Cognitive and Systems-Theoretic Implications of Using NLP-Based Intelligent Systems in Strategic IT Management and Decision-Making

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Abstract

This study aimed to examine the cognitive and systems-theoretic implications of using NLP-based intelligent systems in strategic IT management and decision-making among managers, experts, and specialists in Tehran. This applied descriptive-analytical study was conducted using a mixed qualitative–quantitative design. The statistical population included senior IT managers, strategic planning managers, digital transformation specialists, business intelligence experts, organizational decision-makers, and academic specialists in information systems and technology management in Tehran. Using purposive sampling, 186 participants were selected, including 24 participants in the qualitative interview phase and 162 participants in the quantitative survey phase. Data were collected through a semi-structured interview protocol and a researcher-made questionnaire developed based on cognitive decision-making, systems theory, strategic IT management, and NLP-based intelligent systems. The validity of the questionnaire was confirmed by experts, and its reliability was assessed using Cronbach's alpha. Qualitative data were analyzed through thematic analysis, and quantitative data were analyzed using descriptive statistics, Pearson correlation coefficients, and multiple regression analysis. The inferential findings showed that strategic IT decision-making effectiveness had significant positive correlations with cognitive support, strategic alignment, system integration, interpretability, trust in intelligent systems, and decision quality, and a significant negative correlation with perceived risk of excessive reliance. The regression model was significant, $F(6, 155) = 41.73$, $p < .001$, and explained 61.8% of the variance in strategic IT decision-making effectiveness. Strategic alignment was the strongest positive predictor, followed by cognitive support, trust in intelligent systems, system integration, and interpretability. Perceived risk of excessive reliance was a significant negative predictor of strategic IT decision-making effectiveness. The results indicated that NLP-based intelligent systems can enhance strategic IT decision-making when they provide cognitive support, align with organizational strategy, integrate with organizational systems, and generate interpretable and trustworthy outputs. However, excessive reliance on automated recommendations may reduce the effectiveness of decision-making by weakening human judgment and critical reflection.

Keywords: *Natural language processing; intelligent systems; strategic IT management; decision-making; cognitive support; systems theory; artificial intelligence*

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1. Introduction

The rapid diffusion of artificial intelligence into organizational life has altered the logic through which firms collect information, interpret complexity, allocate resources, and formulate strategic choices. In contemporary organizations, strategic IT management is no longer limited to infrastructure planning, software acquisition, cybersecurity governance, or enterprise architecture; rather, it increasingly involves the orchestration of intelligent systems that shape how managers perceive uncertainty, evaluate alternatives, and construct organizational responses. Artificial intelligence has become a central component of modern business systems because it enables organizations to transform large volumes of heterogeneous data into operational and strategic knowledge, thereby

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supporting more timely, evidence-based, and adaptive decision-making [1, 2]. In this context, natural language processing (NLP) occupies a particularly important position, because much of the information used in strategic IT management exists in textual or semi-structured form, including reports, emails, regulatory documents, customer feedback, technical documentation, social media content, expert opinions, and organizational records. Therefore, NLP-based intelligent systems are not merely analytical tools; they are cognitive and organizational mediators that influence how strategic meaning is extracted from language-based information.

Strategic decision-making in IT-intensive environments is characterized by ambiguity, volatility, interdependence, and information overload. Organizations are required to make decisions about digital transformation, cybersecurity, automation, data governance, platform integration, artificial intelligence adoption, and innovation strategy under conditions in which both technological trajectories and market expectations are unstable. In such settings, the concept of the VUCA environment has become increasingly relevant, because strategic planning must account for volatility, uncertainty, complexity, and ambiguity while maintaining organizational coherence and adaptability [3]. AI-based systems have been proposed as mechanisms for enhancing strategic planning in such environments by improving information processing, scenario analysis, prediction, and decision support. However, their value depends on whether they are embedded into organizational processes in a way that strengthens rather than replaces managerial judgment. This distinction is essential for understanding the cognitive and systems-theoretic implications of NLP-based intelligent systems in strategic IT management.

From a cognitive perspective, the use of NLP-based intelligent systems can be interpreted as a form of cognitive augmentation. Managers and strategic IT decision-makers are often confronted with more information than they can process through unaided human cognition. NLP systems can reduce this burden by classifying documents, extracting themes, summarizing large textual datasets, identifying sentiment, detecting patterns, and highlighting anomalies. Previous research has shown that NLP can be employed to analyze consumer opinions toward advertising, classify and manage tacit knowledge, and support advanced visualization in real-time analytics [4-6]. These applications demonstrate that NLP technologies can transform dispersed textual information into organized knowledge structures. In strategic IT management, this capability is crucial because decisions frequently depend on interpreting signals from multiple textual sources, including user needs, market trends, regulatory changes, stakeholder concerns, and internal organizational communications.

At the same time, NLP-based decision support should be examined through a systems-theoretic lens. Organizations are complex adaptive systems composed of interacting subsystems, feedback loops, communication channels, decision routines, technologies, human actors, and environmental inputs. Intelligent systems influence organizational outcomes not only because of their technical accuracy but also because of their position within the broader decision system. For example, AI applications in energy systems are increasingly linked to perception, cognition, decision-making, and deduction, indicating that intelligent systems may reshape the full chain of organizational reasoning from sensing to action [7]. Similarly, industrial foundation models and metaverse-based systems illustrate how digital infrastructures can create complex interactions among data, simulation, decision processes, and organizational coordination [8]. Therefore, NLP-based systems in strategic IT management must be understood as components of a socio-technical system in which human cognition, organizational routines, digital infrastructure, and environmental feedback continuously interact.

The importance of AI in managerial decision-making has also been emphasized in financial and corporate contexts. Studies on AI and financial decisions show that intelligent systems can influence decision quality in developing economies by improving the analysis of financial information and supporting managerial judgment [9]. Similarly, AI has been discussed as a transformative force in financial reporting by increasing accuracy and timeliness, which are essential qualities for strategic control and accountability [10]. Research on the influence of AI on financial management further suggests that finance-related decision processes are increasingly shaped by automated analysis, prediction, and information integration [11]. These developments are relevant to strategic IT management because IT investment, system modernization, cybersecurity programs, and digital transformation initiatives are often resource-intensive decisions that require accurate financial interpretation, risk assessment, and long-term strategic evaluation.

In addition to finance, AI-based systems have transformed other managerial domains, including human resource management, employee engagement, public sector reform, education, health care, and marketing. Cognitive technologies have been examined as tools for improving human resource management experiences, while AI has been linked to employee engagement and knowledge sharing through improved communication and information accessibility [12, 13]. Interdisciplinary reviews of AI in human resource management indicate that intelligent technologies are reshaping managerial practices across recruitment, performance evaluation, workforce analytics, and organizational learning [14]. In public administration, AI has been discussed as a mechanism for reform because it can improve service delivery, administrative responsiveness, and policy-related decision-making [15]. In educational settings, AI has been used to make sense of student feedback and engagement, showing how language-based data can be transformed into actionable institutional insights [16]. These examples indicate that AI-based interpretation of textual and behavioral data is becoming a general feature of organizational governance and not merely a technical function.

The expansion of AI across sectors also demonstrates that intelligent decision-support tools increasingly operate in domains where human judgment, ethics, communication, and contextual interpretation remain central. In nursing and health care, AI has been discussed as a tool that can support professional decision-making while requiring careful attention to clinical judgment, accountability, and human oversight [17]. In cancer survivorship, AI-based symptom monitoring has been systematically reviewed as a means of improving patient-related information processing and follow-up, yet such applications remain dependent on interpretability and responsible integration into care systems [18]. The convergence of AI, machine learning, and psychology further highlights the importance of examining intelligent systems not only as computational mechanisms but also as technologies that interact with human cognition, perception, emotion, and decision behavior [19]. These insights are directly applicable to strategic IT management, where intelligent systems must support managerial reasoning without obscuring responsibility or weakening critical evaluation.

The emergence of large language models has intensified interest in the role of NLP and AI in managerial decision-making. Large language models can generate summaries, interpret documents, identify patterns in managerial discourse, support scenario development, and assist in strategic communication. Research on the role of large language models in managerial decision-making has emphasized both benefits and challenges, including improved analytical efficiency, faster access to information, and concerns related to reliability, bias, and overdependence [20]. Similarly, a large language model approach to managerial sentiment and corporate investment demonstrates that language-based computational methods can extract meaningful managerial signals and connect them to investment behavior [21]. These findings suggest that NLP-based systems may improve strategic IT decision-making by allowing organizations to analyze managerial narratives, stakeholder sentiment, market discourse, and internal communications in ways that were previously difficult or impossible at scale.

Nevertheless, NLP implementation is associated with substantial challenges. A literature review of NLP challenges identifies issues such as ambiguity, semantic complexity, context dependence, multilingual variation, data quality, domain specificity, and model limitations [22]. These problems are particularly important in strategic IT management because strategic decisions often involve specialized terminology, incomplete information, organizational politics, implicit assumptions, and context-sensitive meanings. A system that accurately processes language at a surface level may still fail to grasp organizational priorities, tacit knowledge, or strategic implications. Therefore, NLP-based intelligent systems must be designed, interpreted, and governed with awareness of both linguistic limitations and organizational complexity. The challenge is not simply to deploy technically advanced tools, but to ensure that these tools contribute to meaningful, explainable, and strategically relevant decision processes.

Automation is another important dimension of the present study. Intelligent automation, robotic process automation, and AI-driven workflow systems are increasingly used to improve organizational efficiency, reduce repetitive tasks, and support data-driven processes. Research on intelligent automation and the evolution of robotic process automation shows that organizations are moving toward more integrated automation systems, but also face challenges related to scalability, governance, process redesign, and future adaptation [23]. Similarly, work on robotic process automation highlights advancements, design standards, applications, and limitations, suggesting that automation must be aligned with organizational goals and operational constraints [24]. In strategic IT management, NLP-based intelligent systems may become part of broader automation infrastructures, but their use in decision-making requires more caution than routine process automation because strategic decisions involve uncertainty, value judgments, and long-term consequences.

Risk is especially significant when intelligent systems are applied to cybersecurity, telecommunications, corporate reporting, climate-related risk disclosure, and strategic financing. AI has been proposed as a conceptual tool for strengthening cybersecurity in telecommunications, where rapid detection, pattern recognition, and automated response are critical [25]. However, cybersecurity decision-making also requires an understanding of social engineering, human vulnerability, and psychological manipulation, which shows that technological defenses must be integrated with human-centered risk awareness [26]. In corporate management and reporting, technology is increasingly used to manage climate-related risks, emphasizing the importance of digital tools in strategic accountability and regulatory responsiveness [27]. In strategic financing decisions, innovations in risk measurement and management demonstrate the growing role of advanced analytics in evaluating uncertainty and supporting long-term decisions [28]. These studies collectively show that intelligent systems can strengthen risk-oriented decision-making, but they may also introduce new risks if outputs are misunderstood, unverified, or treated as neutral representations of reality.

The strategic value of AI is also linked to business model transformation and innovation. Digital-era business value models indicate that technological disruption changes how organizations create, deliver, and capture value [29]. In marketing, machine learning and AI have been classified through taxonomies that demonstrate their diverse applications in segmentation, prediction, recommendation, personalization, and customer analytics [30]. AI-powered narrative building has also been proposed as a means of facilitating public participation and engagement, showing that AI can shape how collective meaning is produced in participatory processes [31]. These developments are relevant because strategic IT management increasingly requires organizations to connect technical systems with value creation, stakeholder engagement, user experience, and strategic communication. NLP-based systems may therefore contribute not only to internal decision support but also to the broader transformation of organizational narratives, customer understanding, and strategic positioning.

The cognitive and communicative dimensions of AI also raise deeper theoretical questions about how organizations interpret reality. Ontological and communicative perspectives on AI and big data suggest that intelligent technologies influence not only what organizations know but also how knowledge is structured, communicated, and acted upon [1]. From this perspective, NLP-based systems are not passive tools that simply report information; they participate in the construction of organizational knowledge by filtering, categorizing, summarizing, and prioritizing textual signals. This creates a systems-theoretic issue: when intelligent systems become embedded in decision routines, they can shape feedback loops, reinforce certain interpretations, and influence strategic attention. If properly governed, this can enhance organizational learning. If poorly governed, it may create blind spots, automation bias, and excessive confidence in machine-generated interpretations.

Recent studies have further emphasized that AI adoption is influenced by leadership characteristics and executive orientation. IT-oriented executives appear to play a significant role in driving AI adoption, indicating that strategic leadership and technological competence are central to organizational readiness for intelligent systems [32]. In strategic project management, AI has also been identified as a factor influencing project development, portfolio management, and strategic execution [33]. These findings suggest that the effectiveness of NLP-based intelligent systems depends not only on technical performance but also on leadership capability, organizational culture, decision governance, and the strategic maturity of IT management. In this regard, the integration of AI into strategic decision-making is both a technological and managerial challenge.

Finally, the development of more advanced and possibly more general AI architectures has intensified debate about the future of intelligent systems in organizational decision-making. Modular frameworks for artificial general intelligence reflect ongoing efforts to conceptualize more comprehensive AI systems with broader reasoning capabilities [34]. Research on multimodal interactive robots for military communication similarly shows that future intelligent systems may combine language, perception, interaction, and decision support in complex operational contexts [35]. Although the present study focuses specifically on NLP-based intelligent systems in strategic IT management, these broader developments indicate that language-processing tools are part of a larger movement toward intelligent organizational systems that combine cognition, communication, automation, and adaptive response. Therefore, examining their cognitive and systems-theoretic implications is essential for understanding how organizations can use such systems responsibly and effectively.

Despite the growing literature on AI, NLP, intelligent automation, and managerial decision-making, there remains a need for an integrated framework that explains how NLP-based intelligent systems influence strategic IT management through both cognitive-level and systems-level mechanisms. Existing studies often focus on technical applications, sector-specific outcomes, automation capabilities, or general AI adoption, while less attention has been given to the combined role of cognitive support, interpretability, trust, organizational feedback, system integration, and perceived risk in strategic IT decision-making. This gap is important because strategic IT decisions are not produced by algorithms alone; they emerge from the interaction of human cognition, organizational systems, digital infrastructures, and environmental uncertainty. Accordingly, the aim of this study was to examine the cognitive and systems-theoretic implications of using NLP-based intelligent systems in strategic IT management and decision-making.

2. Methodology

This study was conducted using an applied, descriptive-analytical research design with a mixed qualitative–quantitative orientation. The purpose of the study was to examine the cognitive and systems-theoretic implications of using NLP-based intelligent systems in strategic IT management and organizational decision-making. The research design was selected because the subject required both an interpretive understanding of expert perceptions and a structured analysis of the relationships among cognitive, technological, managerial, and systemic factors. The statistical population consisted of senior IT managers, strategic planning managers, digital transformation specialists, business intelligence experts, organizational decision-makers, and academic specialists in information systems and technology management working in Tehran. Participants were selected from technology-based companies, financial and banking institutions, consulting firms, public-sector organizations, and universities located in Tehran. Using purposive sampling, individuals were included if they had at least five years of professional or academic experience in IT management, strategic decision-making, artificial intelligence, natural language processing, business analytics, or organizational systems design. The final sample consisted of 186 participants from Tehran. Of these, 24 participants took part in the qualitative interview phase, and 162 participants participated in the quantitative survey phase. The qualitative sample size was determined based on theoretical saturation, meaning that interviews continued until no substantially new conceptual categories emerged. The quantitative sample was considered adequate for examining the proposed conceptual relationships and identifying dominant patterns in perceptions regarding the use of NLP-based intelligent systems in strategic IT management.

Data were collected using two main instruments: a semi-structured interview protocol and a researcher-made questionnaire. The semi-structured interview protocol was designed to explore participants' views on the cognitive, managerial, technological, and systems-level consequences of applying NLP-based intelligent systems in strategic IT decision-making. The interview questions focused on issues such as decision support, information processing, reduction of cognitive overload, interpretation of unstructured textual data, strategic sensemaking, organizational learning, feedback mechanisms, interdepartmental coordination, uncertainty management, and the risks of excessive reliance on intelligent systems. The interview protocol was reviewed by experts in information systems, strategic management, and artificial intelligence to ensure content relevance, conceptual clarity, and alignment with the objectives of the study. Each interview was conducted individually, and participants were encouraged to describe their practical experiences with intelligent systems, digital decision-support tools, automated text analysis, chatbots, intelligent dashboards, or NLP-based analytics platforms used in organizational contexts.

The quantitative data collection tool was a researcher-made questionnaire developed based on the theoretical foundations of cognitive decision-making, systems theory, strategic IT management, and the qualitative findings obtained from the interview phase. The questionnaire included items related to cognitive support, decision quality, strategic alignment, environmental scanning, organizational feedback, system integration, interpretability, trust in intelligent systems, perceived risks, and managerial acceptance of NLP-based tools. Responses were measured using a five-point Likert scale ranging from strongly disagree to strongly agree. The face and content validity of the questionnaire were assessed by a panel of university faculty members and professional experts in IT management and artificial intelligence. Revisions were made to improve the wording, remove ambiguity, and ensure that each item accurately reflected the intended construct. The reliability of the questionnaire was examined using internal consistency analysis, and the obtained Cronbach's alpha coefficient indicated acceptable reliability for the overall instrument and its major dimensions. Participation in the study was voluntary, and all participants were informed about the academic purpose of the research, confidentiality of responses, and their right to withdraw from the study at any stage.

The qualitative data were analyzed using thematic analysis. After transcribing the interviews, the texts were read several times to obtain a comprehensive understanding of the participants' experiences and perspectives. Initial codes were extracted from meaningful units related to cognitive processes, strategic decision-making, NLP-based system use, organizational feedback, information flows, uncertainty, and systemic interactions. Similar codes were then grouped into broader categories, and the main themes were developed through continuous comparison and refinement. The qualitative analysis focused on identifying how NLP-based intelligent systems influence managerial cognition, strategic interpretation, decision speed, collective sensemaking, organizational learning, and the dynamic interaction between technological systems and human decision-makers. To increase the credibility of the qualitative findings, the coding process was reviewed several times, and selected interpretations were compared with participants' statements to ensure consistency between the extracted themes and the original data.

The quantitative data were analyzed using descriptive and inferential statistical procedures. Descriptive statistics, including frequency, percentage, mean, and standard deviation, were used to summarize the demographic characteristics of the participants and the distribution of responses across the main research variables. Before conducting inferential analyses, the normality of the data, reliability of the constructs, and suitability of the dataset for multivariate analysis were examined. Correlation analysis was used to assess the relationships among cognitive support, strategic alignment, system integration, trust, decision quality, and perceived usefulness of NLP-based intelligent systems. Regression analysis was then applied to determine the predictive role of cognitive and systems-theoretic factors in explaining strategic IT decision-making effectiveness. The qualitative and quantitative findings were integrated during the interpretation stage to provide a comprehensive explanation of how NLP-based intelligent systems affect decision-making not only as technical tools but also as cognitive and organizational subsystems embedded within broader strategic management processes. Data analysis was conducted with attention to both statistical patterns and conceptual meanings so that the final interpretation would reflect the complex interaction between human cognition, intelligent technologies, and organizational systems.

3. Findings and Results

The findings of the study are presented in two integrated parts. First, the demographic characteristics of the participants are reported to clarify the composition of the research sample. Then, the quantitative and qualitative results are presented through descriptive statistics, correlation analysis, regression analysis, thematic findings, and the final integrated cognitive–systems model. The total sample consisted of 186 participants from Tehran, including 24 experts who participated in the qualitative interview phase and 162 participants who completed the quantitative questionnaire. All participants had professional or academic experience in information technology management, strategic planning, artificial intelligence, natural language processing, business intelligence, organizational decision-making, or digital transformation. In terms of gender, 102 participants were male, representing 54.8% of the total sample, and 84 participants were female, representing 45.2%. Regarding age, 44 participants were between 28 and 34 years old, 67 participants were between 35 and 41 years old, 45 participants were between 42 and 48 years old, and 30 participants were 49 years old or older. The educational level of the participants showed that 32 individuals held a bachelor's degree, 98 held a master's degree, and 56 held a doctoral degree. With respect to professional background, 65 participants had between 5 and 9 years of experience, 57 had between 10 and 14 years of experience, 39 had between 15 and 19 years of experience, and 25 had 20 years or more of professional experience. The participants were drawn from different organizational and academic settings in Tehran, including technology-based and consulting companies, banking and financial institutions, public-sector organizations, universities and research centers, and industrial or service organizations. This distribution indicates that the sample included individuals with sufficient knowledge of both strategic IT management and intelligent digital systems, making it appropriate for examining the cognitive and systems-theoretic implications of NLP-based intelligent systems in decision-making contexts.

Table 1. Descriptive Statistics of the Main Research Variables

Variable	Number of Items	Minimum	Maximum	Mean	Standard Deviation	Skewness	Kurtosis	Interpretation
Cognitive support of NLP-based systems	6	2.17	5.00	3.91	0.61	-0.42	0.31	High
Strategic alignment	6	1.83	5.00	3.84	0.66	-0.38	0.27	High
System integration	5	1.80	5.00	3.70	0.69	-0.29	-0.12	Moderate to high
Interpretability of intelligent outputs	5	1.60	5.00	3.64	0.72	-0.21	-0.18	Moderate to high
Trust in intelligent systems	5	1.80	5.00	3.76	0.68	-0.34	0.16	High
Perceived risk of excessive reliance	5	1.00	4.80	2.82	0.77	0.18	-0.36	Moderate
Decision quality	6	2.00	5.00	3.88	0.63	-0.40	0.22	High
Strategic IT decision-making effectiveness	7	2.00	5.00	3.86	0.65	-0.36	0.19	High

The descriptive statistics in Table 1 show that participants generally evaluated the role of NLP-based intelligent systems in strategic IT management positively. The highest mean score was related to cognitive support, indicating that participants perceived these systems as useful tools for reducing information-processing pressure, organizing unstructured textual information, supporting managerial attention, and improving the cognitive capacity of decision-makers. Strategic IT decision-making effectiveness and decision quality also received high mean scores, suggesting that participants believed NLP-based intelligent systems could contribute to more accurate, timely, and evidence-based strategic decisions. Strategic alignment and trust in intelligent systems were also evaluated at a high level, showing that participants viewed these technologies as relevant to organizational goals and sufficiently reliable when used within a structured managerial framework. System integration and interpretability were evaluated at a moderate-to-high level, indicating that although participants recognized the value of NLP-based systems, they also considered technical integration and explainability to be important conditions for effective use. Perceived risk of excessive reliance received a moderate mean score, which shows that participants were aware of possible limitations, including automation bias, overdependence on algorithmic outputs, reduced human judgment, and the risk of misinterpreting machine-generated recommendations. The skewness and kurtosis values were within acceptable ranges, indicating that the distribution of the main variables was sufficiently normal for conducting further inferential analyses.

Table 2. Correlation Matrix of the Main Research Variables

Variable	1	2	3	4	5	6	7	8
1. Cognitive support	1							
2. Strategic alignment	.58**	1						
3. System integration	.46**	.52**	1					
4. Interpretability	.49**	.44**	.48**	1				
5. Trust in intelligent systems	.53**	.50**	.42**	.56**	1			
6. Perceived risk of excessive reliance	-.31**	-.28**	-.24**	-.35**	-.41**	1		
7. Decision quality	.66**	.63**	.51**	.54**	.59**	-.37**	1	
8. Strategic IT decision-making effectiveness	.62**	.68**	.55**	.50**	.57**	-.39**	.74**	1

The correlation results presented in Table 2 indicate significant relationships among all main variables of the study. Cognitive support had a strong positive relationship with decision quality and strategic IT decision-making effectiveness, suggesting that when participants perceived NLP-based systems as cognitively supportive, they also reported higher levels of decision accuracy, speed, clarity, and strategic usefulness. Strategic alignment had the strongest correlation with strategic IT decision-making effectiveness among the independent variables, showing that the effectiveness of intelligent systems depends heavily on their compatibility with organizational goals, IT strategy, and managerial priorities. System integration was also positively associated with decision-making effectiveness, indicating that NLP-based systems are more useful when they are connected to existing organizational information systems, data infrastructures, communication platforms, and feedback mechanisms. Interpretability showed a significant positive relationship with both trust and decision-making effectiveness, demonstrating that explainable outputs increase managerial confidence and make intelligent recommendations more actionable. Trust in intelligent systems was positively related to decision quality and decision-making effectiveness, which means that managers are more likely to benefit from NLP-based tools when they perceive them as reliable, transparent, and relevant. Perceived risk of excessive reliance had negative correlations with all positive decision-related variables, showing that concerns about automation bias, dependency on machine-generated outputs, and reduced human oversight may weaken the perceived value of NLP-based systems. Overall, the correlation matrix supports the assumption that the effective use of NLP-based intelligent systems in strategic IT management depends on the interaction of cognitive, technological, organizational, and systemic factors.

Table 3. Multiple Regression Analysis Predicting Strategic IT Decision-Making Effectiveness

Predictor Variable	B	Standard Error	Beta	t	p	Tolerance	VIF
Constant	0.612	0.296	—	2.07	.040	—	—
Cognitive support	0.232	0.066	.261	3.52	< .001	.57	1.75
Strategic alignment	0.291	0.060	.334	4.85	< .001	.62	1.61
System integration	0.146	0.057	.168	2.56	.011	.69	1.45
Interpretability	0.105	0.053	.129	1.98	.049	.61	1.64
Trust in intelligent systems	0.159	0.061	.181	2.61	.010	.54	1.85
Perceived risk of excessive reliance	-0.103	0.045	-.143	-2.29	.023	.73	1.37

The regression analysis in Table 3 shows that the proposed predictors explained 61.8% of the variance in strategic IT decision-making effectiveness. This indicates that cognitive support, strategic alignment, system integration, interpretability, trust, and perceived risk collectively formed a strong explanatory model for understanding how NLP-based intelligent systems influence strategic IT decision-making. Strategic alignment was the strongest positive predictor, indicating that NLP-based systems are most effective when they are not treated as isolated technical tools but are embedded within the strategic direction, objectives, and decision architecture of the organization. Cognitive support was also a significant predictor, showing that the ability of NLP-based systems to process large volumes of textual information, summarize complex content, detect patterns, and support managerial sensemaking contributes substantially to strategic decision effectiveness. Trust in intelligent systems had a positive and significant effect, suggesting that managerial confidence in the reliability and relevance of system outputs is necessary for the practical use of these systems in high-level decision-making. System integration was another significant predictor, confirming that the strategic value of NLP-based tools increases when they are integrated with organizational databases, dashboards, reporting systems, enterprise platforms, and decision-support processes. Interpretability also had a significant positive effect, although its beta coefficient was smaller than those of strategic alignment and cognitive support. This finding shows that explainable and understandable system outputs improve decision-making by allowing managers to evaluate, question, and contextualize algorithmic recommendations. Perceived risk of excessive reliance had a significant negative effect, meaning that concerns about automation bias, loss of human judgment, and uncritical acceptance of machine-generated recommendations reduce the perceived effectiveness of NLP-based intelligent systems. The tolerance and VIF values indicate that multicollinearity was not a serious problem in the regression model.

Table 4. Qualitative Themes Extracted from Expert Interviews

Main Theme	Subthemes	Frequency of Emphasis Among Interviewees	Interpretive Meaning
NLP-based systems as cognitive augmentation tools	Reduction of cognitive overload; faster text interpretation; prioritization of complex information; support for managerial attention	21 of 24	NLP-based systems were viewed as tools that extend managerial cognition by helping decision-makers process large volumes of unstructured textual data more efficiently.
Strategic sensemaking and environmental scanning	Market monitoring; competitor analysis; policy and regulatory interpretation; identification of weak signals	19 of 24	Participants emphasized that NLP-based systems improve strategic awareness by transforming scattered textual information into interpretable patterns for decision-making.
Systems integration and organizational feedback	Connection with dashboards; integration with enterprise systems; feedback loops; cross-unit information flow	18 of 24	The usefulness of NLP-based systems was linked to their ability to operate as part of an organizational system rather than as independent analytical tools.
Trust, interpretability, and managerial acceptance	Explainable outputs; reliability of recommendations; transparency of data sources; human validation	17 of 24	Interviewees believed that trust depends on the degree to which managers understand how system outputs are produced and how they can be verified.
Risks of excessive reliance and automation bias	Overdependence on algorithms; reduced critical thinking; biased training data; misinterpretation of recommendations	20 of 24	Participants warned that NLP-based systems may weaken decision quality if managers replace judgment with passive acceptance of automated outputs.
Organizational learning and strategic adaptability	Knowledge creation; experience accumulation; continuous improvement; adaptive decision routines	16 of 24	NLP-based systems were considered valuable when their outputs contributed to organizational learning and helped firms adapt to environmental change.

The qualitative findings in Table 4 provide a deeper explanation of the statistical results by showing how experts understood the role of NLP-based intelligent systems in real organizational contexts. The most frequently emphasized theme was the role of NLP-based systems as cognitive augmentation tools. Participants repeatedly stated that strategic IT managers face large volumes of textual and semi-structured information, including reports, emails, customer feedback, policy documents, market news, technical documentation, and internal organizational records. In this context, NLP-based systems were perceived as tools that can reduce cognitive overload, support attention allocation, summarize complex information, and help decision-makers identify relevant signals from noisy information environments. The second major theme was strategic sensemaking and environmental scanning. Participants explained that NLP-based systems can support strategic management by detecting trends, monitoring competitors, interpreting regulatory changes, and identifying weak signals that may affect IT planning and organizational competitiveness. The third theme concerned systems integration and organizational feedback. Interviewees emphasized that the value of NLP-based systems depends on whether they are connected to organizational workflows, dashboards, enterprise systems, and feedback structures. In other words, NLP-based tools become strategically meaningful when their outputs circulate through the organization and influence planning, coordination, and corrective action. The fourth theme focused on trust, interpretability, and managerial acceptance. Participants argued that decision-makers are more likely to use intelligent recommendations when outputs are explainable, data sources are transparent, and human validation remains possible. The fifth theme highlighted the risks of excessive reliance and automation bias. Experts warned that NLP-based systems should not replace human judgment, because algorithmic outputs may reflect incomplete data, biased models, contextual misunderstanding, or technically correct but strategically inappropriate recommendations. The final theme showed that NLP-based systems can contribute to organizational learning and strategic adaptability when their outputs are stored, reviewed, compared with outcomes, and used to improve future decision routines.

Table 5. Integrated Mixed-Methods Interpretation of the Main Findings

Quantitative Finding	Supporting Qualitative Evidence	Integrated Interpretation
Cognitive support positively predicted strategic IT decision-making effectiveness.	Experts emphasized that NLP-based systems reduce cognitive overload, summarize complex textual data, and help managers identify relevant information.	NLP-based systems improve decision-making when they strengthen managerial cognition rather than replace human judgment.
Strategic alignment was the strongest predictor of decision-making effectiveness.	Participants stated that intelligent systems are useful only when connected to organizational goals, IT strategy, and managerial priorities.	The strategic value of NLP-based systems depends on their alignment with organizational direction and decision requirements.
System integration had a significant positive effect on decision-making effectiveness.	Interviewees highlighted the importance of linking NLP-based systems with dashboards, enterprise systems, databases, and organizational feedback mechanisms.	NLP-based systems become effective when embedded in the broader organizational system and decision infrastructure.
Interpretability and trust significantly improved decision-making effectiveness.	Experts noted that managers need transparent outputs, understandable recommendations, and opportunities for human validation.	Explainability and trust are necessary for the managerial acceptance and responsible use of intelligent systems.
Perceived risk of excessive reliance negatively predicted decision-making effectiveness.	Participants warned about automation bias, overdependence on algorithms, biased data, and reduced critical thinking.	The benefits of NLP-based systems are limited when organizations fail to preserve human oversight and critical judgment.
Decision quality had the strongest correlation with strategic IT decision-making effectiveness.	Participants described better decisions as those that are faster, evidence-based, context-aware, and strategically relevant.	Decision effectiveness improves when NLP-based systems enhance both the informational quality and the strategic relevance of managerial decisions.

Table 5 integrates the quantitative and qualitative findings and demonstrates that both phases of the study produced complementary evidence. The quantitative results showed that strategic alignment, cognitive support, system integration, interpretability, trust, and perceived risk significantly explain strategic IT decision-making effectiveness. The qualitative findings clarified why these relationships exist and how they operate in practice. For example, the statistical effect of cognitive support was supported by expert statements that NLP-based systems help managers process large volumes of unstructured information and reduce mental pressure during strategic analysis. Similarly, the strong predictive role of strategic alignment was explained by the qualitative finding that intelligent systems are effective only when their outputs are directly relevant to organizational objectives and IT strategy. The positive role of system integration was reinforced by participants' emphasis on feedback loops, dashboards, data flows, and cross-unit coordination. The effects of interpretability and trust were also supported by the interview findings, which showed that managers need to understand and verify system outputs before using them in strategic decisions. Finally, the negative effect of perceived risk was consistent with expert concerns about automation bias, algorithmic dependency, and reduced critical judgment.

Figure 1 summarizes the integrated interpretation of the quantitative and qualitative findings. The model shows that NLP-based intelligent systems influence strategic IT decision-making through two interconnected mechanisms: cognitive support and systems-level integration. At the cognitive level, these systems assist managers by reducing information overload, improving textual analysis, supporting sensemaking, increasing attention to strategic signals, and improving the clarity of decision alternatives. At the systems level, NLP-based tools contribute to organizational decision-making when they are integrated with information systems, strategic dashboards, organizational feedback loops, and cross-functional communication channels. The model also indicates that trust and interpretability act as enabling conditions. When system outputs are understandable and verifiable, managers are more likely to accept and use them in strategic decisions. However, perceived risk functions as a limiting condition, because excessive reliance on intelligent systems may reduce critical reflection and weaken human oversight. Therefore, the figure represents NLP-based intelligent systems not merely as technical applications but as socio-technical and cognitive-organizational subsystems that reshape how organizations collect information, interpret complexity, coordinate decisions, and adapt to strategic uncertainty.

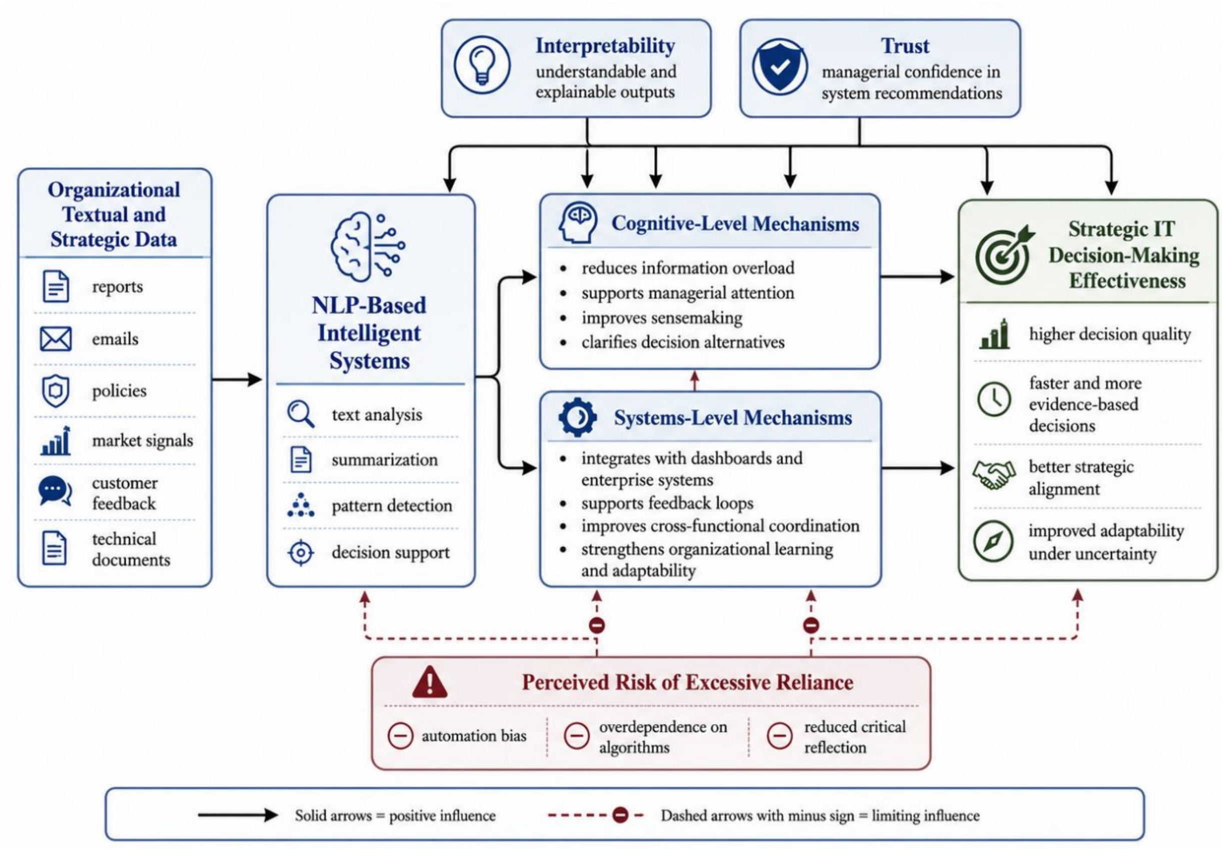

Figure 1. egrated Cognitive–Systems Model of NLP-Based Intelligent Systems in Strategic IT Management and Decision-Making

4. Discussion and Conclusion

The present study examined the cognitive and systems-theoretic implications of using NLP-based intelligent systems in strategic IT management and decision-making. The findings showed that participants perceived NLP-based intelligent systems as valuable tools for improving decision quality, reducing cognitive overload, supporting strategic sensemaking, strengthening organizational feedback, and increasing the effectiveness of strategic IT decision-making. The descriptive results indicated that cognitive support, decision quality, strategic alignment, and trust in intelligent systems were evaluated at high levels, while system integration and interpretability were evaluated at moderate-to-high levels. Perceived risk of excessive reliance was evaluated at a moderate level, suggesting that although participants recognized the benefits of NLP-based intelligent systems, they were also aware of the potential dangers of automation bias, algorithmic dependence, and reduced managerial critical reflection. These findings indicate that NLP-based systems are not perceived merely as technical instruments but as cognitive-organizational tools that reshape the way managers process information, interpret complexity, and formulate strategic decisions.

One of the central findings of the study was that cognitive support had a significant positive relationship with decision quality and strategic IT decision-making effectiveness. This result suggests that NLP-based intelligent systems improve strategic decision processes by helping managers organize, summarize, classify, and interpret large volumes of textual and semi-structured information. In strategic IT contexts, managers frequently work with reports, technical documentation, market signals, regulatory texts, internal communications, customer feedback, and policy documents. Without intelligent support, these information flows may generate cognitive overload and reduce the clarity of decision alternatives. The present finding is consistent with studies showing that NLP and AI can support the analysis of consumer opinion, tacit knowledge, real-time analytics, and narrative data by transforming unstructured information into interpretable patterns [4-6, 31]. It also aligns with research emphasizing the cognitive and communicative dimensions of AI and big data in modern business environments, where intelligent systems help organizations construct meaning from complex information ecosystems [1]. Therefore, the cognitive value of NLP-based systems can be understood as their capacity to extend managerial attention and support evidence-based reasoning.

The regression results showed that strategic alignment was the strongest predictor of strategic IT decision-making effectiveness. This finding is particularly important because it indicates that the usefulness of NLP-based intelligent systems depends less on their technical novelty and more on their alignment with organizational goals, IT strategy, decision routines, and managerial priorities. An intelligent system may be technically advanced, but if its outputs are not connected to strategic objectives, organizational performance indicators, or decision-making requirements, its practical value remains limited. This result is consistent with research on AI and strategic planning in VUCA environments, which emphasizes that AI must be incorporated into the strategic planning process in a way that enhances organizational adaptability and strategic coherence [3]. It also supports findings that IT-oriented executives are important drivers of AI adoption, because strategic leadership determines whether AI is used as a peripheral technology or as an integrated element of business and IT strategy [32]. Similarly, research on strategic project management under the influence of AI emphasizes that AI contributes to strategy execution when it is embedded in project, portfolio, and program management processes [33]. Thus, the present study confirms that strategic alignment is a necessary condition for converting NLP-based technical capacity into strategic decision-making effectiveness.

Another important finding was that system integration significantly predicted strategic IT decision-making effectiveness. This result shows that NLP-based intelligent systems become more useful when they are connected to dashboards, enterprise systems, databases, reporting structures, feedback loops, and cross-functional communication channels. From a systems-theoretic perspective, the effectiveness of an intelligent tool cannot be evaluated independently from the organizational system in which it is embedded. This finding is aligned with studies on intelligent automation and robotic process automation, which show that automation technologies generate organizational value when they are integrated into workflows, governance structures, and operational systems [23, 24]. It is also consistent with research on industrial foundation models and systems-oriented AI architectures, where digital infrastructures are understood as interconnected environments that support decision-making, simulation, feedback, and coordination [8]. Moreover, AI applications in energy systems have been described as influencing perception, cognition, decision-making, and deduction, which confirms that intelligent technologies operate across several interconnected levels of organizational functioning [7]. The present findings therefore support the view that NLP-based systems should be designed as components of socio-technical systems rather than as isolated analytical applications.

The findings also showed that interpretability and trust significantly contributed to strategic IT decision-making effectiveness. Participants were more likely to perceive NLP-based systems as useful when their outputs were understandable, explainable, verifiable, and relevant to managerial concerns. This result is theoretically meaningful because strategic decisions require accountability, contextual judgment, and the ability to justify choices to stakeholders. If managers do not understand the basis of system-generated recommendations, they may either reject the outputs or accept them uncritically. Both reactions can weaken decision quality. This finding is consistent with studies on AI in managerial decision-making and large language models, which identify reliability, transparency, and interpretability as key challenges in the adoption of AI-supported decision tools [20, 21]. It also aligns with research in health care and nursing, where AI systems are recognized as useful but must remain interpretable and professionally accountable because decisions affect human outcomes and require responsible judgment [17, 18]. In addition, studies on the convergence of AI, machine learning, and psychology emphasize that intelligent technologies must be examined in relation to human cognition, perception, and trust, because their effectiveness depends on how users understand and interact with them [19]. Therefore, the present study reinforces the idea that trust is not simply a psychological attitude toward technology; it is a function of explainability, relevance, and responsible system design.

The negative effect of perceived risk of excessive reliance on strategic IT decision-making effectiveness was another key finding. Participants believed that NLP-based intelligent systems may weaken decision-making if managers become overly dependent on algorithmic recommendations or treat machine-generated outputs as objective truth. This finding is consistent with the broader literature on NLP challenges, which shows that language-processing systems face problems related to ambiguity, context dependence, semantic complexity, domain specificity, and data quality [22]. In strategic IT management, such limitations can have serious consequences because decisions often involve long-term investments, organizational restructuring, cybersecurity governance, and digital transformation. The finding also corresponds with research on social engineering and cybersecurity, which shows that technical systems cannot fully replace human awareness, contextual reasoning, and psychological insight [26]. Similarly, studies on AI in cybersecurity and telecommunications emphasize that intelligent systems can strengthen detection and response, but their effectiveness depends on governance, monitoring, and human oversight [25]. Therefore, the present study suggests that the strategic use of NLP-based systems must be accompanied by critical reflection, validation procedures, and managerial responsibility.

The qualitative findings deepened the interpretation of the quantitative results by identifying six major themes: cognitive augmentation, strategic sensemaking and environmental scanning, systems integration and organizational feedback, trust and interpretability, risks of excessive reliance, and organizational learning and adaptability. These themes show that experts viewed NLP-based systems as tools that support both individual cognition and organizational systems. The theme of strategic sensemaking is especially important because strategic IT management requires managers to identify weak signals, interpret environmental changes, and connect technological developments to organizational direction. This finding is supported by studies showing that AI can enhance decision-making in finance, financial reporting, strategic financing, and risk management through improved accuracy, timeliness, and analytical depth [9-11, 28]. It also aligns with research on business analytics and AI as a roadmap to data-driven success, where intelligent systems are positioned as enablers of systematic analysis and strategic responsiveness [2]. Therefore, NLP-based intelligent systems can be understood as mechanisms for strengthening organizational sensemaking under uncertainty.

The findings further suggest that NLP-based intelligent systems may contribute to organizational learning and strategic adaptability. Participants emphasized that these systems become more valuable when outputs are stored, evaluated, compared with outcomes, and used to improve future decisions. This interpretation is consistent with studies showing that AI can foster employee engagement and knowledge sharing, support public-sector reform, and improve the interpretation of feedback and engagement data [13, 15, 16]. It is also compatible with research on cognitive technology in human resource management and AI in HRM, where intelligent systems are viewed as tools that can improve managerial experience, workforce analytics, and organizational knowledge processes [12, 14]. In strategic IT management, the same logic applies: NLP-based systems can support learning by converting dispersed textual experiences into structured organizational knowledge. This learning function is central to a systems-theoretic interpretation because it shows that intelligent systems influence not only individual decisions but also the feedback loops through which organizations adapt over time.

The results also have implications for business model transformation and strategic value creation. The positive association between NLP-based system use and decision-making effectiveness suggests that intelligent systems can support organizations in identifying new opportunities, improving responsiveness, and aligning IT investments with business value. This interpretation is consistent with research on disruptive business value models in the digital era, which shows that digital technologies reshape how firms create and capture value [29]. It is also supported by studies in marketing that classify AI and machine learning applications as tools for segmentation, personalization, prediction, and customer understanding [30]. In addition, research on climate-related risk reporting indicates that technology can improve corporate governance and strategic accountability by supporting the management and reporting of complex risk information [27]. These findings suggest that NLP-based systems are relevant not only for internal IT management but also for broader organizational transformation, stakeholder communication, and strategic positioning.

Finally, the integrated model developed in this study indicates that NLP-based intelligent systems influence strategic IT decision-making through the interaction of enabling and limiting conditions. Cognitive-level mechanisms and systems-level mechanisms jointly explain how these tools enhance decision effectiveness. Interpretability and trust function as enabling conditions, while perceived risk of excessive reliance functions as a limiting condition. This integrated interpretation is consistent with broader discussions of advanced AI systems, including modular approaches to artificial general intelligence and multimodal intelligent systems, which suggest that future AI will increasingly combine language, perception, communication, and decision support [34, 35]. However, the present findings emphasize that even as AI systems become more advanced, their organizational value depends on how they are governed, interpreted, integrated, and used by human decision-makers. Therefore, the study contributes to the literature by showing that the strategic use of NLP-based intelligent systems should be understood as a cognitive and systems-level transformation rather than a purely technical implementation.

This study had several limitations that should be considered when interpreting the findings. First, the study was conducted among IT managers, strategic planning specialists, digital transformation experts, and related professionals in Tehran; therefore, the findings may not be fully generalizable to organizations in other cities, countries, or institutional environments. Second, the quantitative phase relied on self-reported questionnaire data, which may be influenced by participants' subjective perceptions, professional optimism toward AI, or previous experiences with intelligent systems. Third, although the mixed-methods design provided both statistical and interpretive evidence, the study was cross-sectional and therefore could not establish causal relationships over time. Fourth, NLP-based intelligent systems vary substantially in terms of technical sophistication, domain specialization, explainability, data quality, and organizational integration; therefore, participants may have evaluated different types of systems based on different organizational experiences. Finally, the study focused on cognitive and systems-theoretic implications at the managerial level and did not directly evaluate the technical performance of specific NLP models or platforms.

Future studies should examine the use of NLP-based intelligent systems in strategic IT management across different organizational sectors, geographic regions, and cultural contexts to determine whether the model proposed in this study remains stable across diverse environments. Longitudinal research is also recommended to investigate how the effects of NLP-based systems on decision quality, strategic alignment, trust, and organizational learning change over time as users gain experience and systems become more deeply embedded in organizational routines. Future research could also compare different types of NLP applications, such as large language models, sentiment analysis tools, document classification systems, intelligent dashboards, and conversational decision-support agents. In addition, experimental and quasi-experimental studies could be designed to assess whether the use of NLP-based systems actually improves decision accuracy, speed, and strategic consistency compared with traditional decision-making methods. Further research should also explore the ethical, psychological, and governance-related dimensions of automation bias, explainability, accountability, and human oversight in strategic decision environments.

Organizations that intend to use NLP-based intelligent systems in strategic IT management should treat these systems as decision-support mechanisms rather than substitutes for managerial judgment. Before implementation, managers should ensure that NLP tools are aligned with organizational strategy, IT governance structures, and specific decision-making needs. Practical deployment should include clear procedures for validating system outputs, documenting assumptions, reviewing recommendations, and preserving human accountability. Organizations should also invest in training managers and decision-makers to understand the capabilities and limitations of NLP-based systems, especially in relation to interpretability, data quality, bias, and contextual judgment. In addition, NLP systems should be integrated with enterprise platforms, dashboards, knowledge management systems, and feedback mechanisms so that their outputs contribute to organizational learning rather than remaining isolated technical results. Finally, organizations should develop policies to prevent excessive reliance on automated recommendations and encourage a balanced decision culture in which intelligent systems enhance, but do not replace, critical strategic thinking.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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