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Artificial intelligence integration in decision support systems enhancing decision quality organizational performance and sustainable value creation

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Abstract

The study will present a rigorously conducted empirical evaluation of the magnitude of the increase in the effectiveness of Decision Support Systems (DSS) with the help of the Artificial Intelligence (AI) integration within the organizational context. Using the survey data collected among ninety professionals recruited into the sample of the telecommunications industry in the Arab state of Jordan, it examines the processes by which AI-enhanced DSS can impact the choice and performance of the organization. Partial Least Squares Structural Equation Modelling (PLS -SEM) is applied in assessing the relationship between AI integration, DSS performance, decision quality and organizational performance. The findings indicate that the integration of AI reinforces the DSS analytical performance significantly, which is why it improves the quality of decisions. The quality of the decisions comes out as the main channel with which AI-powered DSS improve organizational performance, yet no direct impacts of AI inclusion on the quality of decisions and organizational performance are supported. The study makes contributions to the literature of information systems scholarship by embedding the analysis into the contexts of Task-Technology Fit (TTF) and Technology-Organization-Environment (TOE), which explains how AI can create organizational value via decision-support processes and not through direct technological impacts. The findings contribute to Sustainable Development Goals 9 and 16 by demonstrating how AI-enabled decision support systems strengthen institutional decision quality, enhance organizational resilience, and promote sustainable value creation through improved governance and data-driven strategic management.

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Keywords: Artificial intelligence, Decision support systems, Decision quality, Organizational performance, Intelligent decision support

1. Introduction

The modern telecommunications environment can be described as the growing complexity of data, fierce rivalry, and catalytic technological change, which require organizations to build increasingly advanced and receptive decision-making units [1]. Decision Support Systems (DSS) within such a volatile environment have long been established as a keystone managerial tool, allowing decision-makers to solve structured and semi-

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structured issues via systematic data assessment and model-driven reasoning [2]. Nonetheless, the rapid development of Artificial Intelligence (AI) solutions, especially machine learning, natural language processing and predictive analytics, have completely transformed the decision support paradigm [3]. These technologies bring in more sophisticated automation, responsive learning and predictive intelligence, bringing a shift in the use of largely descriptive DSS to intelligent, adaptive and more autonomous Intelligent Decision Support Systems (IDSS) [4].

In the Jordanian telecommunications sector, AI-enabled decision support has become increasingly relevant because firms operate in a highly competitive and data-intensive environment. Telecommunications providers rely on customer data, network performance indicators, service-quality reports, digital payment records, and market-behavior analytics to support managerial and operational decisions. In such settings, AI-enabled DSS can assist managers in forecasting customer demand, identifying network or service problems, improving customer-retention decisions, supporting resource allocation, and responding more rapidly to competitive and regulatory changes. Therefore, Jordan Orange provides an appropriate empirical context for examining how AI integration within DSS can enhance decision quality and organizational performance.

At the same time, the strategic topicality of AI-based decision-making has increased the academic attention to investigating how smart systems can generate organizational value beyond operational automation [5]. Previous studies argue that AI-based analytics would improve organizational agility and foresight by facilitating judgments based on data in the uncertain conditions [6], [7]. However, the growing body of knowledge warns that technological sophistication is not all that is needed to achieve better organizational performances. Rather, the value-generation depends on the capability of the AI-enabled systems to significantly enhance the quality of managerial decisions [8], [9]. The view places the quality of decisions at the heart of a micro-level process by which digital technologies impact the performance of firms [10].

Although the possible synergies between AI and DSS have been thoroughly discussed in theoretical literature, there is still limited empirical data to support the claim that strictly measures the organizational effect of the integration of both. The conceptual models indicate that AI-enhanced DSS is supposed to enhance the accuracy, speed, and efficiency of decision-making [11], and there is limited systematic, theory-based quantitative verification in the real organizational environments. This scarcity reminds of the old issues related to the information technology productivity paradox according to which sophisticated technologies cannot deliver the expected performance improvements because of lack of fit on decision tasks, organizational processes, or managerial cognition [12], [13]. The recent reviews hence demand empirical studies that explicitly study the manner in which the AI capabilities are incorporated into the decision-support systems and how such incorporation reflects in the form of better decision quality and organizational performance outcomes [14]. This is especially acute in data intensive sectors like telecommunications where organizations needed to constantly make sense of high velocity data flows, predict demand, and react rapidly to competitive and regulatory forces [15]. The presence of telecommunication companies in the emerging economies provides a good empirical base on exploring AI-DSS integration because these companies tend to integrate high levels of technology adoption with unique and unique organizational and environmental factors [16]. However, such contextual evidences are still sparse, which limits the generalizability of current AI-based decision support systems and leaves open questions about the mechanisms by which AI-based decision support systems are able to create organizational value.

To fill this gap, the current study empirically investigates how the concept of AI integration in DSS can influence the performance of decision-making and organizational performance in a major telecommunication organization in Jordan Orange. In particular, the study seeks to: (1) measure the likelihood of AI capabilities to improve the analytical performance of DSS in operational decision setting; (2) measure the resulting impacts on the quality of managerial decision; and (3) measure the impacts of AI-driven DSS to the overall performance of organizations. In order to realize these, Partial Least Squares Structural Equation Modelling (PLS-SEM) is used to analyze survey data of ninety professionals in managerial, analytical and decision-oriented positions at Jordan

Orange. This method allows studying the complicated causal relationships and mediating mechanisms simultaneously and empirically verifying the proposed research model in a very strong way [17], [18].

Beyond operational efficiency, the integration of artificial intelligence into decision support systems has significant implications for sustainable development. In particular, AI-enabled decision infrastructures contribute to Sustainable Development Goal 9 (Industry, Innovation and Infrastructure) by strengthening digital innovation capabilities, and to Sustainable Development Goal 16 (Peace, Justice and Strong Institutions) by enhancing transparency, accountability, and evidence-based managerial governance. By improving decision quality as the primary transmission mechanism, intelligent decision systems support institutional resilience, responsible resource allocation, and long-term sustainable organizational performance in data-intensive sectors such as telecommunications.

There are three major contributions made by this study. First, it contributes to the theory of decision support and information systems by empirically defining AI integration as a significant technological antecedent in a decision-quality transmission framework, based on the frameworks of complementary concepts of Task Technology Fit (TTF) and Technology Organization Environment (TOE). Second, it builds on the existing empirical research by offering context-specific data in the telecommunications market of an emerging economy thus filling one of the still standing research gaps on AI and DSS. Third, it provides the practical implications to practitioners who may wish to design, implement, and govern AI-enabled decision support systems to attain sustainable competitive advantage.

2. Literature review and theoretical foundation

2.1. Decision support systems: evolution and architecture

The term decision Support Systems (DSS) refers to interactive computer systems, which are meant to support the decision-makers to handle unstructured or semi-structured problems by making use of data and analytical models in systematic manner [19]. Classical DSS architecture is integrated into four sub systems: (1) data management component which store, retrieve and manipulates data; (2) model management component which supports analytical and simulation model and optimization models; (3) knowledge management component which embeds rules, heuristics and domain expertise; and (4) user interface which provides effective human-computer interaction [20]. DSS is not intended to replace managerial judgment, but to supplement it with the aim of enhancing the quality of decisions in the areas of accuracy, timeliness, and confidence to the decision-maker [21].

Although relevant over a long period of time, traditional DSS have limitations that are inherent to modern organizational settings. Such systems tend to be inefficient in dealing with large-scale, high-velocity data, capable of adapting to changing and unpredictable situations, and can learn new patterns of decisions [22]. These limitations are especially high in information-rich sectors like telecommunications, where decision-makers are expected to constantly process complicated streams of data and to react promptly to operational and strategic issues. Such barriers have increased enthusiasm towards adding Artificial Intelligence (AI) functions to DSS to increase their analysis capabilities, flexibility, and decision relevance.

2.2. The role of artificial intelligence in organizational decision-making

Artificial Intelligence is defined as the process of simulating human intelligence processes by computer systems or other machines, especially those that are able to learn, reason and correct themselves [23]. Machine learning (ML), natural language processing (NLP), and predictive analytics are the most common examples of AI technologies in the field of organizational decision-making. ML algorithms allow the system to extract patterns and make predictions based on past and real-time data; NLP allows the system to extract meanings of human language and enhance the usability and extract insights of unstructured information; predictive analytics to make predictions and anticipatory decisions under uncertainty. Together, these AI attributes allow automating the routine decision-making process, deriving non-obvious insights using a complex data set, and coming up with

data-driven recommendations that assist managerial judgment [3]. According to previous studies, AI implementation increases the agility, accuracy of decisions, and adapting ability of an organization by allowing responding to environmental changes faster and more wisely [11]. Nevertheless, researchers are becoming more adamant that the successful implementation of AI technologies does not necessarily result in better results. Rather, it is through the proper integration of AI abilities into decision-making through mechanisms that improve decision quality instead of burdening and replacing human cognition that organizational value is created.

2.3. The convergence of DSS and AI: intelligent decision support systems

With the introduction of AI capabilities into DSS, all otherwise, have become Intelligent Decision Support Systems (IDSS) that use data-driven/ model-driven data with adaptive learning and reasoning capabilities [4]. IDSS, in contrast to conventional DSS, offer prescriptive and predictive information as well as descriptive and diagnostic information, which helps to make proactive and proactive decisions. The telecommunications industry is just one of these, for instance, IDSS can forecast network requirement, help in real-time resource allocation or even, let's say, analyze customer service transcripts to look for service issues that arise [22]. Empirical studies have shown that there is a positive correlation between DSSs with AI and positive outcomes in strategic planning, operational efficiency and decision responsiveness in organizations [10], [5]. Despite the extensive amount of literature available, however, the current literature is mostly theoretical or qualitative regarding quantitative evidence of the effect of AI-enhanced DSS on the quality of decisions and business performance. It highlights the importance of the empirical investigations that are theoretically oriented and explicitly deal with the mechanisms by which organizations create value using the support of the AI-related DSS [23].

In aggregate, the findings of the past studies have suggested that AI-based DSS can positively influence the analytical capacity, the responsiveness of decision and the strategic planning, but the relationship between the benefit of AI and organizational outcomes is ambiguous; where does the benefit of AI lie, in the actual organizational outcomes or in the intermediate decision support process? Some studies focus on the direct impact of AI and business analytics on agility and performance, while others suggest that the value of technology lies in its ability to enhance task results, managerial interpretation, and decision quality. The inconsistency underscores the importance of exploring the mediating role of DSS performance and decision quality between AI integration and organizational performance [24]. The present study extends prior research by testing the direct effect of the integration of AI on organizational performance as well as the role of DSS performance and decision quality as the intermediate variables [25].

2.4. Theoretical underpinnings: task–technology fit and TOE framework

The research is based on two theoretical viewpoints that appear to complement each other and create a solid base to analyze the effects of AI-based DSS: TaskTechnology Fit (TTF) theory and Technology Organization Environment (TOE) framework. The Task Technology Fit (TTF) theory assumes that technology can only enhance the performance when the features of technology fit the demands of the activity that it is used for [12]. In this regard, AI-based DSS are likely to improve the decision outcomes when the AI's operations (such as learning, prediction, and automation) dovetail with the cognitive and analytical needs of managerial decision making. In complex and data rich environments like the telecom sector, this type of communication is vital to enable the sophisticated use of technology to produce useful decision support. In addition to this micro-level perspective, there exist additional frameworks from a macro-level perspective, such as Technology-Organization-Environment (TOE) framework which proposes applications and effects of technological advances as a function of the nature of technology, organizational resources and organization, and environmental factors [16].

In the scope of Jordan Orange, it is possible to consider the organizational readiness, the technological infrastructure as well as the competitive and regulatory forces of the Jordanian telecommunication market with

the help of the TOE framework. The study conceptualizes the improvement of DSS performance by AI capabilities and decision tasks alignment to the micro level by synthesizing TTF and TOE which, as in certain organizational and environmental conditions, is then associated with the quality of decision and organizational performance. In this regard, the quality of the decisions is given the highest value generation process, linking AI-powered DSS with the overall performance of the organization.

2.5. Research model and hypothesis development

Based on the literature review and theoretical bases presented in Section 2, the given study suggests the conceptual research model represented in Figure 1. The model combines the findings of Task Technology Fit (TTF) theory and the Technology Organization Environment (TOE) theory in explaining how the integration of Artificial Intelligence (AI) into the Decision Support Systems (DSS) affects the effectiveness of decision-making and the performance of the organization [12], [16].

The concept of Artificial Intelligence Integration (AII) is viewed as a constructive phenomenon that sums up the extent to which various artificial intelligence opportunities, such as machine learning, natural language processing, and predictive analytics, are integrated into organizational decision-support systems (DSS) [3], [11], [23]. These competences are not fungible, but complementary; the sum of the dimensions determines the overall degree of AI integration, and does not represent a single underlying latent construct [3], [11]. Decision Support System Performance (DSSP) is operationalized as a reflective construct, which captures users judgments towards the effectiveness of a system in giving relevant, timely, and accurate analytical support [2], [4], [21]. Decision Quality (DQ) is a conceptualized high-order reflective construct which generalizes the dimensions of accuracy, timeliness, and comprehensiveness defining managerial decisions [7], [12]. Organizational Performance (OP) is also defined as a reflective construct, which it measures through various indicators associated with efficiency, profitability, and outcomes of innovation [6], [10].

In line with the Technology-Task Fit (TTF) theory, the suggested model assumes the hypothesis that the use of AI will improve the performance of DSS by improving the fit between the system capabilities and the decision-task demands [12], [13]. As a result, the high level of the use of DSS is expected to improve the quality of decisions, allowing making more adequate, accurate, and evidenced based managerial decisions [2], [21]. Decision quality is located at the organizational level as the most prominent value-creating mechanism on how AI-enhanced DSS can translate the technological capability into performance results [6], [7], [10]. In this respect, both direct and mediated relationships between AII, DSSP, DQ, and OP are included in the model [17], [18].

2.6. Hypothesis development

2.6.1. Artificial intelligence integration and DSS performance

Artificial Intelligence technologies enhance directly the analytical functions of the traditional DSS by contributing to adaptive learning, advanced pattern recognition and predictive modelling [3], [11], [23]. Machine learning enhances data processing and insight creation; natural language processing (NLP) makes the system easier to use, and unstructured data easier to interpret; predictive analytics takes DSS beyond descriptive analysis to anticipatory decision support [1], [3]. The capabilities, as understood in a TTF sense, are used to streamline the process of matching the system capabilities to the demanding analytical tasks faced by decision-makers in data-intensive settings, including telecommunications [12], [16].

H1: Artificial Intelligence Integration has a positive and significant effect on Decision Support System Performance.

2.6.2. DSS performance and decision quality

A well-functioning DSS will provide decision-makers with timely, high quality, and properly organized information, thus making the alternatives assessment easier and reducing the level of cognitive uncertainty [2], [19], [21]. Strong analytics models with user friendly interfaces assist in managerial sense-making and foster

quicker diagnostic of problems, which improves the accuracy, timeliness and comprehensiveness of decision making [11], [4]. Empirical research is consistent that the effectiveness of DSS is related to better decision outcomes when there are congruencies between system outputs and managerial information requirements [12], [13].

H2: Decision Support System Performance has a positive and significant effect on Decision Quality.

2.6.3. Artificial intelligence integration and decision quality

Integration and Quality of Decision In addition to enhancing the functionality of DSS, AI capabilities might impact the quality of the decision directly, due to the generation of sophisticated insights that shape managerial opinion [3], [11], [14]. An example is the direct improvement in the relevance and accuracy of decisions in the absence of complete mediation by traditional processes of the DSS, such as AI-based anomaly detection, sentiment analysis, or predictive forecasting [1], [3]. However, the existing literature has identified that these direct effects might be contingent on the effectiveness of the AI outputs incorporated into decision processes, thus, implying potential inconsistency in the strength of such a relationship [6], [7], [10], [26].

H3: Artificial Intelligence Integration has a positive and significant direct effect on Decision Quality.

2.6.4. Decision quality and organizational performance

Performance Decision quality is a micro-level critical determinant of organizational performance [6], [7], [10]. Highly accurate, fast and comprehensive decisions facilitate successful implementation of strategies, optimal resource deployment, reduction of risks, and innovation [4], [10]. In a dynamic and competitive environment like telecommunications, quality decisions are essential in maintaining efficiency in operations and achievement of strategic goals [1], [3], [27].

H4: Decision Quality has a positive and significant effect on Organizational Performance.

2.6.5. DSS performance and organizational performance

Performance Not all the organizational performance may depend on the indirect impact of DSS performance which may exist only through the channels of decision quality but not only through them [6], [10]. These channels include automated decision-making on routine decisions, real-time process optimization, and an increase in organizational coordination with the help of ubiquitous data visibility [3], [11], [5]. However, the existing literature indicates that these direct effects are not so strong as effects mediated by improvement of the decision results [7], [12], [13].

H5: Decision Support System Performance has a positive and significant direct effect on Organizational Performance.

2.6.6. The mediating role of decision quality

Although operational efficiencies may be achieved through the DSS performance, their key strategic value output is likely to come through their ability to improve the quality of the decisions [6], [7], [10]. In terms of both TTF and information systems value, technology creates organizational value primarily through the enhancement of the outcomes of the tasks, but not through the direct impact on the performance of the firms [12], [10], [13]. In turn, the quality of decisions is postulated to serve as a key transmission channel connecting the performance of DSS to the performance of the organization [6], [7].

H6: Decision Quality mediates the relationship between Decision Support System Performance and Organizational Performance.

3. Research methodology

The present study would be a quantitative-explanatory research with a cross sectional survey strategy to test the hypothesized model. This is suitable because the study involves relationships between the categories of AI

integration, DSS performance, decision quality and organizational performance at a single point in time, based on structured survey data [17], [18]. The empirical setting is Jordan Orange (JO), one of the major telecommunication providers, where the environment has a high level of technology and data hence is a suitable setting to study the integration of AI-DSS [3], [15].

The target group were Jordan Orange professionals who were highly motivated to participate in decision making and had experience of using DSS. These ranged from managers to IT experts, data analysts and decision makers. A purposive sampling method was used to make sure that the respondents can have first-hand and substantive experiences with DSS and AI-based decision-making tools. A web based questionnaire was used to survey the participants, which was sent via internal organizational platforms. There was no coercion and no identification of the participants. The questionnaire consisted of two sections: (1) demographic and experience questions and (2) questions on a 5-point Likert scale that measured the four major constructs. A pilot test was carried out with 15 participants to improve the clarity of the items and their preliminary reliability.

The response from professionals working in Jordan Orange was 90 complete and valid. The demographic details of respondents, such as their age, education level, professional experience, and the frequency of using DSS are summarized in Table 1. Because the study focused on higher level managers, IT specialists, data analysts, and decision makers with first-hand experience of using DSS and AI tools for decisions making, the sample is deemed to be adequate for this study. Specifically, 53.3 per cent of respondents indicated that their experience was 4-6 years, and 82.2 per cent indicated using DSS at least once per week. This indicates that the respondents had sufficient practical exposure to decision-support systems and were therefore suitable for evaluating AI-DSS integration and decision-making performance [2], [4], [21].

The respondents were drawn from organizational units where decision-support activities are most relevant, including managerial, information technology, data analysis, customer service, and operational decision-making functions. Their work involves using DSS outputs to support decisions related to customer behavior analysis, service-quality monitoring, operational planning, resource allocation, and performance evaluation. The AI-enabled DSS context in this study therefore reflects practical decision-making situations in which data-driven insights are used to support both operational and strategic decisions within the telecommunications sector.

Table 1. Demographic profile of respondents (N = 90)

Variable	Category	Frequency	Percentage
Age	25–34 years	21	23.3%
	35–44 years	39	43.3%
	45 years and above	30	33.4%
	Total	90	100.0%
Education	Bachelor’s degree	42	46.7%
	Master’s degree	34	37.8%
	PhD degree	14	15.5%
	Total	90	100.0%
Experience	1–3 years	17	18.9%
	4–6 years	48	53.3%
	7–10 years	25	27.8%
	Total	90	100.0%
DSS Usage Frequency	2–3 times weekly	37	41.1%
	Once a week	37	41.1%
	Rarely	16	17.8%
	Total	90	100.0%

The scales were operationalized as reflective multi-item measures based on well-established measures in the literature. The responses were measured using a five-point Likert scale ranging from 1 = Strongly Disagree to

5 = Strongly Agree. Table 2 summarizes the construct sources, sample items, and number of items. The measurement items were adapted from established scales in prior information systems and decision-support research. Minor wording modifications were made to fit the context of AI-enabled DSS usage in Jordan Orange while preserving the conceptual meaning of the original constructs. AI Integration items captured the extent to which AI tools such as machine learning, predictive analytics, and automated data-processing capabilities were embedded in DSS. DSS Performance items measured the perceived accuracy, reliability, timeliness, and usefulness of system outputs. Decision Quality items assessed the accuracy, comprehensiveness, timeliness, and evidence-based nature of managerial decisions. Organisational Performance items captured perceived improvements in efficiency, responsiveness, innovation, and overall organizational outcomes.

Table 2. Construct measurement overview

Construct	Adapted From	Sample Item	Number of Items
AI Integration (AII)	Duan et al. [3]; Shollo and Galliers [11]	"AI technologies are integrated into our organization's decision support systems."	5
DSS Performance (DSSP)	Arnott and Pervan [4]; Power [24]	"Our DSS provides accurate and reliable information for decision-making."	4
Decision Quality (DQ)	Goodhue and Thompson [12]; Marakas and O'Brien [25]	"The decisions made with our DSS are accurate and evidence-based."	4
Organizational Performance (OP)	Raghupathi and Wu [26]; Shollo and Galliers [11]	"DSS-supported decisions have improved our organization's efficiency."	4

The analysis was conducted in two phases using SmartPLS 4.0 [17], following the guidelines for variance-based structural equation modelling [18]. First, the measurement model was assessed using indicator reliability, Cronbach's alpha, composite reliability, convergent validity through Average Variance Extracted (AVE), and discriminant validity using the Fornell-Larcker criterion and HTMT ratio. Second, the structural model was evaluated using path coefficients, t-values, p-values, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and bootstrapping with 5,000 resamples to test the proposed direct and mediating relationships [17], [18]. PLS-SEM was considered appropriate because it can handle relatively small samples and complex mediation models, especially when respondents are purposively selected experts with direct knowledge of the research context [18]. The study adhered to strict ethical standards. Respondents were informed of the research purpose, assured of anonymity and confidentiality, and participation was voluntary. No personally identifiable information was collected. The research protocol complied with standard institutional ethical guidelines for survey-based research.

4. Result

In this section, the results of an empirical study are provided in form of findings of a Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis carried out in SmartPLS 4.0. The results have been reported in two stages according to the set analytical procedures. The measurement model is first tested to determine the reliability of the indicators, internal consistency, and convergent and discriminant validity. Second, the structural model is investigated in order to test the hypothesized relationships, test explanatory and predictive power, and test the mediating role of decision quality. The resulting analyses all provide a strong empirical foundation on which to justify the proposed research model.

Table 3. Measurement model assessment: outer loadings, reliability, and convergent validity

Construct	Indicator	Outer Loading	Cronbach's Alpha	rho_A	Composite Reliability (CR)	AVE
AI Integration (AII)	AI1	0.815	0.744	0.76	0.827	0.521
	AI2	0.689				
	AI3	0.693				
	AI4	0.669				
	AI5	0.622				
DSS Performance (DSSP)	DSSP1	0.789	0.847	0.854	0.898	0.687
	DSSP2	0.777				
	DSSP3	0.876				
	DSSP4	0.868				
Decision Quality (DQ)	DQ1	0.613	0.724	0.745	0.829	0.55
	DQ2	0.824				
	DQ3	0.77				
	DQ4	0.743				
Organizational Performance (OP)	OP1	0.759	0.815	0.873	0.876	0.639
	OP2	0.783				
	OP3	0.77				
	OP4	0.88				

The measurement model assessment, the indication outer loadings, internal consistency reliability, and convergent validity of all the constructs are presented in Table 3. All the indicators are loaded on their target constructs with outer loading between 0.613 and 0.880. Following the instructions of PLS-SEM, all loadings are above the minimum acceptable value of 0.60, which is taken to mean that the indicators actually measured were sufficient to be considered to represent the latent constructs that they are meant to measure. Indicators with loadings that were slightly less than 0.70 were included because of their theoretical applicability, and because their contribution to construct reliability was acceptable.

Internal reliability was determined through the Cronbachs alpha, rho A and Composite Reliability (CR). The values of all constructs are greater than the recommended range of reliability of 0.70 and the value of CR ranges between 0.827 and 0.898. These findings affirm good internal consistency and scale reliability among all the constructs. The Average Variance Extracted (AVE) was used to assess convergent validity. The AVE values are all above the recommended value of 0.50 and this means that every construct explains greater than half the variance in its indicators. This proves that the measurement items are converging the constructs they are measuring. Taken together, the results suggest that the measurement model meets the predetermined PLS-SEM quality criteria of the reliability of indicators, internal consistency, and convergent validity. The constructs are therefore considered to be reliable and valid thus provide a good base on which the structural model analysis and hypothesis testing can be conducted in the future. In general, the measurement model shows a good level of reliability and convergent validity which confirms the suitability of the constructs in the assessment of the structural models.

Table 4. Discriminant validity assessment (Fornell–Larcker Criterion)

Construct	AI Integration	DSS Performance	Decision Quality	Organizational Performance
AI Integration	0.701			
DSS Performance	0.717	0.829		
Decision Quality	0.419	0.569	0.742	
Organizational Performance	0.281	0.287	0.653	0.799

Table 4 checked the discrimination validity through the Fornell-Larcker criterion. The diagonal scores are the square roots of the AVE of each construct and the off-diagonal scores show correlations amid constructs. These findings show that at least in all constructs, the square root of AVE is larger than is the inter-construct correlation. In particular, AI Integration (0.701) and DSS Performance (0.829), Decision Quality (0.742) and Organizational Performance (0.799) have more shared variance with their respective indicators than with other indicators. Though each of some correlations, specifically, the correlations between AI Integration and DSS Performance, and between Decision Quality and Organizational Performance, has a relatively strong value, they are still below the corresponding values of the square root of AVE and are consistent with the proposed model structure. The results prove that all constructs are empirically different and that discriminant validity is achieved, which proves the strength of the measurement model sufficiently.

Table 5. Discriminant validity assessment using the Heterotrait–Monotrait ratio (HTMT)

Construct	AI Integration	DSS Performance	Decision Quality	Organizational Performance
AI Integration	—			
DSS Performance	0.782	—		
Decision Quality	0.663	0.737	—	
Organizational Performance	0.376	0.324	0.776	—

Note: HTMT = Heterotrait–Monotrait ratio of correlations

Table 5 shows the Heterotraitmonomethod Ratio (HTMT) findings that were obtained to further evaluate the discriminant validity. The value of all the HTMTs is below the conservative value of 0.85 and even the more liberal value of 0.90, which shows that the discriminant validity is adequately realized across all constructs. The largest HTMT is between Decision Quality and Organizational Performance (0.776), which is not too high and consistent with the theoretical framework offered in the article, considering the fact that the strong connection between the quality of the decisions and organizational performance is expected. All in all, the HTMT findings support the view that the constructs are empirically differentiated and give a solid argument on the sufficiency of the measurement model. The HTMT analysis, in conjunction with Fornell-Larcker criterion, proves that all constructs have their discriminant validity, which supports the strength of the measurement model.

Table 6. Structural model explanatory power and effect sizes

Endogenous Construct	R Square (R^2)	Adjusted R Square
DSS Performance	0.513	0.508
Decision Quality	0.324	0.309
Organizational Performance	0.437	0.424
Panel B: Effect Size (f^2)		
Predictor → Outcome	f^2	
AI Integration → DSS Performance	1.055	
AI Integration → Decision Quality	0	

Endogenous Construct	R Square (R^2)	Adjusted R Square
DSS Performance → Decision Quality	0.22	
DSS Performance → Organizational Performance	0.019	
Decision Quality → Organizational Performance	0.629	

Note: f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively

The results of the explanatory power of the structural model and the size of the effects of the relationships between the variables that were tested are reported in Table 6. The model accounts for 51.3 per cent of the variation in DSS Performance, 32.4 per cent of the variation in Decision Quality, and 43.7 per cent of the variation in Organizational Performance, a moderate to high degree of explanatory power of all the endogenous constructs. Adjusted R^2 values are similar to the values of R^2 implying that there is model stability with minimal over-fitting. Table 6 contains the results of the effect size (f^2) and it indicates the relative contribution made by each of the exogenous constructs to the explained variance of the endogenous constructs. The effect of AI Integration on DSS Performance is very large (f^2= 1.055), which is why it is a key factor in improving system-level capabilities. DSS Performance has a medium impact on Decision Quality (f^2 = 0.220) but little impact on Organizational Performance (f^2 = 0.019). Conversely, the influence of Decision Quality on Organizational Performance (f^2 = 0.629) emphasizes the key contribution of this metric as the key value-creating tool with the help of which AI-enabled DSS can turn technological capability into performance in organizations. All in all, these results seem to support the suggested mediation framework, as well as contribute to the theoretical focus on the quality of the decisions as the most important transmission pathway.

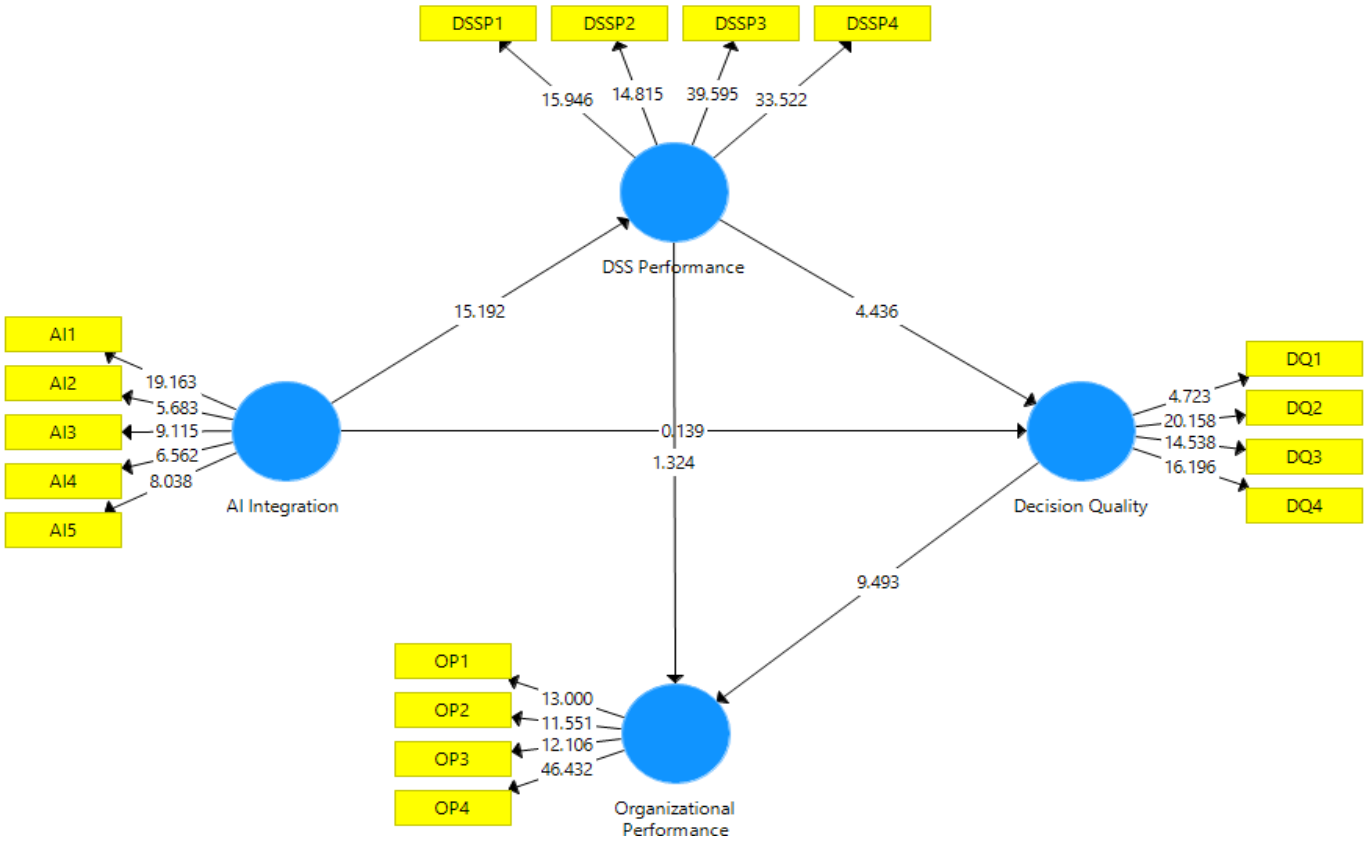


Figure 1. The study model of Smart PLS hypotheses results

The estimated structural model and the results of hypothesis testing obtained after SmartPLS analysis are presented in Figure 1. The hypotheses put forward explore the direct and indirect relationship between Artificial Intelligence Integration (AII), Decision Support System Performance (DSSP), and Decision Quality (DQ) and Organizational Performance (OP). The empirical findings provide a solid contribution to the research model and highlight the critical importance of the quality of decisions in mediating AI-enabled DSS functionality to tangible organizational performance deliverables.

Table 7. Summary of hypotheses testing results

Hypothesis	Structural Path	Path Coefficient (β)	f^2	t-value	p-value	Result
H1	AI Integration → DSS Performance	0.716	0.711	15.624	0	Supported
H2	DSS Performance → Decision Quality	0.137	0.22	4.197	0	Supported
H3	AI Integration → Decision Quality	0.543	0.002	0.126	0.9	Not Supported
H4	Decision Quality → Organizational Performance	0.734	0.629	9.98	0	Supported
H5	DSS Performance → Organizational Performance	−0.125	0.007	1.287	0.199	Not Supported
H6	DSS Performance → Decision Quality → Organizational Performance	0.4	0.274	3.662	0	Supported

Note: Significance assessed using bootstrapping with 5,000 resamples

The hypothesis is as follows: H1 Artificial Intelligence Integration has a positive effect on the Decision Support System Performance. This relationship is proved by the empirical evidence ($\beta = 0.716$, $p < 0.001$), which shows that the effect is strong and statistically significant, which supports the paramount role of AI potentialities in increasing DSS analytical functionality. Thus, H1 is supported. H2 is the role of the DSS Performance in Quality of Decisions. Result shows that there is positive and significant relationship ($\beta = 0.137$, $p < 0.001$), with a moderate effect size ($f^2 = 0.220$). This implies that successful DSS are useful in enhancing the accuracy, timeliness, and completeness of managerial decisions so we have empirical support of H2. H3 postulates the positive impact of AI Integration on Decision Quality. Unfortunately, such a correlation is not statistically significant ($\beta = 0.543$, $p = 0.900$), and the effect size was negligible ($f^2 = 0.00$). As a result, AI functionality has no direct contribution to the quality of decisions unless properly adhered to in DSS processes, and H3 is not corroborated. H4 explores how there is a correlation between Decision Quality and Organizational Performance. The outcome shows a high and very significant effect ($\beta = 0.734$, $p < 0.001$), with a large effect size ($f^2 = 0.629$). This ratifies the fact that quality managerial decisions are one of the main causes of organizational efficiency, effectiveness, and performance results, which prove H4. The H5 is used to test the direct relationship between DSS Performance and Organizational Performance. The correlation shows that there is a negative but statistically non-significant relationship ($\beta = -0.125$, $p = 0.199$), with a very small effect size ($f^2 = 0.007$). In this way, there is no direct relationship between DSS performance and organizational performance improvement without enhancing quality of decisions, and H5 is not proved. H6 examines the mediating effect of Decision Quality on the relationship between DSS Performance and Organizational Performance. The indirect effect was positive and statistically significant ($\beta = 0.400$, $p < 0.001$). Furthermore, the direct effect of DSS Performance on Organizational Performance was statistically nonsignificant ($\beta = -0.125$, $p = 0.199$). These findings indicate full mediation, suggesting that DSS Performance contributes to Organizational Performance indirectly through improvements in Decision Quality. Therefore, H6 is supported.

In general, the results indicate that Artificial Intelligence mainly leads to improvements in the organizational performance due to its influence on the performance of the DSS and, consequently, the quality of the decision-making process, but not through direct technological implications.

5. Discussion

The results are significant in the context of empirical evidence regarding the effectiveness of integrating artificial intelligence in the improvement of Decision Support System (DSS) and in the organizational decision-making process. Based on Task-Technology Fit (TTF) and the Technology-Organization-Environment (TOE) theory, the findings indicate that the use of AI for organizational integration must be considered beyond the technology level. Rather, it serves as a strategic organizational capability to optimize the information processing, analytical responsiveness and decision-support capabilities in a data-intensive telecommunications context [3], [12], [16].

The positive impact of AI Integration on the performance of DSS is evident, thereby reinforcing the significance of the perspective of TTF. This suggests that AI, especially machine learning, predictive analytics and automated pattern recognition, are well suited for complex decision making in telecommunications. This discovery aligns with existing studies suggesting that when AI and analytics are integrated into decision support systems and meet the managerial requirements, it can enhance organizational decision-making processes [3], [11], [4]. It is also aligned with recent research in your list that AI tools, business intelligence, and decision models can complement digital transformation, service quality, and decision effectiveness when integrated with organizational processes as it is done in the research [27], [28], [29], [30], [31].

One of the important results is that AI Integration did not significantly impact Decision Quality directly. The findings indicate that, by itself, using an AI technology does not necessarily lead to better managerial decisions. Instead, the AI-generated output must be interpreted, validated and applied to the context to enhance decision quality. In telecommunications, AI predictions can inform decisions about customer behavior, service quality, network performance, and resource allocation, but the impact of these predictions is contingent on the subsequent processing in DSS routines and managerial judgment [6], [10], [32-36]. This discovery demonstrates the indirect nature of AI value creation, process-dependency, and the mediation by decision support performance, which refute technology-deterministic assumptions.

The results also show that DSS Performance has a positive effect on Decision Quality. This is an attestation that effective DSSs deliver relevant, timely, accurate and reliable information in structured format to aid managers assess the options, minimize uncertainty, and make more evidence-based decisions [2], [21], [4]. Decision Quality further, has a positive and strong impact on Organisational Performance. High-quality decisions are the primary way that AI-enabled DSS can improve organizational efficiency, responsiveness, innovation, and outcomes of organizational activities [6], [7], [10].

The direct effect of DSS Performance on Organisational Performance is also of theoretical interest because it is statistically insignificant. It suggests that an increase in system efficiency is not sufficient to achieve organizational performance gains [37]. The benefits of DSS, however, take on significance when there is an improvement in the quality of decision making in the system. The result is congruent with the TTF theory that suggests that the effects of technology on performance are mediated by better task outcomes rather than direct use of technology [12]. Hence, the study identifies Decision Quality as the core value-creating process between the DSS and the organizational performance through the AI [38].

5.1. Theoretical contributions

Theoretically, this study has several contributions. It contributes to extend DSS and information systems research by empirically validating AI Integration as an important antecedent of DSS Performance. This study is a quantitative study of the potential of the AI-based DSS, in a real environment in an emerging economy, while previous studies have addressed this conceptually [3], [11], [4]. Second, the study enhances the integration of the TTF and TOE perspectives. The results indicate that the effectiveness of the DSS using AI relies not only on technological complexity, but also on the compatibility of the AI features, decision tasks, organizational readiness and environmental conditions [12], [16]. This offers a more comprehensive theoretical lens to understand the value contribution of AI to organizational decision-making.

Third, the study is useful for the theory of the creation of value in AI by demonstrating that Decision Quality is the main mediator between DSS Performance and Organisational Performance. This research builds on previous studies on business intelligence, business analytics, and digital transformation, which show that technology and technology products generate organizational value primarily by enhancing decision processes and managerial outcomes [11], [10], [27], [28], [37], [38].

5.2. Practical implications

The results have a number of implications for managers involved in telecommunications and other data-intensive sectors. First, organizations need to view investments in AI-enabled DSS as strategic investments and not technology projects. The usefulness of AI tools lies in their ability to be embedded in existing DSS, data systems and managerial processes [27], [28]. Second, managers need to emphasize the match between tasks and technologies. They should be applied to particular decision requirements like customer retention analysis, demand forecasting, network planning, service-quality monitoring, and operational risk assessment [3] [12] [29]. Third, organizations need to build up human-AI partnerships. AI systems should complement, not supplant, managerial decision-making. Managers need to trust and consider the recommendations made by the AI, and then translate the analytical results into actual actions [11], [39-41]. Fourth, use decision-quality indicators, rather than just system-performance indicators, in the performance monitoring. Managers need to assess the accuracy, timeliness, comprehensiveness, usefulness, and actionability of the DSS outputs. This is significant as the results demonstrated that the quality of the decision is the primary contributor to the organizational performance [6], [7], [10].

5.3. The relevance of this to sustainable development and SDGs

The findings also give some insights into sustainable development. AI-powered DSS can contribute to SDG 9 in several ways, including: strengthening innovation capacity, strengthening digital infrastructure, strengthening technological readiness of organizations. They can also help achieve SDG16 to promote and foster the public support for responsible decision-making, accountability, and evidence-based governance and transparency. Intelligent decision systems can have positive impacts in industries with high information density, such as telecommunications, by improving resource utilization, reducing uncertainty, facilitating adaptive planning, and strengthening institutions. This is reflective of recent research by your list on governance for sustainable organizational development via AI, digital transformation and governance for the SDGs [27], [30], [31], [42].

In this study, sustainable value creation is understood as a potential long-term organizational implication of improved Decision Quality and Organisational Performance rather than a directly measured construct. Specifically, AI-enabled decision support systems may contribute to sustainable value creation by improving resource allocation, operational efficiency, organizational resilience, and responsible decision-making. These improvements can support the development of sustainable organizational capabilities and strengthen the organization’s ability to maintain performance over time. However, the sustainability implications are derived from the observed relationships among the measured constructs and require further empirical investigation using explicit sustainability indicators.

5.4. Limitations and further research directions for this study

There are a number of restrictions in this study. Firstly due to the cross sectional design, causal statements cannot be made. Longitudinal studies should be conducted to investigate the effect of the implementation of AI-DSS on decision quality and performance in the long run.

Secondly, the study was conducted in a single telecommunications organization Jordan Orange with 90 professionals. The findings should therefore not be generalized to other telecom markets, in need of further empirical validation. Studies of larger samples, from various telecommunications companies and geographical areas, are recommended as a way to validate the results with generalizability. Third, future research needs to incorporate objective assessment measures along with perceptual measures. Furthermore, other factors related

to the use of the mediator, like data maturity, leadership support, digital culture, AI governance, and digital organizational learning can be investigated in future research.

6. Conclusion

The results of this study offer compelling support that artificial intelligence enhances organizational performance primarily via DSS performance and decision quality, but not directly due to tech effects. AI Integration greatly boosts DSS Performance, which in turn boosts Decision Quality and Decision Quality greatly boosts Organizational Performance. Hence, the quality of decision is the main mechanism through which AI-enabled DSS contributes to the creation of organizational value. Organizations that leverage AI in their DSS, with a human-centered decision governance framework are more likely to be agile, innovative, resilient and sustainable.

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Author contribution

Methodology, Saed Adnan Mustafa and Ruqiyah Jaber Al Darwashi; software, Saed Adnan Mustafa; validation, Maha Alkhaffaf and Ruqiyah Jaber Al Darwashi; formal analysis, Saed Adnan Mustafa and Maha Alkhaffaf; resources, Saed Adnan Mustafa; writing—original draft preparation, Maha Alkhaffaf; writing—review and editing, Saed Adnan Mustafa; supervision, Saed Adnan Mustafa; project administration, Maha Alkhaffaf and Ruqiyah Jaber Al Darwashi. Authors have read and approved the final version of the manuscript.

Ethical approval statement

Ethical approval for this study was obtained from the Research Ethics Committee of the Faculty of Business, Applied Science Private University. The study was conducted in accordance with relevant institutional ethical guidelines and regulations.

Informed consent

Informed consent to participate was obtained from all respondents before completing the questionnaire. Participation was voluntary and anonymous, and no personally identifiable information was collected. No individual participants' personal data are reported or published in this study.

Declaration of competing interests

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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