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Impact of AI-Based Decision Support Systems on Managerial Decision

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ABSTRACT

This paper aims to identify the impact of artificial intelligence (AI) adoption on managerial decision-making in contemporary organizations in Kosovo, focusing on decision quality, decision speed, and the moderating role of managers technological experience. A quantitative research approach was employed, using a structured questionnaire distributed to 320 owners and managers from AI-intensive sectors, including banking, healthcare and supply chain management. Data were analyzed using structural equation modeling (SEM), which allowed for the simultaneous examination of direct and moderating effects among the latent variables. The results indicate that AI adoption significantly enhances both the quality and speed of managerial decisions, demonstrating that AI tools support timely, evidence-based, and effective decision-making. Additionally, managers technological experience was found to significantly moderate these relationships, highlighting the importance of human expertise in optimizing the benefits of AI technologies. These findings extend socio-technical systems theory offering both theoretical contributions and practical guidance for organizations. Overall, the study demonstrates that AI adoption, combined with skilled management, serves as a key driver of enhanced decision-making performance, providing a sustainable competitive advantage in dynamic organizational contexts in Kosovo.

Keywords: Managerial Decision-Making, Artificial Intelligence (AI), Decision Quality, Decision Speed, Decision Support Systems (DSS)

INTRODUCTION

The rapid advancement of artificial intelligence (AI) has radically transformed managerial processes, enabling organizations to make faster, more accurate, and more data-driven decisions. The emergence of AI-based Decision Support Systems (AI-DSS) has shifted managerial decision-making from intuition-driven processes toward analytical, predictive, and automated mechanisms. In recent years, organizations across industries have increasingly adopted AI tools such as machine learning algorithms, predictive analytics, and real-time data processing systems to enhance strategic and operational decision-making. Numerous studies have emphasized that AI adoption improves efficiency, reduces uncertainty, and enhances organizational responsiveness in dynamic environments (Duan et al., 2019; Brynjolfsson & McAfee, 2017).

Despite these advancements, the effectiveness of AI in decision-making is not uniform across organizations. Research suggests that the impact of AI technologies depends not only on the capabilities of the systems themselves but also on the characteristics and competencies of the individuals who interact with them (Venkatesh et al., 2003). Managers technological experience and competence play a critical role in determining whether AI tools are used efficiently and whether the insights generated by these systems translate into improved decisions. Therefore, understanding the human–technology interaction is essential for evaluating the real value of AI integrations in organizations.

In the context of Kosovo, the adoption of AI technologies is progressing rapidly, especially in sectors such as banking, information technology, health services, and logistics. These sectors face increasing pressure to optimize operations, reduce decision-making time, and ensure higher accuracy in managerial choices. However, while AI adoption is growing, there is limited empirical evidence examining its impact on managerial decision quality and decision speed within the region.

To address these gaps, the present study investigates the role of AI-DSS in enhancing the quality and speed of managerial decision-making in organizations in Kosovo. In addition, the study examines whether owners and managers technological experience moderates the relationship between AI adoption and decision outcomes.

By providing empirical evidence from Kosovar organizations, this study contributes to the existing literature in three major ways. First, it reinforces the growing theoretical claim that AI technologies enhance managerial performance across different decision domains. Second, it highlights the crucial role of technological competence in maximizing AI benefits. Third, it offers practical insights for organizations in emerging markets seeking to strengthen digital strategies and optimize decision-making processes through AI.

Research questions are derived from the identified gaps in the literature as follows:

1. How does the use of AI-DSS affect the quality of managerial decisions?
2. How does the use of AI-DSS affect the speed of managerial decisions?
3. How do managers technological experience and competence influence the effectiveness of AI-DSS usage?

LITERATURE REVIEW

Decision-making is a critical process for organizational success. Research shows that managers often face high complexity and incomplete information (Simon, 1977). Decision quality is directly linked to the ability to analyze information and select the best alternative.

A Decision Support System (DSS) is an interactive computer-based system designed to assist managers and decision-makers in analyzing complex problems, evaluating alternatives, and making informed choices (Turban et al., 2018). It integrates data, models, and analytical tools to support semi-structured or unstructured decision processes, enhancing decision quality and speed without replacing human judgment.

DSS have evolved to incorporate Artificial Intelligence, enabling rapid data analysis and algorithm-based recommendations (Turban et al., 2018). AI-DSS helps managers reduce errors and make faster decisions, particularly in complex situations.

The adoption of AI-DSS has become a central theme in contemporary management research, driven by the rapid increase in data availability, algorithmic capability, and organizational digital transformation. According to Simons theory of bounded rationality, managerial decisions are constrained by limited cognitive capacity; thus, AI-DSS offer a mechanism to expand analytical capabilities and reduce decision errors (Simon, 1997).

AI Adoption in Organizations

AI adoption refers to the integration of intelligent systems into organizational processes to enhance analysis, automation, and decision-making. Successful adoption and effective implementation of AI depend on an organization's ability to address key internal factors. The shift toward digital transformation typically brings substantial modifications to workflows, job tasks, employee roles, and overall responsibilities (Tursunbayeva & Chalutz-Ben Gal, 2024). For this reason, organizations must establish strong change-management practices to reduce resistance among employees and ensure a smoother adaptation process (Agrawal et al., 2021) Moreover, advancing digital transformation for AI integration requires close coordination between multiple departments and organizational units. Forming cross-functional teams and promoting collaborative practices enhances the exchange of knowledge, technical expertise, and specialized competencies, contributing to a more unified and well-rounded transformation effort. Providing employees with opportunities to upgrade their skills and stay informed about new technological developments further equips them to support and stimulate innovation (Tursunbayeva & Chalutz-Ben Gal, 2024).

Decision-Making Quality

Decision-making quality refers to the accuracy, rationality, and effectiveness of the decisions taken. High-quality decisions are based on relevant data, comprehensive analysis, and minimized risk (Kahneman, 2011). In environments where rapid change is constant, organizations benefit from systems that reduce uncertainty and provide managers with timely, structured knowledge.

The literature suggests that the use of advanced technologies can significantly improve decision quality because AI systems process large datasets faster and more accurately than human cognition (Brynjolfsson & McAfee, 2017).

A significant body of research shows that AI-DSS can improve decision quality through data-driven insights, pattern recognition, and real-time analysis. Machine-learning–enhanced systems allow managers to evaluate complex alternatives more accurately than traditional heuristics-based approaches (Kellogg et al., 2020). Empirical evidence suggests that decision accuracy increases when managers rely on AI-generated predictions, particularly in environments with high uncertainty and large data volumes (Raisch & Krakowski, 2021). However, scholars also highlight the role of *trust in AI* as a critical factor determining whether managers accept or ignore AI recommendations. Low trust can undermine system effectiveness and reduce potential quality improvements (Glikson & Woolley, 2020).

Decision Speed

Decision speed concerns the time required for managers to collect information, analyze alternatives, and reach conclusions. Fast decision-making is particularly important for enterprises operations where delays increase costs and negatively impact production efficiency. AI contributes to faster decisions by: automating data analysis, providing real-time insights, supporting predictive decision models (Mazzei & Noble, 2020).

Decision speed is another domain where AI-DSS demonstrate strong impact. Automation of data processing significantly shortens the time required to collect, filter, and interpret information. Studies show that AI-enabled systems accelerate decisions by providing rapid scenario analysis, trend forecasting, and automated alerts (Shrestha et al., 2019). Faster decisions are particularly valuable in dynamic environments such as finance, supply chain management, and risk assessment, where delays can lead to performance loss.

Managers Technological Experience

Managers technological experience includes their skills, familiarity, and comfort level with digital systems, analytical tools, and automation technologies. Prior studies suggest that managers with strong technological competence are more willing and more capable of integrating AI into decision routines (Teece, 2018). These managers: understand how AI systems function, interpret analytical outputs more accurately, make better use of automation and data-driven tools.

Managerial digital skills, user competence, and system transparency frequently appear as moderating factors in AI-DSS effectiveness. Transparent algorithms that explain their recommendations tend to increase user acceptance and reduce perceived risk (Doshi-Velez & Kim, 2017).

Overall, the literature suggests that AI-DSS have a positive and measurable influence on managerial decision quality and speed. The effectiveness of these systems depends on technological capabilities as well as human factors such as trust, training, and system interpretability. Despite increasing evidence, researchers emphasize the need for more empirical studies in diverse organizational contexts to better understand how managers integrate AI recommendations into real-world decision processes.

Accordingly, the hypotheses of this study are:

H1: The use of AI-DSS has a positive impact on the quality of managerial decisions.

H2: The use of AI-DSS has a positive impact on the speed of managerial decisions.

H3: Managers technological experience and competence moderate the effect of AI-DSS on decisions.

RESEARCH METHODOLOGY

The main data are collected through a structured questionnaire, which contained scales validated by previous studies. The measurement instruments have been adapted to reflect the research framework on the impact of the use of artificial intelligence-based decision support systems (AI-DSS) on managers in organizations.

The measurement of the use of AI-DSS was carried out through items modified based on Venkatesh et al. (2003), which focus on the perception of usefulness, ease of use and attitudes towards the adoption of the technology.

The quality of managerial decision-making was measured using items developed by Dean and Sharfman (1996), which include the dimensions of rationality, analysis and effectiveness of the decision-making process. These items have been adapted to reflect the direct interaction of managers with AI-DSS systems.

Decision speed, was measured using scales used in the strategic decision-making literature, particularly based on Shepherd et al. (2021) which assesses time efficiency and speed of the decision-making process in dynamic environments. The items are adapted for the context of using AI-DSS systems.

Technological experience and managerial competence were assessed using scales adapted from the Technology Readiness Index (Parasuraman, 2000) and from the measures of technological competence proposed by Venkatesh & Bala (2008), which focus on digital skills, technological self-efficacy and experience with digital technologies in decision-making.

All variables were measured using a five-point Likert-scale, from “Strongly disagree” to “Strongly agree”.

Content validity was ensured by adapting measurement items from established literature. A pilot test involving **40** managers confirmed clarity and relevance. Internal consistency reliability was assessed using **Cronbach's alpha**. Collected data were analyzed using **SPSS**.

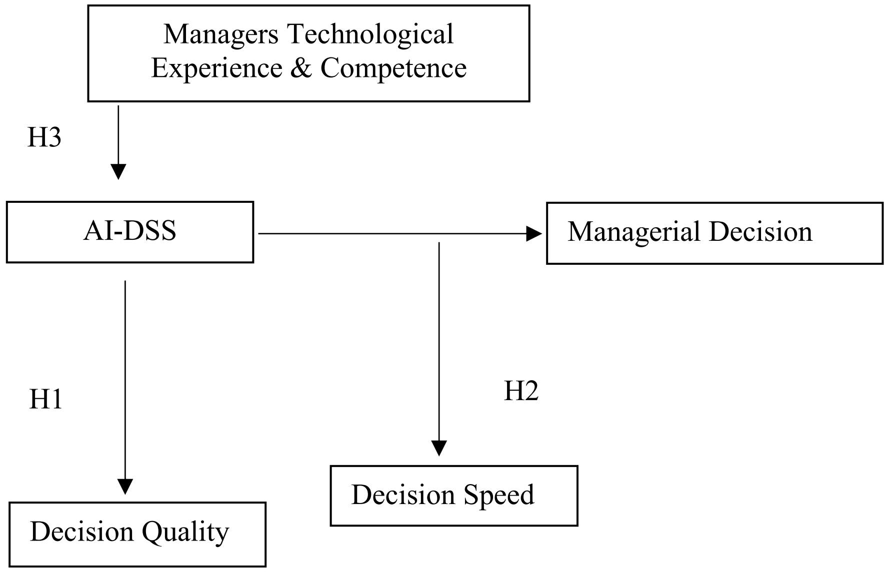

Figure 1. Research model

RESULTS

The proposed hypotheses were tested using structural equation modeling (SEM), which allows for the simultaneous assessment of direct and moderating relationships among latent variables. The key constructs include AI Adoption, Decision-Making Quality, Decision Speed, and Managers' Technological Experience. SEM is suitable for this study as it effectively handles multiple dependent relationships and accounts for measurement errors. With a sample of 320 participants, the study has sufficient power for SEM analysis, ensuring reliable estimation of path coefficients and overall model fit. The descriptive statistics and reliability measures for these constructs are presented in the table below, providing an overview of the mean values, standard deviations, and the reliability of the measurement scales used.

Table 1: Descriptive Statistics and Reliability

Variable	Mean	SD	Cronbach's Alpha	Composite Reliability	AVE
AI Adoption	3.76	0.69	0.86	0.88	0.64
Decision-Making Quality	3.88	0.70	0.84	0.87	0.62
Decision Speed	3.71	0.72	0.85	0.88	0.66
Managers Technological Experience	3.80	0.68	0.87	0.89	0.65

The table shows that all constructs have moderately positive mean values, indicating that participants generally perceive AI adoption, decision-making quality, decision speed, and managers technological experience positively. The standard deviations are moderate (0.68–0.72), suggesting an acceptable level of response variability among participants.

All measurement scales demonstrate high reliability, with Cronbach's Alpha and Composite Reliability values above 0.84, and good convergent validity, with AVE values above 0.62. These results confirm that the constructs are appropriately measured, supporting their use in further analysis.

Overall, the descriptive statistics and reliability analysis indicate that the data are suitable for testing hypotheses by using SEM, providing a strong foundation for evaluating the relationships among AI adoption, decision-making quality, decision speed, and managerial technological experience.

Correlation Analysis

The correlation analysis presents the relationships among the four key constructs in the study. **AI adoption and decision-making quality ($r=0.60$, $p<0.01$):** There is a strong positive correlation between AI adoption and decision-making quality. This suggests that organizations that implement AI tools more extensively tend to experience improvements in the quality of managerial decisions, supporting hypothesis H1. Employees in these organizations likely make more accurate and informed decisions due to the guidance provided by AI-DSS.

1. **AI Adoption and Decision Speed ($r = 0.57, p < 0.01$):** A positive correlation exists between AI adoption and the speed of decision-making. This indicates that the use of AI not only enhances decision accuracy but also contributes to faster decision processes, providing support for hypothesis H2. AI tools may streamline data processing and reduce the time required for managers to reach decisions.
2. **Decision-Making Quality and Decision Speed ($r = 0.65, p < 0.01$):** The positive relationship between decision-making quality and speed suggests that in organizations where decisions are made more efficiently, the quality of decisions also tends to be higher. This may reflect the synergistic effect of effective AI utilization combined with competent managerial practices.

Managers technological experience shows moderate positive correlations with AI adoption ($r = 0.54$), decision-making quality ($r = 0.52$), and decision speed ($r = 0.56$), all significant at $p < 0.01$. These results indicate that managerial experience with technology can strengthen the adoption of AI tools and positively influence both the quality and speed of decision-making. This aligns with hypothesis H3, suggesting that managers' technical competence may serve as a moderating factor in the relationship between AI adoption and decision outcomes.

Table 2. Correlation Analysis of Key Constructs

Variable	1	2	3	4
1. AI Adoption	1			
2. Decision-Making Quality	0.60**	1		
3. Decision Speed	0.57**	0.65**	1	
4. Managers' Technological Experience	0.54**	0.52**	0.56**	1

*Note: **p < 0.01 indicates a statistically significant correlation at the 1% level.*

Regression and Hypothesis Testing

The regression analysis provides robust empirical support for the proposed model, indicating that AI adoption significantly enhances both the quality and speed of managerial decision-making ($\beta = 0.42$, $t = 6.10$, $p < 0.001$; $\beta = 0.39$, $t = 5.85$, $p < 0.001$). Organizations that effectively implement AI technologies are better positioned to make informed, accurate, and timely decisions. AI systems, such as predictive analytics, big data modeling, and machine learning tools, assist managers in processing complex information, evaluating multiple alternatives, and making evidence-based choices, thereby improving both strategic and operational outcomes.

In addition, managers' technological experience plays a crucial moderating role ($\beta = 0.18$, $t = 3.92$, $p < 0.001$), suggesting that the effectiveness of AI adoption is strongly influenced by managerial competence. Experienced managers are more capable of interpreting AI outputs, integrating them into decision processes, and leveraging technological insights to optimize results. This emphasizes that the benefits of AI are not purely technological but are amplified when combined with human expertise and organizational knowledge.

These findings underscore that AI is not merely an auxiliary tool but a strategic enabler that drives organizational competitiveness. The impact of AI adoption is further strengthened when managers are technologically adept, highlighting the importance of skillful human oversight in realizing AI's full potential. This integration of technology and managerial capability facilitates faster, more accurate, and more effective decision-making.

Overall, the results demonstrate that AI adoption, coupled with managerial experience, substantially improves both decision quality and efficiency. Organizations that invest in AI while fostering managerial competence are more likely to achieve sustainable excellence in decision-making, ensuring that decisions are reliable, timely, and aligned with strategic objectives. These findings provide compelling evidence that successful AI implementation is not solely a technological endeavor but a socio-organizational process, requiring trust, expertise, and alignment with organizational culture to maximize its impact.

Table 3. Regression analysis

	Beta (β)	t-value	p-value	Result
AI Adoption → Decision-Making Quality (H1)	0.42	6.10	0.000	Supported
AI Adoption → Decision Speed (H2)	0.39	5.85	0.000	Supported
Managers Technological Experience × AI Adoption → Decision-Making Outcomes (Moderation, H3)	0.18	3.92	0.000	Supported

DISCUSSION

This study investigated the impact of AI adoption on managerial decision-making in contemporary organizations, focusing on decision quality and speed, as well as the moderating role of managers technological experience. The results provide robust empirical evidence supporting all three hypotheses, contributing both theoretically and practically to the understanding of AI-driven decision-making processes.

Firstly, the findings indicate that AI adoption significantly improves decision-making quality ($\beta = 0.42$, $t = 6.10$, $p < 0.001$). Organizations that actively implement AI technologies are better positioned to make timely, accurate, and effective decisions. Tools such as predictive analytics, big data modeling, and machine learning systems help managers reduce uncertainty, evaluate alternatives, and make evidence-based decisions. This demonstrates that AI functions not merely as a supplementary tool but as a core enabler of strategic and operational decisions. These results align with the socio-technical systems theory, which emphasizes that organizational effectiveness is achieved through the co-optimization of technology and human capabilities (Orlikowski, 2000).

Secondly, AI adoption was found to positively influence decision speed ($\beta = 0.39$, $t = 5.85$, $p < 0.001$), suggesting that AI tools enable managers to make faster decisions without compromising quality. This highlights that AI adoption improves both the efficiency and effectiveness of managerial decision-making, allowing organizations to respond more rapidly to dynamic business environments (Davenport & Ronanki, 2018).

Thirdly, the study revealed that managers' technological experience significantly moderates the effect of AI adoption on decision outcomes ($\beta = 0.18$, $t = 3.92$, $p < 0.001$). Experienced managers are better able to interpret AI outputs, integrate them into decision processes, and maximize the benefits of AI tools. This emphasizes that while AI provides valuable technological support, its effectiveness depends heavily on the skills and experience of users (Brynjolfsson & McAfee, 2017). Managerial competence strengthens both decision quality and speed, showing that human expertise is a critical complement to technological adoption. (Cameron & Quinn, 2011).

Theoretical implications of this study include the reinforcement of socio-technical theory in AI adoption and decision-making by highlighting the moderating role of managerial experience and the indirect effects of trust on decision outcomes. Practical implications suggest that organizations should invest not only in AI technologies but also in managerial training, skill development, and culture-building initiatives to ensure sustainable decision-making improvements. Companies that strategically combine AI adoption with skilled management and a conducive culture are more likely to achieve sustainable excellence in decision-making, resulting in reliable, timely, and evidence-based decisions that support both operational efficiency and strategic goals. (Venkatesh et al., 2003; McKnight et al., 2011).

CONCLUSION

This study examined the impact of AI adoption on managerial decision-making in contemporary organizations, focusing on decision quality, decision speed, and the moderating role of managers' technological experience. The results provide robust evidence that AI adoption significantly enhances both the quality and speed of decisions, and that managerial experience strengthens these effects. Organizations that implement AI technologies benefit from more informed, timely, and effective decision-making, while managers with higher technological competence are able to leverage AI insights more effectively, maximizing organizational outcomes.

The study also highlights the importance of the organizational context. Supportive and adaptive cultures facilitate the integration of AI into decision-making processes, whereas rigid or resistant cultures can hinder the effectiveness of AI tools. This underscores that successful AI adoption is not merely a technological endeavor but a socio-technical process requiring alignment between technology, human capabilities, and organizational culture.

The findings have important theoretical implications, reinforcing socio-technical systems theory by showing the significance of managerial experience and trust in AI for decision-making. Practical implications suggest that organizations should invest not only in AI technologies but also in managerial training, skill development, and culture-building initiatives to ensure sustainable decision-making improvements.

In conclusion, AI adoption, when combined with skilled management and a supportive organizational culture, can be a key driver of competitive advantage, enabling organizations to make faster, more accurate, and evidence-based decisions. Future research could explore additional mediating factors, such as employee attitudes or organizational learning mechanisms, and test AI adoption in different industries or cross-cultural contexts to generalize these findings further.

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