Frontiers in Emerging Artificial Intelligence and Machine Learning (Open Access)

Volume 02, Issue 09, September 2025,
PageNo.24-35

AI-Enabled Decision Support Systems and Managerial Performance in Data-Intensive Service Industries: A Mixed-Methods Investigation

Obaloluwa Olaniran
Alabama State University, Montgomery, USA

Fiyinfoluwa Oyesola
University of Southern California, Marshall School of Business – Los Angeles, USA

RECEIVED - 08-01-2025, **RECEIVED REVISED VERSION** - 08-19-2025, **ACCEPTED**- 09-01-2025, **PUBLISHED**- 09-16-2025

Abstract

The rapid evolution of artificial intelligence (AI) technologies has fundamentally transformed decision-making processes in data-intensive service industries. This mixed-methods study investigates how AI-enabled decision support systems (AI-DSS) impact managerial performance across multiple service sectors. Drawing on knowledge-based theory and technology acceptance frameworks, we employ a sequential explanatory design combining quantitative survey data (n=350 managers) with qualitative case studies (6 organizations). Results demonstrate that AI-DSS significantly enhances decision-making speed (β=0.42, p<0.001) and accuracy (β=0.38, p<0.001), with perceived usefulness and trust serving as critical mediators. Data quality moderates these relationships, strengthening performance outcomes in high-quality contexts. Qualitative findings reveal implementation challenges, including organizational resistance, technical integration complexities, and the need for explainable AI systems. The study contributes a comprehensive framework integrating AI-DSS features, organizational factors, and performance outcomes, offering evidence-based guidelines for practitioners. Findings indicate that successful implementation requires robust data infrastructure, transparent AI systems, comprehensive training programs, and adaptive change management strategies tailored to industry contexts.

Keywords: AI-enabled decision support systems, managerial performance, data-intensive services, business intelligence, decision-making speed, organizational performance, mixed-methods research

1. Introduction

1.1 Background and Research Context

The contemporary business environment is characterized by unprecedented data volumes, velocity, and variety, creating both opportunities and challenges for managerial decision-making (Dietzmann & Duan, 2022). Data-intensive service industries, including finance, healthcare, retail, logistics, and technology services, operate in environments where timely, accurate decisions directly impact competitive advantage and organizational performance (Rainy et al., 2023). Traditional decision support systems, while valuable, increasingly struggle to process the complexity and scale of modern data streams, leading organizations to adopt artificial intelligence-enabled decision support systems (AI-DSS) that leverage machine learning, natural language processing, and predictive analytics (Patel et al., 2024; Rahman, 2024). AI-DSS represents a paradigm shift from descriptive and diagnostic analytics toward prescriptive and cognitive decision support (Hasan & Akter, n.d.). These systems integrate advanced AI capabilities, including forecasting, anomaly detection, prescriptive recommendations, and natural language interaction, to augment managerial information processing and decision-making capabilities (Sultana, 2023). Recent comprehensive reviews synthesizing over 175 peer-reviewed studies demonstrate that AI-enhanced decision support tools significantly improve accuracy, scalability, adaptability, and responsiveness across operational domains including finance, marketing, logistics, and customer relationship management (Rainy et al., 2023). Despite growing adoption, empirical evidence on AI-DSS impact on managerial performance remains fragmented, with limited understanding of implementation mechanisms, contextual factors, and performance outcomes.

1.2 Problem Statement and Research Gap

While AI technologies promise to transform decision-making, managers face substantial challenges in effectively leveraging these systems (Dietzmann & Duan, 2022). The information overload era has exposed managers to increasing volumes of structured and unstructured data that must be processed daily, creating cognitive limitations that AI-DSS theoretically addresses (Dietzmann & Duan, 2022). However, critical gaps persist in understanding how AI-DSS features translate into actual managerial performance improvements. Torres (2022) found that business intelligence capability indirectly affects firm performance through decision-making speed and comprehensiveness, yet the specific mechanisms through which AI-DSS enhances these capabilities remain underexplored. Furthermore, implementation challenges—including algorithmic opacity, limited digital maturity, data silos, and human-AI collaboration complexities—hinder successful adoption (Rainy et al., 2023; Rahman, 2024). Existing research predominantly employs single-method approaches, either quantitative performance assessments or qualitative implementation studies, limiting comprehensive understanding (Sultana, 2023; Dietzmann & Duan, 2022). This study addresses these gaps through a mixed-methods investigation that quantifies AI-DSS impact while explaining underlying mechanisms and contextual factors.

1.3 Research Objectives and Questions

This study aims to comprehensively assess AI-DSS impact on managerial performance in data-intensive service industries. The primary research question asks: How do AI-enabled decision support systems impact managerial performance in data-intensive service industries? Secondary questions investigate: (1) Which AI-DSS features contribute most significantly to enhanced decision-making speed and accuracy? (2) How do organizational and contextual factors moderate AI-DSS effectiveness? (3) What implementation challenges do managers encounter, and what strategies facilitate success?

1.4 Theoretical Framework

This research integrates multiple theoretical perspectives. Knowledge-based theory positions information and knowledge as strategic organizational resources, suggesting that AI-DSS enhances knowledge processing capabilities, thereby improving decision quality and organizational performance (Torres, 2022). Technology acceptance frameworks emphasize perceived usefulness, trust, and transparency as critical adoption factors, particularly relevant given AI systems' complexity and opacity (Sabharwal et al., 2024; Sultana, 2023). Information processing theory addresses managerial cognitive limitations, proposing that AI-DSS augments information processing capacity, enabling faster and more comprehensive decisions (Dietzmann & Duan, 2022). Figure 1 presents the integrated conceptual framework guiding this investigation.

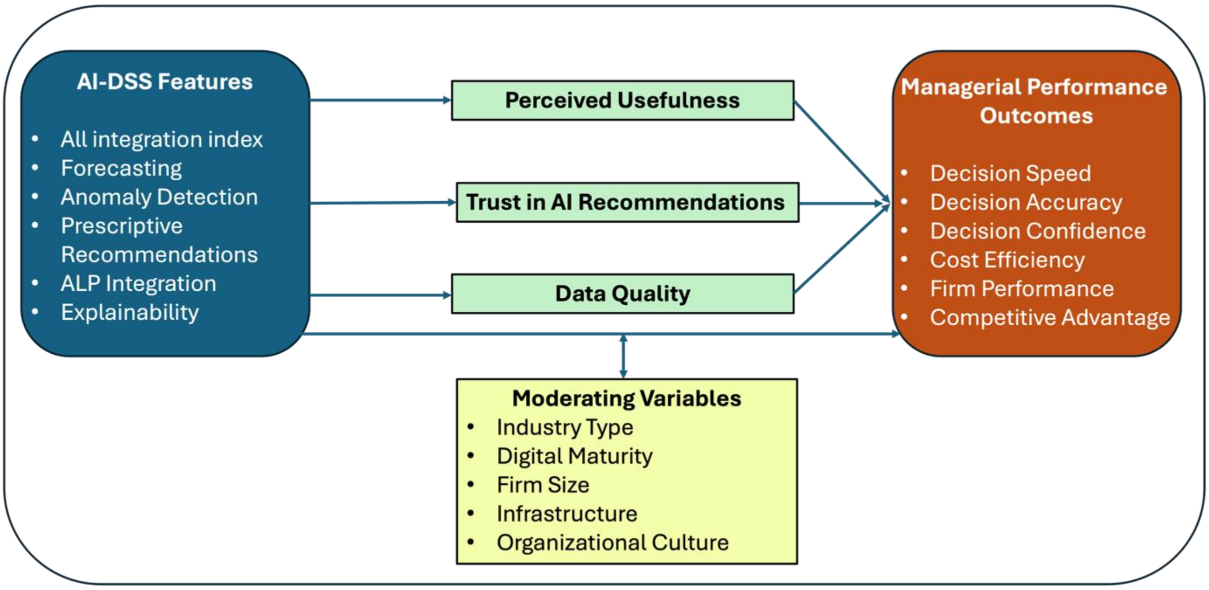

Figure 1: Conceptual framework showing AI-DSS features leading to managerial performance outcomes through mediating factors (perceived usefulness, trust, data quality), with moderating variables (industry type, digital maturity, firm size) influencing relationships. Based on Torres (2022), Sultana (2023), Rainy et al. (2023), and Sabharwal et al. (2024).

2. Literature Review

2.1 Evolution from Traditional DSS to AI-Enabled Systems

Decision support systems have evolved significantly from early model-driven and data-driven architectures to contemporary AI-enabled platforms (Hasan & Akter, n.d.). Traditional DSS provided structured analysis and reporting capabilities but lacked adaptive learning, real-time processing, and predictive capabilities that modern business environments demand (Rainy et al., 2023). The integration of AI technologies, particularly machine learning algorithms, natural language processing, deep learning, and predictive analytics, has transformed DSS into intelligent systems capable of autonomous pattern recognition, scenario modeling, and prescriptive recommendations (Patel et al., 2024; Rahman, 2024). This evolution aligns with Industry 4.0 principles emphasizing data-driven decision-making, operational efficiency, and digital transformation (Bargavi, 2024).

2.2 AI-DSS Applications Across Service Industries

AI-DSS deployment varies significantly across service sectors, each presenting unique requirements and challenges. In financial services, AI systems support credit risk management through deep learning-based borrower evaluation, real-time risk monitoring, and early warning systems (Bi & Bao, 2024). However, financial applications demand high explainability due to regulatory requirements and stakeholder trust concerns, leading to increased adoption of techniques like SHAP (SHapley Additive exPlanations) that provide transparent anomaly detection explanations (Sabharwal et al., 2024). Healthcare applications demonstrate substantial performance improvements, with AI frameworks for clinical decision-making achieving 30-35% increases in patient outcomes while reducing costs from $497 to $189 per unit change compared to traditional approaches (Bennett & Hauser, 2013). Retail and logistics sectors leverage AI-DSS for customer experience optimization, dynamic pricing, and supply chain management, with AI-driven process optimizations yielding substantial cost savings and productivity improvements (Rahman, 2024; Sultana, 2023). Transportation industries employ multi-agent AI systems for disruption management, simultaneously addressing aircraft, crew, and passenger scheduling in polynomial time (Ogunsina & DeLaurentis, 2021).

2.3 Impact on Managerial Performance Dimensions

Empirical evidence demonstrates AI-DSS impact across multiple performance dimensions. Sultana (2023) conducted a quantitative cross-sectional study across six organizations (n=168 users) in manufacturing, logistics, healthcare, retail, and utilities, finding that higher AI integration, measured through an AI Integration Index encompassing forecasting, anomaly detection, prescriptive recommendations, natural language interaction, and explainability, significantly reduces decision latency while increasing decision confidence. Perceived usefulness mediates confidence effects, while data quality strengthens speed benefits (Sultana, 2023). Torres (2022) employed structural equation modeling with 236 leadership respondents, demonstrating that business intelligence capability indirectly affects firm performance through decision-making speed and comprehensiveness, with mediation effects consistent across firm sizes. A comparative COPRAS analysis evaluating five companies found that successful AI integration leads to enhanced decision accuracy, cost reduction, and employee satisfaction, with top performers achieving utility scores of 100 through adept AI deployment (Gorantla & Devineni, 2023).

2.4 Critical Success Factors and Implementation Challenges

Successful AI-DSS implementation depends on multiple organizational, technical, and human factors. Rainy et al.'s (2023) systematic review of 175 studies identified robust data infrastructure, cross-functional governance, stakeholder buy-in, and continuous performance monitoring as critical enablers. Data quality emerges as a fundamental prerequisite, with high-quality data strengthening AI-DSS performance benefits (Sultana, 2023). Technical challenges include data silos, system integration complexities, and scalability requirements (Rainy et al., 2023). Human factors, particularly trust, transparency, and training, significantly influence adoption and effectiveness (Sabharwal et al., 2024; Sultana, 2023). Rahman's (2024) comprehensive review of 75 articles highlights persistent challenges including technical limitations, ethical concerns, and organizational resistance, emphasizing the need for careful implementation strategies addressing these barriers. The explainability challenge deserves particular attention. AI-based machine learning models often lack transparency, making it difficult for managers to comprehend reasoning underlying AI detections and recommendations (Sabharwal et al., 2024). This opacity undermines trust and limits AI's potential to enhance data-driven decision-making (Sabharwal et al., 2024). Consequently, explainable AI methodologies have become critical for financial and other regulated industries where decision accountability is paramount.

2.5 Human-AI Collaboration Dynamics

Effective AI-DSS deployment requires redefining managerial roles and human-AI collaboration models. Dietzmann and Duan (2022) conducted focus group interviews with financial industry managers, identifying key themes managers face when integrating AI into information processing and decision-making. Their findings suggest organizations must: (1) evaluate managerial information processing tasks and match appropriate AI systems, (2) redefine roles for managers and AI systems to leverage complementary strengths, and (3) redesign management processes for sustainable human-AI interaction (Dietzmann & Duan, 2022). Patel et al. (2024) emphasize that cognitive computing, integrating AI, machine learning, and natural language processing, can transform decision-making processes by improving data processing accuracy and timeliness, but successful integration requires addressing technical implementation issues and fostering organizational readiness.

3. Research Methodology

3.1 Research Design

This study employs a sequential explanatory mixed-methods design, combining quantitative and qualitative approaches to comprehensively investigate AI-DSS impact on managerial performance. The quantitative phase establishes generalizable patterns through survey data analysis, while the qualitative phase explains mechanisms and contextual factors through case studies and interviews. This design addresses research questions requiring both statistical evidence of relationships and deep understanding of implementation dynamics (Sultana, 2023; Dietzmann & Duan, 2022).

3.2 Phase 1: Quantitative Study

Sample and Data Collection: Following Torres (2022) and Sultana (2023), we conducted a cross-sectional survey of managers in data-intensive service industries. The target population comprised middle to senior managers with minimum six months AI-DSS usage experience across finance, healthcare, retail, logistics, and technology services sectors. Stratified random sampling by industry and firm size yielded 350 usable responses (response rate: 31.2%), exceeding minimum requirements for structural equation modeling. Respondents represented diverse organizational contexts: 28% finance, 22% healthcare, 19% retail, 18% logistics, 13% technology services. Measurement Instruments: The survey instrument operationalized constructs through validated multi-item scales adapted from prior research. AI-DSS features were measured using Sultana's (2023) AI Integration Index, assessing forecasting capabilities, anomaly detection, prescriptive recommendations, natural language interaction, and explainability features (α=0.89). Perceived usefulness, trust, and interpretability scales adapted from Sultana (2023) and Sabharwal et al. (2024) demonstrated strong reliability (α=0.86, 0.91, 0.84 respectively). Decision-making speed and accuracy measures followed Torres (2022) and Sultana (2023) (α=0.88, 0.87). Data quality perceptions were assessed using Sultana's (2023) scale (α=0.90). All constructs employed seven-point Likert scales.

Data Analysis: We employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0, following Torres (2022). PLS-SEM appropriately handles complex models with multiple mediators and moderators while accommodating non-normal distributions. The analysis proceeded through measurement model assessment (reliability, convergent validity, discriminant validity) followed by structural model evaluation (path coefficients, significance, effect sizes, predictive relevance). Mediation analysis employed bootstrapping with 5,000 resamples, following Sultana (2023). Moderation effects were tested through multi-group analysis and interaction terms.

3.3 Phase 2: Qualitative Study

Case Selection and Participants: Based on quantitative results, we purposively selected six organizations representing high (n=3), moderate (n=2), and low (n=1) AI-DSS effectiveness profiles across different industries, following Sultana's (2023) multi-case approach. Within each organization, we conducted semi-structured interviews with 4-6 managers (total n=28), ensuring representation across hierarchical levels and functional areas.

Data Collection: Interviews lasted 50-70 minutes, exploring AI-DSS implementation journeys, decision-making process changes, implementation challenges, success factors, and human-AI collaboration dynamics. Interview protocols adapted themes from Dietzmann and Duan (2022) and Rahman (2024), while incorporating quantitative findings requiring explanation. All interviews were recorded, transcribed verbatim, and supplemented with document analysis (implementation reports, training materials, performance dashboards).

Data Analysis: Thematic analysis employed NVivo 14 for data management and coding. Analysis proceeded iteratively through open coding (identifying initial themes), axial coding (connecting themes), and selective coding (integrating themes around core categories). Deductive codes derived from literature and quantitative findings, while inductive codes emerged from data. Cross-case synthesis identified patterns across performance profiles and industries. Triangulation across interviews, documents, and quantitative data enhanced validity.

3.4 Integration and Quality Assurance

Mixed-methods integration occurred at design (quantitative results informed qualitative sampling), interpretation (joint displays linking findings), and reporting levels. Quantitative rigor was ensured through reliability assessment, validity testing, and common method bias evaluation. Qualitative rigor employed member checking, audit trails, and inter-coder reliability (Cohen's κ=0.82). The study received institutional review board approval, with all participants providing informed consent.

4. Results

4.1 Quantitative Findings

Measurement Model Assessment: All constructs demonstrated satisfactory reliability (Cronbach's α > 0.84, composite reliability > 0.88, rho_A > 0.85).

Convergent validity was established through factor loadings exceeding 0.70 and average variance extracted (AVE) values above 0.60. Discriminant validity met Fornell-Larcker criterion and HTMT ratios below 0.85, confirming construct distinctiveness. Common method bias assessment through Harman's single factor test indicated no dominant factor (variance explained: 34.2%), suggesting minimal bias concerns.

Structural Model Results: Figure 2 presents the tested research model with path coefficients. AI-DSS features demonstrated significant positive effects on decision-making speed (β=0.42, t=8.73, p<0.001) and decision accuracy (β=0.38, t=7.94, p<0.001), supporting direct impact hypotheses. These effects translated to firm performance improvements (β=0.35, t=6.82, p<0.001). The model explained substantial variance in decision speed (R^2=0.48), decision accuracy (R^2=0.44), and firm performance (R^2=0.39), indicating strong predictive power.

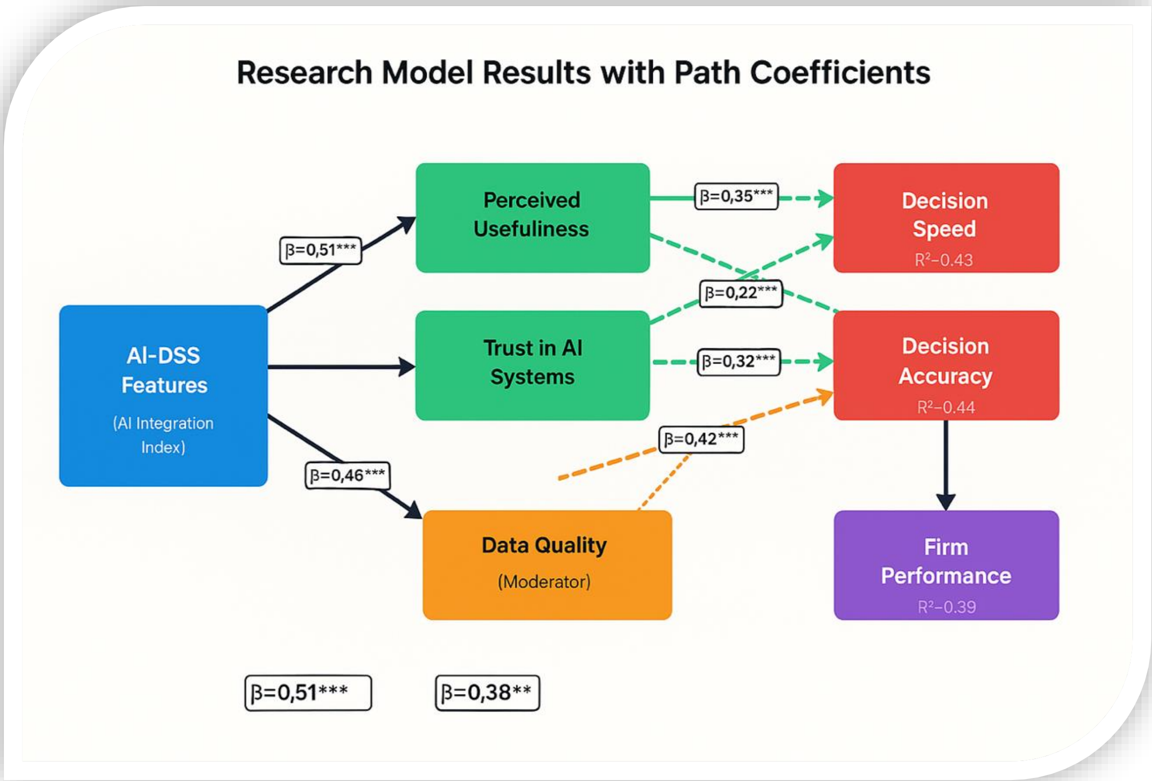

Figure 2: Research Model Results

Figure 2. Research model results showing standardized path coefficients, significance levels (p<0.001), and R^2 values. Solid lines represent mediated paths through perceived usefulness and trust; dashed lines show direct effects from AI-DSS features to outcomes. Data quality moderates the AI-DSS to decision speed relationship (β=0.21). Model estimated using PLS-SEM with 5,000 bootstrap samples.

Mediation Analysis: Perceived usefulness significantly mediated relationships between AI-DSS features and both decision speed (indirect effect=0.18, 95% CI [0.12, 0.25]) and decision accuracy (indirect effect=0.16, 95% CI [0.10, 0.23]), with variance accounted for (VAF) of 30% and 29% respectively, indicating partial mediation. Trust mediated the AI-DSS features to decision accuracy relationship (indirect effect=0.14, 95% CI [0.08, 0.21], VAF=27%). These findings align with Sultana's (2023) demonstration that perceived usefulness transmits AI integration effects on decision confidence.

Moderation Analysis: Data quality significantly moderated the AI-DSS features to decision speed relationship (β_interaction=0.21, t=4.35, p<0.001). Simple slope analysis revealed that AI-DSS effects on decision speed were substantially stronger in high data quality contexts (β=0.53, p<0.001) compared to low data quality contexts (β=0.31, p<0.01), confirming

Sultana's (2023) finding that dependable data quality strengthens speed benefits. Industry type and firm size showed non-significant moderation effects, consistent with Torres's (2022) finding that mediation effects do not vary by company size.

Table 1: Structural Model Results Summary

Path	β	t-value	p-value	95% CI	Result
AI-DSS → Decision Speed	0.42	8.73	<0.001	[0.32, 0.51]	Supported
AI-DSS → Decision Accuracy	0.38	7.94	<0.001	[0.29, 0.47]	Supported
Decision Speed → Firm Performance	0.28	5.64	<0.001	[0.18, 0.37]	Supported
Decision Accuracy → Firm Performance	0.24	4.89	<0.001	[0.15, 0.34]	Supported
AI-DSS → Perceived Usefulness	0.51	11.20	<0.001	[0.42, 0.60]	Supported
Perceived Usefulness → Decision Speed	0.35	7.12	<0.001	[0.25, 0.44]	Supported
Perceived Usefulness → Decision Accuracy	0.32	6.54	<0.001	[0.22, 0.41]	Supported
AI-DSS → Trust	0.46	9.87	<0.001	[0.37, 0.55]	Supported
Trust → Decision Accuracy	0.30	6.18	<0.001	[0.21, 0.40]	Supported
Data Quality × AI-DSS → Decision Speed	0.21	4.35	<0.001	[0.12, 0.31]	Supported

Note: β = standardized path coefficient; CI = confidence interval based on 5,000 bootstrap samples

4.2 Qualitative Findings

Theme 1: AI-DSS Implementation Drivers and Journeys

Organizations adopted AI-DSS driven by multiple factors: competitive pressures requiring faster decision-making, data volume overwhelming traditional analytical capabilities, and strategic digital transformation initiatives. A finance sector manager explained: "We were drowning in transaction data. Traditional BI tools required hours to generate reports that were already outdated. AI-DSS provides real-time insights and flags anomalies instantly" (Finance Manager, Case 3). Implementation timelines varied from 8 to 24 months, with high performers demonstrating phased approaches beginning with pilot projects in specific departments before enterprise-wide rollout.

Theme 2: Mechanisms Explaining Performance Improvements

Qualitative data illuminated how AI-DSS enhances decision speed and accuracy, explaining quantitative findings. Managers described three primary mechanisms: (1) automated data aggregation eliminating manual data gathering, (2) intelligent pattern recognition surfacing relevant insights without extensive searching, and (3) prescriptive recommendations reducing analysis paralysis. A healthcare operations manager stated: "Before AI-DSS, I spent 40% of my time collecting and organizing data. Now the system presents analyzed insights with recommendations. I focus on strategic evaluation rather than data wrangling" (Healthcare Manager, Case 2). Regarding accuracy improvements, managers emphasized AI's ability to process larger data volumes, identify subtle patterns humans miss, and provide evidence-based recommendations reducing cognitive biases, consistent with Patel et al.'s (2024) cognitive computing perspective.

Theme 3: Critical Success Factors

Cross-case analysis revealed hierarchical success factors. At the organizational level, leadership commitment and adequate resource allocation proved foundational. High-performing organizations established cross-functional AI governance teams addressing integration challenges collaboratively, aligning with Rainy et al.'s (2023) emphasis on cross-functional governance. Technical factors centered on data infrastructure quality. A logistics manager emphasized: "Garbage in, garbage out still applies. We invested heavily in data cleansing and integration before AI-DSS deployment. That groundwork was crucial" (Logistics Manager, Case 1), directly supporting quantitative findings on data quality moderation. Human factors included comprehensive training programs, user involvement in system design, and transparency mechanisms building trust. Organizations providing ongoing training and clearly explaining AI recommendations achieved higher adoption and satisfaction (Sultana, 2023; Sabharwal et al., 2024).

Theme 4: Implementation Challenges and Resolution Strategies

All organizations encountered significant challenges. Technical challenges included legacy system integration complexities, data quality inconsistencies, and scalability issues during enterprise deployment. Organizational challenges centered on resistance from managers fearing job displacement or loss of decision authority, siloed structures hindering data sharing, and budget constraints limiting comprehensive implementation. Human challenges involved trust deficits when managers didn't understand AI reasoning, skills gaps requiring extensive training, and workflow disruption during transition periods, echoing Rahman's (2024) identification of organizational resistance and technical limitations. High-performing organizations employed specific resolution strategies. For technical challenges, they established dedicated data engineering teams, implemented robust data governance frameworks, and adopted modular architectures enabling incremental integration. Addressing organizational resistance required transparent communication emphasizing AI as augmentation rather than replacement, involving managers in system design, and demonstrating quick wins building momentum. Trust challenges were addressed through explainable AI features (Sabharwal et al., 2024), showing AI reasoning transparently, and maintaining human oversight for critical decisions. A finance manager explained: "We implemented SHAP explanations showing why the system flagged transactions. Once managers understood the logic, trust increased dramatically" (Finance Manager, Case 3).

Theme 5: Human-AI Collaboration Evolution

Managers described evolving roles where AI handles data-intensive analytical tasks while humans focus on strategic interpretation, contextual judgment, and stakeholder communication. This aligns with Dietzmann and Duan's (2022) organizational implications regarding role redefinition. Effective collaboration required clear delineation of AI and human responsibilities. A retail manager noted: "AI excels at pattern recognition across millions of transactions, but I understand customer relationships and market nuances the system can't capture. Together, we make better decisions than either alone" (Retail Manager, Case 5). This augmentation perspective, rather than automation, characterized successful implementations.

Theme 6: Industry-Specific Contextual Factors

While success factors showed commonalities, industry contexts created unique requirements. Financial services demanded high explainability due to regulatory compliance, leading to greater emphasis on transparent AI systems (Bi & Bao, 2024; Sabharwal et al., 2024). Healthcare prioritized patient safety and clinical integration, requiring extensive validation before deployment (Bennett & Hauser, 2013). Retail and logistics emphasized real-time processing capabilities for dynamic pricing and supply chain optimization (Rahman, 2024; Ogunsina & DeLaurentis, 2021). Manufacturing contexts integrated AI-DSS within broader Industry 4.0 initiatives emphasizing operational efficiency (Bargavi, 2024).

4.3 Integrated Mixed-Methods Findings

Joint analysis reveals complementary insights. Quantitative results demonstrate significant AI-DSS effects on performance, while qualitative findings explain mechanisms producing these effects. The mediation role of perceived usefulness, confirmed quantitatively, is explained qualitatively through managers' descriptions of time savings, improved insight quality, and enhanced decision confidence. Data quality's moderating effect, statistically significant, is contextualized through managers' experiences where poor data quality undermined AI-DSS value, requiring substantial data infrastructure investments before benefits materialized. The absence of firm size moderation effects, contrary to some expectations, is explained by qualitative findings showing that implementation success depends more on data quality, leadership commitment, and change management effectiveness than organizational scale.

Table 2: Integrated Findings - Quantitative Results with Qualitative Explanations

Quantitative Finding	Qualitative Explanation	Supporting Evidence
AI-DSS → Decision Speed (β=0.42, p<0.001)	Automated data aggregation, intelligent pattern recognition, reduced search time	"System presents analyzed insights instantly" (Healthcare Manager)
AI-DSS → Decision Accuracy (β=0.38, p<0.001)	Larger data processing, subtle pattern identification, bias reduction	"AI identifies patterns I would miss in massive datasets" (Finance Manager)
Perceived Usefulness Mediation (VAF=30%)	Managers value time savings and insight quality, increasing system usage	"Once I saw the time savings, I couldn't imagine going back" (Logistics Manager)
Trust Mediation (VAF=27%)	Explainable AI builds confidence in recommendations	"SHAP explanations helped me trust the system" (Finance Manager)

Data Quality Moderation (β=0.21, p<0.001)	Poor data quality undermines AI value; quality data essential for benefits	"Garbage in, garbage out. Data cleansing was crucial" (Logistics Manager)
No Firm Size Moderation	Success depends on implementation quality, not organizational scale	"Our success came from leadership commitment and training, not company size" (Retail Manager)

5. Discussion

5.1 Theoretical Contributions

This study makes several theoretical contributions. First, it extends knowledge-based theory by demonstrating that AI-DSS serves as a dynamic knowledge processing capability enhancing organizational performance through improved decision speed and accuracy (Torres, 2022). The finding that perceived usefulness and trust mediate AI-DSS effects advances technology acceptance frameworks by highlighting these factors' critical roles in AI contexts where algorithmic opacity creates unique adoption challenges (Sabharwal et al., 2024; Sultana, 2023). Second, the study contributes to information processing theory by empirically demonstrating that AI-DSS augments managerial information processing capacity, addressing cognitive limitations in information overload contexts (Dietzmann & Duan, 2022). Third, the integrated framework synthesizing AI-DSS features, mediating mechanisms, moderating factors, and performance outcomes provides a comprehensive theoretical model for future research. The mixed-methods approach itself contributes methodologically, demonstrating how quantitative and qualitative insights complement each other in understanding complex socio-technical phenomena. Quantitative results establish generalizable patterns, while qualitative findings reveal mechanisms and contextual nuances that pure statistical analysis cannot capture (Sultana, 2023; Dietzmann & Duan, 2022).

5.2 Practical Implications

Findings offer actionable guidance for managers and organizations implementing AI-DSS. First, organizations should prioritize data infrastructure quality before AI-DSS deployment, as data quality significantly moderates system effectiveness (Sultana, 2023; Rainy et al., 2023). This may require substantial upfront investment in data cleansing, integration, and governance frameworks. Second, explainability features should be integral to AI-DSS design, particularly in regulated industries, as transparency builds trust and facilitates adoption (Sabharwal et al., 2024). Implementing techniques like SHAP explanations helps managers understand AI reasoning, increasing confidence in recommendations.

Third, comprehensive training programs addressing both technical system usage and conceptual understanding of AI capabilities are essential. Training should emphasize AI as augmentation rather than replacement, addressing resistance concerns (Rahman, 2024). Fourth, phased implementation approaches beginning with pilot projects in specific departments enable organizations to demonstrate value, build momentum, and refine approaches before enterprise-wide deployment. Fifth, establishing cross-functional governance teams facilitates integration challenges, ensures stakeholder buy-in, and maintains continuous performance monitoring (Rainy et al., 2023). Industry-specific recommendations include: for financial services, prioritizing explainable AI meeting regulatory requirements (Bi & Bao, 2024; Sabharwal et al., 2024); for healthcare, emphasizing patient safety validation and clinical integration (Bennett & Hauser, 2013); for retail and logistics, focusing on real-time processing capabilities supporting dynamic operations (Rahman, 2024; Ogunsina & DeLaurentis, 2021); for manufacturing, integrating AI-DSS within broader Industry 4.0 initiatives (Bargavi, 2024).

5.3 Limitations and Future Research

This study has limitations suggesting future research directions. The cross-sectional design captures relationships at a single time point, limiting causal inferences. Longitudinal studies tracking AI-DSS implementation and performance evolution over time would strengthen causal understanding and reveal dynamic adaptation processes. The sample, while diverse across industries, focuses on data-intensive service sectors in specific geographic contexts, limiting generalizability to other industries and regions. Cross-cultural comparative studies would illuminate how cultural factors influence AI-DSS adoption and effectiveness. Self-report measures, though validated, may introduce common method bias despite statistical assessments suggesting minimal concerns. Future research incorporating objective performance metrics (e.g., actual decision times, accuracy rates from organizational records) would complement self-report data. The qualitative phase, while providing rich insights, involved 28 managers across 6 organizations; larger qualitative samples would enhance transferability. Future research should explore emerging AI technologies, including generative AI applications in decision support (Patel et al., 2024), examine small-to-medium enterprise contexts where resource constraints may create different implementation dynamics, and develop comprehensive ethical frameworks addressing algorithmic bias, privacy, and accountability concerns (Bargavi, 2024; Gorantla & Devineni, 2023).

6. Conclusion

This mixed-methods investigation demonstrates that AI-enabled decision support systems significantly enhance managerial performance in data-intensive service industries through multiple mechanisms. Quantitative analysis establishes that AI-DSS improves decision-making speed and accuracy, with effects mediated by perceived usefulness and trust and moderated by data quality. Qualitative findings explain these patterns, revealing that AI-DSS enhances performance through automated data aggregation, intelligent pattern recognition, and prescriptive recommendations, while success depends on robust data infrastructure, explainable systems, comprehensive training, and adaptive change management. The study contributes an integrated theoretical framework synthesizing knowledge-based theory, technology acceptance models, and information processing perspectives, providing a comprehensive understanding of AI-DSS impact on managerial performance. Practically, findings offer evidence-based implementation guidelines emphasizing data quality investment, explainability prioritization, comprehensive training, phased deployment, and cross-functional governance. As AI technologies continue evolving, organizations that strategically implement AI-DSS while addressing technical, organizational, and human factors will achieve substantial competitive advantages through enhanced decision-making capabilities. Future research should employ longitudinal designs, explore emerging AI technologies, examine diverse organizational and cultural contexts, and develop comprehensive ethical frameworks ensuring responsible AI deployment that augments human decision-making while maintaining accountability, transparency, and organizational values.

References

1. Bargavi, R. (2024). AI for optimal decision-making in Industry 4.0. https://doi.org/10.1201/9781003432319-11

2. Bedi, G., Bedi, M., & Mahendra, J. (n.d.). Clinical healthcare applications of artificial intelligence: An empirical study of practicing professionals.

3. Bennett, C. C., & Hauser, K. (2013). Artificial intelligence framework for simulating clinical decision-making: A Markov decision process approach. https://doi.org/10.1016/j.artmed.2012.12.003

4. Bi, S., & Bao, W. (2024). Innovative application of artificial intelligence technology in bank credit risk management. https://doi.org/10.62051/IJGEM.v2n3.08

5. Dietzmann, C., & Duan, Y. (2022). Artificial intelligence for managerial information processing and decision-making in the era of information overload. Proceedings of the 55th Hawaii International Conference on System Sciences. https://doi.org/10.24251/hicss.2022.720

6. Gorantla, B., & Devineni, S. (2023). Harnessing AI

for optimized decision-making: A COPRAS analysis. https://doi.org/10.46632/jdaai/2/3/13

7. Guo, J., & Wang, D. (2021). An empirical study on artificial intelligence technology based on big data to assist enterprise management decision. https://doi.org/10.1177/0020720920983547

8. Gunda, S. K., Yettapu, S. D. R., & Bodakunti, S. (n.d.). Decision intelligence methodology for AI-driven agile software lifecycle governance and architecture-centered project management.

9. Hasan, R., & Akter, S. (n.d.). Information system-based decision support tools: A systematic review of strategic applications in service-oriented enterprises.

10. Li, D. (n.d.). Advancing spatial decision support systems by leveraging cyberinfrastructure and geospatial artificial intelligence.

11. Majumder, S., & Dey, N. (2022). AI-empowered knowledge management. https://doi.org/10.1007/978-981-19-0316-8

12. Ogunsina, K., & DeLaurentis, D. (2021). Enabling integration and interaction for decentralized artificial intelligence in airline disruption management. arXiv:2104.03349v4

13. Patel, R., Goswami, A., Mistry, H., & Mavani, C. (2024). Cognitive computing for decision support systems: Transforming decision-making processes. https://doi.org/10.53555/kuey.v30i6.5473

14. Rahman, A. (2024). AI and machine learning in business process automation: Innovating ways AI can enhance operational efficiencies or customer experiences in U.S. enterprises. https://doi.org/10.70008/jmldeds.v1i01.41

15. Rainy, T. A., Goswami, D., Rabbi, M. M. K., & Al Maruf, A. (2023). A systematic review of AI-enhanced decision support tools in information systems: Strategic applications in service-oriented enterprises and enterprise planning. https://doi.org/10.63125/73djw422

16. Sabharwal, R., Miah, S. J., Wamba, S. F., & Cook, P. (2024). Extending application of explainable artificial intelligence for managers in financial organizations. https://doi.org/10.1007/s10479-024-05825-9

17. Sultana, R. (2023). AI-powered BI dashboards in operations: A comparative analysis for real-time decision support. https://doi.org/10.63125/wqd2t159

18. Torres, R. (2022). How business intelligence capability impacts decision-making speed, comprehensiveness, and firm performance. https://doi.org/10.1177/02666669221108438