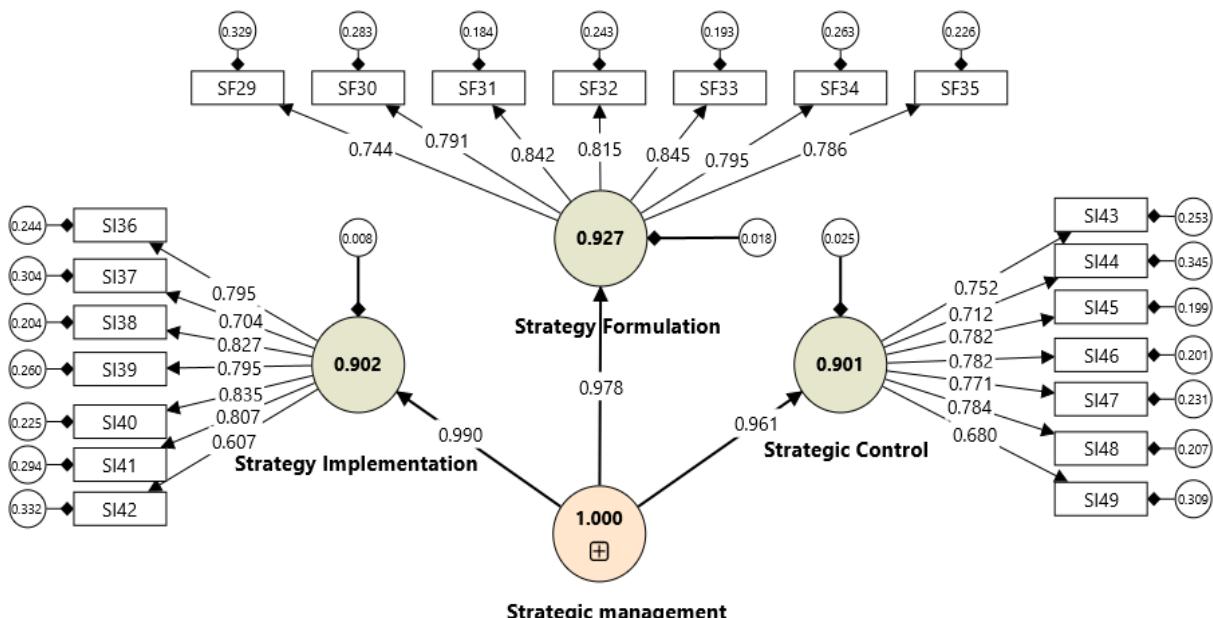
Based on the above, the statistical results of the factor analysis and stability criteria confirm that all dimensions of the strategic management variable have a high level of validity and internal consistency, justifying their use in the subsequent structural analysis to test the research hypotheses

Figure 4

Saturation ratios for strategic management paragraphs

**Figure 5**

Stability coefficient test for strategic management dimensions



For the purpose of checking the discriminant validity between latent variables, the HTMT (Heterotrait-Monotrait Ratio) criterion was used, which is one of the most accurate and up-to-date methods in the framework of structural equation modeling using SmartPLS. This indicator is used to

assess the extent to which the conceptual variables are conceptually distinct, i.e., whether each variable measures a different dimension from the rest of the variables in the model. The model is considered to have good discriminant validity if all HTMT values are less than the normative limit

(0.85) or (0.90) depending on the nature of the study. This test was conducted to ensure that there is no conceptual

overlap between the study variables, as shown in Table above below

Table 12

Results of the HTMT test

	Strategic management	Strategy Formulation	Strategy Implementation	Strategic Control
Strategic management				
Strategy Formulation	0.526			
Strategy Implementation	0.658	0.626		
Strategic Control	0.593	0.612	0.726	

In order to check the discriminant validity between the three dimensions, the HTMT coefficient test was conducted, and the results showed that all values between the dimensions were below the acceptable statistical threshold of 0.85. The HTMT value between "strategy formulation" and "strategy implementation" (0.658), between "strategy formulation" and "strategic control" (0.593), and between "strategy implementation" and "strategic control" (0.612), while the value between strategic management as a whole and the strategic control dimension (0.726), which are all within the limits that confirm the achievement of conceptual differentiation between the dimensions.

Thus, it can be said that the results of the analysis confirm that the strategic management measurement model with its three dimensions has strong and coherent measurement properties in terms of reliability and stability, allowing it to

be used with confidence within the structural equation model to test its relationships with other variables within the study.

In this part of the study, a descriptive analysis of the main variables was conducted using the SPSS statistical program (version 28), with the aim of identifying the trends of the respondents' answers on the dimensions of: Artificial Intelligence, Corporate Governance, and Strategic Management. The arithmetic means and standard deviations were presented for each item within each dimension, which contributes to clarifying the level of respondents' perception of the components of these variables. Ordinal tables are also included for the dimensions according to their averages, with the aim of identifying the most and least important dimensions from the sample's point of view. This analysis is a preliminary step to understand the possible relationships between the variables, and will later be built upon in the deductive analysis.

Table 13

Descriptive Analysis of the Artificial Intelligence Variable

Variable	Paragraph	Mean	Std. Deviation
Artificial Intelligence	AI1	3.51	0.788
	AI2	3.85	0.678
	AI3	3.84	0.618
	AI4	3.79	0.788
	AI5	3.88	0.818
	AI6	3.74	0.868
	AI7	3.86	0.703
	AI8	3.77	0.738
	AI9	3.71	0.618
	AI10	3.23	0.818
	AI11	3.82	0.802
	AI12	3.65	0.738
	AI13	3.88	0.708
	AI14	3.76	0.648
	AI15	3.87	0.876
	AI16	3.64	0.701
	AI17	3.76	0.818

AI18	3.89	0.829
AI19	3.73	0.808
AI20	3.23	0.798
AI21	3.86	0.718
AI22	3.83	0.712
AI23	3.85	0.714
AI24	3.46	0.736
AI25	3.86	0.727
AI26	3.84	0.724
AI27	3.73	0.731
AI28	3.81	0.717

The descriptive analysis of the artificial intelligence variable was conducted with the aim of identifying the general trends in the opinions of the sample members towards the extent of their awareness and interaction with AI applications within the target organizations. This was measured by analyzing the means and standard deviations of the 28 items of the scale, using SmartPLS (version 4.11.4) and SPSS (version 26). The results showed that the overall arithmetic mean of the AI variable reached (3.737), which is higher than the hypothetical mean (3.00) on the five-point Likert scale, indicating a relatively positive trend among the sample members towards the level of use or availability of AI tools in their organizational environments. The total standard deviation amounted to (0.747), indicating moderate dispersion in the responses and reflecting a degree of consistency in the respondents' views.

At the level of individual paragraphs, the arithmetic means ranged between (3.23) as the lowest value for AI10 and AI20, and (3.89) as the highest value for AI18, indicating a relative disparity in the participants' assessment of certain areas or applications of AI, which may reflect a difference in their availability or practical application. Other items such as AI2, AI5, and AI13 also recorded relatively high means (3.85 and 3.88, respectively), reflecting a consensus on the effectiveness of those aspects of AI. The standard deviations ranged between (0.618) and (0.876),

with the highest value recorded in paragraph AI15 (0.876), indicating a relatively large divergence in views about that paragraph. In contrast, paragraphs AI3 and AI9** were the least dispersed with a standard deviation of (0.618), indicating greater agreement among respondents on the content of these paragraphs.

These results indicate that the AI variable was positively evaluated by the majority of respondents, with limited variation in some items, reflecting a general awareness of its importance, offset by a disparity in the extent of its practical application among organizations. This assessment can be considered an initial indicator that enhances the validity of the variable and qualifies it to study its causal relationships with other variables within the structural model of the research

The descriptive analysis of the strategic management variable is an essential step in understanding the nature of the general attitudes of the sample members towards strategic planning, implementation, and control practices within their organizations. This analysis aims to provide a preliminary quantitative picture of the level of activation of strategic management by calculating the arithmetic means and standard deviations of the scale items, thus contributing to the interpretation of individuals' behaviors and attitudes before moving on to advanced analyses such as structural modeling and hypothesis testing.

Table 14

Descriptive analysis of the strategic management variable

	Paragraph	Mean	Std. Deviation
Strategy Formulation		3.81	0.618
		3.83	0.654
		3.88	0.754
		3.94	0.761
		3.89	0.783
		3.80	0.759
		3.68	0.743
Strategy Implementation		3.57	0.728

	3.73	0.729
	3.81	0.794
	3.98	0.758
	3.40	0.729
	3.23	0.749
	3.71	0.783
Strategic Control	3.86	0.801
	3.64	0.743
	3.75	0.678
	3.63	0.698
	3.86	0.775
	3.81	0.745
	3.76	0.782

Table 15

The ordinal importance of the dimensions of the strategic management variable

Variable	Mean	Std. Deviation	Ordinal importance
Strategy Formulation	3.832	0.724	First
Strategy Implementation	3.632	0.752	Third
Strategic Control	3.758	0.746	Second
Strategic management	3.740	0.740	

The results showed that the overall mean of the strategic management variable was (3.740) with a standard deviation of (0.740), which indicates a moderate to high positive evaluation by the sample members towards the reality of applying strategic management in the work environment under study, with a moderate degree of variance in the responses. When analyzing the sub-dimensions separately, the data for the strategy formulation dimension showed that it had the highest arithmetic mean among the three dimensions, reaching (3.832) with a standard deviation of (0.724), reflecting a greater relative focus of the target entities on the strategic planning stage and defining goals and future vision. The averages in the paragraphs of this dimension ranged between (3.68) and (3.94), which indicates a stability in attitudes towards the importance of formulation as a foundational stage. The strategic monitoring dimension ranked second in terms of importance, with an arithmetic mean of (3.758) and a standard deviation of (0.746), indicating an acceptable awareness among organizations of the importance of monitoring and continuous evaluation of strategic performance. The highest mean for this dimension was (3.86), while the lowest was (3.63), indicating a limited variation in the sample's opinions about the effectiveness of organizational control.

In contrast, the strategy implementation dimension came last, with a mean of (3.632) with a standard deviation of (0.752), indicating that this stage may represent the greatest

challenge in the strategic management application chain, and this result may be attributed to difficulties in converting plans into actions, or weaknesses in human or technological resources. The averages of its paragraphs ranged between (3.23) and (3.98), and the lowest average was recorded in one of the paragraphs measuring the extent of consistency between implementation and strategic plans, reflecting a potential gap in this area. Based on the above, it can be concluded that the strategic management variable received a positive overall assessment, with slight variations between the three dimensions. The findings highlight the importance of focusing in future applied studies on supporting the implementation stage, as the weakest link, to ensure the effectiveness of the strategy from the formulation stage to the monitoring and evaluation stage.

The first main hypothesis: The first main hypothesis (H0) states: There is no significant correlation between artificial intelligence and strategic management, and with regard to proving the validity of this hypothesis, the table above related to the correlation matrix showed that there is a significant correlation between (artificial intelligence and strategic management), the value of the correlation coefficient between them (0.468**) at the significance level (0.000), and this calls for rejecting the null hypothesis and accepting the alternative hypothesis (H1), and three sub hypotheses branch off from this hypothesis, namely:

- There is no significant correlation between AI and strategic formulation:

Table above related to the correlation matrix shows that there is a significant correlation between AI and strategic formulation, the value of the correlation coefficient between them reached (**0.403) at a significant level (0.000), and this calls for the rejection of the null hypothesis and acceptance of the alternative hypothesis.

- There is no significant correlation between AI and strategy implementation:

Table above related to the correlation matrix shows that there is a significant and positive correlation between AI and strategy implementation, the value of the correlation

coefficient between them amounted to (0.467**) at the level of significance (0.000), which calls for rejecting the null hypothesis and accepting the alternative hypothesis.

- There is no significant correlation between AI and strategic control:

Table above related to the correlation matrix shows that there is a significant correlation between AI and strategic control, the value of the correlation coefficient between them amounted to (0.663**) at a significant level (0.000), and this calls for rejecting the null hypothesis and accepting the alternative hypothesis.

Figure 6

Correlation matrix between artificial intelligence and strategic management

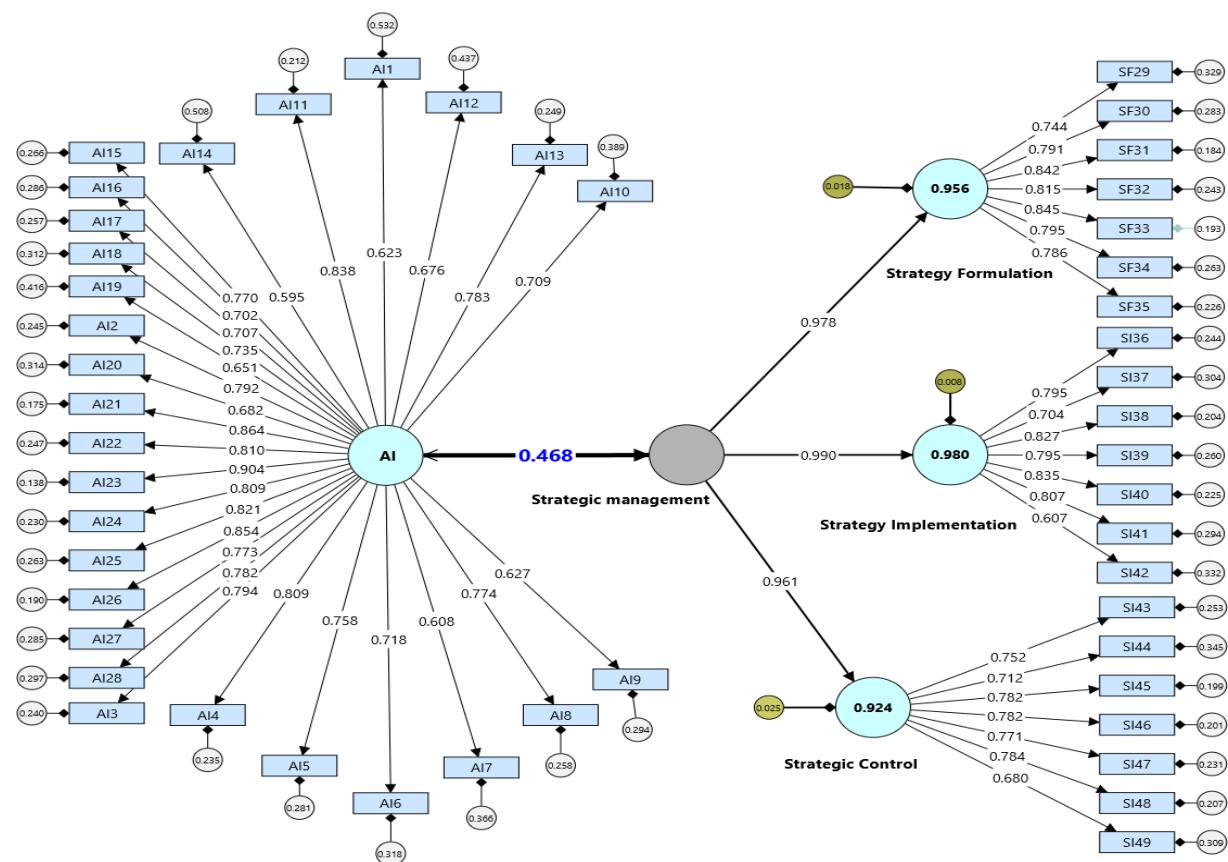


Table 16

Correlation matrix between artificial intelligence and strategic management

		Correlations	Artificial Intelligence	Strategic management	Strategy Formulation	Strategy Implementation	Strategic Control
Artificial Intelligence	Pearson Correlation	1	.468**	.403**	.467**	.663**	
	Sig. (2-tailed)		.000	.000	.000	.000	
	N	238	238	238	238	238	
Strategic management	Pearson Correlation	.468**	1	.940**	.958**	.914**	
	Sig. (2-tailed)	.000		.000	.000	.000	

	N	238	238	238	238	238
Strategy Formulation	Pearson Correlation	.403**	.940**	1	.865**	.764**
	Sig. (2-tailed)	.000	.000		.000	.000
Strategy Implementation	N	238	238	238	238	238
	Pearson Correlation	.467**	.958**	.865**	1	.827**
Strategic Control	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	238	238	238	238	238
Strategic Control	Pearson Correlation	.663**	.914**	.764**	.827**	1
	Sig. (2-tailed)	.000	.000	.000	.000	
Strategic Control	N	238	238	238	238	238

**. Correlation is significant at the 0.01 level (2-tailed).

Table 17

Criteria for evaluating the structural model

Criterion	Acceptable threshold
linear correlation assessment VIF	Variance inflation factor (VIF) < 5
significance of path coefficients	P value < 0.05, t value > 1.96
coefficient of determination R ²	0.25, 0.50, 0.75 indicates small, medium, large effect
effect size f ²	0.02, 0.15, 0.35 indicates small, medium, large effect
predictive fit Q ²	must be greater than zero

The second main hypothesis (H2) states: (There is no significant effect of the independent variable (artificial intelligence) on the dependent variable (strategic management), and for the purpose of testing this hypothesis,

the structural model was built in Figure above, and Table above reviews the results of evaluating the structural model for this hypothesis.

Figure 7

Structural model for testing the second main hypothesis

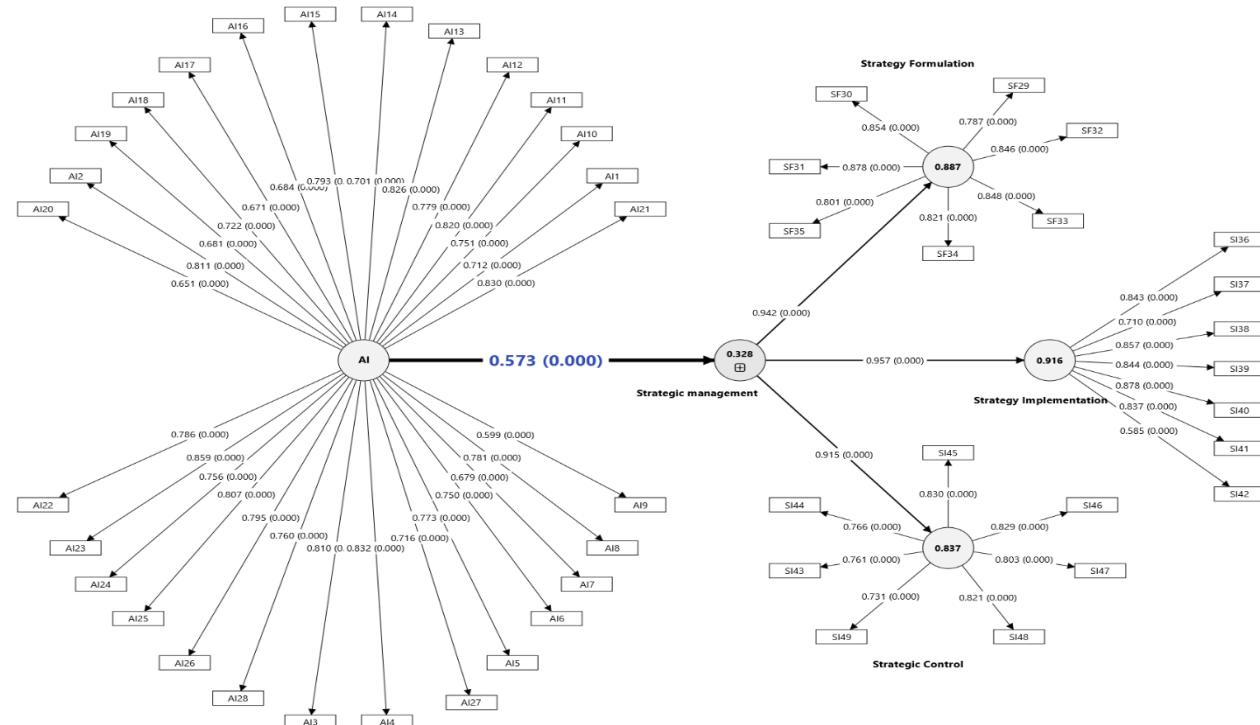
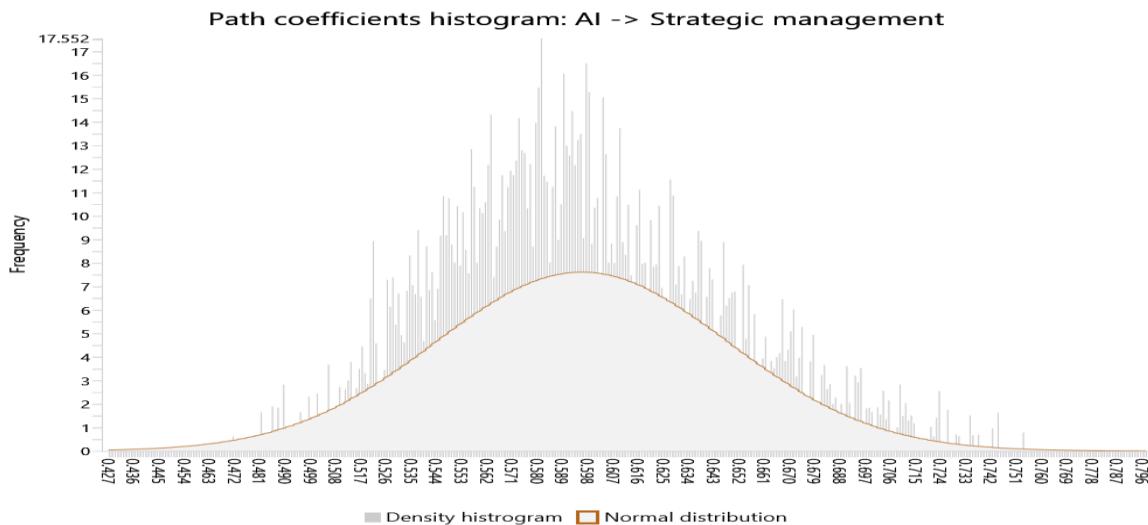


Figure 8

Structural model for testing the second main hypothesis

**Table 18**

Results of the evaluation of the second main hypothesis model

Hypothesis	Track	VIF	Path coefficient	t Value	p Value	Result	f^2	R^2	Adjusted R^2	Q2
H2	Artificial Intelligence -> Strategic Management	1.81	0.573	17.651	0.000	Rejecting the null hypothesis and accepting the alternative hypothesis	0.162	0.316	0.328	0.423

Table above reviews the results of the evaluation of the structural model for the second main hypothesis, which found that the path coefficient (effect) amounted to (0.573), which is significant when the value of (t) exceeds 1.96 and the value of (P) does not exceed 0.05 according to the rule (Hair et al., 2017), thus rejecting the null hypothesis and accepting the alternative hypothesis.

The results also showed that the values of the adjusted coefficient of determination amounted to (0.328), which indicates that the variable (artificial intelligence) was able to explain the dependent variable (strategic management) by (0.328) and the rest of the ratio is other factors that were not addressed in the study. On the basis of the above result, the hypothesis that states: (There is no significant effect of the independent variable (Artificial Intelligence) on the dependent variable (Strategic Management). Testing the sub-hypotheses of the second main hypothesis. The sub-hypotheses of the second main hypothesis state the following:

- There is no significant influence relationship between: Artificial intelligence and strategic formulation: The figure above and table above show the existence of a significant influence relationship between artificial intelligence and strategic formulation, the value of the influence coefficient between them amounted to (0.345) at a non-significant level (0.016), which calls for rejecting the null hypothesis and accepting the alternative hypothesis.

- There is no significant impact relationship between AI and strategy implementation: The figure above and table above show that there is a significant impact relationship between AI and strategy implementation, the value of the impact coefficient between them amounted to (0.396) at a significance level (0.003), which calls for rejecting the null hypothesis and accepting the alternative hypothesis.

-There is no significant relationship between artificial intelligence and strategic control: The figure above and table above show that there is a significant influence relationship between AI and strategic control, as the value of the influence coefficient between them amounted to (0.643) at a

significance level of (0.000), which calls for rejecting the null hypothesis and accepting the alternative hypothesis.

Figure 9

Structural model for testing the sub-hypotheses of the second main hypothesis

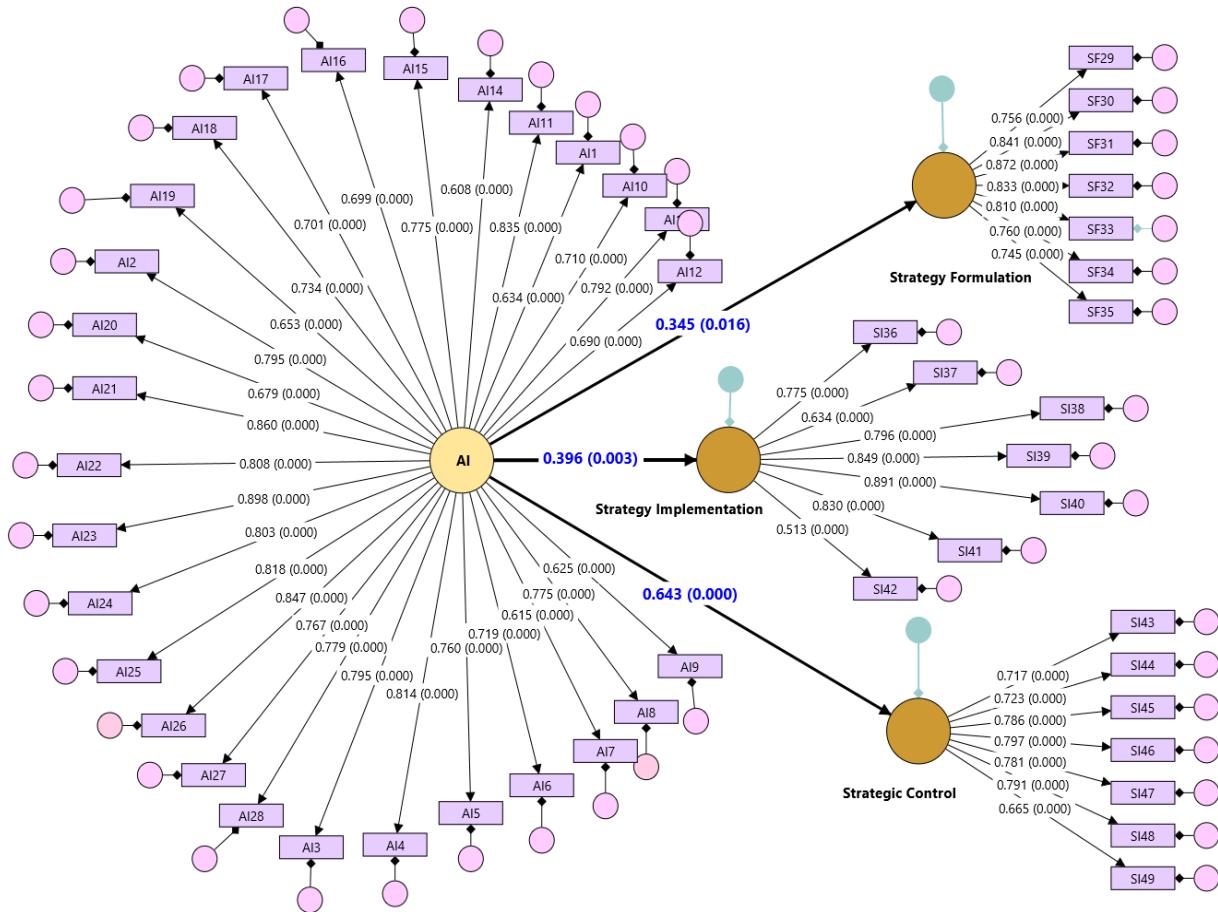


Table 19

Results of evaluating the sub-hypothesis model for the second main hypothesis

Track	VIF	Path coefficient	t Value	p Value	Result	f2	R2	Adjusted R2	Q2
AI and strategic formulation	3.65	0.345	0.016	17.028	Rejecting the null hypothesis	0.113	0.306	0.315	0.419
AI and strategy implementation	3.21	0.396	0.003	19.023	Rejecting the null hypothesis	0.126			
AI and strategic control	1.42	0.643	0.000	27.120	Rejecting the null hypothesis	0.183			

Table above presents the results of evaluating the structural model for the sub-hypotheses of the second main hypothesis, which found that the path coefficients of the sub-hypotheses are significant, which is significant when the value of (t) exceeds 1.96 and the value of (P) does not exceed 0.05 according to the rule (Hair et al, (H2-1, H2-2, H2-3),

and the results showed that the values of the adjusted coefficient of determination amounted to (0.315), indicating that the dimensions of the independent variable (artificial intelligence) were able to explain the dependent variable (strategic management) by (0.315) and the rest of the ratio is other factors not addressed by the study. On the basis of the

above results, the sub-hypotheses (H2-1, H2-2, H2-3) will be rejected:

- (H2-1) There is no significant impact relationship between AI and strategy formulation.
- (H2-2) There is no significant impact relationship between AI and strategy implementation.
- (H2-3) There is no significant influence relationship between AI and strategy monitoring.

4 Discussion

The present study set out to empirically examine the role of artificial intelligence in strategic management and to validate its impact on strategy formulation, strategy implementation, and strategic control within organizational settings. The quantitative findings clearly demonstrate that artificial intelligence exerts a statistically significant and positive influence on strategic management as an integrated construct, as well as on each of its core dimensions. These results provide strong empirical support for the growing body of literature that conceptualizes AI not merely as an operational technology, but as a strategic capability that reshapes how organizations think, decide, and act at the highest levels of management.

At the aggregate level, the findings indicate that artificial intelligence significantly enhances overall strategic management effectiveness. This result is consistent with contemporary strategic management research that emphasizes AI's ability to transform strategic cognition by enabling data-driven insight generation, reducing uncertainty, and supporting adaptive decision-making in complex environments (Gusai & Rani, 2022; Nazari Zadeh et al., 2023; Shaddel, 2023). The positive and substantial path coefficient obtained in the structural model suggests that organizations that invest in AI capabilities are better positioned to align strategic intent with environmental realities and internal capabilities. This finding aligns with Biloslavo's argument that AI strengthens strategic coherence in VUCA environments by integrating real-time analytics with long-term planning processes (Biloslav, 2024).

More specifically, the results confirm a significant positive effect of artificial intelligence on strategy formulation. The empirical evidence suggests that AI enhances the quality of strategic planning by supporting environmental scanning, opportunity recognition, and predictive analysis. This finding is strongly aligned with previous studies that emphasize AI's role in strengthening

analytical depth during the strategy formulation phase. For example, Alizadeh and Foroughi demonstrated that AI-driven SWOT and strategic intelligence tools improve the accuracy of strategic assessments and competitive positioning (Alizadeh & Foroughi, 2023). Similarly, Meena et al. found that AI-supported analytics enable organizations to map strategic landscapes more effectively, particularly in data-intensive and regulated industries (Meena et al., 2024).

The present results also resonate with Kiakojouri's strategic governance perspective, which argues that AI contributes to transcendent governance by enabling evidence-based strategic formulation that goes beyond intuitive or politically driven decision-making (Kiakojouri, 2025). From this viewpoint, AI functions as a cognitive extension of top management, allowing decision-makers to process complexity and anticipate future scenarios with greater precision. The observed positive relationship between AI and strategy formulation therefore reinforces the idea that AI acts as an enabler of strategic foresight rather than a substitute for managerial judgment.

With regard to strategy implementation, the findings reveal that artificial intelligence has a significant and positive impact on translating strategic plans into operational action. This result is particularly important, as strategy implementation is often identified as the weakest link in the strategic management process. The empirical evidence suggests that AI contributes to improved execution by facilitating automation, optimizing resource allocation, and enabling real-time decision support. This finding is consistent with Gusai and Rani's assertion that AI-driven decision intelligence systems enhance strategic execution by reducing delays, minimizing human error, and increasing coordination across organizational units (Gusai & Rani, 2022).

The results are also aligned with Mohammadi et al., who demonstrated that AI technologies improve strategic decision-making outcomes through organizational innovation mechanisms (Mohammadi et al., 2024). In a similar vein, Rezaei et al. found that AI strengthens strategic flexibility, enabling organizations to adjust implementation paths in response to environmental turbulence (Rezaei et al., 2024). The present study extends these insights by empirically validating the direct impact of AI on strategy implementation, rather than treating implementation outcomes as indirect or secondary effects.

Furthermore, the positive effect of AI on implementation is consistent with research in strategic marketing and human resource management, which highlights AI's role in

operationalizing strategic goals through intelligent systems. Anjorin emphasizes that AI-driven systems allow organizations to operationalize strategic marketing objectives more efficiently by linking strategic intent to execution metrics (Anjorin, 2024). Likewise, Musthafa's work on AI and HRM suggests that AI enhances execution by aligning human capital practices with strategic priorities (Musthafa, 2024). These findings collectively support the argument that AI bridges the traditional gap between planning and execution by embedding strategic logic into operational processes.

The strongest empirical effect observed in this study relates to strategic control, where artificial intelligence exhibited the highest impact coefficient among the three strategic dimensions. This finding underscores AI's critical role in performance monitoring, feedback, and corrective action. AI-enabled control systems provide organizations with real-time performance indicators, anomaly detection, and predictive alerts, enabling proactive rather than reactive strategic control. This result aligns closely with Tong et al.'s findings on AI feedback systems, which demonstrate that AI enhances performance outcomes when deployed as a continuous monitoring and feedback mechanism (Tong et al., 2021).

Similarly, Saadati et al. argue that AI-based accounting and management control systems enhance strategic oversight by integrating auditing, forecasting, and performance evaluation into a unified strategic control framework (Saadati et al., 2025). The present study empirically confirms these theoretical claims by showing that AI-driven control mechanisms significantly strengthen the organization's ability to monitor strategic alignment and intervene when deviations occur. This is particularly relevant in complex organizational environments where traditional control systems struggle to cope with data volume and decision speed requirements.

Taken together, the findings provide strong support for an integrated view of artificial intelligence as a strategic enabler across the full strategic management cycle. Rather than influencing isolated stages, AI appears to function as a unifying capability that links formulation, implementation, and control into a coherent, adaptive system. This interpretation is consistent with Nazarian-Jashnabadi et al.'s framework on business intelligence maturity, which emphasizes that strategic value emerges when analytical capabilities are integrated across organizational processes (Nazarian-Jashnabadi et al., 2023). It also aligns with Mahmoud El Sayed El Khouly et al.'s proposed AI-based

strategic management model, which conceptualizes AI as a central coordinating mechanism for strategic activities (Mahmoud El Sayed El Khouly et al., 2022).

From a theoretical perspective, the results reinforce resource-based and capability-oriented views of strategic management. Artificial intelligence can be interpreted as a valuable, rare, and difficult-to-imitate strategic resource that enhances organizational capabilities when effectively embedded within strategic processes (Biloslav, 2024; Nazari Zadeh et al., 2023). However, the findings also suggest that the strategic value of AI is contingent upon its integration with managerial competencies, organizational culture, and governance structures. This interpretation is consistent with Sestino and Mauro's argument that AI delivers strategic value only when complemented by human judgment and organizational learning (Sestino & Mauro, 2021).

5 Conclusion

Moreover, the results have important implications for public and hybrid organizations operating under increasing pressure for accountability, efficiency, and adaptability. Studies such as Pérez-Campuzano et al. and Yamin et al. have shown that AI enhances strategic resilience and agility in highly regulated and resource-constrained environments (Pérez-Campuzano et al., 2021; Yamin et al., 2024). The present study extends this line of research by providing quantitative evidence that AI systematically strengthens strategic management functions, thereby supporting organizational sustainability and long-term performance.

Despite its contributions, this study has several limitations that should be acknowledged. First, the research relied on cross-sectional data, which limits the ability to draw causal inferences about the long-term strategic impact of artificial intelligence. Second, the study focused on perceptual measures of AI use and strategic management, which may be influenced by respondent bias or differences in individual interpretation. Third, the research context may limit the generalizability of the findings to other sectors or institutional environments with different technological maturity levels or governance structures.

Future studies are encouraged to adopt longitudinal research designs to examine how the strategic impact of artificial intelligence evolves over time. Researchers may also explore mediating and moderating variables, such as organizational culture, leadership style, or analytical maturity, to better understand the mechanisms through

which AI influences strategic outcomes. Comparative studies across industries or countries would further enhance the generalizability of findings, while qualitative or mixed-method approaches could provide deeper insight into managerial sensemaking and human-AI interaction in strategic contexts.

From a practical standpoint, managers should approach artificial intelligence as a strategic investment rather than a purely technical solution. Organizations are advised to integrate AI capabilities across all stages of strategic management, ensuring alignment between strategic objectives, implementation mechanisms, and control systems. Emphasis should be placed on developing managerial competencies, data governance frameworks, and ethical guidelines to support effective AI use. Finally, decision-makers should prioritize gradual, learning-oriented AI adoption strategies that enhance strategic coherence, organizational adaptability, and long-term value creation.

Authors' Contributions

M.D.T. conceptualized the study, designed the qualitative research framework, and led the thematic analysis process. A.E. contributed to the development of the interview protocol, supervised data collection, and participated in coding and theme refinement. M.S. assisted in data analysis, verified the credibility and trustworthiness procedures, and contributed to the interpretation of findings. M.H.P. collaborated in literature review, organization of themes and subthemes, and drafting the manuscript. All authors jointly reviewed and revised the manuscript, approved the final version for publication, and take full responsibility for the integrity and accuracy of the work.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

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