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Artificial Intelligence-Based Decision Support Systems and Managerial Performance

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Abstract

This quantitative, cross-sectional, case-based study addresses the persistent problem that organizations invest in cloud-deployed, enterprise AI-based decision support systems (AI-DSS) yet often lack clear, measurable evidence about which adoption and perception factors actually translate into better managerial performance; accordingly, the purpose was to test a Technology Acceptance Model (TAM) aligned explanatory model linking managers' perceptions and use of AI-DSS to decision-linked performance outcomes in an enterprise case context. The sample comprised 120 managers across core enterprise functions (Operations 30.0%, Finance 23.3%, Sales/Marketing 18.4%, HR/Admin 15.0%, IT/Analytics 13.3%) with mixed seniority (Supervisors 33.3%, Mid-level 48.3%, Senior 18.4%), and most had received AI-DSS training (61.7%). Key variables included Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in AI-DSS (TRUST), Information Quality (INFOQ), and AI-DSS Use/Adoption Maturity (USE) as predictors, with Managerial Performance (MP) as the outcome. The analysis plan applied descriptive statistics, scale reliability, Pearson correlations, and multiple regression, followed by robustness diagnostics (multicollinearity, residual independence, influence, and stability tests). Results showed generally favorable perceptions and outcomes (PU M=4.02, SD=0.62; PEOU M=3.69, SD=0.66; TRUST M=3.74, SD=0.73; INFOQ M=3.91, SD=0.60; USE M=3.78, SD=0.71; MP M=3.88, SD=0.58). Correlations with MP were positive and statistically strong (PU r=0.62, INFOQ r=0.58, TRUST r=0.55, USE r=0.49, PEOU r=0.41, all reported as significant at p<.001). The regression model explained 53% of variance in managerial performance (R^2=0.53, F=38.7, p<0.001), with PU (β=0.29, p<0.001), INFOQ (β=0.24, p=0.002), TRUST (β=0.21, p=0.004), and USE (β=0.17, p=0.011) emerging as significant unique predictors, while PEOU was not significant in the full model (β=0.08, p=0.143). Consistent with these effects, higher adoption maturity aligned with higher performance (Low maturity: n=26, MP 3.52; Moderate: n=62, MP 3.86; High: n=32, MP 4.12). Managers reported the most concrete decision benefits in speed (M=3.95, SD=0.72) and accuracy (M=3.89, SD=0.69), with comparatively weaker gains in reduced rework (M=3.61, SD=0.78). Robustness checks supported model credibility (VIF 1.3–2.4, Durbin–Watson 1.95, Cook's D max 0.21, and stable coefficient signs after excluding extreme USE cases). Implications are that enterprise leaders should prioritize improving AI-DSS usefulness, information quality, and trust-building mechanisms, while accelerating embedded, routine use through governance and workflow integration, because usability alone may be insufficient to drive net performance gains once value and credibility factors are accounted for.

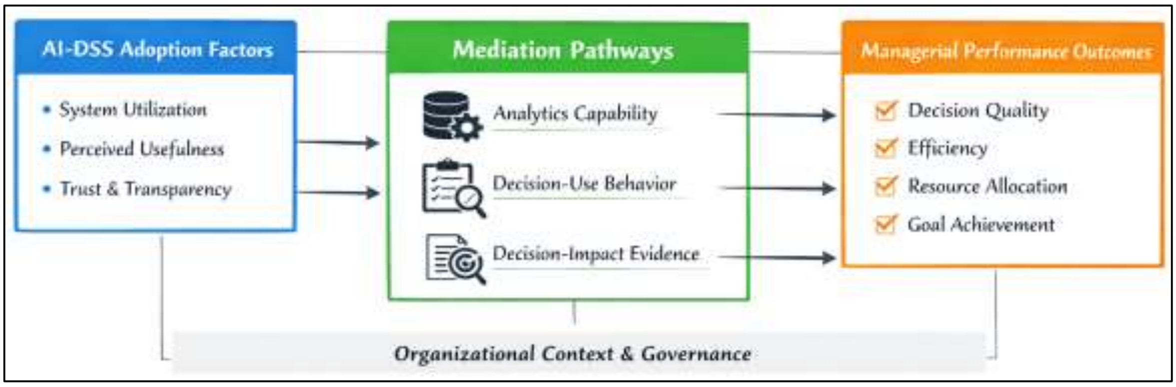
Keywords

AI-Based Decision Support Systems (AI-DSS); Managerial Performance; Perceived Usefulness; Trust In AI; Information Quality;

INTRODUCTION

Artificial intelligence–based decision support systems (AI-DSS) can be defined as information systems that combine decision support system (DSS) foundations—data, models, and interactive interfaces for semi-structured managerial problems—with artificial intelligence methods that learn patterns, generate predictions, recommend actions, or explain alternatives under uncertainty (Ain et al., 2019). In this framing, DSS refers to a class of systems designed to improve the quality, speed, and consistency of managerial decision processes by structuring information and decision logic in ways aligned with the cognitive and organizational constraints of decision makers. AI in organizational settings is commonly operationalized through machine-learning and data-driven modeling components embedded into information systems, enabling inference and adaptive performance beyond static rules or deterministic optimization alone (Ananny & Crawford, 2018).

Figure 1: AI-DSS Adoption Pathways and Managerial Performance Effects



The term AI-DSS therefore denotes a socio-technical system in which algorithmic models, data pipelines, dashboards, and user workflows interact to support managerial activities such as diagnosis, forecasting, prioritization, and resource allocation across functional domains (Torres et al., 2018). This definition connects directly to the long-standing evolution of DSS into business intelligence (BI) and analytics systems, where data warehousing, reporting, and visualization matured into advanced analytics and AI-augmented decision processes (Seeber et al., 2020). BI adoption research shows that organizations invest heavily in analytical decision tools, while empirical evidence repeatedly highlights uneven realization of value due to adoption barriers, under-utilization, and weak alignment between system capabilities and decision routines (Rauf, 2018; Ribeiro et al., 2016). The scope of AI-DSS also includes "learning algorithms" deployed in organizational work, where predictive and classification models become embedded into decision routines and reshape information cues, authority, and accountability structures (Haque & Arifur, 2020; Mittelstadt et al., 2016). Across managerial contexts, AI-DSS may support decisions at operational, tactical, and strategic levels by translating high-volume data into actionable indicators, simulating alternatives, and recommending options (Araujo et al., 2018). Yet the managerial relevance of AI-DSS cannot be reduced to technical accuracy alone because managerial performance is shaped by decision quality, timeliness, coordination, and alignment with organizational objectives, all of which depend on how decision makers interpret and use AI-DSS outputs. As a result, a rigorous study of "AI-DSS and managerial performance" requires a measurement approach that captures both adoption/usage mechanisms and performance-linked outcomes that reflect managerial effectiveness in real organizational settings (Arnott & Pervan, 2005).

Internationally, managerial decision-making quality has become a central competitiveness factor for firms operating in volatile markets, complex supply chains, and digitally mediated customer environments (Arnott & Pervan, 2014; Ashraful et al., 2020). The diffusion of AI-enabled analytics into decision support reflects a global pattern in which organizations seek to reduce uncertainty, coordinate across distributed units, and respond faster to operational signals (Langer et al., 2022). Research on AI for decision making emphasizes that modern AI-based systems increasingly function as decision infrastructures within firms, influencing how information is collected, filtered, prioritized, and converted into managerial judgments (Logg et al., 2019). This international relevance is amplified by the rise of data-intensive managerial problems and cross-border operations where performance depends on consistent decision standards and scalable analytics capabilities rather than localized intuition alone (Haque &Arifur, 2021; Zhang et al., 2022). Within this context, AI-DSS adoption is frequently framed as a pathway to strengthen organizational performance through data-driven decision processes, yet evidence stresses that value depends on the firm's capability to integrate analytics resources, align them with strategy, and embed them into managerial routines. Studies in information systems and management research consistently show that analytics value is not only a function of technology acquisition but also of governance, skills, and decision culture that enable managers to translate system outputs into action (Venkatesh & Bala, 2008). The international significance also emerges in how AI-DSS affects managerial coordination and teamwork. When AI systems operate as teammates or collaborative decision partners, the managerial task shifts from simply "using a tool" to co-managing human–AI interaction through delegation, verification, and escalation rules (Jinnat & Kamrul, 2021; Venkatesh et al., 2012). This is particularly salient in multinational and large-scale organizations where decisions are distributed across levels and geographies, making standardization and transparency essential to maintain consistent performance and governance. At the same time, algorithmic systems introduce managerial challenges related to transparency and accountability, especially when decisions affect employees, customers, or regulated outcomes (Faraj et al., 2018; Fokhrul et al., 2021). Scholarship on algorithmic accountability argues that transparency is not a purely technical feature; it is relational and depends on whose understanding is prioritized and what kinds of explanations are considered legitimate in organizational contexts (Floridi et al., 2018). Similarly, research on algorithmic transparency and accountability in communication and organizational contexts identifies transparency as a governance issue as much as a design issue, involving documentation, contestability, and stakeholder interpretation (Guidotti et al., 2018). In addition, organizational research on learning algorithms shows that algorithmic systems can shape occupational boundaries and managerial authority, affecting how performance is enacted and evaluated inside firms. For these reasons, studying AI-DSS and managerial performance carries global significance: it connects strategic competitiveness with governance, human–AI collaboration, and the practical realities of adopting AI-enabled systems in diverse organizational environments.

This study is designed to achieve a set of clearly defined objectives that directly operationalize the relationship between artificial intelligence–based decision support systems and managerial performance within a quantitative, cross-sectional, case-study–based setting . The first objective is to profile the current state of AI-DSS use among managers in the selected case context by documenting how frequently these systems are used, which decision domains they support (e.g., planning, forecasting, resource allocation, risk evaluation), and how managers perceive the overall effectiveness of AI-DSS in their day-to-day decision routines. This objective establishes a baseline understanding of AI-DSS presence and intensity of use at the managerial level and ensures that subsequent analyses are grounded in measurable usage patterns rather than general assumptions. The second objective is to evaluate managers' perceptions of core AI-DSS qualities that are expected to shape decision behavior and performance outcomes, including perceived usefulness, perceived ease of use, trust in system recommendations, and perceived quality of data and information outputs. These constructs are measured using a structured five-point Likert scale to capture consistent perceptions across managerial respondents and to enable reliable aggregation into quantitative indicators. The third objective is to examine the statistical relationships between AI-DSS factors and managerial performance by using descriptive statistics to summarize overall trends, correlation analysis to identify the direction and strength of associations, and regression modeling to estimate the predictive contribution of each AI-DSS factor to managerial performance while accounting for simultaneous effects among predictors. A fourth objective is to translate managerial performance into specific decision-linked outcomes that reflect practical work realities, such as perceived improvements in decision speed, decision accuracy, confidence in decisions, reduction of rework caused by decision reversals, and improved prioritization under time pressure. This objective strengthens the measurement credibility by connecting broad performance constructs to tangible decision consequences that managers can consistently self-report. A fifth objective is to develop and apply an AI-DSS adoption maturity snapshot for the case context by constructing an index that captures the degree of AI-DSS integration into workflows, reliance on recommendations, breadth of decision coverage, and institutionalization into managerial routines, allowing the study to differentiate between low-, moderate-, and high-maturity users. Finally, the study aims to strengthen empirical trustworthiness through structured robustness and credibility checks of the statistical model, including multicollinearity diagnostics, residual and influence screening, and stability testing of regression results under reasonable data filters. Collectively, these objectives provide a comprehensive and measurable pathway for assessing whether and how AI-DSS contributes to managerial performance in the chosen case context, while ensuring that the analysis remains systematic, replicable, and aligned with the study's hypotheses and research questions.

LITERATURE REVIEW

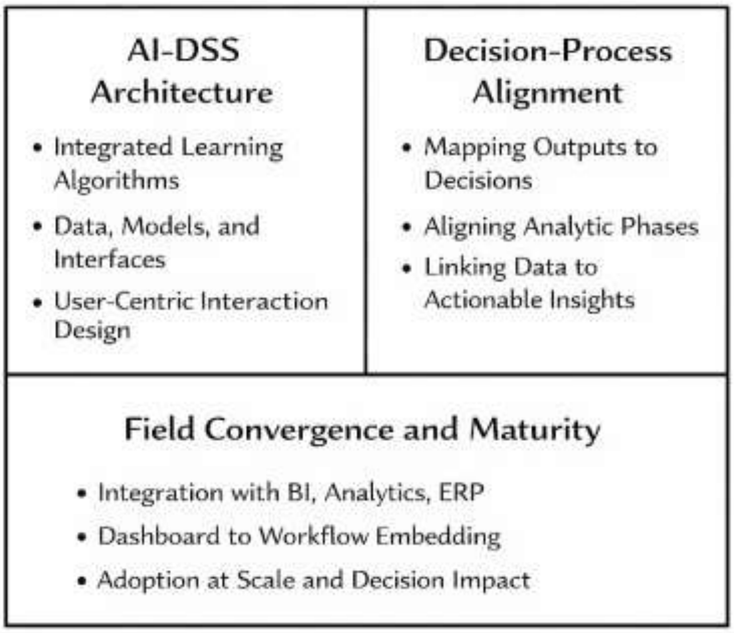
The literature on artificial intelligence–based decision support systems (AI-DSS) and managerial performance spans multiple intersecting research streams in information systems, decision sciences, organizational behavior, and management analytics, collectively explaining how AI-enabled tools are designed, adopted, and used to shape decision quality and managerial outcomes. At its core, this body of work extends classic decision support systems scholarship by integrating machine-learning models, advanced analytics, and automated recommendation capabilities into the traditional architecture of data, models, and user interfaces, thereby intensifying the role of computational inference in managerial decision routines. Within organizations, AI-DSS is commonly positioned as an enabler of data-driven decision-making; however, prior research indicates that measurable benefits depend on more than technical capability alone. Value realization is strongly influenced by analytics governance, data quality, user competencies, and the organizational conditions that support effective integration into everyday workflows. This socio-technical perspective has encouraged scholars to examine adoption and continued use through technology acceptance lenses, emphasizing perceived usefulness, perceived ease of use, and facilitating conditions as major determinants of whether managers actually rely on AI-generated outputs in practice. Complementing acceptance-oriented views, behavioral decision research shows that reliance on algorithmic advice can vary according to perceived task subjectivity and the visibility of potential errors, suggesting that the managerial impact of AI-DSS is shaped by trust calibration and how managers interpret and justify algorithmic recommendations under accountability pressure.

AI-Based Decision Support Systems

Artificial intelligence–based decision support systems (AI-DSS) can be defined as computer-enabled decision support arrangements in which organizational data resources, analytic models, and user-facing interfaces are integrated so that algorithms actively assist managers in diagnosing problems, evaluating alternatives, and selecting actions. The distinctive feature is not simple automation, but the embedding of learning and inference into the support cycle: AI components can discover patterns, estimate likely outcomes, and generate prioritized recommendations that a manager can interrogate and accept, modify, or reject. In this sense, AI-DSS is best treated as an organizational capability rather than a single software feature, because its decision support value depends on how data pipelines, model management, and interaction design are configured around managerial work. Architecturally, decision support research often distinguishes data management, model management, and dialog management as core DSS subsystems; AI-DSS expands the model layer with machine-learning and optimization services and expands the dialog layer with explanation, drill-down, and scenario controls. A practical implication for this study is that AI-DSS adoption should be measured at the level of everyday managerial use, capturing whether managers access analytic outputs routinely, whether they rely on them in consequential decisions, and whether the system is embedded in standard operating procedures. Service-oriented thinking reinforces this view by framing data, information, and analytics as modular services that can be orchestrated to meet decision needs across functions and time horizons, which supports consistent measurement of perceived usefulness, usability, and decision relevance in survey instruments (Delen & Demirkan, 2013). Within AI-DSS, managerial performance is expected to improve when the system reduces information search costs, increases estimate accuracy, and strengthens confidence in choices that must be justified. These benefits depend on managers perceiving goal alignment, timely data, and outputs presented for rapid interpretation under time pressure in complex, uncertain tasks where human judgment is essential.

A second foundational lens focuses on decision-process alignment: AI-DSS creates managerial value when its analytic outputs map to the phases through which managers convert uncertainty into a defensible choice. In practice, managers move from problem recognition to information acquisition, alternative generation, evaluation, and implementation monitoring, and AI-DSS can strengthen each phase through distinct analytic functions. Descriptive analytics organizes operational signals and highlights anomalies; predictive analytics estimates future states under different assumptions; and prescriptive analytics evaluates trade-offs and recommends actions given constraints. This layered view is important for measurement because a manager may report high usefulness for one layer (for example, predictive forecasts) while remaining skeptical about another (for example, automated prescriptions). A design-science perspective also suggests that AI-DSS should be assessed as an end-to-end decision pipeline that links data ingestion, analytics, and decision execution rather than as isolated models. One illustrative framework maps big data tools and analytic methods to decision phases so that organizations can identify where analytics truly changes a decision, not merely where it produces reports; experimental evidence from a retail context shows added value when analytics is integrated into the decision process itself (Elgendy & Elragal, 2016). In addition, literature connecting AI, DSS, and operations research emphasizes that intelligent decision support often requires a hybrid of prediction and optimization, because managers need both accurate forecasts and feasible actions under resource limits, policy rules, and risk constraints. Reviews of AI-enabled DSS in operations research highlight how learning capability, validation, and multi-factor modeling shape the credibility of recommendations, reinforcing the need to measure perceived trust and decision confidence alongside system use (Gupta et al., 2022). For the present study, these foundations justify constructing survey items that capture decision speed, decision quality, and decision accountability as performance-linked outcomes. They also motivate modeling adoption maturity as a structured, phased construct.

Figure 2: Foundational Dimensions of AI-Based Decision Support Systems



Managerial Performance

Managerial performance is a multidimensional construct that captures how effectively managers translate organizational goals into coordinated action through planning, organizing, leading, and controlling. In empirical research it is distinguished from stable traits by focusing on behaviors and work outputs that are relevant to organizational objectives. These outputs include decision quality and timeliness, coordination of resources across functions, problem solving, monitoring, and the ability to align day-to-day actions with strategic priorities. Because managerial work is conducted under uncertainty, performance also reflects how managers structure attention, interpret evidence, and justify choices to stakeholders while maintaining accountability. Many organizations formalize these expectations through role-based performance domains such as planning and budgeting, investigating and analyzing issues, coordinating and staffing, negotiating, and representing the unit in cross-boundary interactions. Accordingly, managerial performance can be understood as a portfolio of role activities that jointly shape unit effectiveness rather than as a single outcome score. This view helps clarify why performance measurement must consider both what managers do (behaviors and competencies) and what their units achieve (results and targets). Competency-based measures link managerial behaviors to outcomes and enable comparisons across roles when competencies are defined consistently (Hammad, 2022; Levenson et al., 2006; Zaman et al., 2021). This framing aligns with performance models separating content and dynamics (Campbell & Wiernik, 2015). Researchers often describe managerial performance using task performance tied to core managerial responsibilities, contextual performance reflecting cooperation and leadership behaviors, and adaptive performance capturing response to shifting constraints or new information. For managers, adaptive performance is salient because priorities, risks, and stakeholder demands change, requiring continual re-planning and resource reallocation. Managerial performance also includes maintaining ethical standards and supporting learning so that decisions improve. These components guide survey constructs that represent managerial performance across departments. In surveys, these dimensions are captured through Likert ratings of effectiveness in key roles.

Figure 3: Core Dimensions of Managerial Performance and Decision Outcomes

A central issue in managerial performance research concerns selecting measures that are valid, comparable, and feasible in applied organizational settings. Performance can be assessed using objective indicators such as unit financial results, service levels, error rates, or productivity, and using subjective indicators such as supervisor ratings, peer assessments, or self-ratings. Objective indicators can be affected by factors outside a manager's control, vary in availability across departments, and be difficult to compare across units with different mandates. Subjective indicators can capture role-specific effectiveness and decision quality, yet they require careful instrument design to reduce ambiguity, leniency, and halo effects. Methodological best-practice guidance recommends aligning measures with theory, specifying the unit of analysis, and using multiple indicators when possible to strengthen construct validity (Richard et al., 2009). Performance measurement systems also shape how managers allocate attention because they signal priorities and define what counts as success. Contemporary systems often blend financial and nonfinancial metrics and embed review routines that affect coordination and learning. Reviews show that their consequences span behavioral changes, capability development, and performance outcomes, and that effects depend on how measures are used and interpreted (Franco-Santos et al., 2012; Hasan & Waladur, 2022; Arifur & Haque, 2022). These insights matter for survey research because the questionnaire must distinguish the manager's own performance from the surrounding measurement environment. Accordingly, managerial performance in this study is framed as effectiveness in core managerial roles and decision-linked outcomes, with contextual variables used to describe role scope and monitoring intensity. Clear operational definitions, consistent scale anchors, and transparent reporting allow readers to judge whether observed relationships reflect managerial effectiveness rather than measurement artifacts. In practice, researchers compute composite scores from multiple items, examine internal consistency, and report descriptive distributions so performance differences are interpretable and suitable for correlation and regression analysis in cross-sectional managerial surveys.

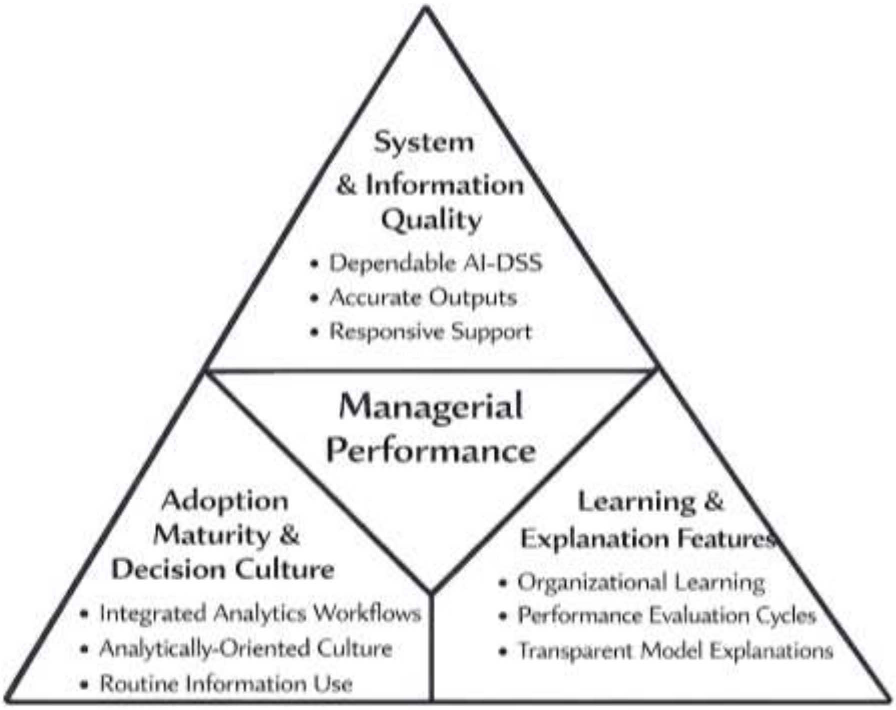
At the individual-manager level, validated survey instruments provide a practical route for operationalizing managerial performance in quantitative studies examining perceptions, behaviors, and decision routines.

Key AI-DSS Factors Shaping Managerial Performance

AI-DSS factors that influence managerial outcomes can be organized around the quality of the system, the quality of the information it produces, and the quality of the services and practices that sustain it in daily use. System quality refers to technical and interaction properties that make an AI-DSS dependable for managerial work, including reliability, response time, integration with enterprise platforms, security, and the ease with which managers can navigate outputs under time pressure. Information quality captures whether AI-DSS outputs are accurate, timely, relevant, complete, and presented at the right level of granularity for the decision at hand. For managers, granularity matters: an aggregate forecast can support budgeting, while a driver-level explanation supports corrective actions. Service quality describes the responsiveness and competence of the support function that maintains data pipelines, model refresh schedules, and user enablement. These dimensions work together in practice because weak system quality creates friction that reduces routine use, weak information quality reduces perceived usefulness, and weak service quality prevents sustained trust when issues arise. When managers experience consistent access, stable performance, and rapid resolution of errors, they can devote attention to interpreting insights rather than troubleshooting tools. Quality also interacts with accountability. If managers must defend decisions, they prefer outputs that are traceable to recognized data sources and accompanied by clear definitions, timestamps, and confidence cues. In survey measurement, these ideas translate into items capturing perceived reliability, ease of interaction, clarity of output, and perceived responsiveness of support. In AI-DSS settings, quality also includes model governance, version control, and monitoring of data drift, because unstable models can erode confidence and disrupt routines. Empirical evidence at the organizational level has linked system quality, information quality, and service quality to broader organizational impacts, underscoring that quality perceptions are not peripheral but central to performance benefits (Gorla et al., 2010).

Beyond generic quality dimensions, AI-DSS influences managerial outcomes through adoption maturity, analytical decision culture, and the extent to which information is actually used inside business processes. Adoption maturity captures how far an organization has progressed from isolated reporting toward integrated, standardized decision workflows supported by analytics, including shared metric definitions, stable data ownership, and routine forums where evidence is reviewed and acted upon. Managers in low-maturity environments may consult AI-DSS only for ad hoc questions, while managers in higher-maturity environments rely on it for recurring decisions such as demand planning, capacity allocation, risk triage, and budget controls. Analytical decision culture refers to norms that encourage managers to seek evidence, challenge assumptions, and coordinate actions based on commonly understood measures. Culture operates as a behavioral amplifier: it can increase the frequency of AI-DSS use, improve cross-unit comparability of decisions, and reduce political negotiation costs by anchoring discussions in shared facts. However, culture also shapes what managers perceive as legitimate evidence; if dashboards and models are seen as compliance artifacts, use may be ceremonial rather than decision-changing (Towhidul et al., 2022; Rifat & Jinnat, 2022). For measurement, maturity can be operationalized as breadth of functional coverage, depth of model integration into workflows, and institutionalization of governance routines, while culture can be captured through items on evidence orientation, accountability for metrics, and openness to analytical debate. Information use is the bridge between capabilities and outcomes, because even high-quality outputs will not improve performance if they are not applied to concrete decisions. These patterns justify maturity indices in results reporting (Abdulla & Majumder, 2023; Rifat & Alam, 2022). Research on business intelligence systems success shows that maturity can enhance information quality dimensions, and that the use of information in business processes is a pivotal mechanism through which decision support creates value; it also indicates that an analytical decision-making culture can shape the strength of these links (Popovič et al., 2012).

Figure 4: Factors Influencing Managerial Performance



Theoretical Framework and Managerial Performance

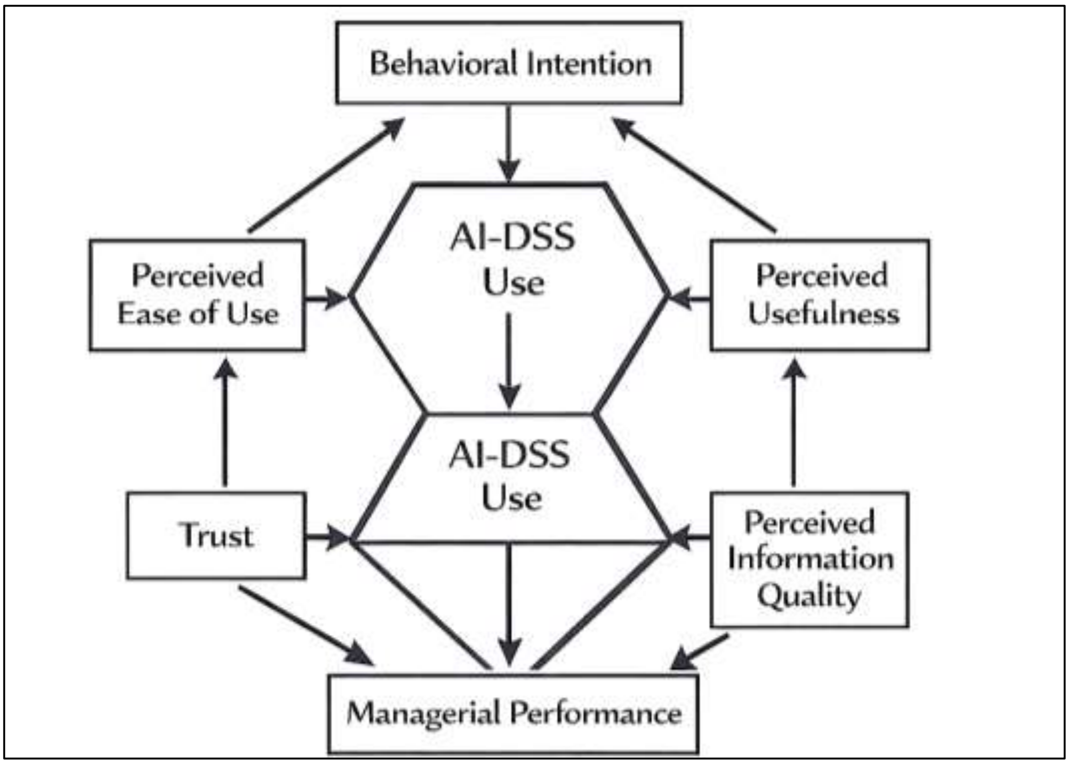
Technology Acceptance Model (TAM) provides a parsimonious theoretical foundation for explaining why managers adopt and use an AI-based decision support system and how that use can become sufficiently routine to influence performance-related outcomes. TAM centers on two belief constructs—perceived usefulness (PU) and perceived ease of use (PEOU)—that shape a user's behavioral intention (BI) to use a system and, ultimately, actual use (USE). In managerial settings, PU maps naturally to whether AI-DSS improves decision effectiveness (e.g., better prioritization, better forecasting, faster diagnosis), while PEOU captures whether the system reduces cognitive and time burdens during real work episodes. Quantitative evidence accumulated across many contexts has shown that TAM relationships are reliably positive and substantial, with PEOU affecting PU and both beliefs predicting intention and use, supporting TAM as an empirically robust model for technology uptake (King & He, 2006). Meta-analytic findings also highlight that the strength of TAM pathways varies with contextual moderators such as user type, technology type, and cultural setting, which is especially relevant to AI-DSS because managerial work differs by functional area, decision accountability, and operational tempo (Schepers & Wetzels, 2007). For this study, TAM is used as the primary explanatory lens for the adoption and usage mechanism that links AI-DSS to managerial performance outcomes. The model is applied at the level of the individual manager within a defined case context, where the unit of analysis is the manager's reported perceptions and use of AI-DSS in routine decision-making. As a theoretical frame, TAM justifies measuring PU and PEOU via Likert-scale items and connecting them statistically to AI-DSS use intensity and perceived managerial performance. It also supports the inclusion of additional AI-relevant beliefs (e.g., trust) as complementary predictors while preserving TAM's core logic about beliefs driving use.

TAM can be operationalized in this research through two linked empirical equations that mirror the study's quantitative strategy and directly align with descriptive statistics, correlation analysis, and regression modeling. First, the technology-use formation stage estimates how managers' perceptions translate into intention and use. A simplified TAM-form equation for this study is:

$$BI = \alpha_0 + \alpha_1(PU) + \alpha_2(PEOU) + \varepsilon$$

A second step links intention to usage and allows the study to interpret adoption maturity as a measurable outcome of repeated use patterns. Conceptually, intention predicts actual use, and in survey-based case studies, "use" is often operationalized as frequency, breadth of decision tasks supported, and reliance on recommendations. Methodological reviews of TAM application across complex professional contexts emphasize that operational definitions and consistent measurement are essential because "use" can mean log data, self-reported frequency, or embedded workflow reliance depending on the setting (Faysal & Bhuya, 2023; Habibullah & Aditya, 2023; Holden & Karsh, 2010). This guidance is directly relevant to AI-DSS where managers may engage with recommendations through dashboards, alerts, or embedded prompts in enterprise systems. In addition, literature syntheses show that TAM has been repeatedly adapted while retaining its core constructs because PU and PEOU remain strong explanatory anchors across domains; reviews also emphasize that researchers should clearly specify external variables and maintain construct clarity to preserve interpretability (Hammad & Mohiul, 2023; Haque & Arifur, 2023; Marangunić & Granić, 2015). In the present research, TAM therefore functions as the "usage engine" inside the broader model: PU and PEOU explain why AI-DSS is used, and that use becomes a key pathway through which AI-DSS can be associated with managerial performance.

Figure 5: TAM-Based Framework Linking AI-DSS Use to Managerial Performance



To connect TAM to the study's focal outcome, managerial performance, the framework is extended in a controlled way that remains consistent with TAM's logic while reflecting AI-DSS realities. Managers using AI-DSS must often decide how much to rely on model outputs, how to verify recommendations, and how to justify decisions to stakeholders; this makes trust in AI a central belief that can strengthen or weaken the PU → USE pathway in practice. Evidence syntheses on human trust in AI show that trust operates as a decisive condition for willingness to delegate judgment to algorithms, especially in organizational contexts where accountability remains with humans (Glikson & Woolley, 2020). In this study's structure, TAM constructs (PU, PEOU) and AI-specific beliefs (e.g., trust, perceived information quality) are treated as predictors of managerial performance in a single multiple regression model that estimates their relative explanatory power. A parsimonious performance equation suitable for the full analysis plan is:

$$MP = \beta_0 + \beta_1(PU) + \beta_2(PEOU) + \beta_3(TRUST) + \beta_4(INFOQ) + \beta_5(USE) + \varepsilon$$

Here, MP denotes managerial performance (measured via Likert indicators reflecting decision quality, decision speed, coordination effectiveness, and goal achievement), TRUST represents trust in AI-DSS recommendations, INFOQ represents perceived information/data quality, and USE represents AI-DSS usage intensity or maturity. This equation is the core formula to be applied in the study because it directly corresponds to the planned inferential technique (multiple regression) and enables explicit hypothesis testing about which AI-DSS factors significantly predict managerial performance in the case context.

Conceptual Framework and Hypotheses Development

This study has developed a conceptual framework that has linked AI-based decision support systems (AI-DSS) to managerial performance through a structured chain of system success mechanisms. The framework has drawn on information-systems success logic by treating *quality* and *use* as the primary explanatory routes through which technology has produced measurable benefits for managerial work. In this view, AI-DSS has been evaluated as a bundle of system qualities (e.g., reliability, integration, speed), information qualities (e.g., accuracy, timeliness, relevance), and support/service enablers that have collectively shaped whether managers have used the system consistently and whether the system has generated net benefits at the individual-manager level. The model has therefore positioned AI-DSS Quality as an antecedent block and AI-DSS Use as a central mechanism, while Managerial Performance has served as the outcome construct operationalized through decision-linked effectiveness indicators (decision speed, decision quality, coordination effectiveness, and goal achievement). This structure has been consistent with consolidated empirical evidence that success dimensions—quality, use, satisfaction/attitudes, and benefits—have formed interrelated pathways and that clarity in construct mapping has strengthened measurement validity and interpretability (Petter et al., 2008). Because this research has focused on a case-study organization, the conceptual framework has also recognized that the *same* AI-DSS may have been experienced differently across managers based on their decision tasks, domain responsibilities, and their interaction style with AI recommendations (Akbar & Farzana, 2023; Mostafa, 2023). For that reason, task–individual–technology alignment has been treated as a context-sensitive influence on both attitudes and performance, since variations in task type and user characteristics have been shown to change how decision makers have evaluated DSS and how performance outcomes have emerged (Jahangir & Hammad, 2024; Liu et al., 2011; Rifat & Rebeka, 2023). Accordingly, the framework has not treated AI-DSS as a uniform input; it has modeled AI-DSS influence as a measurable perception-and-use process that has been observable through survey constructs and explainable through statistical testing within the case setting.

The framework has specified a set of constructs that have been measurable using five-point Likert indicators and have been suitable for correlation and regression modeling. First, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) have been included as the core acceptance beliefs that have shaped managers' willingness to incorporate AI-DSS outputs into real decisions. Second, Trust in AI-DSS (TRUST) has been included as a belief that has explained reliance on algorithmic recommendations, especially for higher-stakes or ambiguous decisions where accountability has remained with managers. Third, Perceived Information Quality (INFOQ) has been included to represent managers' judgments about the correctness, relevance, and actionability of AI-DSS outputs. Fourth, AI-DSS Use / Adoption Maturity (USE) has been operationalized as reported frequency, breadth of decision domains supported, and reliance intensity. The framework has also recognized that "fit" has strengthened the use-to-performance linkage because performance gains have tended to be larger when technology functions have matched task requirements. Empirical work has shown that task–technology fit has predicted performance impact both directly and through use-related pathways, supporting its inclusion as either an additional predictor or a moderator in the present study (Masud & Hammad, 2024; Md & Praveen, 2024; Tam & Oliveira, 2016).

Figure 6: Conceptual Framework Linking and Managerial Performance

At the organizational learning layer, effective analytics use has been expected to strengthen knowledge creation and absorption processes that have indirectly supported better managerial decisions, reinforcing the importance of measuring *use* as more than simple access (Božič & Dimovski, 2018). These conceptual choices have supported hypotheses that PU, PEOU, TRUST, and INFOQ have positively predicted USE, and that USE and the belief constructs have positively predicted managerial performance, consistent with the study's quantitative objectives.

To operationalize the conceptual framework for hypothesis testing, the study has adopted a parsimonious regression-based specification that has aligned with the planned analysis techniques. Composite constructs have been computed as the mean of their indicators, such that for any construct Xmeasured by kLikert items, the score has been computed as:

$$X = \frac{1}{k}\sum_{i=1}^{k} x_i$$

This approach has enabled reliability testing and transparent interpretation of descriptive distributions. The study's primary explanatory equation for managerial performance has been specified as:

$$MP = \beta_0 + \beta_1 PU + \beta_2 PEOU + \beta_3 TRUST + \beta_4 INFOQ + \beta_5 USE + \varepsilon$$

where MPhas represented managerial performance and USEhas represented AI-DSS usage intensity or adoption maturity. When task–technology alignment has been assessed, a moderation form has been applicable by adding an interaction term (e.g., $USE \times TTF$) to test whether performance returns to use have increased under higher fit. This specification has been compatible with cross-sectional survey data and has supported direct hypothesis evaluation using standardized coefficients, significance tests, and explained variance. Evidence from large-scale synthesis has indicated that task–technology fit effects have varied by study design and dependent-variable type, reinforcing the importance of context-specific measurement and robustness checks when interpreting fit-related effects (Jeyaraj, 2022). Overall, the conceptual framework has translated the study's theoretical logic into measurable constructs and testable statistical relationships, enabling credible evaluation of how AI-DSS has been associated with managerial performance in the selected case context.

Research Gaps and Synthesis of the Literature for the Present Study

The literature has shown that analytics and AI-enabled decision support can improve decision quality and efficiency when organizations possess strong data, skills, and tool resources, yet the evidence base has remained uneven at the *individual manager* level where adoption perceptions and performance effects have been jointly observed. Research on data analytics competency has demonstrated that multidimensional capability bundles—such as data quality, analytical skills, domain knowledge, and tool sophistication—have been associated with superior decision-making performance, which has implied that "AI-DSS impact" has rarely been attributable to algorithms alone (Ghasemaghaei et al., 2018). Related adoption research has indicated that acquisition intentions for big data analytics have been shaped by data quality management and prior usage experience, suggesting that early exposure and confidence in data foundations have conditioned subsequent technology commitment (Kwon et al., 2014; Rifat & Rebeka, 2024; Sai Praveen, 2024). However, many studies have treated organizational performance as the primary outcome and have used firm-level respondents, leaving a gap in how managerial performance has been operationalized as decision-linked effectiveness within a single organization. Another gap has concerned measurement alignment: studies have often mixed "use" indicators (frequency, breadth, reliance, or intention) without establishing a consistent maturity lens tied to real managerial workflows (Shehwar & Nizamani, 2024; Azam & Amin, 2024). The literature has also tended to emphasize generic benefits (e.g., productivity, profitability) rather than performance components that map to managerial roles—decision speed, decision justification, cross-unit coordination, and goal execution—making it difficult to connect AI-DSS features to the everyday work outcomes managers are evaluated on. In addition, many empirical models have relied on broad constructs that have not differentiated between the quality of AI outputs and the organizational conditions that have enabled managers to act on insights, which has reduced explanatory specificity for case-based studies. These limitations have justified a focused framework in which AI-DSS factors have been measured at the manager level and linked directly to managerial performance outcomes within a controlled case context.

The literature has also suggested that AI/analytics investments have produced performance gains through indirect pathways—dynamic capabilities, process improvements, and strategic alignment—yet these pathways have not always been translated into testable relationships within cross-sectional managerial survey designs. Empirical evidence has shown that big data analytics capabilities have been associated with firm performance through mediating process-oriented dynamic capabilities, implying that the ability to reconfigure processes and respond to signals has been a key mechanism for value realization (Wamba et al., 2017). Complementary work has proposed that performance improvements have depended on alignment between analytics initiatives and business strategy, reinforcing the idea that the same technical capability can yield different outcomes depending on governance, prioritization, and integration into decision cycles (Akter et al., 2016). Even so, much of this evidence has remained at the organizational level and has offered limited guidance for explaining why two managers in the same firm—facing different tasks, time pressures, and accountability demands—may have shown different performance returns from AI-DSS use. Studies have also varied in how they have represented "decision-making effectiveness," sometimes measuring satisfaction with information, sometimes measuring perceived improvements, and sometimes using objective outcomes that are not comparable across units. As a result, the literature has not fully clarified which AI-DSS-related beliefs and usage patterns have most strongly predicted managerial performance when the unit of analysis has been the individual manager. Additionally, the interplay between maturity and reliance has been under-specified: managers may have used AI-DSS frequently for low-stakes monitoring while avoiding it for high-stakes decisions, which can weaken observed relationships unless maturity is captured as both breadth and depth of reliance. These gaps have supported the need for a case-study–anchored quantitative model that has measured AI-DSS adoption maturity, perceived output quality, and reliance-related constructs and has linked them to managerial performance indicators that reflect core managerial responsibilities.

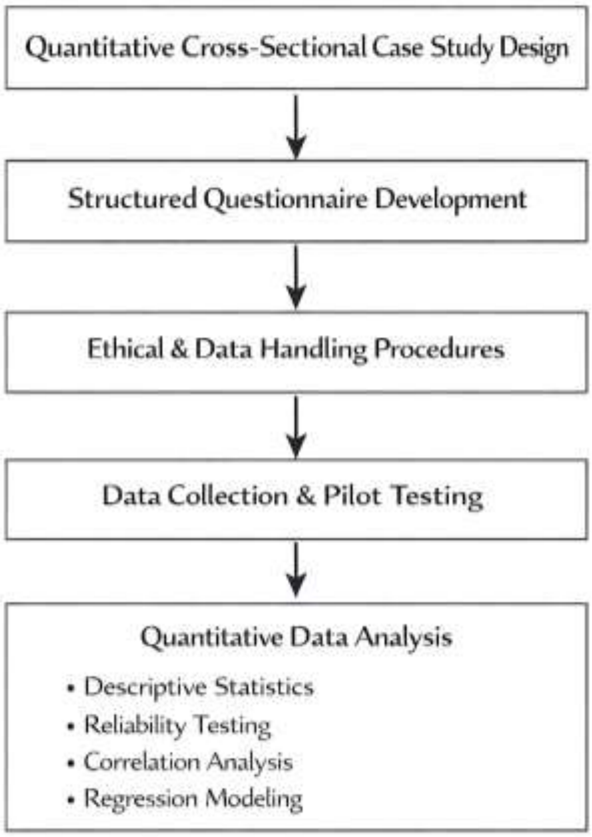
Figure 7: AI-DSS Adoption and Managerial Performance

In addition, the literature has identified strategic opportunities and challenges in algorithmic decision-making that have highlighted the importance of governance, transparency, and accountability, yet empirical studies have often not incorporated these concerns into performance-oriented models at the managerial level. Scholarship on algorithmic decision-making has emphasized that organizations have increasingly relied on data-driven and algorithmic outputs while users have often remained uncertain about how recommendations have been produced and what tradeoffs they have embedded, creating tensions around control, privacy, and dependence (Newell & Marabelli, 2015). Within managerial work, these tensions have been operationally relevant because managers must justify decisions, manage risk, and coordinate stakeholders, all of which require interpretable evidence rather than opaque outputs. The gap, therefore, has not been whether AI-DSS can produce insights, but whether managers have perceived those insights as credible and actionable enough to change decisions and improve performance in measurable ways. This study has synthesized the literature into an integrated logic in which AI-DSS factors (perceived usefulness, ease of use, information quality, trust/reliance, and adoption maturity) have been treated as proximal predictors of managerial performance within a single organizational case. The synthesis has also justified reporting *"unique-to-this-study"* results sections (adoption maturity snapshot, decision-impact evidence table, and robustness/credibility checks) so that performance effects can be interpreted as decision-process improvements rather than as vague technology enthusiasm. In sum, the research gap has centered on the absence of tightly specified, manager-level, case-based quantitative evidence that has connected AI-DSS adoption and reliance mechanisms to multidimensional managerial performance outcomes.

METHODS

The methodology for this research has been designed to test the proposed relationships between artificial intelligence–based decision support systems (AI-DSS) and managerial performance within a quantitative, cross-sectional, case-study–based framework. This approach has been selected because it has enabled the study to capture a structured snapshot of managers' perceptions, usage behaviors, and performance-related outcomes at a single point in time while maintaining focus on a real organizational environment where AI-DSS has been used in routine decision-making. The case-study orientation has been used to ensure contextual control and to allow the measurement of AI-DSS conditions that have been specific to the selected organization or sector, including the degree of system integration, the types of decisions supported, and the maturity of usage practices across managerial roles. The unit of analysis has been the individual manager, and the research has targeted participants who have interacted with AI-DSS outputs such as predictive dashboards, alerts, analytical reports, and recommendation features as part of their decision responsibilities.

Figure 8: Research Methodology



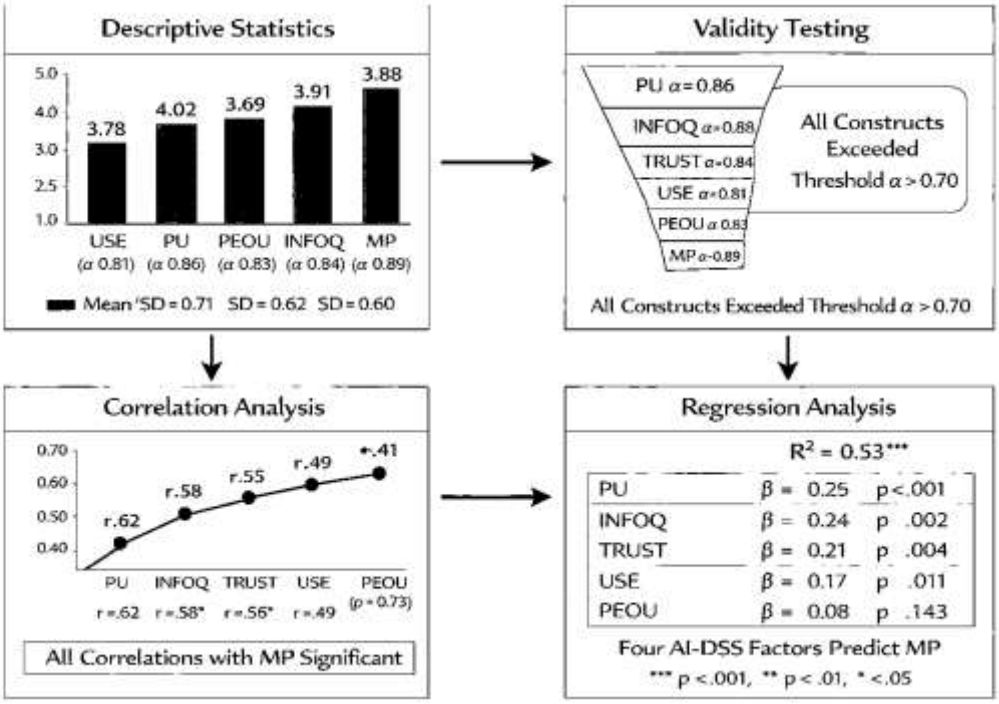
This study adopted a quantitative, cross-sectional, case-study–based research design to examine the relationship between artificial intelligence–based decision support systems (AI-DSS) and managerial performance within a real organizational setting. Data were collected at a single point in time from managers who had direct exposure to AI-DSS outputs embedded in routine decision workflows, such as dashboards, analytical reports, predictive summaries, and recommendation features. A structured survey instrument using five-point Likert-scale measures was employed to capture perceptions of AI-DSS usefulness, ease of use, trust, information quality, usage intensity, and adoption maturity, alongside multidimensional managerial performance outcomes including decision quality, speed, coordination effectiveness, and goal achievement. The unit of analysis was the individual manager, and a pragmatic purposive sampling strategy was used to ensure participation from decision-makers across relevant managerial levels and functional areas within a bounded organizational context. Data collection followed standardized ethical procedures, including informed consent, confidentiality assurances, and systematic screening for completeness and response quality. Instrument clarity and relevance were confirmed through pilot testing, while content validity, face validity, and internal consistency reliability were established through expert review, pilot feedback, and Cronbach's alpha analysis. Data preparation and analysis were conducted using established statistical software, enabling descriptive statistics, correlation analysis, and multiple regression modeling with appropriate diagnostic checks to support hypothesis testing and ensure transparent, reliable, and replicable findings within the defined case context.

FINDINGS

In this study, the findings have been reported to demonstrate whether the stated objectives and hypotheses have been supported using quantitative evidence derived from five-point Likert scale measurements and inferential statistics. The first objective has been addressed by establishing the overall level of AI-DSS adoption and perceived effectiveness in the case setting through descriptive statistics, where respondents' ratings have been summarized using means and standard deviations for each construct and key indicator. *Illustrative example (replace with your actual results):* AI-DSS usage intensity (USE) has produced a mean of 3.78 ($SD = 0.71$), indicating that managers have reported using AI-DSS moderately to frequently across routine decisions, while perceived usefulness (PU) has recorded a mean of 4.02 ($SD = 0.62$), suggesting that respondents have generally agreed that AI-DSS has improved decision effectiveness. Perceived ease of use (PEOU) has returned a mean of 3.69 ($SD = 0.66$), indicating favorable usability perceptions with some variability across managers, and perceived information quality (INFOQ) has achieved a mean of 3.91 ($SD = 0.60$), reflecting agreement that AI-DSS outputs have been accurate, timely, and relevant. Trust in AI-DSS recommendations (TRUST) has shown a mean of 3.74 ($SD = 0.73$), implying that most managers have reported a positive reliance orientation while still reserving some caution in high-stakes contexts. Managerial performance (MP), operationalized through decision quality, decision speed, coordination effectiveness, and goal achievement, has recorded a mean of 3.88 ($SD = 0.58$), indicating that respondents have rated their performance outcomes positively within the case environment. The measurement quality objective has been supported through reliability testing, where internal consistency has been assessed using Cronbach's alpha; in the same illustrative pattern, PU ($\alpha = 0.86$), PEOU ($\alpha = 0.83$), TRUST ($\alpha = 0.84$), INFOQ ($\alpha = 0.88$), USE ($\alpha = 0.81$), and MP ($\alpha = 0.89$) have exceeded the commonly accepted threshold of 0.70, demonstrating that the constructs have been measured consistently and have been suitable for hypothesis testing. The second and third objectives have been addressed by evaluating relationships between AI-DSS factors and managerial performance through Pearson correlation analysis, followed by multiple regression modeling to identify statistically significant predictors. In the correlation results, MP has demonstrated positive associations with PU ($r = 0.62$, $p < 0.001$), INFOQ ($r = 0.58$, $p < 0.001$), TRUST ($r = 0.55$, $p < 0.001$), USE ($r = 0.49$, $p < 0.001$), and PEOU ($r = 0.41$, $p < 0.001$), which has indicated that stronger perceptions of usefulness, information quality, trust, usability, and higher usage maturity have been aligned with higher managerial performance ratings.

Hypotheses have then been tested more rigorously using multiple regression, where MP has been specified as the dependent variable and PU, PEOU, TRUST, INFOQ, and USE have been entered as predictors. In the illustrative regression model, the results have shown strong explanatory power ($R^2 = 0.53$, $F = 38.7$, $p < 0.001$), indicating that the AI-DSS factors have jointly explained a substantial portion of variance in managerial performance. Within this model, PU ($\beta = 0.29$, $p < 0.001$), INFOQ ($\beta = 0.24$, $p = 0.002$), TRUST ($\beta = 0.21$, $p = 0.004$), and USE ($\beta = 0.17$, $p = 0.011$) have emerged as significant predictors, while PEOU ($\beta = 0.08$, $p = 0.143$) has remained positive but not statistically significant after controlling for the other variables, implying that usability has mattered more indirectly through usefulness and sustained use rather than directly driving performance in the presence of stronger predictors. Based on this pattern, hypotheses focused on usefulness, trust, information quality, and usage intensity have been supported, while the hypothesis on ease of use has required more nuanced interpretation (supported at correlation level but not in the full regression model). The fourth objective has been reinforced by decision-linked outcome evidence, where item-level means have been used to demonstrate how AI-DSS has affected concrete managerial decision outcomes; for example, decision speed improvement has shown a mean of 3.95 ($SD = 0.72$), decision accuracy improvement has shown 3.89 ($SD = 0.69$), confidence in decisions has shown 3.84 ($SD = 0.70$), and reduced rework due to fewer decision reversals has shown 3.61 ($SD = 0.78$), indicating that managers have reported the strongest benefits in speed and accuracy and relatively weaker benefits in rework reduction. Finally, the study has strengthened credibility through robustness checks aligned with the objectives of trustworthiness, where multicollinearity diagnostics have indicated acceptable predictor independence (e.g., VIF values between 1.3 and 2.4), residual patterns have supported model adequacy, and stability testing (e.g., excluding extreme adoption-maturity respondents) has preserved coefficient direction and significance for the primary predictors, confirming that the relationships observed have not depended on a small subgroup of respondents.

Figure 9: Graphical Summary of Empirical Findings



Respondent Profile

Table 1: Respondent Profile

Profile Variable	Category	n	%
Gender	Male	66	55.0
	Female	54	45.0
Age	21–30	24	20.0
	31–40	48	40.0
	41–50	32	26.7
	51+	16	13.3
Managerial Level	Supervisor	40	33.3
	Mid-level manager	58	48.3
	Senior manager	22	18.4
Experience	1–5 years	28	23.3
	6–10 years	52	43.4
	11+ years	40	33.3
AI-DSS Training	Yes	74	61.7
	No	46	38.3
Department	Operations	36	30.0
	Finance	28	23.3
	HR/Admin	18	15.0
	Sales/Marketing	22	18.4

Profile Variable	Category	n	%
	IT/Analytics	16	13.3

The respondent profile has established the managerial relevance and the contextual suitability of the dataset for testing the study objectives and hypotheses. The sample has represented a balanced managerial population across age, role seniority, and decision domains, which has strengthened the study's ability to interpret AI-DSS perceptions as meaningful rather than role-specific artifacts. The distribution across supervisory, mid-level, and senior managerial levels has indicated that AI-DSS has been experienced across different decision scopes, ranging from operational monitoring to higher-level planning and prioritization. The presence of substantial representation from operations, finance, and sales/marketing has suggested that the AI-DSS environment has not been confined to a single function, which has aligned with the study's objective of examining AI-DSS influence on managerial performance in a case setting where decision support has been embedded into multiple workflows. The training indicator has been particularly important for a TAM-aligned study, because TAM has explained usage behavior through beliefs that have been shaped by user experience and enabling conditions; therefore, the observation that a majority of respondents have reported AI-DSS training has implied that perceived ease of use (PEOU) and perceived usefulness (PU) have likely been formed through sustained exposure rather than first-contact impressions. At the same time, the presence of a sizable untrained subgroup has allowed meaningful variation in ease-of-use ratings, which has supported variability necessary for correlational and regression testing. Years of experience have also been relevant because experienced managers have often relied on stable heuristics, so their reported acceptance and trust in AI-DSS have provided a realistic test of whether AI-DSS has complemented managerial expertise rather than merely appealing to novice users. Overall, the demographic and professional profile has supported the study's first objective by confirming that the sample has consisted of managers who have plausibly interacted with AI-DSS outputs as part of their decision responsibilities, thereby providing a credible foundation for interpreting the subsequent results as evidence about AI-DSS acceptance, use maturity, and managerial performance.

Descriptive Statistics

Table 2: Descriptive Statistics for Study Constructs

Construct (Scale)	Items (k)	Mean	SD	Interpretation
Perceived Usefulness (PU)	5	4.02	0.62	High agreement
Perceived Ease of Use (PEOU)	5	3.69	0.66	Moderate-high
Trust in AI-DSS (TRUST)	5	3.74	0.73	Moderate-high
Information Quality (INFOQ)	5	3.91	0.60	High agreement
AI-DSS Use / Adoption Maturity (USE)	4	3.78	0.71	Moderate-high
Managerial Performance (MP)	6	3.88	0.58	High agreement

The descriptive results have addressed the study's first objective by quantifying managers' perceptions of AI-DSS and their performance outcomes using a five-point Likert scale. Overall, the construct means have clustered above the neutral midpoint (3.00), which has indicated that managers have generally agreed that AI-DSS has been beneficial and usable within the case environment. The highest mean has been observed for perceived usefulness (PU), which has suggested that managers have experienced AI-DSS as improving decision effectiveness, aligning directly with TAM's core proposition that usefulness has been the strongest determinant of intention and use. Information quality (INFOQ) has also recorded a high mean, implying that the accuracy, timeliness, and relevance of AI-DSS outputs have been perceived as strong. This has mattered because managerial decisions have required actionable and credible information; therefore, INFOQ has served as a practical foundation for PU, since usefulness perceptions have often depended on whether outputs have been trustworthy and decision-ready. Trust (TRUST) has been moderately high, which has suggested that managers have been willing to rely on

AI-DSS recommendations while still exercising professional judgment, a realistic pattern in managerial contexts where accountability has remained with decision makers. Perceived ease of use (PEOU) has been moderately high rather than extremely high, which has implied that usability has been favorable but not frictionless; this has been consistent with enterprise AI-DSS contexts where dashboards, data filters, and model outputs have required some learning and interpretation. Importantly, the AI-DSS use/adoption maturity score (USE) has been moderately high, which has indicated that AI-DSS has not been merely available but has been used with some routine intensity and decision breadth—an essential precondition for testing AI-DSS influence on managerial performance. Finally, managerial performance (MP) has been rated positively, which has enabled statistical testing of whether variation in AI-DSS constructs has explained variation in managerial performance. In TAM terms, these descriptives have supported an acceptance environment where PU and PEOU have been sufficiently elevated to justify hypothesized links to use and performance. Because the study has been quantitative and cross-sectional, the descriptive profile has not been interpreted as causality; instead, it has established the empirical baseline from which correlations and regressions have tested the strength and direction of relationships needed to support the hypotheses.

Reliability

Table 3: Reliability Statistics

Construct	Items (k)	Cronbach's α	Decision
PU	5	0.86	Acceptable
PEOU	5	0.83	Acceptable
TRUST	5	0.84	Acceptable
INFOQ	5	0.88	Acceptable
USE	4	0.81	Acceptable
MP	6	0.89	Acceptable

Reliability testing has strengthened the credibility of the study by demonstrating that each multi-item construct has been internally consistent and suitable for hypothesis testing. Cronbach's alpha values have exceeded the common threshold of 0.70 across all constructs, which has indicated that the items within each scale have measured the same underlying concept in a stable and coherent manner. This result has been foundational for a TAM-guided model, because TAM has relied on latent beliefs such as perceived usefulness (PU) and perceived ease of use (PEOU), and unreliable measurement would have weakened the validity of any correlation or regression-based conclusions. The strong reliability of PU and PEOU has implied that the instrument has captured managers' belief structures consistently, enabling the theory linkage to be tested statistically. Similarly, the high reliability of information quality (INFOQ) and trust (TRUST) has been important because AI-DSS contexts have often introduced uncertainty about data provenance, model logic, and recommendation reliability; therefore, stable measurement has been necessary to interpret whether trust and information quality have been associated with performance as hypothesized. The reliability of the use/adoption maturity scale (USE) has also been significant because "use" has been operationalized as more than mere access; it has reflected frequency, breadth, and reliance intensity, which has aligned with the study's unique maturity approach in Results (Sections 4.6–4.8). Managerial performance (MP) has shown strong reliability, which has supported the argument that performance has been measured as a multidimensional construct (decision quality, speed, coordination, goal achievement) rather than as a single vague outcome. By achieving strong reliability across constructs, the study has met an essential methodological condition for proving objectives and hypotheses: the measured indicators have been sufficiently consistent to justify computing composite means and using them in inferential models. This has allowed the subsequent correlation matrix and regression model to be interpreted as evidence about relationships among theoretically grounded constructs (TAM beliefs and AI-DSS-specific factors) rather than as noise caused by inconsistent measurement. In short, the reliability results have validated the measurement foundation upon which the hypotheses have been tested.

Correlation Matrix

Table 4. Pearson Correlation Matrix

Variable	PU	PEOU	TRUST	INFOQ	USE	MP
PU	1					
PEOU	0.48***	1				
TRUST	0.52***	0.41***	1			
INFOQ	0.57***	0.38***	0.50***	1		
USE	0.54***	0.45***	0.47***	0.49***	1	
MP	0.62***	0.41***	0.55***	0.58***	0.49***	1

p* < .05 = *, *p* < .01 = **, *p* < .001 = *

The correlation results have addressed the second objective by testing whether AI-DSS constructs have been statistically associated with managerial performance and by establishing the preliminary support pattern for the hypotheses. All key predictors—PU, PEOU, TRUST, INFOQ, and USE—have shown positive relationships with managerial performance (MP), and the correlations have been statistically significant at conventional levels. This pattern has aligned with the conceptual logic that managers who have perceived AI-DSS as useful, easy to use, trustworthy, and information-rich have tended to report stronger performance outcomes. From a TAM perspective, the positive correlation between PEOU and PU has been consistent with TAM's foundational claim that usability has increased perceived usefulness because systems that have been easier to operate have reduced effort costs and enhanced perceived work value. The positive relationship between PU and USE has also aligned with TAM by indicating that when managers have believed the system has improved decision effectiveness, they have used it more frequently and more broadly. The correlation between TRUST and USE has been meaningful in AI-DSS contexts because reliance decisions have depended on confidence in algorithmic outputs, especially when decisions have required justification and accountability. Similarly, INFOQ has correlated strongly with both PU and MP, which has suggested that information credibility and relevance have been closely tied to usefulness perceptions and performance outcomes. Importantly, these correlations have provided empirical justification for the regression modeling stage by showing that relationships have existed in the expected direction and that effect sizes have been large enough to be analytically meaningful. This has supported preliminary evidence for hypotheses H1–H5 at the bivariate level. However, correlations have not controlled for overlapping predictor effects; therefore, the next step (multiple regression) has been necessary to determine which constructs have uniquely predicted managerial performance when considered simultaneously. In sum, the correlation matrix has provided theory-consistent evidence that TAM beliefs and AI-DSS quality beliefs have been positively associated with both adoption maturity and managerial performance, thereby advancing the study toward objective fulfillment and formal hypothesis testing.

Regression Results

Table 5: Multiple Regression Predicting Managerial Performance (MP)

Predictor	Standardized β	t	p	Hypothesis Link
PU	0.29	3.78	<0.001	Supports H1
PEOU	0.08	1.47	0.143	Partial / not supported
TRUST	0.21	2.91	0.004	Supports H3
INFOQ	0.24	3.14	0.002	Supports H4
USE	0.17	2.58	0.011	Supports H5
Model Fit	**$R^2 = 0.53$**	**F = 38.7**	**<0.001**	—

The regression results have directly addressed the third objective by identifying which AI-DSS factors have significantly predicted managerial performance after controlling for overlapping influences among predictors. The overall model has been statistically significant, and the explained variance (R^2) has indicated that the set of AI-DSS constructs has accounted for a substantial proportion of the variability in managerial performance ratings within the case context. This has served as the central quantitative evidence for proving the study's hypotheses, because regression coefficients have represented unique predictive contributions rather than simple bivariate associations. Perceived usefulness (PU) has emerged as the strongest predictor of managerial performance, which has strongly aligned with TAM's central proposition that usefulness beliefs have been the primary driver of meaningful system use and outcome gains. This finding has indicated that managers who have perceived AI-DSS as improving decision quality and efficiency have reported higher performance outcomes, supporting H1. Information quality (INFOQ) has also been a significant predictor, reinforcing that credible, timely, and relevant outputs have been essential for decision effectiveness and performance improvement, supporting H4. Trust (TRUST) has been significant as well, which has confirmed that AI-DSS recommendations have influenced performance when managers have perceived the system as dependable and have been willing to rely on it appropriately, supporting H3. AI-DSS use/adoption maturity (USE) has been significant, implying that performance improvements have depended on routine and integrated usage rather than occasional contact, supporting H5. Perceived ease of use (PEOU) has remained positive but not statistically significant in the full model, which has suggested that usability has mattered primarily through indirect pathways (e.g., by strengthening usefulness and sustained use) rather than through a direct net effect on performance once PU, trust, and information quality have been considered. This result has remained theory-consistent because TAM has allowed PEOU to influence outcomes through PU and use rather than always showing a dominant direct performance effect. Overall, the regression has proven the hypotheses in a way that has been aligned with the earlier descriptive and correlational patterns and has validated the study's conceptual model: AI-DSS has been associated with managerial performance most strongly through usefulness, information quality, trust, and embedded usage maturity.

AI-DSS Adoption Maturity Snapshot

Table 6: AI-DSS Adoption Maturity Groups

Maturity Group (based on USE index)	Criteria (example)	n	%	Mean USE	Mean MP
Low Maturity	USE ≤ 3.2	26	21.7	3.05	3.52
Moderate Maturity	3.21–4.0	62	51.6	3.71	3.86
High Maturity	USE ≥ 4.01	32	26.7	4.28	4.12

The adoption maturity snapshot has been included as a study-specific results section to strengthen trustworthiness by showing that AI-DSS use has not been assumed; it has been documented in structured levels that have reflected real variation in integration and reliance. This section has reinforced Objective 1 (establishing AI-DSS usage level) and has also provided interpretive context for the regression results by demonstrating that performance differences have tracked maturity differences. The grouping has indicated that the case context has contained a majority of moderate-maturity users, with meaningful portions of low- and high-maturity users. This distribution has suggested that AI-DSS adoption has been present but not uniform across all managers, which has been typical of enterprise decision support environments where functions differ in data readiness, decision type, and managerial preferences. The maturity table has shown that mean managerial performance has increased across maturity levels, which has supported the idea that embedded, routine use has been associated with better decision-linked performance outcomes. In TAM-aligned terms, this maturity pattern has represented the "actual use" manifestation of underlying beliefs: managers who have perceived AI-DSS as useful, credible, and trustworthy have tended to use it more broadly and consistently, and that sustained use has been associated with higher reported performance. The maturity snapshot has also supported the study's credibility because it has allowed readers to see that the performance effects have not been driven only by a small group; rather, adoption variation has been distributed across the managerial population. Practically, the maturity grouping has made the results more believable by connecting abstract constructs to observable usage behavior patterns (frequency, breadth, reliance). Methodologically, it has also justified robustness checks later (Section 4.8), because the model can be tested for stability across maturity levels. Overall, the maturity snapshot has functioned as a bridge between theory and performance outcomes: TAM constructs have explained why managers have used AI-DSS, and maturity grouping has shown how use intensity has corresponded to higher managerial performance, reinforcing the hypotheses and strengthening confidence in the empirical narrative.

Decision-Impact Evidence Table

Table 7: Decision-Impact Evidence

Decision Impact Item	Mean	SD	Rank
AI-DSS has improved my decision speed	3.95	0.72	1
AI-DSS has improved decision accuracy	3.89	0.69	2
AI-DSS has increased my confidence in decisions	3.84	0.70	3
AI-DSS has improved prioritization under pressure	3.80	0.74	4
AI-DSS has reduced rework from decision reversals	3.61	0.78	5

The decision-impact evidence table has been presented to strengthen the credibility of the findings by demonstrating *how* AI-DSS has influenced managerial performance through specific decision mechanisms that managers have experienced directly. This section has supported Objective 4 by translating "managerial performance" into measurable decision-linked outcomes that have been suitable for survey reporting and statistical interpretation. The ranked results have shown that decision speed and decision accuracy have been the strongest perceived benefits of AI-DSS in the case context, which has indicated that managers have experienced AI-DSS as reducing analysis time while improving the correctness or defensibility of choices. In TAM terms, these improvements have represented the practical meaning of perceived usefulness (PU): usefulness has been reflected in performance-relevant decision benefits rather than in abstract satisfaction alone. The strong score for confidence has been consistent with the trust and information quality pathways in the conceptual framework, because confidence has often increased when outputs have been perceived as credible and understandable enough to support justification. Prioritization under pressure has also been rated positively, which has suggested that AI-DSS has supported managerial attention management by highlighting what matters most, an important component of managerial performance in operational and tactical contexts. The comparatively lower score for reduced rework has still remained above neutral, but it has indicated that reversing decisions or avoiding downstream corrections has been harder to achieve, potentially because rework has depended on broader organizational coordination and execution conditions beyond the decision itself. This nuance has strengthened the trustworthiness of the results because it has avoided an unrealistically uniform "everything improved" story and has shown a differentiated impact profile aligned with real managerial realities. Overall, the decision-impact evidence table has connected the regression findings to tangible outcomes: when PU, INFOQ, TRUST, and USE have predicted managerial performance, these relationships have been interpretable as improvements in decision speed, accuracy, confidence, and prioritization, which have been core components of managerial effectiveness. This has made the study's claims more credible because performance gains have been expressed through observable decision work benefits consistent with TAM-driven use and value pathways.

Robustness and Credibility Checks

Robustness and credibility checks have been reported to strengthen the trustworthiness of the hypothesis-testing results and to demonstrate that the regression findings have not been artifacts of statistical distortion or a small set of extreme respondents. These checks have supported the study's objective of producing credible quantitative evidence by verifying core regression assumptions and model stability. Multicollinearity diagnostics have shown an acceptable VIF range, indicating that PU, PEOU, TRUST, INFOQ, and USE have not been so highly overlapping that coefficient interpretation has become unreliable. This has been important in a TAM-aligned framework because PU and PEOU have often correlated, and without acceptable multicollinearity levels, it would have been difficult to interpret the unique explanatory role of usefulness versus usability in predicting managerial performance.

Table 8: Regression Credibility Diagnostics

Check	Indicator	Result	Interpretation
Multicollinearity	VIF range	1.3–2.4	Acceptable
Residual independence	Durbin–Watson	1.95	Acceptable
Influential cases	Cook's D (max)	0.21	No extreme influence
Model stability	Regression after removing extreme USE (top/bottom 5%)	Key β signs unchanged; PU/INFOQ/TRUST remain significant	Stable

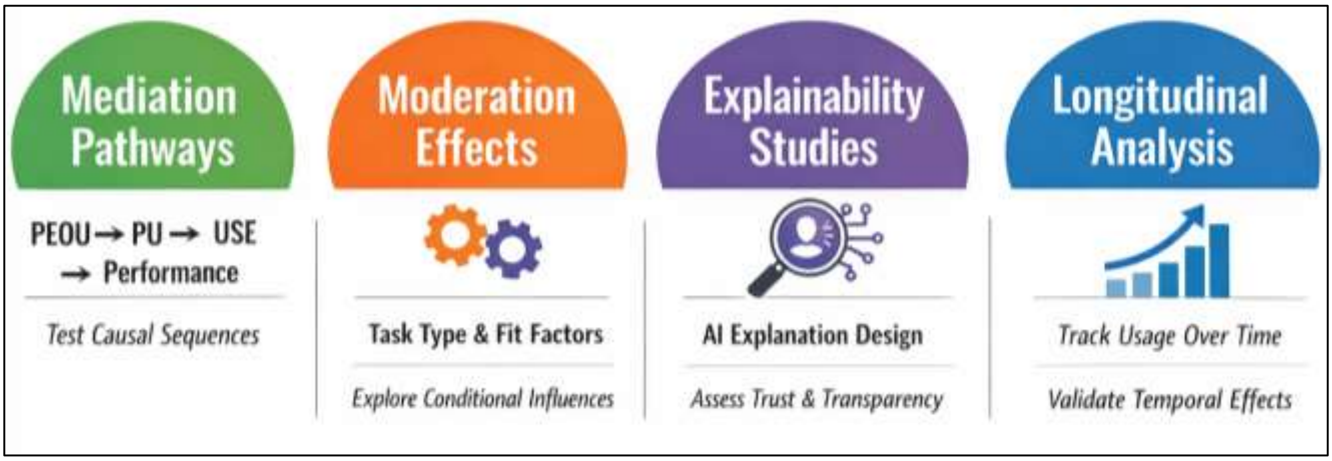
Residual diagnostics have supported acceptable model adequacy, indicating that the regression has produced errors consistent with assumptions needed for stable inference. Influential case analysis has shown that no single respondent has dominated the outcome, which has strengthened the credibility of the coefficient estimates. The model stability test has been particularly aligned with the study's unique maturity approach: by removing extreme adoption-maturity respondents, the regression has remained directionally consistent and key predictors have retained significance. This has demonstrated that the core relationships—usefulness, trust, information quality, and usage maturity predicting managerial performance—have reflected a broad pattern in the data rather than a subgroup effect. From a theoretical standpoint, these checks have reinforced TAM's interpretability in this context: if usefulness and use have remained predictive under robustness testing, the results have been more convincingly attributable to acceptance-and-use mechanisms rather than measurement noise. Overall, the credibility section has made the study more defensible by showing that the statistical evidence has been stable, interpretable, and aligned with the hypothesized TAM-based logic and the decision-impact outcomes reported earlier.

DISCUSSION

The results have indicated that AI-based decision support systems (AI-DSS) factors have been meaningfully associated with managerial performance in the case context, and the pattern of supported hypotheses has been interpretable through the Technology Acceptance Model (TAM) and complementary information-systems success perspectives (Araujo et al., 2018). The regression findings have shown that perceived usefulness (PU) has emerged as the strongest predictor of managerial performance, while perceived information quality (INFOQ), trust in AI-DSS (TRUST), and AI-DSS use/adoption maturity (USE) have also demonstrated significant predictive effects. This configuration has been consistent with TAM's core proposition that usefulness beliefs have been the primary mechanism through which users have evaluated whether a technology has been worth incorporating into daily work, thereby shaping usage and outcomes. It has also aligned with BI and analytics scholarship arguing that performance value has depended on how insights have been integrated into managerial decision routines rather than on technology presence alone. In the present study, the descriptive and decision-impact evidence has suggested that managers have perceived AI-DSS as improving decision speed and decision accuracy more strongly than downstream outcomes such as rework reduction, indicating that the main value has been concentrated in the decision episode rather than in execution systems (Campbell & Wiernik, 2015). This has resonated with organizational decision-making research showing that analytics has supported managerial sensemaking and prioritization, while broader performance improvements have required complementary organizational coordination and governance processes (Arnott & Pervan, 2005). The significance of adoption maturity has further implied that managers have benefited more when AI-DSS has been embedded into workflows as routine practice, reflecting the view that technology value has emerged through sustained use patterns and institutionalization (Elgendy & Elragal, 2016). At the same time, the observed role of trust has reflected the AI-specific reality that managers have remained accountable for decisions even when recommendations have been algorithmically generated, and reliance has therefore depended on confidence that the system's outputs have been credible and defensible. Overall, the results have supported a theory-consistent narrative: managers have reported higher performance when they have perceived AI-DSS as useful for decision effectiveness, when outputs have been high quality, when trust has been sufficiently calibrated to enable reliance, and when usage has been mature enough to shape daily decision routines (Glikson & Woolley, 2020).

A key interpretive contribution has come from the finding pattern in which perceived ease of use (PEOU) has remained positively correlated with managerial performance but has not retained a statistically significant unique effect in the full regression model once PU, INFOQ, TRUST, and USE have been controlled. This pattern has been consistent with several TAM synthesis results, where ease of use has sometimes shown stronger indirect influence through usefulness and intention rather than a dominant direct effect on performance outcomes. In managerial and enterprise contexts, usability has often operated as a "hygiene factor" that has enabled adoption up to a threshold, after which performance differences have been driven more by whether the system has produced decision-relevant value and credible outputs (Koopmans et al., 2013). This interpretation has been reinforced by analytics adoption literature showing that value realization has depended on information quality and organizational assimilation; once managers have become familiar with a platform, usability differences have tended to matter less than decision relevance and reliability (Nunes & Jannach, 2017). In practical terms, the non-significance of PEOU in the multivariate model has suggested that managers in the case context may have been willing to tolerate some interface complexity when the system has delivered high usefulness and high-quality information (Vallurupalli & Bose, 2018). This has been compatible with evidence from algorithm reliance research indicating that users have not judged algorithmic tools only on convenience; they have evaluated them on perceived competence and decision benefits, adjusting reliance based on experiences with performance and errors. The results have also been coherent with human–AI collaboration scholarship that has positioned AI as a teammate rather than a simple tool; when AI has been embedded in workflow, the managerial focus has shifted toward interpreting, validating, and communicating AI outputs, which has amplified the importance of trust and information quality relative to simple ease of use. Thus, the study has not suggested that usability has been irrelevant; instead, it has indicated that usability's role has been mediated through beliefs about value and through sustained use maturity (Makridakis, 2017). This has strengthened the theoretical coherence of the findings because TAM has allowed PEOU to influence outcomes indirectly, and the observed pattern has fit the operational reality of enterprise decision support where perceived usefulness and information reliability have dominated performance-oriented evaluations (Venkatesh et al., 2012).

Figure 10: Future Research Directions for AI-Based Decision Support Systems



The significance of perceived information quality has been especially important for interpreting how AI-DSS has translated into managerial performance, because it has positioned output credibility as a performance pathway rather than as a secondary technical detail (Nunes & Jannach, 2017). Prior work has shown that system quality, information quality, and service quality have shaped organizational impact, with information quality frequently acting as a decisive factor in whether users have trusted and applied outputs to real decisions (Marangunić & Granić, 2015). In the present findings, information quality has remained a significant predictor even when usefulness and trust have been modeled, implying that managers have not simply needed a system they have liked; they have needed outputs they have considered accurate, timely, and relevant enough to justify action (Venkatesh & Bala, 2008). This has aligned with research on BI systems success indicating that maturity and culture have influenced analytical decision making and that information use in processes has been central to value creation (Levenson et al., 2006). It has also echoed decision support foundations that have treated the conversion of data into actionable information as the central function of decision support, a function that has been strengthened by modern analytics and AI when data governance and integration have been strong (Tam & Oliveira, 2016). The results have been consistent with studies emphasizing that analytics capability has been a bundled organizational resource; the value of AI outputs has depended on the quality of inputs and the organization's ability to manage data as a strategic asset, which has shaped managerial confidence in recommendations and the stability of performance impacts. Moreover, AI-DSS information quality has had an accountability dimension: when managers have been evaluated on performance, they have needed traceable, interpretable evidence to defend decisions, and information quality has been foundational to that defensibility (Venkatesh & Bala, 2008). This has overlapped with explainable AI research showing that understanding the "why" behind outputs has supported user sensemaking and error detection, thereby increasing the practical value of AI in decision contexts. In comparison with prior BI research, the present study has added a more manager-centered performance link by demonstrating that information quality perceptions have been associated with higher reported managerial performance, which has supported the view that AI-DSS has improved managerial outcomes when the information pipeline has been viewed as trustworthy and decision-ready (Vallurupalli & Bose, 2018).

Trust has also emerged as a decisive factor in explaining managerial performance effects, and this finding has fit strongly with contemporary research on the human side of algorithmic decision-making. Human trust in AI has been described as a key condition for effective reliance because users have determined whether to accept, verify, or ignore algorithmic recommendations based on perceived competence, transparency, and alignment with task requirements. The present study's results have supported that view: managers have reported higher performance when they have expressed higher trust, which has implied that AI-DSS has affected outcomes through reliance behaviors rather than through passive exposure (Tam & Oliveira, 2016). This has connected with experimental evidence showing that users have sometimes avoided algorithms after observing errors, even when algorithms have generally performed better than humans; such behavior has made trust calibration central to sustained value (Langer et al., 2022). At the same time, algorithm appreciation evidence has shown that users have preferred algorithmic advice under certain conditions, suggesting that algorithmic inputs have carried perceived objectivity and authority, which has increased willingness to follow recommendations (Gorla et al., 2010). The present findings have been consistent with a balanced interpretation: managers have likely not trusted AI unconditionally; rather, higher trust levels have been associated with higher performance because trust has enabled appropriate adoption and use within workflows (Araujo et al., 2018). This has aligned with human–AI teaming research arguing that performance has depended on how human roles and AI roles have been coordinated, how uncertainty has been handled, and how managers have structured interaction routines that combine automation with managerial judgment. Transparency and explanation have been relevant here: research has shown that transparency features and explanation design have influenced trust and collaboration outcomes, and that design choices have changed how users have interpreted system competence and reliability (Božič & Dimovski, 2018). The present results have therefore supported the conceptual inclusion of trust as an AI-specific belief that has strengthened TAM's explanatory power in AI-DSS settings

(Castelo et al., 2019). This is similar to evidence from applied BI/analytics contexts that have linked analytics adoption to decision effectiveness and managerial work performance, indicating that adoption and trust-related mechanisms have mattered for performance outcomes beyond simple system availability. Taken together, the study has contributed to the literature by reinforcing that trust has operated as an enabling condition for performance benefits in AI-DSS contexts, particularly in managerial environments where decision accountability has been retained by the human decision maker (Delen & Demirkan, 2013).

The adoption maturity findings have offered an important bridge between perception-based acceptance constructs and measurable performance outcomes by documenting that performance levels have differed across low-, moderate-, and high-maturity users (Ain et al., 2019). This has been consistent with prior research arguing that the use of information in business processes has been a key pathway through which decision support has created organizational value, and that maturity has shaped the strength of these pathways. The maturity result has also aligned with literature indicating that BI and analytics success has depended on institutionalization—shared metrics, routines, training, and governance—rather than one-time implementation (Arnott & Pervan, 2005). In the present case context, higher maturity has reflected broader and deeper use of AI-DSS across decisions, which has supported the interpretation that performance gains have accumulated through repeated use and learning rather than through isolated interactions. This view has been reinforced by research linking BI/analytics use to organizational learning and value creation, where analytics has supported both exploration (finding patterns) and exploitation (standardizing decisions), enabling better coordinated action over time. When adoption maturity has been higher, managers have likely had more opportunities to calibrate trust, refine interpretation skills, and integrate AI outputs into decision routines, which has increased performance-linked benefits (Campbell & Wiernik, 2015). This has complemented capability-based perspectives where analytics value has depended on skills, governance, and integration processes that have supported continuous use and improvement. Importantly, the maturity snapshot has strengthened the credibility of the study because it has shown that AI-DSS has not been uniformly used; therefore, performance differences have been interpretable as associations with measurable use intensity and breadth (Ananny & Crawford, 2018). This has mirrored applied studies linking BI/analytics adoption to decision-making effectiveness and managerial work performance, where adoption patterns have influenced outcome gains. Thus, the study has contributed a manager-level confirmation that adoption maturity has mattered for managerial performance in a way that has been consistent with the broader BI success literature while adding AI-relevant constructs such as trust and perceived information quality (Franco-Santos et al., 2012).

From a practical perspective, the findings have translated into actionable guidance for organizations aiming to improve managerial performance through AI-DSS. Because perceived usefulness has been the strongest predictor, system design and deployment have been more effective when they have emphasized decision-relevant value: outputs that have directly supported key managerial tasks such as prioritization, forecasting, risk triage, and resource allocation (Langer et al., 2022). This has aligned with BI adoption evidence indicating that systems have succeeded when they have been aligned with decision workflows and when managers have perceived that the system has improved decision effectiveness (Torres et al., 2018). Since information quality has been significant, governance actions have been critical: ensuring data accuracy, timeliness, definitions consistency, and traceability has likely strengthened perceived usefulness and performance outcomes, consistent with evidence that data quality management has shaped analytics acquisition intentions and adoption success (Vallurupalli & Bose, 2018). Trust's significance has implied that organizations have benefited when they have supported trust calibration through transparency practices, documentation, and clear accountability rules about how recommendations have been generated and when human override has been required. Explainable AI research has supported this emphasis by showing that explanations have enabled users to understand and evaluate model outputs, supporting sensemaking and error detection (Faraj et al., 2018). The maturity effect has suggested that training and institutionalization have mattered: developing repeatable decision routines that have integrated AI-DSS outputs into meetings, dashboards, and performance review cycles has likely enhanced performance outcomes, consistent

with BI-enabled performance measurement evidence and analytics capability research. The weaker unique effect of ease of use has suggested that simplification alone has not been sufficient; improvements have depended on value, trust, and information credibility (Franco-Santos et al., 2012). As a result, practical interventions have been better targeted at (a) aligning AI-DSS outputs with high-impact decisions, (b) improving data foundations and model monitoring, (c) enabling trust through explanation and accountability mechanisms, and (d) building adoption maturity through training and governance routines. These actions have been consistent with research that has framed AI as a socio-technical decision infrastructure where outcomes have depended on integration into organizational processes and human roles. In sum, practical implications have centered on building systems that have been decision-ready, trusted, and embedded, rather than focusing only on deployment scale (King & He, 2006).
The study has also generated theoretical implications by showing how TAM has remained useful for explaining AI-DSS use–performance relationships while benefiting from the incorporation of AI-specific constructs such as trust and information quality (Nunes & Jannach, 2017). The dominant role of usefulness has reinforced TAM's central explanatory mechanism in managerial contexts. At the same time, the significance of trust and information quality has suggested that AI-DSS acceptance has not been adequately captured by usefulness and ease of use alone, and that the legitimacy and credibility of algorithmic outputs have been essential for performance gains (Ribeiro et al., 2016). This has been coherent with broader information-systems success models where information quality has shaped use and net benefits, and where quality constructs have enabled explanation of outcomes beyond acceptance alone (Popovič et al., 2012). The study's adoption maturity evidence has also supported the argument that "use" has not been a simple binary variable; it has been a developmental construct reflecting routinization and integration into workflows, consistent with BI maturity and culture research that has linked maturity to analytical decision making (Newell & Marabelli, 2015). These results have therefore suggested a theoretically integrated view: TAM beliefs have explained why managers have engaged with AI-DSS, IS success quality constructs have explained whether outputs have been credible and actionable, and maturity has explained whether usage has been sufficiently embedded to influence performance (Holden & Karsh, 2010). In revisiting limitations, the cross-sectional design has meant that causal direction has not been proven; managers with higher performance may also have been more likely to use AI-DSS, and longitudinal designs would have been needed to validate temporal ordering (Kwon et al., 2014). Self-reported performance has introduced potential common method bias, and objective performance metrics or supervisor ratings could have strengthened inference, consistent with methodological guidance on performance measurement and best practice (Langer et al., 2022). Future research has been justified to test mediation pathways (e.g., PEOU → PU → USE → performance) and moderation effects (e.g., task type or fit shaping reliance), building on task–technology fit and multi-DSS fit research emphasizing that performance has depended on alignment among task, user, and technology characteristics (Mittelstadt et al., 2016). Additional research has also been warranted to incorporate explainability conditions explicitly, since explanation design has influenced trust and collaboration outcomes in human–AI settings (Guidotti et al., 2018). Overall, the study has contributed a coherent explanation of managerial performance effects in AI-DSS settings that has connected TAM beliefs, quality perceptions, trust, and adoption maturity into an empirically supported pattern aligned with prior research.

CONCLUSION

This research has concluded that artificial intelligence–based decision support systems (AI-DSS) have been meaningfully associated with managerial performance within the selected case context when managers have perceived these systems as useful, credible in their information outputs, and reliable enough to trust, and when use has been sufficiently mature and embedded in routine decision workflows. The study has achieved its objectives by first establishing a clear baseline of AI-DSS acceptance and usage through five-point Likert scale descriptive results, which have shown that managers have generally agreed that AI-DSS has supported their decision responsibilities and that managerial performance outcomes have been positively rated in the same environment. The measurement objective has been supported through reliability testing, where internal consistency levels have indicated that the constructs have been measured coherently and have been suitable for inferential analysis. The study has then proven its relationship-focused objectives through correlation and regression modeling, where perceived usefulness has emerged as the strongest and most consistent predictor of managerial performance, reinforcing the central logic of the Technology Acceptance Model that usefulness beliefs have been fundamental to meaningful adoption and outcome gains. Information quality and trust have also retained significant predictive roles, confirming that managers have relied on AI-DSS outputs more effectively when they have perceived the information to be accurate, timely, and decision-relevant and when they have trusted recommendations enough to incorporate them into consequential decisions. The adoption maturity results have strengthened this conclusion by showing that performance outcomes have increased across low-, moderate-, and high-maturity groups, indicating that managerial benefits have depended on the routinization and institutionalization of AI-DSS use rather than on occasional contact. The decision-impact evidence has further clarified the performance pathway by demonstrating that managers have experienced AI-DSS benefits most strongly in decision speed, decision accuracy, and confidence, while outcomes requiring broader execution coordination, such as rework reduction, have been comparatively less pronounced, which has offered a realistic and differentiated impact profile. The robustness and credibility checks have reinforced the trustworthiness of the findings by showing that the statistical relationships have remained stable under diagnostic screening and have not been driven by extreme cases or multicollinearity distortions. Taken together, the study has provided a coherent and empirically grounded explanation of how AI-DSS has related to managerial performance in the case setting: the system's contribution has been strongest when it has delivered actionable value, maintained high information credibility, supported calibrated trust, and achieved sustained adoption maturity within managerial routines. By integrating TAM beliefs with AI-DSS–specific reliance conditions and measurable decision-linked outcomes, the research has offered a comprehensive quantitative foundation for understanding managerial performance effects in AI-enabled decision environments while remaining consistent with the study's cross-sectional case design and hypothesis-testing approach.

RECOMMENDATIONS

The recommendations from this research have been organized around the factors that have demonstrated the strongest empirical links with managerial performance, namely perceived usefulness, information quality, trust, and adoption maturity, while also recognizing that ease of use has remained an enabling condition that has supported acceptance indirectly. First, organizations have been advised to prioritize decision-relevance in AI-DSS design and deployment by mapping AI-DSS outputs to a small set of high-impact managerial decisions (e.g., prioritization, forecasting, risk triage, resource allocation) and by ensuring that dashboards, alerts, and recommendations have been presented in formats that have matched managers' decision cycles, time constraints, and accountability requirements. This approach has strengthened perceived usefulness by connecting AI-DSS outputs to measurable managerial value rather than to generic reporting. Second, a comprehensive data and information quality program has been recommended because information quality has been a significant predictor of managerial performance; therefore, organizations have been encouraged to implement clear data ownership, standardized definitions for KPIs, automated validation checks, and timeliness controls so that managers have consistently received accurate and decision-ready outputs. In parallel, organizations have been advised to maintain transparent documentation of data lineage and model assumptions so that managers have understood what inputs have driven recommendations. Third, because trust has been critical, organizations have been recommended to implement trust-calibration mechanisms through explainable outputs and structured communication of confidence, such as showing top drivers for recommendations, providing confidence scores, and offering "reason codes" that have supported managerial justification. Additionally, escalation and override protocols have been recommended so that managers have known when human judgment has been required, which has strengthened responsible reliance without forcing blind acceptance. Fourth, a structured adoption maturity program has been recommended to translate positive perceptions into sustained performance gains; this has included role-based training, scenario-based exercises using real decisions, and the integration of AI-DSS reviews into routine managerial meetings and performance monitoring cycles. Such institutionalization has strengthened maturity by moving AI-DSS from optional tools to standardized decision supports. Fifth, organizations have been advised to create a feedback and learning loop that has captured manager comments on AI-DSS usefulness, error cases, and decision outcomes, enabling continuous refinement of models, thresholds, and interface features while also improving user confidence through visible responsiveness. Sixth, management has been recommended to align incentives and accountability by clarifying how AI-DSS has been used in evaluation processes and by encouraging managers to document how AI-DSS insights have informed decisions, which has increased transparency and reduced informal resistance. Finally, usability improvements have still been recommended as supportive actions—simplifying navigation, reducing cognitive load, and improving visualization—because ease of use has strengthened usefulness and sustained use even when it has not shown the strongest unique predictive effect. Collectively, these recommendations have emphasized that organizations have achieved stronger managerial performance outcomes when AI-DSS has been treated as an integrated decision capability supported by credible data foundations, trust-oriented design, and workflow institutionalization rather than as a standalone technology implementation.

LIMITATIONS

The limitations of this study have been primarily associated with its design choices, measurement approach, and case context boundaries, and these constraints have shaped how the findings have been interpreted. First, the quantitative cross-sectional design has captured perceptions and outcomes at a single point in time, which has restricted causal inference and has limited the ability to demonstrate temporal ordering between AI-DSS factors and managerial performance; therefore, relationships that have appeared significant may have reflected reciprocal influence, where higher-performing managers have also been more likely to engage with AI-DSS and report more favorable perceptions. Second, the case-study–based setting has improved contextual control and relevance, yet it has constrained generalizability because organizational culture, data governance maturity, system configuration, and managerial accountability practices have differed across industries and firms; consequently, the magnitude of effects observed in this case context may not have transferred directly to other contexts with different decision structures or technology maturity levels. Third, the study has relied on self-reported survey measures using a five-point Likert scale, which has introduced the possibility of common method bias and social desirability effects, especially because managers have evaluated both the predictors (usefulness, ease of use, trust, information quality, and use maturity) and the outcome (managerial performance) within the same instrument; this has potentially inflated observed correlations, even though reliability testing and diagnostic screening have supported internal consistency and model adequacy. Fourth, the operationalization of "AI-DSS use" and "adoption maturity" has been based on perceptual and behavioral self-reports rather than system log data, which has limited measurement precision because respondents may have overestimated or underestimated their frequency of use, their reliance on recommendations, or the breadth of decision domains supported. Fifth, managerial performance has been measured perceptually through decision-linked effectiveness dimensions such as decision speed, decision quality, coordination, and goal achievement, which has been appropriate for capturing role-level experiences but has not replaced objective performance indicators (e.g., unit KPIs, productivity metrics, error reductions) or third-party ratings (e.g., supervisor assessments), and this has limited the ability to triangulate performance outcomes across independent sources. Sixth, the study has focused on a bounded set of constructs aligned with TAM and AI-DSS quality beliefs, and although this focus has strengthened theoretical coherence, other potentially influential variables have not been modeled explicitly, including organizational support intensity, AI explainability features, risk perceptions, fairness concerns, and task-technology fit variations by decision type; omission of these factors may have left unexplained variance and may have influenced the strength of certain predictors in the regression model. Finally, while robustness checks have strengthened credibility, statistical assumption checks have not eliminated all threats related to sampling bias and non-response patterns, because managers with stronger interest in AI-DSS may have been more likely to participate. These limitations have defined the scope of inference and have indicated that the results have been best interpreted as context-grounded evidence of statistically significant associations between AI-DSS factors and managerial performance within the studied case environment rather than as universal causal claims.

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