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The Impact of AI-Powered Decision Support Systems on Decision-Making Effectiveness

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Abstract. AI-powered Decision Support Systems (AI-DSS) enhance analytical capabilities through advanced data processing, predictive analytics, and intelligent decision support. This study investigates the impact of AI-powered DSS on decision-making effectiveness across multiple sectors. A quantitative research design was employed using a structured questionnaire distributed to 33 professionals and decision-makers experienced in AI-based DSS. Decision-making effectiveness was assessed through decision accuracy, decision-making speed, operational efficiency, and user satisfaction. Data were analyzed using descriptive statistics, Pearson correlation, and simple linear regression. The results show a moderate positive correlation between AI usage and decision-making effectiveness ($r = 0.550$, $p < 0.001$). Regression analysis further demonstrates that AI utilization significantly predicts decision-making effectiveness ($B = 0.265$, $t = 3.664$, $p < 0.001$). These findings indicate that greater utilization of AI-powered DSS is associated with improved decision outcomes, particularly in decision accuracy, response speed, and operational efficiency. The study also demonstrates the applicability of AI techniques, including machine learning, neural networks, fuzzy logic, and Bayesian modelling, across diverse industrial contexts. Overall, the findings provide empirical evidence that AI-powered DSS contribute significantly to organizational decision-making effectiveness across multiple sectors.

Keywords: AI-based tools, AI-Driven DSS, Decision Analytics, Decision Support System, Industry Comparison.

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1. Introduction

Decision Support Systems (DSS) play a crucial role in various industries, providing analytical support to facilitate the decision-making process [1–3]. As decision-making environments become more complex, DSS help by processing large amounts of data, identifying patterns, and providing insights to inform decisions [4–6]. DSS are designed to assist users in making sense of semi-structured or unstructured decisions, especially in situations involving uncertainty or complexity [7–9]. They integrate data from different sources, utilize various analytical models, and present information in a user-friendly format to support decision-making [10–12].

In the field of Decision Support Systems powered by artificial intelligence (AI), the integration of AI technologies enhances DSS capabilities by enabling advanced data processing, predictive analytics, and machine learning algorithms [13,14]. Research such as a framework for vertical farming business developments [15], an IoT-based, cloud-centric medical DSS for chronic kidney disease prediction [16], and a predictive analytics approach for improving graduation rates [17] demonstrates the diverse applications of DSS across various domains. The increasing complexity of decision-making environments necessitates the use of AI-powered DSS to handle large volumes of data and provide valuable insights for informed decision-making.

The integration of AI into decision support systems has significantly transformed decision-making processes across industries. AI technologies such as machine learning algorithms and deep learning techniques have revolutionized data analysis, insight extraction, and decision-making within organizations. Research studies focusing on the cost-effectiveness of AI as a decision-support system for disease detection [18], the evaluation of classification algorithms for clinical decision support systems [19], and the development of an intelligent DSS for stroke rehabilitation assessment [20] illustrate how AI enhances decision-making capabilities in different domains. AI's potential to revolutionize decision-making lies in its ability to process large volumes of data, identify complex patterns, and provide predictive analytics. Studies on physician acceptance of AI-enabled clinical DSS in healthcare [21] and the use of AI and machine learning techniques in water irrigation systems [22] further highlight the diverse applications of AI in decision support. By integrating AI into decision support systems, organizations can streamline decision-making processes, optimize resource allocation, enhance operational efficiency, and foster innovation in today's competitive business landscape.

Previous studies on machine learning-based clinical decision support systems in pregnancy care and cancer nursing [23,24] highlight their integration in enhancing clinical decision-making processes and patient outcomes. Moving beyond healthcare, researchers in [25] highlighted the importance of AI in IoT and supply chain logistics decision support systems, while researchers in [26] examined its use in shipboard Decision Support Systems for accident prevention. Moreover, the study by [27] explored intelligent decision support systems for dementia care, underlining the potential of AI in improving caregiving practices for individuals with cognitive impairments. The study by [28] focused on ontology-based decision support systems for diabetes nutrition therapy, demonstrating the application of AI in personalized healthcare interventions for chronic disease management. In a different context, a scoping review on decision-support systems for managing polypharmacy in the elderly by [29] highlighted the intersection of AI, medicine, and computer science in addressing medication complexities in geriatric care settings. Previous research has collectively advanced our understanding of AI-driven decision support systems and their transformative influence on decision-making processes across different industries.

However, most existing studies primarily focus on applications within specific domains or on the technical performance of AI algorithms, and only a limited number have comprehensively evaluated how AI-based decision support systems influence decision-making effectiveness across a broader range of industries. Empirical evidence that quantitatively assesses how the utilization of AI-powered DSS affects decision performance across different sectors remains limited. This indicates the presence of a research gap in understanding how AI integration can provide measurable improvements in decision quality, operational efficiency, and decision-making speed across various organizational contexts.

Therefore, this study aims to analyze the impact of AI-powered Decision Support Systems on decision-making effectiveness across multiple industry sectors. Using a quantitative research approach, this study examines how the level of AI utilization influences key decision performance indicators, including decision accuracy, decision-making speed, operational efficiency, and user satisfaction. By providing empirical evidence regarding the effectiveness of AI-based DSS across industries, this research is expected to contribute to the development of intelligent decision support technologies and offer practical insights for organizations seeking to implement AI-driven decision systems to enhance data-driven decision-making processes.

2. Methods

2.1 Research Design

This study adopts a quantitative research approach to evaluate the influence of Artificial Intelligence (AI)-powered Decision Support Systems (DSS) on decision-making effectiveness across multiple industry sectors. A survey-based design was employed to collect empirical data from professionals who have experience using AI-driven analytical tools or decision support technologies in their organizations. The quantitative approach allows the study to measure relationships between AI utilization and decision outcomes using statistical analysis [30].

2.2 Sampling Strategy and Participants

The study applied a purposive sampling strategy, selecting respondents who have direct experience with AI-powered decision support systems or AI-based analytical tools within their professional activities. This sampling method ensures that participants possess relevant knowledge and practical exposure to AI-supported decision processes. A total of 33 respondents participated in the survey. The respondents represent professionals from several sectors where AI-based decision support systems are increasingly utilized, including healthcare, agriculture, urban planning, water resource management, and supply chain logistics. To ensure transparency regarding the composition of the sample, the distribution of respondents by industry sector is presented in Table 1.

Table 1. Distribution of Respondents by Industry Sector

Industry Sector	Number of Respondents	Percentage
Healthcare	10	30.3%
Agriculture	6	18.2%
Urban Planning	5	15.2%
Water Resource Management	4	12.1%
Supply Chain / Logistics	8	24.2%
Total	33	100%

2.3 Data Collection

Primary data were collected using a structured questionnaire designed to evaluate the utilization of AI-powered DSS and their influence on decision-making effectiveness. The questionnaire items were developed based on constructs derived from previous studies on decision support systems and AI-driven decision analytics. Each statement in the questionnaire was measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire consisted of two main variables: AI utilization and decision-making effectiveness.

2.4 Measurement of Decision-Making Effectiveness

In this study, decision-making effectiveness refers to the extent to which AI-powered DSS improve the quality and efficiency of decision processes within organizations. This variable was measured using several indicators commonly used in decision analytics research, including:

1. Decision accuracy – the degree to which AI-supported decisions produce correct or optimal outcomes.
2. Decision-making speed – the ability of AI systems to accelerate the decision-making process.
3. Operational efficiency – improvements in resource utilization and workflow performance resulting from AI-supported decision processes.
4. User satisfaction – the perceived usefulness and usability of AI-powered DSS by decision-makers.

These indicators collectively capture both the performance and perceived benefits of AI-assisted decision-making.

2.5 Instrument Validity and Reliability

To ensure the quality of the research instrument, validity and reliability tests were conducted before performing the main statistical analysis. Construct validity was evaluated using Pearson product–moment correlation analysis, where each questionnaire item was correlated with the total score of its corresponding variable. An item was considered valid if the significance value was less than 0.05. The reliability of the measurement instrument was assessed using the Cronbach's Alpha coefficient to evaluate internal consistency among the questionnaire items. A Cronbach's Alpha value greater than 0.60 indicates acceptable reliability, meaning the instrument consistently measures the intended constructs.

2.6 Data Analysis

The collected data were analyzed using SPSS statistical software. Several statistical techniques were applied to examine the relationship between AI utilization and decision-making effectiveness. Descriptive statistics is used to summarize respondent characteristics and provide an overview of variable distributions. The Shapiro–Wilk test was applied to determine whether the data followed a normal distribution. Pearson correlation analysis was conducted to measure the strength and direction of the relationship between AI utilization and decision outcomes. Next, simple linear regression model was used to analyze the effect of AI usage on decision-making effectiveness. This analysis determines whether increased utilization of AI-powered DSS significantly improves decision outcomes. Statistical significance was evaluated using a 5% significance level ($p < 0.05$).

3. Results and Discussion

3.1 Results

Table 2. Descriptive Statistics

Variable	Mean	Std. Dev	Min	Max	N
AI Usage	3.87	0.62	2.60	4.80	33
Decision Effectiveness	4.02	0.58	2.90	4.90	33

Table 2 shows that respondents generally reported a relatively high level of AI utilization in decision support systems. The mean score for AI usage is 3.87, suggesting that most respondents agree that AI-based tools are actively used in their organizational decision processes. Similarly, the mean value for decision-making effectiveness is 4.02, indicating that respondents perceive decision outcomes to be relatively effective when supported by AI-based analytical tools. The relatively small standard deviation values (0.62 and 0.58) suggest that the responses are moderately concentrated around the mean, indicating a relatively consistent perception among respondents.

These descriptive findings provide an initial indication that the use of AI-powered decision support systems is associated with improved decision performance, including higher decision accuracy, faster decision-making processes, and improved operational efficiency. However, further statistical analyses such as correlation and regression analysis are required to determine whether the observed relationship between AI utilization and decision-making effectiveness is statistically significant.

Table 3. Validity Test Results

		AI Usage	**Decision Outcomes**
AI Usage	Pearson Correlation	1	.550**
	Sig. (2-tailed)		<.001
	N	33	33
Decision Outcomes	Pearson Correlation	.550**	1
	Sig. (2-tailed)	<.001	
	N	33	33

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

Based on Table 3 of the validity test results, there is a significant positive correlation between the AI-Powered Decision Support Systems variable and Decision-Making Effectiveness with a Pearson coefficient of 0.550 and a significance value (p-value) of less than 0.001. This shows that the higher the level of utilization of AI-based decision support systems, the higher the effectiveness in decision-making. Since the significance value is below 0.01, this relationship is declared significant, and the AI-Powered Decision Support Systems variable can be considered valid as an indicator that affects Decision-Making Effectiveness.

Table 4. Reliability Test Results

Reliability Statistics

Cronbach's Alpha	**N of Items**
.602	2

Table 4 shows that the Cronbach's Alpha value obtained for the two variables used was 0.602. This value is slightly above the minimum acceptable threshold of 0.60, indicating that the instrument has adequate reliability. Therefore, the instrument can be considered reliable and is suitable to proceed to the next stage of analysis.

Table 5. Normality Test Results

Normality Test

	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
	Statistic	**Df**	**Sig.**	**Statistic**	**df**	**Sig.**
AI Usage	.128	33	.184	.937	33	.054
Decision Outcomes	.090	33	.200*	.977	33	.686

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Table 5 shows the Shapiro-Wilk normality test results, the significance values for both variables are above the 0.05 threshold. The AI Usage variable has a significance value of 0.054, while the Decision Outcomes variable has a value of 0.686. These results indicate that the data for both variables are normally distributed, fulfilling the assumption of normality required for further parametric statistical analysis.

Table 6. Correlation Matrix

Variable	AI Usage	Decision Effectiveness
AI Usage	1	0.550**
Decision Effectiveness	0.550**	1

Table 6 shows the Pearson correlation analysis which revealed a moderate positive relationship between AI usage and decision-making effectiveness ($r = 0.550$, $p < 0.001$). This result indicates that higher levels of AI utilization are associated with improved decision outcomes. The significance level below 0.01 confirms that the relationship is statistically significant.

Table 7. Simple Linear Regression Test Results

Coefficients[a]

Model		B	Std Error	t	p-value	95% CI
1	(Constant)	36.133	7.323	4.934	<.001	
	AI Usage	.265	.072	3.664	<.001	[0.121 – 0.409]

a. Dependent Variable: Decision Outcomes

Table 7 shows that AI utilization significantly predicts decision-making effectiveness ($B = 0.265$, $t = 3.664$, $p < 0.001$). The 95% confidence interval for the regression coefficient ranges from 0.121 to 0.409, indicating that the positive effect of AI usage on decision outcomes is statistically reliable.

3.2 Discussion

The results of this study demonstrate that the utilization of AI-powered Decision Support Systems (AI-DSS) has a statistically significant influence on decision-making effectiveness across multiple industries. The regression analysis indicates that AI usage positively predicts decision outcomes, with a regression coefficient of $B = 0.265$ ($p < 0.001$). This finding suggests that increased integration of AI technologies contributes to measurable improvements in decision quality, speed, and operational efficiency. The correlation analysis ($r = 0.550$) further indicates a moderate and statistically significant relationship between AI utilization and decision-making effectiveness, confirming that organizations that adopt AI-based analytical tools tend to achieve better decision outcomes.

These findings are consistent with several previous studies that emphasize the effectiveness of AI-powered decision support systems in improving decision quality and operational outcomes across various domains. For example, Rossi *et al.* demonstrated that AI-powered decision support systems (DSS) in medical imaging significantly enhanced diagnostic accuracy and cost-efficiency [18]. In the field of education, Fahd and Miah found that predictive analytics models could identify students' learning challenges early, allowing for more effective interventions [31]. Similarly, Masood et al. (2020) applied machine learning to lung cancer detection and showed that AI significantly improves clinical decision support by increasing accuracy and response time [32].

In the education sector, previous studies showed that predictive analytics and cognitive state estimation models can aid educational institutions in early intervention and learning optimization [17,33]. AI-powered educational tools have likewise been shown to support informed decision-making and enhance learner engagement in educational settings [43]. In agriculture, researchers have implemented AI-based DSS for irrigation and nutrient management, utilizing neural networks and fuzzy control systems to boost productivity and sustainability. These sector-specific implementations confirm the adaptability of AI-powered DSS across contexts, supporting the current study's findings on its cross-industry effectiveness [22,34].

Moreover, AI techniques are increasingly employed in smart manufacturing and logistics. AI-driven simulation and computational intelligence have been applied in zero-defect production systems, enhancing process optimization and quality control [35,36]. In the supply chain domain, studies [37,38] highlighted the role of AI in enhancing resilience and inventory management using interpretable machine learning models. Such implementations underline the predictive power and strategic advantage offered by AI-powered DSS.

The present research aligns well with these findings by providing quantitative evidence of the practical benefits of AI integration in decision-making frameworks. Respondents across various sectors confirmed that AI-supported DSS improved their decision accuracy and operational agility. The perceived usefulness and satisfaction reported by users also reflect the importance of system, information, and service quality as determinants of effective technology-supported decision-making. This supports the growing body of literature, including works that emphasize the value of explainable AI and transparent decision-making models, especially in government and public service contexts [39,40].

A comparative analysis across industries reveals variations in the degree to which AI-driven decision support systems contribute to decision effectiveness. Sectors such as healthcare and supply chain management demonstrate relatively higher levels of decision performance compared with sectors such as urban planning or water resource management. This difference can be explained by the availability of structured datasets and the maturity of AI applications in these industries. Healthcare organizations typically utilize large-scale clinical datasets, medical imaging data, and predictive models for disease diagnosis and treatment planning. Similarly, supply chain and logistics sectors rely heavily on predictive analytics for demand forecasting, inventory optimization, and route planning. These data-rich environments provide favorable conditions for AI models to generate accurate and timely decision recommendations.

In contrast, sectors such as urban planning or water resource management often rely on heterogeneous or less structured datasets, which may limit the immediate effectiveness of AI-driven analytical tools. This indicates that the impact of AI-powered decision support systems is partially influenced by data availability, data quality, and the technological maturity of AI adoption within each industry.

The results also provide insights into the causal relationship between AI utilization and decision-making effectiveness. While this study uses a cross-sectional quantitative approach, the regression results suggest that increased AI utilization significantly contributes to improved decision outcomes. The positive regression coefficient indicates that AI integration enhances analytical capability by enabling advanced data processing, predictive modeling, and automated recommendations. These capabilities allow organizations to make faster and more accurate decisions compared with conventional analytical approaches.

Traditional DSS typically rely on rule-based logic, manual data interpretation, and historical data analysis. While these systems can assist decision-makers, their analytical capabilities are often limited when dealing with large-scale and complex datasets. Conventional multi-criteria decision support systems—for example, those based on Simple Additive Weighting (SAW), the Simple Multi-Attribute Rating Technique (SMART), and TOPSIS—have been widely used to improve the effectiveness of organizational decisions such as employee bonus determination, staff discipline evaluation, and lecturer performance appraisal [41,42]. In contrast, AI-driven DSS integrate machine learning algorithms and predictive analytics to process large volumes of data, identify hidden patterns, and generate real-time decision recommendations.

Consequently, AI-assisted decision systems demonstrate superior performance in several aspects of decision-making, particularly in terms of decision accuracy, decision speed, and analytical capability. Organizations using AI-powered decision support systems are better equipped to handle complex decision environments where rapid analysis and predictive insights are required. This benchmarking comparison highlights the technological advantage of AI-driven DSS over conventional decision support models.

The findings of this study reinforce the growing body of literature emphasizing the transformative potential of AI-driven decision support technologies in improving decision-making performance across industries. By enabling organizations to process complex datasets, generate predictive insights, and automate analytical processes, AI-powered DSS represent an important technological innovation for modern data-driven decision environments.

4. Conclusion

This study examined the impact of AI-powered Decision Support Systems (AI-DSS) on decision-making effectiveness across multiple industry sectors using a quantitative approach. The statistical analysis demonstrates that AI utilization has a significant positive influence on decision outcomes. The comparative analysis across industries shows that sectors such as healthcare and supply chain management tend to benefit more strongly from AI-driven decision support systems due to the availability of structured datasets and the widespread use of predictive analytics in these sectors. In healthcare, AI-DSS contributes to improved diagnostic support, disease prediction, and treatment planning. Meanwhile, in supply chain management, AI-based predictive models support demand forecasting, inventory optimization, and logistics decision-making. These sector-specific applications highlight the importance of aligning AI technologies with the characteristics of industry data environments and operational decision processes.

Despite these contributions, this study has several limitations. The relatively small sample size (N = 33) may limit the generalizability of the findings, and the cross-sectional survey design restricts the ability to fully establish long-term causal relationships between AI utilization and decision performance. In addition, the study mainly relies on perceived decision effectiveness rather than objective performance indicators. Future research should involve larger datasets across more industries and organizations to strengthen empirical evidence. Further studies may also focus on improving AI-DSS design through enhanced model explainability, better data interoperability, and industry-specific system customization to support more reliable and transparent AI-assisted decision-making.

Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT in order to assist in language refinement, grammar checking, sentence restructuring, and improving the clarity of academic writing. After using this tool/service, the author(s) carefully reviewed and edited the content as needed and take full responsibility for the publication's content.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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