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Enhancing Strategic Decision Performance Through AI: The Task-Technology Fit and Managerial Behaviour Link

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Abstract

This study examines how artificial intelligence improves strategic decision-making by focusing on the alignment between managerial task requirements and AI capabilities through the lens of Task Technology Fit. The objective is to explain whether the performance benefits associated with AI emerge from mere adoption or from a more precise fit between task demands, AI characteristics, and actual patterns of use. Methodologically, the study relies on a quantitative design based on survey data collected from 360 managers working in medium and large enterprises in Morocco. The proposed research model was tested using Partial Least Squares Structural Equation Modeling to assess the direct and indirect relationships among task characteristics, AI characteristics, Task AI Technology Fit, effective AI use, and strategic decision-making performance. The findings show that both task characteristics and AI characteristics positively and significantly influence Task AI Technology Fit. In turn, this fit strongly enhances effective AI use and strategic decision-making benefits, while effective AI use partially mediates the relationship between fit and performance. These results indicate that organizational value does not arise from symbolic or superficial AI adoption but from purposeful integration aligned with strategic requirements. The study's novelty lies in extending Task Technology Fit theory to AI enabled strategic contexts and in demonstrating that AI should be understood not as a substitute for managerial judgment but as a mechanism for cognitive augmentation and performance enhancement.

Keywords:

AI-Assisted Decision-Making;
Task-Technology Fit;
Managerial Behavior;
AI Usage Intensity;
Strategic Performance;
PLS-SEM.

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1- Introduction

Strategic decision-making remains one of the most demanding domains of managerial activity because it unfolds under conditions of uncertainty, incomplete information, organizational interdependence, and bounded rationality. From this standpoint, strategy cannot be reduced to a purely analytical exercise governed by formal models alone [1]. It is also a behavioral process through which managers frame problems, allocate attention, interpret signals, evaluate alternatives, and assume responsibility for consequential choices [2]. Recent work in behavioral strategy has reaffirmed that strategic outcomes are shaped not only by resources and structures but also by the cognitive and interpretive mechanisms through which decision makers make sense of complex environments [2, 3]. This behavioral dimension becomes even more salient when organizations operate in turbulent contexts where probabilistic guidance is weak, ambiguity is high, and judgment must be exercised despite incomplete visibility over future consequences [1, 3, 4].

The rapid diffusion of artificial intelligence (AI) has renewed this debate in important ways. Organizations increasingly use AI systems, particularly generative AI (GenAI) tools, to support information search, synthesis,

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comparison, option generation, and evaluative reasoning in complex decision environments [5]. Emerging strategy research indicates that AI can reshape core components of the strategic decision process by extending search breadth, enriching representations of alternatives [6], and supporting aggregation across large volumes of information [7]. At the same time, the literature does not suggest that AI displaces managerial judgment [8]. Rather, its effects depend on how effectively AI-generated outputs are interpreted, validated, and incorporated into organizational reasoning. Recent evidence shows that AI can contribute to the speed, scale, and quality of strategic analysis, yet these benefits remain contingent on the continued role of human oversight, particularly in settings marked by uncertainty and contextual ambiguity [9, 10].

This point is particularly important because the literature does not support a deterministic view of AI-enabled performance. Research on algorithm aversion and algorithm appreciation shows that individuals do not respond uniformly to algorithmic recommendations [10]. Under some conditions, they discount algorithmic advice after observing errors; under others, they defer excessively to automated outputs. What matters, therefore, is not only the technical capacity of the system but also the behavioral conditions under which reliance is calibrated. This includes perceived quality, trust formation, interpretability, and the communication of uncertainty [11]. In other words, the value of AI in decision-making does not follow automatically from adoption. It depends on the quality of its integration into managerial work and on whether it augments rather than undermines human judgment [12].

Within this debate, the Task Technology Fit (TTF) perspective offers a particularly suitable theoretical foundation [13–15]. The central argument of TTF is that technology improves performance when its functionalities align with the requirements of the task being performed, rather than simply because the technology is available or frequently used. This logic is especially relevant in AI-supported strategic decision contexts, where task complexity, ambiguity, and interdependence vary substantially, while AI tools differ in their analytical, generative, and interpretive capacities [13, 16, 17]. In such settings, a linear assumption linking AI adoption to better strategic outcomes is theoretically weak. A fit-based perspective is more appropriate because it directs attention to whether managers perceive AI as genuinely suited to the informational, evaluative, and cognitive demands of strategic work [13].

Despite the growing interest in AI and strategic decision-making, three important gaps remain. First, a considerable share of the recent literature still concentrates on what AI can do in principle, rather than on the behavioral mechanism through which it produces, or fails to produce, superior strategic decision outcomes. Second, prior studies tend to examine trust, use, technological capability, or performance in isolation, while giving limited attention to the perceived fit between strategic task requirements and AI functionalities as the core explanatory link. Third, empirical evidence remains comparatively limited in emerging organizational contexts, where institutional conditions, digital maturity, and managerial practices may shape AI appropriation in distinctive ways. As a result, the literature still provides only a partial answer to a central question: under what conditions do managers perceive AI as appropriate for strategic tasks, and how does that perception translate into actual use and realized performance benefits? Recent studies on AI and strategic decision-making have mapped this emerging terrain, but the contingent pathway linking fit, use, and decision performance remains insufficiently theorized and empirically tested [9, 10].

To address this gap, the present study draws on TTF theory to examine the behavioral mechanisms through which AI can enhance strategic decision-making performance. More specifically, it proposes that task characteristics and AI technology characteristics shape managers' perceptions of Task-AI Technology Fit (TATF), which in turn influences effective AI use and, ultimately, the performance benefits associated with strategic decision-making. This perspective shifts the discussion away from generalized claims about AI adoption and toward a more rigorous explanation grounded in alignment, purposeful use, and cognitive augmentation. In doing so, the study contributes to the intersection of behavioral strategy, information systems, and AI management by arguing that AI should not be approached as an automatic substitute for managerial judgment but as a technological resource whose value depends on its fit with the concrete demands of strategic work [9, 13, 18].

Although human–AI collaboration is typically invoked to describe a broad set of joint interactions in which human actors and AI systems contribute to task execution, the concept of cognitive augmentation captures a more delimited and theoretically meaningful phenomenon. In this study, cognitive augmentation designates a specific configuration of human–AI interaction in which AI enhances managerial cognitive functioning by supporting information search, pattern identification, synthesis, comparison, representation, and the reduction of uncertainty, while the manager preserves interpretive primacy, contextual discernment, and final accountability for the decision. This distinction is not merely semantic. Broad human–AI collaboration frameworks may encompass task coordination, division of labor, or workflow complementarity, regardless of whether the technology meaningfully strengthens managerial reasoning. By contrast, cognitive augmentation refers explicitly to the extension of higher-order cognitive work involved in managerial judgment, rather than to task substitution or procedural assistance alone. AI, in this sense, operates as a decision-enabling resource that amplifies the depth, scope, and structure of managerial cognition without displacing human responsibility. Such a definition is consistent with research that treats AI as an organizational support mechanism for decision processes, and it accords closely with the logic of TTF, which holds that the value derived from a technological system depends on the degree to which its capabilities correspond to the informational and cognitive demands of the focal task.

Against this background, the article pursues a dual objective. Theoretically, this article extends the concept of TTF to the domain of AI-assisted strategic decision-making by identifying perceived fit, actual use, and decision performance as the core elements of the explanatory model. Empirically, it examines these relationships in the context of Moroccan firms, where the integration of AI into managerial practice creates both considerable opportunities and significant implementation challenges. Following the introduction, the paper is structured as follows. Section 2 develops the conceptual foundation of the study by first clarifying the role of uncertainty and behavioral strategy in strategic decision processes and then drawing on the logic of TTF to show that performance gains are likely to arise from the alignment between the informational and cognitive requirements of strategic tasks and the effective capabilities of AI technologies, rather than from the mere availability or use of such tools. Section 3 presents the empirical design, including the research approach, sampling strategy, measurement of constructs, their adaptation to the Moroccan organizational context, and the analytical procedure adopted. Section 4 reports the results of the PLS-SEM analysis, with a clear distinction between the evaluation of the measurement model and the assessment of the structural relationships. Section 5 discusses the findings in relation to prior literature, emphasizes the study’s theoretical contributions, and derives managerial implications for the responsible and value-creating integration of AI into strategic work. Finally, Section 6 brings together the main findings, talks about the study's limitations, and suggests areas for future research.

2- Theoretical Background

2-1- Behavioral Strategy Under Uncertainty

Strategic decision-making is not merely a matter of selecting optimal alternatives from a known set of options. It is a behavioral process shaped by bounded rationality, selective attention, interpretation, and accountability, all of which become more consequential when decision-makers operate under uncertainty [19]. Behavioral strategy has, therefore, argued that strategic outcomes depend not only on external conditions or formal planning systems but also on how managers cognitively frame problems, attend to cues, interpret ambiguous evidence, and justify action within organizational settings [20]. This perspective is especially relevant when strategic issues are characterized by complexity, interdependence, and incomplete information, because under such conditions managerial cognition becomes inseparable from the quality of strategic outcomes [2].

Uncertainty intensifies these dynamics because it alters the informational and behavioral requirements of decision-making. In relatively analyzable settings, managers can rely more heavily on established routines and evidence-based comparison [21]. In more ambiguous contexts, by contrast, they must often proceed with incomplete signals, provisional interpretations, and imperfect causal understanding. What matters then is not simply having more information but structuring search, comparison, and deliberation in ways that reduce premature closure, limit overconfidence, and preserve the defensibility of decisions [22]. From this viewpoint, strategic performance depends in part on the quality of the process through which managers organize judgment under uncertainty rather than on information volume alone [2].

Decision support technologies enter this setting as tools that can reshape how managers perform core cognitive tasks such as information search, synthesis, comparison, and justification. Yet the presence of technological support does not eliminate behavioral frictions [23]. Research on algorithm aversion and algorithm appreciation shows that decision-makers may either discount algorithmic input after observing errors or rely too heavily on automated recommendations when they perceive the system as superior or easier to defer to Mahmud et al. [24]. Accordingly, the central issue is not whether AI is available, but whether managerial reliance is calibrated appropriately to the task, the system, and the decision context [18].

2-2- Task–Technology Fit Model as an Explanatory Lens of AI-Enabled Strategic Decision-Making

The theoretical approach adopted in this study combines two complementary perspectives. The first is behavioral strategy, which explains why strategic decision-making must be understood as a cognitively and socially mediated process [2]. The second is TTF, which explains when and how a technology contributes to performance. Their integration is theoretically appropriate because AI assisted strategic decision-making is simultaneously a behavioral phenomenon and a fit-dependent technological phenomenon. Managers do not derive value from AI in the abstract. They derive value when AI capabilities correspond to the informational, analytical, and evaluative requirements of the strategic tasks they face and when those capabilities are incorporated into decision processes in a way that supports rather than distorts managerial judgment [9, 13, 25–27].

TTF theory provides the central explanatory architecture of the model. Its core proposition is that technology generates performance benefits when the functionalities of the system align with the requirements of the task being performed, rather than simply because the technology is adopted or frequently used [28]. In the original formulation, task characteristics and technology characteristics jointly shape perceived fit, which then influences utilization and performance [29]. This logic remains highly relevant in AI enabled work because AI systems differ substantially in transparency, reliability, adaptability, and support for exploration, while strategic tasks differ in ambiguity, time pressure, interdependence, and analyzability. Under such conditions, treating AI adoption as inherently beneficial would be theoretically weak; a fit-based explanation is more consistent with how value is actually realized in complex managerial work [13].

Recent research reinforces the continued relevance of this perspective in contemporary AI contexts. Przegalinska et al. (2025) [30], for example, show that the performance implications of generative AI vary with task type, task complexity, and human capabilities, which is directly consistent with a TTF interpretation. Likewise, emerging work on AI-enabled strategic decision-making indicates that AI may enhance search, representation, and aggregation, but these benefits depend on whether the tool meaningfully complements the cognitive requirements of the task rather than merely adding computational output to the process [9, 30].

This study therefore conceptualizes AI-TTF as a managerial assessment of the degree to which AI capabilities match the informational, analytical, and coordination requirements of strategic decision tasks. This conceptualization is important for two reasons. First, it treats fit as a perceptual and behavioral mechanism rather than as an objective technological property. Second, it allows the model to explain strategic decision performance through a contingent pathway that links task demands and AI characteristics to actual use and realized benefits. The study thus moves beyond generalized claims about AI adoption and instead advances a theoretically bounded explanation of when AI creates value in strategic work.

The theoretical contribution of the present study lies not only in applying TTF to an AI-enabled context but also in specifying why this perspective becomes especially relevant when strategic decisions are viewed through a behavioral lens. Bounded rationality, selective attention, interpretive ambiguity, and the need to justify action under uncertainty shape strategic decisions, according to behavioral strategy. These conditions define the cognitive burden associated with strategic work. TTF complements this perspective by explaining that technological value does not arise from the mere availability of a system but from the degree to which its capabilities correspond to those cognitive and informational demands. In this sense, behavioral strategy explains the decision context, whereas TTF explains the performance-enabling condition within that context.

This articulation also helps clarify the theoretical role of AI in the model. The study does not treat AI as an autonomous decision-maker nor as a neutral technical artifact whose effects are self-evident. Instead, AI is conceptualized as a bounded cognitive support mechanism whose usefulness depends on whether managers perceive it as capable of supporting search, synthesis, comparison, and evaluative reasoning in ways that remain compatible with human judgment. The notion of cognitive augmentation is therefore central to the present theoretical approach. It captures the idea that AI can extend managerial cognitive capacity without displacing interpretive authority, contextual discernment, or accountability. From this standpoint, the model advances a contingent explanation of AI-enabled strategic performance: task characteristics generate the need for support, AI characteristics determine the credibility and usability of that support, perceived fit links both dimensions, and actual use reflects the extent to which that fit is enacted in managerial practice.

Taken together, this theoretical approach positions AI-assisted strategic decision-making as a process that is simultaneously behavioral, technological, and relational. It is behavioral because strategic judgment remains shaped by attention, interpretation, and bounded rationality. It is technological because AI provides managers new tools that could change how they deal with complicated information, such as advanced data analytics and predictive modeling, which enhance their ability to make informed decisions. It is relational because performance gains depend on the quality of their alignment, not just the task or technology, which means that effective collaboration and communication among team members are essential for maximizing outcomes. This integrated perspective provides the conceptual basis for the hypotheses developed below.

2-3- Conceptual Model and Hypothesis Development

The research model follows the logic of TTF while embedding it in a behavioral strategy setting. More specifically, it assumes that strategic task characteristics and AI technology characteristics shape perceived TATF. Fit then operates as the central explanatory mechanism through which managers decide whether AI is worth integrating into their decision routines and whether such integration yields strategic decision benefits. AI use is positioned as a subsequent behavioral channel through which fit is translated into performance. This ordering reflects the view that performance is not a direct consequence of technical sophistication alone, but the outcome of alignment, integration, and managerial enactment [13].

The first explanatory mechanism concerns the nature of the strategic task itself. Strategic tasks are not uniform. They differ in ambiguity, informational breadth, interdependence, and the extent to which they require managers to compare multiple alternatives under conditions of uncertainty. These differences are important because they affect the functional requirements that any supporting technology must meet. Tasks characterized by broad search requirements, fragmented evidence, and multidimensional comparison create a stronger need for tools capable of organizing complexity and extending analytical capacity. The argument here is not that more demanding tasks automatically induce AI adoption. Instead, managers use task characteristics to set the evaluative benchmark for determining the appropriateness of AI support for the work at hand. In this sense, the mechanism underlying the first hypothesis is demand specification: the structure of the task determines the conditions under which fit can be perceived [9, 13].

H1. *Task characteristics positively influence Task AI Technology Fit.*

The second mechanism shifts attention from the task to the technology. Even when strategic tasks create a strong need for cognitive support, perceived fit will remain limited if the AI system lacks the properties required to address that need credibly. In AI assisted decision settings, relevant technological characteristics include the reliability of outputs, the timeliness and relevance of information provided, the clarity of system responses, and the extent to which the system supports traceable reasoning and communicates uncertainty in a comprehensible manner. These qualities are particularly salient in strategic decision-making because managers are not merely selecting among options; they are also expected to justify choices, defend reasoning, and remain accountable for outcomes. The mechanism proposed here is therefore capability and credibility. Managers are more likely to perceive fit when the AI system exhibits feature that make it trustworthy and usable in contexts where explanation, defensibility, and robustness matter. Unlike H1, which is driven by variation in task requirements, H2 is driven by variation in perceived technological adequacy [13, 18, 31].

H2. *AI technology characteristics positively influence Task AI Technology Fit.*

The third mechanism explains why perceived fit should enhance strategic decision performance benefits. The argument is not simply that aligned technologies are used more often, nor that any use of AI necessarily improves outcomes. The mechanism is cognitive friction reduction. When AI capabilities are well matched to task demands, managers can process information more effectively, structure problems more clearly, compare alternatives more coherently, and synthesize dispersed evidence with greater efficiency. Fit therefore improves performance by reducing the cognitive burden associated with complex strategic work and by enabling managerial attention to shift from information handling to interpretation and judgment. In this formulation, TATF is expected to influence performance because alignment improves the quality of cognitive support available during decision-making, not because it mechanically increases exposure to technology [9].

H3. *Task AI Technology Fit positively influences strategic decision performance benefits.*

The fourth mechanism concerns behavioral incorporation. Perceiving a technology as well aligned with task demands does not merely shape evaluative attitudes; it also increases the likelihood that the technology will be integrated into actual managerial practice. In the TTF tradition, fit is a proximal determinant of utilization because users are more willing to engage with technologies, they consider instrumentally relevant to their work. In the present study, AI technology use refers not only to frequency but also to the depth of integration of AI into key decision stages such as problem framing, alternative generation, evaluation, and justification. The mechanism behind this hypothesis is therefore workflow embedding. When managers perceive AI as genuinely suited to the demands of strategic tasks, they are more likely to allocate attention to it, incorporate it into recurring decision routines, and rely on it as a practical resource in managerial work. This differs from H3 in a fundamental way: H3 concerns the direct consequences of alignment for decision quality, whereas H4 concerns the conversion of perceived alignment into actual behavioral use [13, 30, 32].

H4. *Task AI Technology Fit positively influences AI technology use.*

The fifth mechanism addresses the contribution of enacted use to strategic decision performance. Here, the argument requires particular precision. AI use is not assumed to be inherently beneficial, nor is greater use automatically equated with better decisions. The relevant mechanism is disciplined augmentation. AI contributes to performance when its use enables managers to improve search breadth, comparison quality, synthesis of evidence, and decision efficiency, while preserving critical evaluation and calibrated reliance. This point is important because prior research has shown that algorithmic support can produce both insufficient reliance and excessive dependence. The performance effect of use therefore depends on whether AI is incorporated as a cognitive support system that enriches managerial judgment rather than replaces it uncritically. In this study, greater AI technology use is expected to be positively associated with strategic decision performance benefits to the extent that such use reflects active, thoughtful integration into decision processes [9, 18].

H5. *AI technology use positively influences strategic decision-performance benefits.*

Figure 1 summarizes the theoretical structure derived from this reasoning. The model proposes that task characteristics and AI technology characteristics jointly shape TATF, which in turn influences both AI technology use and strategic decision-making performance benefits. AI technology use is also expected to contribute directly to those benefits. Taken together, the model conceptualizes AI enabled strategic value as the outcome of a contingent process in which task demands, technological properties, perceived alignment, and managerial enactment operate in sequence. AI does not improve strategic decisions through adoption alone but through its fit with the cognitive requirements of the task and its disciplined incorporation into managerial judgment [9, 13, 30].

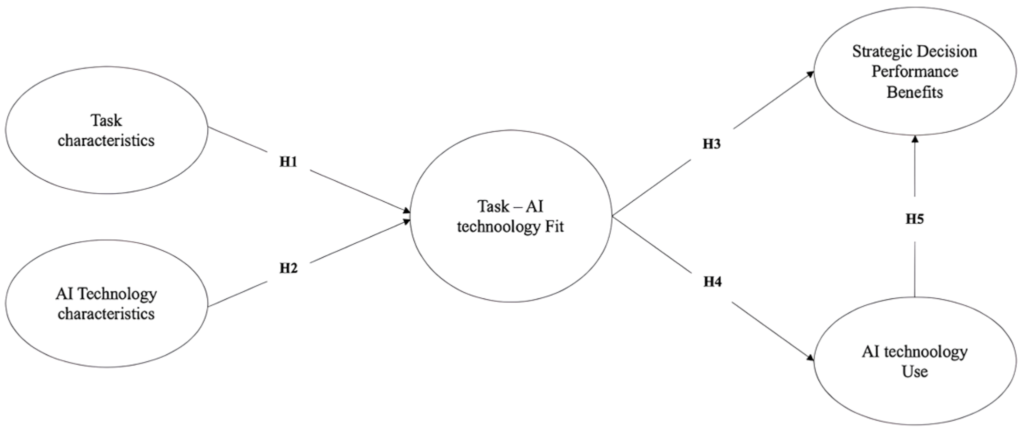

Figure 1. **Research model**

Table 1 reports the results of the structural model estimation, including the standardized path coefficients, standard errors, t-values, and hypothesis decisions.

Table 1. **Presentation of the results of the structural model**

Effect	Original coefficient	Mean value	Standard error	t-value	Decision
H1: MTC to TAITF	0.5528	0.5643	0.0880	6.2807***	Supported
H2: AITC to TAITF	0.4256	0.4142	0.0877	4.8530***	Supported
H3: TAITF to SDPB	0.3349	0.3269	0.1504	2.2263***	Supported
H4: TAITF to AITU	0.8595	0.8624	0.0272	31.5465***	Supported
H5: AITU to SDPB	0.5256	0.5353	0.1487	3.5344***	Supported

*** $p < 0.001$; ** $p < 0.05$; * $p < 0.1$

Note: β = standardized path coefficient; R^2 = coefficient of determination; adjusted R^2 = adjusted coefficient of determination; f^2 = effect size.

Behavioral strategy illuminates the cognitive and social conditions under which strategic decisions are formulated, whereas TTF clarifies whether AI is capable of responding effectively to those conditions. In this study, these two perspectives are not approached as independent or merely complementary lenses. Rather, they are treated as analytically interdependent. Behavioral strategy identifies the constraints that render strategic decision-making cognitively demanding and therefore generate a need for decision support, while TTF explains whether the specific alignment between AI functionalities and task requirements is sufficient for that support to be meaningfully adopted and translated into superior decision performance. Put differently, behavioral strategy clarifies why managers may require cognitive assistance, whereas TTF explains when such assistance is likely to become operationally valuable.

3- Research Method and Data

3-1- Sample Selection

This study seeks to determine the level of AI presence in managerial tasks, particularly through the alignment between tasks and AI technology, as well as its contribution to strategic decision-making. To this end, an empirical approach was adopted to survey managers about their aptitude, use, and perception of AI technologies in the performance of their managerial duties. The study concentrated on medium-sized and large enterprises in Morocco, as these entities typically have the requisite financial, human, and technological resources to implement AI-based solutions. In Morocco, the total number of medium-sized and large companies is projected to reach 5,790 entities in 2024 [33].

The Moroccan setting provides a context that is both empirically instructive and analytically delimited. Although the country has advanced considerably in its digital transformation trajectory, levels of digital maturity continue to vary markedly across organizations and sectors. Such unevenness is likely to shape both the extent to which AI tools are perceived as fitting strategic task requirements and the organizational capacity to incorporate them into established decision routines. Consequently, the relatively strong relationships identified in this study are likely to be more transferable to firms that possess adequate technological and organizational resources within emerging yet digitally advancing environments than to organizations operating under lower levels of technological preparedness.

To determine the sample size, the study relies on Cochran's method (1977) [34], widely used in management research for estimating a representative sample from a finite population. Considering a 95% confidence level, a 5% margin of error, and an estimated proportion of 50% (a conservative assumption maximizing variance), the initial sample size is calculated using the following formula:

$$\mathrm{n}_0 = \frac{Z^2 \times p(1-p)}{e^2} = \frac{(1{,}96)^2 \times 0.5 \times 0.5}{(0.05)^2} = 384 \tag{1}$$

with Z=1.96; p=0.5 and e=0.05, The initial theoretical sample size was 384 respondents. Given that the total population is finite (N=5790), a Cochran adjustment was applied:

$$\mathrm{n} = \frac{n_0}{1+\frac{n_0+1}{N}} = \frac{384}{1+\frac{383}{5790}} = \frac{384}{1.0661} \approx 360 \tag{2}$$

This calculation leads to an adjusted sample size of 360 managers. This threshold is considered statistically sufficient to ensure the representativeness of medium- and large-sized Moroccan companies that have adopted AI technologies while guaranteeing the robustness of the empirical analyses and the validity of the results relating to the integration of AI in managerial missions and strategic decision-making.

3-1- Measurement Model

We highlighted in the literature review that our conceptual framework is primarily based on the TTF model. This model was adapted and contextualized to address the specificities of our research object, particularly the integration of AI into managerial tasks and strategic decision-making. This adaptation entailed modifying the model's initial dimensions and operationalizing variables to correspond with the organizational context of Moroccan enterprises. In this context, the measurement items were developed through a comprehensive review of existing literature, encompassing research in information systems, strategic management, and managerial decision-making. This approach aims to ensure high content validity by ensuring that each item accurately reflects the conceptual dimensions underlying the latent variables under study. The table below presents all the selected items and their main theoretical sources. The choice of five items per latent variable is based on both theoretical and methodological considerations. From a conceptual standpoint, the constructs used in this study are multidimensional in nature and cannot be adequately captured by a limited number of indicators. The use of five items thus allows for the representation of complementary facets of the construct, enhancing its semantic richness and content validity [35].

Methodologically, recommendations for partial least squares structural equation modeling advocate the use of multiple indicators per latent variable, provided that reliability and validity criteria are met. In this regard, a minimum of three to five items per construct is generally considered appropriate to ensure the stability of the estimates, the robustness of the coefficients, and a better overall quality of the measurement model [36, 37]. The use of five items is therefore part of a logic of methodological rigor while remaining compatible with the empirical requirements of the PLS-SEM approach. Therefore, the measurement scales were adapted from established studies and carefully examined to ensure their theoretical consistency with the constructs retained in the research model. Particular care was taken to maintain conceptual correspondence between each item and its underlying latent variable, while also preserving clarity and coherence in wording across the instrument. That said, no formal pilot study or iterative item refinement procedure was conducted prior to the administration of the main survey. This omission should be recognized as a methodological limitation, particularly because certain indicators related to TATF and AI Technology Use may appear conceptually proximate. Nevertheless, the empirical results indicate that discriminant validity remained within acceptable bounds, as evidenced by the reported validity assessments.

For this, Table 2 presents the measurement items retained for each latent construct, together with their corresponding codes and main theoretical sources.

Table 2. Research Items presentation

Latent variable	Code	Items	References
Task Characteristics	MTC1	The strategic decisions I make involve a high level of informational complexity.	Antucheviciene et al. [38]
	MTC2	My managerial tasks require the simultaneous analysis of multiple information sources.	Byström [39]
	MTC3	The strategic decisions I make are characterized by high uncertainty.	Merigó [40]
	MTC4	My tasks require analytical judgment rather than a simple application of rules.	Campbell [41]
	MTC5	The decisions I make have significant long-term consequences for the organization.	Nutt [42]
AI Technology Characteristics	AITC1	The AI tool provides accurate and reliable analyses to support strategic decision-making.	Csaszar et al. [9]
	AITC2	AI is able to process large volumes of data quickly.	Mahadevkar et al. [43]
	AITC3	AI offers recommendations adapted to the decision-making context.	Wang et al. [44]
	AITC4	The AI tool is flexible and adapts to different types of strategic decisions.	Van de Wetering [45]
	AITC5	AI-generated results are easy to interpret and use for decision-making	Júnior et al. [46]
Task AI Technology Fit	TAITF1	AI matches well the analytical requirements of my strategic tasks.	Davenport [47]
	TAITF2	AI effectively supports the way I make decisions.	Reicherts et al. [48]
	TAITF3	AI functionalities are suited to the strategic problems I handle.	Mazzei & Noble [49]
	TAITF4	AI improves the quality of how I carry out my managerial tasks.	Yang [50]
	TAITF5	AI helps me to understand the strategic decision-making process	Spangler [51]
AI Technology Use	AITU1	I regularly use AI tools to analyze strategic information	Mrida et al. [52]
	AITU2	I use AI to enhance data management	Jankovic & Curovic [53]
	AITU3	I rely on AI to support the planning of important decisions	Narne et al. [54]
	AITU4	AI has become an essential tool in my managerial work	Canals [55]
	AITU5	I rely on AI-generated insights when evaluating major strategic decisions	Miedema et al. [56]
Strategic Decision Performance Benefits	SDPB1	AI improves the overall quality of my strategic decisions.	Guthrie et al. [57]
	SDPB2	Decisions made with AI are faster and better informed.	Guthrie et al. [57]
	SDPB3	AI reduces judgment errors in strategic decision-making.	Pearson et al. [58]
	SDPB4	AI-assisted decisions contribute to better organizational performance.	Giachino et al. [59]
	SDPB5	AI transform traditional strategic decisions processes	Joshi [60]

Note: MTC = Managerial Task Characteristics; AITC = AI Technology Characteristics; TATF = Task AI Technology Fit; AITU = AI Technology Use; SDPB = Strategic Decision Performance Benefits.

The various constructs in the study were measured using items rated on a five-point Likert scale, ranging from 1 = "strongly disagree" to 5 = "strongly agree." This measurement format is widely used in management and entrepreneurship research because it reliably and subtly captures respondents' perceptions, attitudes, and judgments. The use of a five-point scale provides a good balance between measurement sensitivity and cognitive simplicity for participants, while also facilitating statistical data analysis, particularly structural equation modeling and multivariate analyses.

3-2- Data Collection

Data collection took place over a seven-month period, from June 2025 to January 2026, to ensure sufficient time coverage and maximize the response rate from targeted managers. A mixed-methods approach was used, combining questionnaires administered using PAPI (Paper and Pencil Interview) and CATI (Computer-Assisted Telephone Interview) methods. The use of these two methods allowed the data collection to be adapted to the organizational constraints of the companies surveyed while also improving respondent accessibility and the reliability of the collected answers.

Once the data collection phase was completed, the data were coded, cleaned, and analyzed using ADANCO software [61], recognized for its suitability for analyses based on partial least squares structural equation modeling. This methodological choice allows us to simultaneously evaluate the relationships between latent variables, the quality of the measurement model, and the robustness of the structural model, in line with the exploratory and explanatory objectives of the study.

4- Results

4-1- Sample Presentation

The respondents' profile reflects a population of experienced managers deeply involved in strategic decision-making processes. The sample structure reveals a male overrepresentation, reflecting the persistent imbalances in access to senior management positions, particularly within medium-sized and large companies. This configuration is consistent with the organizational realities observed in many emerging contexts. For this, Table 3 reports the main demographic and professional characteristics of the respondents included in the empirical sample.

Table 3. Sample presentation

Parameters	N	%
Gender		
Male	268	74%
Female	92	26%
Age		
Under 35 years old	0	0%
Between 35 and 45 years old	55	15%
Between 46 and 55 years old	102	28%
Between 56 and 65 years old	145	40%
Upper to 65 years old	58	16%
Years of experience as a manager		
Under 5 years	10	3%
Between 5 and 10 years	47	13%
Between 11 and 15 years	192	53%
Between 16 and 20 years	67	19%
Upper to 20 years	44	12%
Total	**360**	**100%**

An examination of age indicates that strategic decision-making is predominantly executed by managers in the mid to late stages of their careers, who possess substantial experience and comprehensive understanding of organizational dynamics. This professional maturity is an asset for the study, as integrating AI into long-term decisions requires the capacity for reflection, judgment, and strategic arbitration.

Furthermore, the respondents' level of managerial experience confirms the legitimacy of the chosen unit of analysis. Many managers surveyed have significant seniority in positions of responsibility, which strengthens the credibility of the perceptions gathered regarding the use of AI, the TTF, and its contribution to strategic decision-making. This profile thus contributes to the interpretative robustness of the empirical results and their relevance for understanding actual managerial practices in an organizational context.

Consistent with the methodological framework advocated by Anderson & Gerbing [62], this study employed a two-step analytical procedure. The first step involved validating the measurement model to ensure the reliability and validity of the latent constructs. This phase verifies that the observed indicators adequately represent the underlying theoretical concepts. The second step focused on evaluating the structural model, with the objective of assessing the quality, robustness, and statistical significance of the hypothesized relationships among the latent variables.

4-2- Measurement Model

4-2-1- The Reliability and Convergent Validity of the Measurement Model

Overall, the measurement model demonstrates excellent psychometric quality, with high levels of internal reliability, an absence of multicollinearity, and confirmed convergent validity for all constructs. The results fully support the model's suitability for structural model analysis and the interpretation of causal relationships among latent variables.

The AI Technology Characteristics construct exhibits excellent psychometric quality. The item loadings, which range from 0.7595 to 0.8514, are well above the recommended threshold of 0.70. This means that each indicator makes a strong contribution to the latent variable. VIF values, ranging from 1.87 to 3.23, confirm the absence of problematic multicollinearity. In terms of internal reliability, the coefficients ρA (0.9013), ρc (0.9002), and Cronbach's alpha (0.9003) demonstrate excellent internal consistency. The AVE of 0.6437 confirms high convergent validity, showing that the construct explains a substantial portion of the variance in its indicators. To this end, Table 4 summarizes the main reliability and convergent validity indicators of the measurement model, including item loadings, VIF values, internal consistency coefficients, and average variance extracted.

Table 4. Presentation of the measurement model parameters

Latent variable	Items	Loadings	VIF	Dijkstra-Henseler's rho (ρA)	Jöreskog's rho (ρc)	Cronbach's alpha(α)	Average variance extracted (AVE)
AI Technology Characteristics	AITC1	0.7595	1.8687	0.9013	0.9002	0.9003	0.6437
	AITC2	0.7799	3.1307				
	AITC3	0.8014	3.2270				
	AITC4	0.8162	2.3353				
	AITC5	0.8514	2.2197				
Task Characteristics	MTC1	0.7610	2.2696	0.8173	0.7426	0.7363	0.5995
	MTC 2	0.8214	2.2164				
	MTC 3	0.7343	1.5842				
	MTC 4	0.8498	1.3989				
	MTC 5	0.8769	1.5746				
Task AI Technology Fit	TAITF1	0.7158	1.9580	0.9173	0.9133	0.9122	0.6794
	TAITF2	0.7908	2.5522				
	TAITF3	0.8532	2.9625				
	TAITF4	0.8605	3.0102				
	TAITF5	0.8894	3.9413				
Strategic Decision Performance Benefits	SDPB1	0.6265	2.3343	0.8037	0.7838	0.7975	0.5275
	SDPB2	0.5280	2.5608				
	SDPB3	0.5259	2.2876				
	SDPB4	0.7347	1.9421				
	SDPB5	0.8060	2.0247				
AI Technology Use	AITU1	0.9165	1.2981	0.8069	0.7536	0.7787	0.5956
	AITU2	0.6580	1.6098				
	AITU3	0.5377	1.9576				
	AITU4	0.5244	2.1752				
	AITU5	0.6036	1.2983				

Note: VIF = variance inflation factor; ρA = Dijkstra-Henseler’s rho; ρc = Jöreskog’s rho; α = Cronbach’s alpha; AVE = average variance extracted.

The quality of the measurement model was assessed using standard PLS-SEM indicators. More specifically, item loadings were used to evaluate the contribution of each observed indicator to its latent construct, while variance inflation factor (VIF) values were examined to detect potential multicollinearity. Internal consistency reliability was assessed through Dijkstra-Henseler’s rho (ρA), Jöreskog’s rho (ρc), and Cronbach’s alpha (α). Convergent validity was evaluated using the average variance extracted (AVE), which indicates the proportion of variance captured by a construct relative to measurement error.

The Task Characteristics construct demonstrates strong methodological performance. Item loadings are high, ranging from 0.7343 to 0.8769, indicating good alignment between the indicators and the latent variable. All VIF values are below 2.30, indicating a complete absence of multicollinearity. Internal reliability is satisfactory, with a Dijkstra-Henseler's rho of 0.8173, a Jöreskog's rho of 0.7426, and a Cronbach's alpha of 0.7363, exceeding the minimum recommended thresholds. The AVE of 0.5995 confirms the convergent validity of the construct, suggesting that the task characteristics are well captured by the selected items. The TATF construct stands out for its very strong psychometric robustness. Loads are high, ranging from 0.7158 to 0.8894, reflecting a close relationship between the indicators and the measured concept. Although some VIF values are relatively high (up to 3.94), they remain below the critical threshold of 5, thus ruling out any serious risk of multicollinearity. Internal reliability indices are excellent, with a Dijkstra-Henseler's rho of 0.9173, a Jöreskog's rho of 0.9133, and a Cronbach's alpha of 0.9122. The AVE of 0.6794 confirms very high convergent validity, indicating that the construct effectively captures the coherence between the task and the AI technology.

The Strategic Decision Performance Benefits construct exhibits overall satisfactory psychometric quality. Item loadings range from 0.5259 to 0.8060, which is acceptable in an exploratory or multidimensional context. VIFs, ranging from 1.94 to 2.56, indicate the absence of multicollinearity. Internal reliability coefficients are adequate, with a Dijkstra-Henseler rho of 0.8037, a Jöreskog rho of 0.7838, and a Cronbach's alpha of 0.7975, all exceeding the threshold of 0.70.

The AVE of 0.5275, slightly above the recommended threshold, confirms the convergent validity of the construct while suggesting possible conceptual heterogeneity in perceived strategic benefits.

The AI Technology Use construct exhibits an acceptable to good psychometric structure. The loadings range from 0.5244 to 0.9165, indicating that some items contribute significantly to the latent variable, while others have a moderate but acceptable contribution. The VIF values, which are all less than 2.18, show that there is no collinearity. Internal reliability is satisfactory, with a Dijkstra-Henseler rho of 0.8069, a Jöreskog rho of 0.7536, and a Cronbach's alpha of 0.7787. The AVE of 0.5956 exceeds the threshold of 0.50, validating the convergent validity of the construct and suggesting that the use of AI is generally well measured.

4-2-2- Discriminant Validity Assessment of Common Method Bias

Given that all study variables were obtained from the same respondents through a self-reported survey instrument, the possibility of common method bias was explicitly considered. To minimize this risk at the design stage, several procedural precautions were implemented. Respondents were informed that their answers would remain anonymous, thereby reducing evaluation apprehension and the likelihood of socially desirable responding. In addition, the questionnaire was structured into clearly separated construct sections so as to limit response patterning and consistency motifs across items.

Beyond these procedural safeguards, a statistical assessment was conducted using Harman’s single-factor test based on an unrotated exploratory factor analysis. The results indicated that the first factor accounted for 42.88% of the total variance, which remains below the conventional threshold of 50%. This finding suggests that common method bias is unlikely to pose a substantial threat to the validity of the empirical results. Nevertheless, as with any cross-sectional design relying on self-reported data, the possibility of residual method effects cannot be entirely excluded.

4-2-3- Discriminant Validity

The discriminant validity of the model was assessed using the Heterotrait–Monotrait Ratio of Correlations (HTMT), in accordance with PLS-SEM methodological recommendations. The results indicate that all HTMT values are below the conservative threshold of 0.85 proposed by Antucheviciene et al. [38], suggesting adequate distinction between constructs. Specifically, the relationship between AI Technology Characteristics and TATF has an HTMT value of 0.8386, close to the threshold but still acceptable, reflecting an expected conceptual proximity without indicating problematic overlap. The relationships involving AI Technology Use show moderate values (HTMTs ranging from 0.6284 to 0.8254), confirming that AI use is a construct distinct from technological characteristics and TTF. Similarly, the associations between Strategic Decision Performance Benefits and the other constructs remain below the critical threshold (HTMT ranging from 0.6676 to 0.8266), indicating that perceived strategic decision benefits are conceptually distinct from technological and operational dimensions. Finally, the Task Characteristics construct exhibits HTMT values between 0.7052 and 0.8435, reflecting theoretical consistency with the other variables while maintaining satisfactory discriminant validity. Overall, these results confirm that the model's discriminant validity is established and meets the criteria recommended in the literature, allowing for a reliable interpretation of the structural relationships between the constructs. For this, Table 5 presents the HTMT values used to assess the discriminant validity of the constructs included in the model.

Table 5. Result of the HTMT criterion

Construct	AITC	TAITF	AITU	SDPB	MTC
AITC	**				
TAITF	0.8386	**			
AITU	0.6284	0.7985	**		
SDPB	0.6676	0.7600	0.7722	**	
MTC	0.7052	0.8435	0.8254	0.8266	**

Note: HTMT = Heterotrait-Monotrait ratio of correlations.

Discriminant validity was examined using the Heterotrait-Monotrait ratio of correlations (HTMT). This indicator assesses the extent to which each construct is empirically distinct from the others, with lower values indicating a clearer conceptual separation between latent variables.

4-3- Structural Model

The structural model was interpreted using several complementary indicators. The standardized path coefficient (β) reflects the strength and direction of the relationship between two constructs. The coefficient of determination (R^2) indicates the proportion of variance explained in each endogenous construct, while the adjusted R^2 provides a more conservative estimate that takes model complexity into account. In addition, effect size (f^2) was used to assess the substantive contribution of each exogenous construct to the explanatory power of the model.

The coefficients of determination in Figure 2 indicate a high explanatory power of the structural model, consistent with methodological standards in PLS-SEM. The TATF construct has an R^2 of 0.8394 (adjusted $R^2 = 0.8384$), meaning that nearly 84% of its variance is explained by the model's predictive variables. According to the thresholds proposed by Hair et al. [63], this level corresponds to very high explanatory power, reflecting the model's strong ability to explain the perceived fit between managerial tasks and AI technology. The AI Technology Use construct has an R^2 of 0.7387 (adjusted $R^2 = 0.7379$), indicating that approximately 74% of the variance in AI usage is explained by the model, which also reflects substantial explanatory power. This result suggests that the integrated determinants provide a comprehensive understanding of AI adoption and usage behaviors in a managerial context. Finally, the Strategic Decision Performance Benefits construct exhibits an R^2 of 0.6909 (adjusted $R^2 = 0.6890$), indicating that nearly 69% of the variance in perceived strategic decision performance benefits is explained. This level is considered high enough to be substantial in management research, confirming the model's relevance in explaining the effects of AI on decision performance. Furthermore, the close relationship between the R^2 and adjusted R^2 values for all constructs demonstrate adequate model stability and suggests the absence of overfitting.

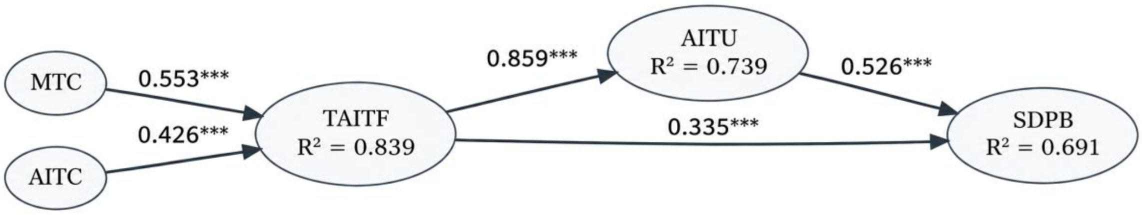

Figure 2. Graphical presentation of the results of the conceptual framework

Figure 2 graphically presents the main results of the structural model, including the standardized relationships and the explanatory power of the endogenous constructs.

Analysis of effect sizes (f^2) reinforces these findings. The relationship between TATF and AI Technology Use has a coefficient $\beta = 0.8595$ associated with an extremely large effect size ($f^2 = 2.8266$), indicating that the perceived fit between the task and the AI technology is a central and dominant determinant of AI use. Similarly, the relationship between AI Task Characteristics and TATF exhibits a substantial effect size ($f^2 = 0.4939$), highlighting the crucial role of AI technology characteristics in constructing TTF. In contrast, although the relationship between TATF and Strategic Decision Performance Benefits has a large total effect size (0.7866), the direct effect size remains small to moderate ($f^2 = 0.0948$). This discrepancy suggests the existence of a mediation mechanism, indicating that the impact of TTF on strategic decision-making performance benefits is largely indirect, particularly through the actual use of AI. Overall, these results confirm the strong explanatory power and theoretical coherence of the structural model while highlighting the central role of TATF as a key mechanism linking AI characteristics, its use, and the benefits in strategic decision-making performance. Table 1 reports the results of the structural model estimation, including the standardized path coefficients, standard errors, t-values, and hypothesis decisions.

The results of the direct effects analysis, estimated using the bootstrap procedure, confirm the robustness and consistency of the structural model, in accordance with PLS-SEM recommendations. First, the effect of AI Technology Characteristics on TATF is positive and statistically significant ($\beta = 0.4256$, $t = 4.8530$, $p < .001$), indicating that the perceived quality of AI technology characteristics contributes substantially to the fit between the technology and job tasks. Similarly, Task Characteristics have a strong and significant positive effect on TATF ($\beta = 0.5528$, $t = 6.2807$, $p < .001$), highlighting the central role of task nature and structure in the perceived TTF. Furthermore, TATF emerges as a key determinant of AI Technology Use, with a very high and highly significant coefficient ($\beta = 0.8595$, $t = 31.5465$, $p < .001$), indicating that the more AI is perceived to be suited to tasks, the more its actual use is intensified. In fact, the very strong effect of TATF on AI Technology Use is fully consistent with the theoretical logic of TTF, according to which perceived fit constitutes a direct and proximal driver of actual technology utilization. At the same time, the magnitude of this coefficient invites a degree of interpretive caution. More specifically, the possibility of partial conceptual overlap between fit and use cannot be entirely excluded, particularly where respondents may perceive a well-aligned technology as one that is, almost by definition, more readily usable. Although the discriminant validity assessments, notably the HTMT criterion, remained within acceptable thresholds, this result should therefore be understood as indicating a substantively dominant relationship rather than demonstrating complete conceptual independence between the two constructs.

TATF also has a positive and significant effect on Strategic Decision Performance Benefits ($\beta = 0.3349$, $t = 2.2263$, $p < .01$), which means that the better AI and tasks fit together, the better and more effective strategic decisions will be. Finally, AI Technology Use positively and significantly influences Strategic Decision Performance Benefits ($\beta = 0.5256$, $t = 3.5344$, $p < .001$), confirming that the effective use of AI is a central driver of decision-making value creation. Overall, all estimated coefficients are positive, statistically significant, and associated with high t-values, while the limited discrepancies between the original coefficients and bootstrapping means indicate the high stability of the estimates. These results fully support the empirical validity of the proposed causal relationships and confirm the explanatory strength of the structural model.

To improve the readability of the structural findings, Figure 3 presents a comparative visualization of the main standardized coefficients and explained variances. The figure clearly shows that the strongest relationship in the model is the effect of Task AI Technology Fit on AI Technology Use ($\beta = 0.8595$), confirming the central role of perceived fit in driving actual AI use. It also illustrates the substantial explanatory power of the model across the three endogenous constructs, with particularly high R^2 values for TATF (0.8394), AITU (0.7387), and SDPB (0.6909). This comparative presentation reinforces the interpretation that TATF constitutes the key explanatory mechanism linking task requirements, AI characteristics, technology use, and strategic performance benefits.

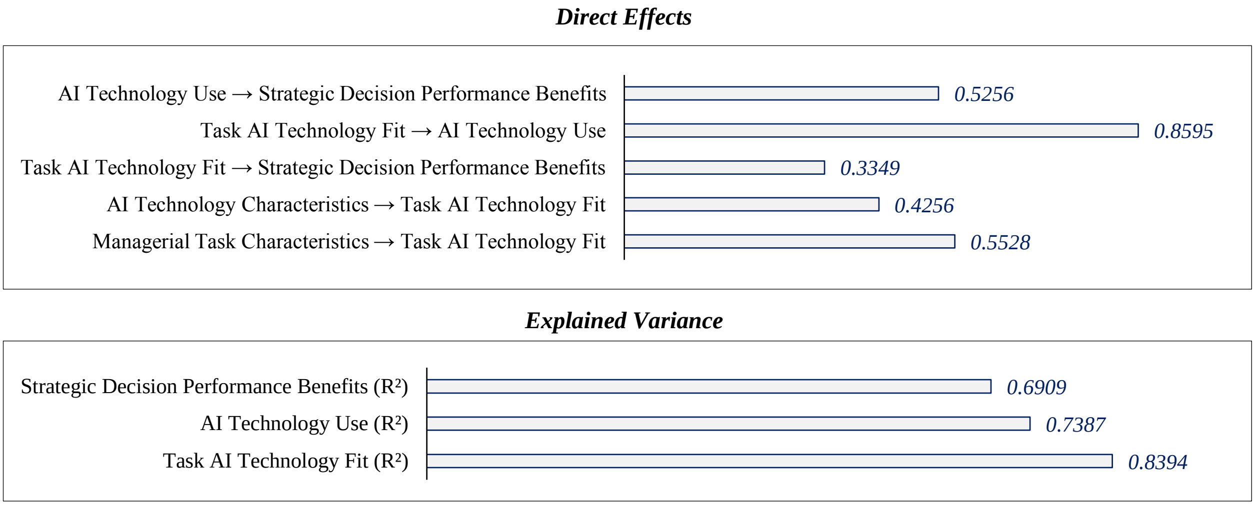

Figure 3. Comparative visualization of path coefficients and explanatory power

Beyond the statistical confirmation of the hypotheses, the structural results offer several substantive insights into the mechanisms through which AI contributes to strategic decision-making. First, the significant effects of managerial task characteristics and AI technology characteristics on TATF indicate that perceived fit is shaped by a dual logic of demand and capability. On the one hand, managerial tasks generate specific informational, analytical, and evaluative requirements. On the other hand, AI systems differ in their perceived capacity to respond to those requirements through information processing, synthesis, comparison, and support for judgment. The positive and significant effects of both antecedents therefore suggest that fit is not simply a technological property, nor merely a reflection of task complexity. Rather, it emerges from the alignment between what strategic work requires and what AI is perceived to offer in practical decision settings.

Second, the magnitude of the relationship between TATF and AI technology use provides important behavioral insight. The forceful coefficient observed for this path suggests that perceived fit acts as the most immediate gateway through which AI becomes integrated into managerial practice. In substantive terms, this means that managers are unlikely to rely on AI in strategic contexts simply because it is available or innovative. They use it when they perceive it as instrumentally relevant to the actual demands of their work. This result is especially meaningful in strategic decision environments, where managers face uncertainty, accountability pressures, and interpretive ambiguity. Under such conditions, the threshold for adopting a technological support system is necessarily high, and perceived fit appears to function as the decisive condition for behavioral incorporation.

Third, the results shed light on the way strategic decision performance benefits are generated. The model shows that TATF has a direct positive effect on strategic decision performance benefits, but this effect remains more modest than its effect on AI Technology Use, while AI Technology Use itself exerts a stronger positive influence on performance. This pattern suggests that the value of fit is only partially direct. Fit improves decision performance to some extent by enhancing the perceived relevance of AI support, but its contribution becomes stronger when this alignment is translated into actual use within decision routines. In other words, the findings support an enacted value creation logic in which perceived alignment facilitates meaningful use, and meaningful use, in turn, helps produce better strategic outcomes. This interpretation reinforces the view that AI creates managerial value not through passive availability, but through disciplined integration into the decision process.

Finally, the high explanatory power observed for TATF, AI Technology Use, and Strategic Decision Performance Benefits confirms that the model captures a substantial share of the relevant variance in the endogenous constructs. This finding is important not only from a methodological standpoint but also from a theoretical one. It suggests that the combination of task-related conditions, perceived technological adequacy, fit, and actual use offers a coherent explanation of how AI supported decision performance emerges in managerial contexts. Taken together, these results indicate that AI enabled strategic benefits should be understood as the outcome of a contingent process in which task demands, technological attributes, perceived alignment, and enacted use operate in sequence rather than in isolation.

5- Discussion

The findings of the present study are broadly consistent with prior TTF research and extend them to the context of AI-assisted strategic decision-making. First, the positive effects of managerial task characteristics and AI technology characteristics on TATF support the foundational logic of TTF, according to which fit emerges from the joint relationship between task requirements and technological functionalities rather than from either dimension taken in isolation. This convergence with prior TTF scholarship is important because it confirms that the explanatory strength of fit remains valid even in contemporary AI contexts, where technologies are more adaptive, generative, and cognitively supportive than the systems examined in earlier information systems research. At the same time, the present study extends this line of work by showing that, in strategic managerial contexts, fit must be interpreted not only in operational terms but also in relation to uncertainty, evaluative burden, and the need for justified judgment.

More broadly, the empirical results confirm the relevance of the TTF model for analyzing the integration of AI into managerial tasks and strategic decision-making. The study indicates that the perceived fit between AI characteristics and task requirements constitutes a central mechanism explaining both the actual use of the technology and the resulting decision-making benefits. In this respect, the results also converge with recent studies suggesting that the organizational value of AI depends less on mere adoption than on the quality of its integration into managerial work. The forceful relationship observed between TATF and AI Technology Use supports recent arguments that AI becomes behaviorally relevant when managers perceive it as genuinely useful for structuring complex reasoning processes, synthesizing dispersed information, and supporting strategic analysis. This finding is consistent with emerging work showing that AI does not transform management through a logic of total substitution, but rather through a gradual reconfiguration of managerial skills and cognitive effort [64]. In the same vein, Marimira & Gumel [65] demonstrated through a qualitative study that AI does not replace managers but instead functions as a lever for enhancing their cognitive and analytical capabilities.

This perspective is closely aligned with the concept of cognitive augmentation, which has emerged as an increasingly relevant lens for understanding the role of AI in complex organizational settings. Cognitive augmentation refers to the use of technology to extend and enhance human mental capacities, particularly in relation to analysis, decision-making, and problem-solving under conditions of uncertainty [66, 67]. Within this perspective, AI is not conceived as an autonomous substitute for managerial cognition but as a support mechanism that strengthens the capacity of decision-makers to process complexity and structure judgment. In that regard, Zhao et al. [68] demonstrates that human-AI interaction is best understood through a complementary approach in which AI supports human reasoning rather than replacing the judgment of decision-makers. Similarly, in the context of leadership, Samuel et al. [69] argues that integrating AI into managerial tasks does not eliminate the manager's role but instead operates as an adaptive mechanism aimed at strengthening the cognitive fit between task requirements, human cognitive capabilities, and the technological tools mobilized. The managerial role therefore evolves toward supervising, interpreting, and regulating AI-supported representations of information so that they remain compatible with human reasoning processes

The present results reinforce this interpretation. The particularly strong effect of AI Technology Fit on AI Technology Use suggests that fit functions as the primary behavioral gateway through which AI becomes meaningfully embedded in strategic work. In high-stakes decision environments, managers are unlikely to rely on AI simply because it is available, innovative, or institutionally promoted. Rather, they appear to adopt it when they perceive its capabilities as closely aligned with the informational, analytical, and evaluative requirements of the task. This finding helps explain why fit may play a more central role in strategic AI use than what has generally been documented in broader technology adoption literature. It also supports the view that the strategic value of AI depends closely on its complementarity with human capabilities. As noted by Mohammed et al. [70], AI can strengthen the analytical and anticipatory dimensions of management, but it does not replace intuition, contextual judgment, or experience. Instead, it repositions the manager as the central actor responsible for interpreting algorithmic recommendations, addressing ethical implications, and preserving a balanced relationship between human agency and technological support.

A further point of convergence with prior literature concerns the relationship between AI Technology Use and Strategic Decision Performance Benefits. The positive effect found in this study is consistent with earlier research showing that AI can improve analytical depth, decision speed, and the structuring of managerial reasoning when it is actively incorporated into decision routines. Keppeler et al. [71], for instance, demonstrate that systems combining human judgment and algorithmic recommendations improve decision quality, especially in complex and uncertain environments. This argument aligns with the findings of Mohammed et al. [70], which suggest that when AI is properly integrated, it assists managers in overcoming the limitations of bounded rationality by structuring information, reducing uncertainty, and facilitating strategic foresight. Yet the present findings add an important nuance. Because the direct effect of TATF on performance is weaker than its effect on use, while use itself exerts a substantial impact on performance, the study suggests that the benefits of fit are only partially realized at the perceptual level and become more fully effective through enacted use. This refines prior work by indicating that fit should not be viewed as a static evaluative state but rather as a mechanism whose value is actualized through behavioral incorporation into managerial routines.

At the same time, some divergence from prior literature should also be acknowledged. Several earlier studies have tended to assume a more direct association between AI adoption and improved managerial outcomes [72, 73]. By contrast, the present findings do not support a simplistic adoption-performance logic. Instead, they demonstrate that performance advantages are contingent upon a sequence that connects task demands, AI attributes, perceived compatibility, and actual utilization. This divergence is theoretically meaningful because it challenges deterministic interpretations of AI-enabled performance and supports a more contingent view of value creation. It also helps explain why some organizations may invest in AI technologies without realizing substantial strategic benefits: adoption alone is insufficient when the technology is not perceived as adequately aligned with the cognitive and decision requirements of managerial work.

Finally, the Moroccan context adds an additional layer of interpretation to the comparison with prior studies. The existing literature has primarily emerged from environments with stronger technological institutionalization and more advanced digital infrastructures. The present results suggest that the core logic of TTF remains robust in an emerging environment, but they also indicate that the strength of the observed relationships may be shaped by contextual features such as uneven digital maturity, differing organizational routines, and variable managerial exposure to AI tools. This does not weaken the findings. On the contrary, it reinforces the value of the study by showing that the fit-based explanation of AI-enabled strategic performance remains valid beyond the contexts most frequently examined in the literature, while also inviting caution in the generalization of effect magnitudes across institutional environments.

5-1- Theoretical Implications

Overall, the findings make a meaningful contribution to the literature on information systems, strategic management, and AI-enabled decision-making. More specifically, they invite a shift away from the predominantly techno-functional interpretations that still characterize much of the research on AI integration in organizations. A large share of prior work has tended to evaluate AI in terms of technical capability, adoption intensity, or system performance, often treating the human actor as a secondary component in a technology-centered process. By contrast, the present study suggests that the value of AI in strategic contexts cannot be understood adequately without placing the manager, their cognitive demands, and their task environment at the center of the analysis. In that sense, this research contributes to a more human-centered academic reading of AI integration, one in which performance outcomes depend not only on what the technology can do, but also on how well it corresponds to the reasoning requirements, interpretive responsibilities, and decision constraints faced by managers.

From this perspective, the use of Person–Job Fit (PJF) theory provides a particularly relevant analytical extension. Traditionally, Person–Job Fit has been employed to explain how alignment between individual characteristics and job requirements influences attitudes, behavior, and performance [74, 75]. Mobilized in the present context, this perspective helps reposition AI-assisted strategic decision-making as a relational phenomenon in which the effectiveness of technology depends on the quality of the fit between the individual, the task, and the technological support available. Such an interpretation broadens the scope of fit theory beyond its conventional organizational and psychological applications. It suggests that, in AI-supported environments, fit should not be reduced to a match between personal abilities and formal job demands. Rather, it also includes the extent to which AI-enabled task environments remain cognitively compatible with the manager's mode of reasoning, judgment formation, and decision responsibility.

The results support this interpretation by showing that AI generates stronger strategic decision-making benefits when it is perceived as aligned not only with task requirements, but also with the way managers structure, interpret, and evaluate information in uncertain contexts. This point is theoretically important because it implies that technology should not be treated as a neutral or external instrument added to an already defined job structure. Instead, AI becomes part of the architecture of work itself, shaping how information is processed, how options are compared, and how judgments are formed. In this sense, the present study extends PJF theory by introducing technology as an active mediating layer in the relationship between the individual and their work. AI is therefore not merely a supporting artifact surrounding the job. It becomes a constitutive dimension of the fit process through which strategic performance is produced.

A second theoretical implication concerns the conceptualization of AI as a mechanism of augmentation rather than substitution. The findings indicate that AI contributes to decision performance primarily by reducing cognitive burdens, structuring dispersed information, and enhancing the analytical capacity of managers while leaving final interpretation and judgment in the hands of humans. This supports a non-substitutional understanding of AI in managerial contexts. Rather than replacing the manager's role, AI appears to reinforce it by enabling better handling of complexity, uncertainty, and information overload. This evidence theoretically challenges deterministic views that primarily measure the contribution of AI through automation or decision replacement. Instead, the study supports a more nuanced interpretation in which AI creates value when it operates in complementarity with human expertise, contextual sensitivity, and evaluative discretion.

Taken together, these insights point toward the relevance of a broader fit configuration that may be described as a Person–Job–Technology fit. Within such a framework, decision-making performance does not stem from technology alone, nor from human expertise alone, but from the complementarity established between managerial capabilities, task characteristics, and AI-based analytical support. This perspective enriches both the PJF and TTF traditions by showing that, in strategic environments, performance emerges from a multidimensional alignment process. Human actors remain central, but their effectiveness is increasingly conditioned by the compatibility between their cognitive orientation, the requirements of the task, and the functionalities of the technology embedded in their work process. Accordingly, the present study contributes to theory by proposing a more integrative and human-centered explanation of AI-enabled strategic performance, one that better reflects the realities of managerial decision-making in contemporary organizations.

5-2- Practical Implications

Beyond its theoretical contribution, this study offers several practical implications for organizations seeking to integrate AI into strategic decision-making in a manner that is both effective and sustainable. These implications can be meaningfully interpreted in relation to the Sustainable Development Goals articulated in the United Nations 2030 Agenda [76], particularly those concerning decent work and economic growth, innovation and resilient infrastructure, responsible production, and effective institutions. From this perspective, the results indicate that AI should not be regarded solely as a functional technological resource or a representation of digital advancement. Instead, it should be considered a strategic enabler whose value to the organization depends on how well it can help align the needs of people making decisions, the tasks that need to be done, and the way information is organized in managerial work. Such an interpretation invites firms to move beyond narrow automation logics and to adopt a more developmental view of AI, one in which the technology contributes to strengthening both individual capabilities and collective decision processes over time.

A first practical implication concerns the criteria according to which organizations evaluate and deploy AI systems. The findings suggest that the performance advantages of AI are most pronounced when the technology is regarded as closely aligned with the analytical, informational, and evaluative requirements of strategic tasks. This means that managers shouldn't base AI investment decisions solely on the technology's performance, computing power, or market pressure. Instead, organizations should evaluate AI based on the specific cognitive requirements of the tasks it will support. In practical terms, this means that organizations should prioritize forms of implementation in which AI demonstrably helps managers synthesize dispersed information, compare alternatives, identify relevant patterns, and reduce uncertainty in complex decision environments. Such an orientation is particularly relevant to Goal 8 and Goal 9 of the United Nations framework, insofar as it promotes a model of innovation that strengthens productive capacity without undermining the centrality of human expertise and responsible work design.

A second implication follows from the finding that AI creates greater value when it is embedded in strategic rather than purely routine decision contexts. The evidence suggests that AI should be mobilized preferentially in domains such as long-term planning, strategic foresight, risk management, scenario evaluation, and resource allocation under uncertainty. These decision environments are characterized by high informational density, interpretive ambiguity, and significant organizational consequences, which makes them especially receptive to technologies capable of structuring complexity and supporting disciplined judgment. In this respect, AI appears less valuable when treated merely as an operational convenience and more valuable when positioned as an aid to strategic discernment. This approach has important consequences for responsible management practice. By improving the quality of resource allocation and strengthening the analytical basis of strategic choices, AI can indirectly support more sustainable production and governance logics, which resonates with the orientation of Goal 12 concerning responsible consumption and production, ultimately leading to enhanced decision-making processes that prioritize environmental and social considerations. The managerial lesson here is not about the extensive use of AI, but rather about identifying where its contribution is most substantively meaningful.

At the same time, the findings caution against simplistic or excessively technocentric approaches to implementation. The results indicate that AI does not generate value through presence alone, nor through symbolic adoption detached from actual patterns of use. Its contribution depends on active, appropriate, and socially accepted use within organizational routines. This implies that successful implementation requires more than technical deployment. It also requires attention to trust formation, perceived relevance, user preparedness, and the social legitimacy of AI-supported decision processes. Organizations should therefore complement technological investment with managerial training, structured experimentation, and internal communication practices that clarify the role of AI and reduce ambiguity regarding its use. In practical terms, phased implementation strategies, pilot applications, and learning-based adoption processes may be more effective than rapid or top-down deployment. Such an approach enables organizations to build familiarity and acceptance while avoiding two symmetrical risks: technological rejection on the one hand and uncritical reliance on automated outputs on the other.

A final implication concerns governance, accountability, and institutional credibility. The findings suggest that AI supported strategic decisions are more likely to be accepted and organizationally productive when managers retain interpretive authority over the decision process. This is especially important in contexts where strategic choices have ethical, social, or long-term consequences. In such situations, the legitimacy of AI-assisted decisions depends not only on technical accuracy but also on the capacity of decision-makers to explain, justify, and contextualize the recommendations produced by the system. This point connects directly with Goal 16, which emphasizes effective, accountable, and inclusive institutions. From a practical perspective, organizations should therefore design AI governance frameworks that preserve human oversight, encourage explainability, and clearly define the boundaries of algorithmic intervention. Doing so helps ensure that AI remains a support for judgment rather than a substitute for responsibility. More broadly, fostering a climate of trust, supporting controlled experimentation, and integrating AI as a collaborative decision partner can contribute to more sustainable forms of organizational learning. Over time, such practices may strengthen not only decision quality but also the resilience, legitimacy, and institutional maturity of firms operating in increasingly data-intensive and strategically uncertain environments.

5-3- Research Limitations

Despite the theoretical and empirical relevance of the findings, several limitations should be acknowledged, both to delimit the scope of the present contribution and to identify fruitful directions for future research. First, the study is based on a cross-sectional research design, which restricts the ability to establish dynamic causal relationships among the variables. Although the structural model is theoretically grounded and the tested associations are consistent with the proposed conceptual logic, the empirical evidence captures these relationships at a single point. As a result, the study cannot fully account for how the alignment between managerial task requirements and AI capabilities may evolve as organizations accumulate experience with AI, as managers refine their usage routines, or as perceptions of usefulness and fit are reshaped through continued interaction with the technology. This limitation is particularly important in AI-related contexts, where learning, adaptation, and organizational sensemaking are likely to unfold progressively rather than instantaneously. Future research would therefore benefit from adopting longitudinal designs capable of tracing how TATF use, and strategic decision-making benefits change over time. Such approaches would make it possible to capture developmental trajectories, identify delayed or cumulative effects, and provide a more robust understanding of the temporal mechanisms through which AI becomes embedded in managerial work.

A second limitation concerns the nature of the data used in the analysis. The empirical model relies exclusively on perceptual measures self-reported by managers, an approach that remains common and legitimate in the information systems and strategic management literature, especially when the constructs under study relate to perceptions, evaluations, and decision practices. Nevertheless, the exclusive use of self-reported data may expose the results to potential sources of bias, including social desirability effects, consistency bias, and common method variance. Even when appropriate procedural and statistical precautions are taken, such a design may still inflate or obscure certain relationships by capturing respondents’ interpretations rather than observable behavior alone. In the present study, this limitation is especially relevant because both the perceived fit of AI and its reported decision-making benefits may partly reflect subjective managerial assessments shaped by expectations, experience, or organizational discourse. Future research could address this limitation by combining perceptual data with more objective indicators, such as observed decision quality, measurable performance outcomes, behavioral traces of AI usage, or evaluations collected from multiple organizational actors. Multi-source and mixed-method designs would be particularly valuable in this regard, as they would allow scholars to triangulate perceptions with actual practices and to build a more comprehensive account of how AI contributes to strategic decision performance.

A third limitation relates to the empirical context of the study. The sample is composed of managers working in medium-sized and large firms operating within a specific national setting, a choice that is coherent with the objective of examining organizations that are more likely to possess the technological, financial, and organizational resources required for meaningful AI implementation. However, this contextual focus inevitably constrains the generalizability of the findings. The mechanisms identified in the model may not operate in the same way in small firms, entrepreneurial ventures, or organizations embedded in institutional environments characterized by different levels of digital maturity, regulatory support, managerial professionalization, or technological infrastructure. In smaller or less formalized settings, for example, the determinants of AI use may be shaped less by perceived fit and more by cost constraints, leadership style, or external pressure. Similarly, cross-national differences in institutional norms, data governance practices, and technological culture may influence both the perception and the actual use of AI in strategic processes. Future research should therefore test the robustness of the proposed model in a wider range of organizational, sectoral, and geographical contexts. Comparative studies would be especially valuable, as they could reveal whether the explanatory power of TATF remains stable across settings or whether its effects are conditioned by contextual variables that remain underexplored in the present study.

Finally, the model developed in this research focuses primarily on the direct relationships among the key variables, an analytical choice that is consistent with the study’s objective of establishing the core explanatory logic linking task characteristics, AI characteristics, perceived fit, use, and strategic decision-making benefits. While this parsimonious structure offers clarity and theoretical discipline, it does not fully capture the broader set of contingencies and process mechanisms that may shape AI enabled value creation in organizations. In particular, the model does not explicitly examine potential moderating or mediating influences such as trust in AI, explainability, algorithmic governance, organizational culture, decision risk, managerial expertise, or the degree of digital maturity within the firm. Yet these factors are likely to affect the conditions under which AI is perceived as legitimate, adopted in practice, and translated into sustainable decision benefits. Future research should therefore move beyond direct effects and explore more elaborate explanatory configurations capable of capturing the contingent nature of AI supported strategic performance. Doing so would not only refine the theoretical understanding of fit-based value creation but also provide a more nuanced picture of the organizational and institutional conditions under which AI can serve as a credible and durable support for managerial judgment.

6- Conclusion

This study examined how AI contributes to strategic decision-making by focusing on the alignment between managerial task characteristics, AI technology characteristics, perceived TATF, AI Technology Use, and Strategic Decision Performance Benefits. Grounded in the TTF perspective and enriched by a behavioral understanding of strategic work, the findings show that AI creates value not simply because it is available or adopted, but because it is perceived as meaningfully aligned with the informational, analytical, and evaluative demands of managerial tasks. More specifically, the results demonstrate that both managerial task characteristics and AI technology characteristics positively shape perceived fit that perceived fit strongly drives actual AI use, and that both fit and use contribute to strategic decision performance benefits. These findings confirm that TATF constitutes the central explanatory mechanism through which AI becomes behaviorally relevant and strategically valuable in managerial contexts.

The study makes several contributions. Theoretically, it expands TTF research to AI-assisted strategic decision-making by demonstrating that fit persists as a robust explanatory framework, even in contexts marked by uncertainty, interpretive complexity, and elevated cognitive demands. It also supports a view of AI as a mechanism of cognitive augmentation rather than substitution, reinforcing the idea that AI enhances managerial analysis and judgment without replacing human interpretive authority. At the managerial level, the results suggest that organizations should not evaluate AI primarily as a stand-alone technology, but rather according to its capacity to support the specific cognitive requirements of strategic tasks. The findings therefore encourage managers to adopt a fit-oriented approach to AI implementation, emphasizing complementarity between human expertise and technological capabilities. Although the study is limited by its cross-sectional design, perceptual measures, and contextual focus, it offers a robust basis for future research on the contingent conditions under which AI generates sustainable decision-making value across organizational environments.

7- Declarations

7-1- Author Contributions

Conceptualization, O.B.; methodology, O.B. and B.S.; software, B.S.; validation, N.M., D.R., and K.S.; formal analysis, N.M.; investigation, B.S.; resources, O.B. and D.R.; data curation, O.B. and K.S.; writing—original draft preparation, O.B. and B.S.; writing—review and editing, O.B., D.R., and K.S.; visualization, O.B. and B.S.; supervision, O.B.; project administration, O.B. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding and Acknowledgments

We confirm that Grammarly and QuillBot Premium version were used exclusively to enhance linguistic clarity, grammatical accuracy, and the overall readability of the manuscript. These tools were not used to generate scientific content, develop arguments, interpret results, or make substantive changes to the study's intellectual contribution. All revisions were reviewed and approved by the authors, who take full responsibility for the content of this publication. Besides, this research received no external fundings.

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Not applicable.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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