Artificial Intelligence Integration in Information Systems for Intelligent Decision Support

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ABSTRACT

This study examines the integration of Artificial Intelligence (AI) into Information Systems to strengthen Intelligent Decision Support and improve organizational Decision-Making Systems. Following a systematic literature review protocol combined with conceptual architecture modeling, the research synthesizes twenty peer-reviewed studies indexed in major academic databases between 2020 and 2026 covering enterprise AI adoption, organizational readiness, and explainable decision support. The review structures five interrelated constructs: Artificial Intelligence, Information Systems, AI Integration, Intelligent Decision Support, and Decision-Making Systems. Findings demonstrate that embedding AI capabilities directly inside information system workflows enhances analytical speed, recommendation quality, predictive compliance, and responsiveness compared with isolated analytical tools. However, implementation outcomes rely heavily on organizational readiness, data governance, transparency, explainable human-AI collaboration, and workflow compatibility. Translating these synthesized themes into practice, the study presents an integrated web-based prototype spanning multi-criteria problem definition, explainable system architecture, and decision tracking dashboards. Overall, the study concludes that AI functions most effectively as a socio-technical capability embedded across organizational workflows rather than as a standalone module.

I. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has fundamentally reshaped how contemporary organizations ingest data, generate predictive analytics, and formulate timely managerial decisions within enterprise information systems (Collins et al., 2021; Shinkarev et al., 2025). Rather than operating as a peripheral software add-on, AI is increasingly positioned as a core socio-technical capability capable of elevating intelligent decision support when tightly aligned with institutional processes (Ågerfalk et al., 2022; Soori et al., 2026).

Nevertheless, empirical investigations reveal that organizations frequently encounter structural implementation barriers, including uneven data quality, lack of model transparency, governance gaps, and insufficient technological readiness (Uren & Edwards, 2022; Alsaigh et al., 2023). Moreover, benefits from AI-enabled decision support do not materialize automatically; tangible decision value depends on how seamlessly algorithms are embedded into daily workflows, interpreted by managers, and governed across business units (Jöhnk et al., 2020; Donmez et al., 2025).

At the same time, recent literature highlights that well-integrated AI tools substantially improve analytical speed, predictive accuracy, and adaptive responsiveness in volatile decision environments (Soori et al., 2026; Banerjee, 2026). When coupled with structured enterprise architectures such as ERP and cloud decision pipelines, AI shifts organizational information systems from passive historical reporting toward proactive decision intelligence (Ashok, 2025; Khilji et al., 2026).

Prior systematic reviews demonstrate that although AI scholarship inside information systems has grown rapidly, findings remain fragmented across technical algorithms, sector-specific case studies, and organizational adoption models (Collins et al., 2021; Muhyi et al., 2025). Furthermore, many conceptual models do not bridge literature synthesis with tangible prototype blueprints explaining how end-users interact with multi-criteria recommendation layers (Putchakayala & Yallavula, 2025; Qazi & Ullah, 2025).

To bridge this gap, the present study investigates how Artificial Intelligence Integration connects foundational Information Systems infrastructure with Intelligent Decision Support and organizational Decision-Making Systems (Collins et al., 2021; Soori et al., 2026). Conceptually, Figure 1 depicts this sequential linkage in which AI provides learning and pattern recognition capabilities, Information Systems supply unified data pipelines, AI Integration anchors workflow embedding, Intelligent Decision Support generates explainable recommendations, and Decision-Making Systems drive agile institutional outcomes.

Table 1: Literature Synthesis on AI Integration in Information Systems

Source	Key Finding	Editorial & Architectural Implication
Collins et al. (2021)	AI in information systems research is expanding rapidly yet remains methodologically fragmented.	AI integration must be studied inside unified socio-technical IS frameworks.
Ågerfalk et al. (2022)	AI triggers deep socio-technical shifts across organizational work and accountability.	Explainability, ethical transparency, and clear research roadmaps are vital.
Uren & Edwards (2022)	Organizational adoption hinges on technology readiness, people skills, and data maturity.	Readiness assessment and data governance precede technical deployment.

Soori et al. (2026)	AI-driven decision support boosts speed, forecasting accuracy, and crisis responsiveness.	AI complements human managerial judgment rather than replacing accountability.

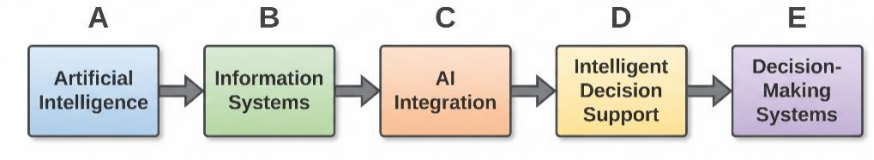

Figure 1: Conceptual Relationship Chain Linking AI, Information Systems, and Decision-Making

II. METHODOLOGY

This This study adopts a Systematic Literature Review (SLR) approach paired with prototype architectural mapping to examine how Artificial Intelligence integrates into Information Systems for Intelligent Decision Support (Collins et al., 2021; Donmez et al., 2025). An SLR methodology was selected because it enables transparent identification, rigorous quality appraisal, and thematic integration of fragmented peer-reviewed evidence across multiple application domains.

The structured search protocol queried Scopus, Crossref, and OpenAlex-indexed databases covering peer-reviewed publications from 2020 to 2026 using Boolean combinations of core terms: ("artificial intelligence" OR "AI integration") AND ("information systems" OR "enterprise systems") AND ("intelligent decision support" OR "decision-making systems" OR "organizational readiness"). Inclusion criteria required English-language peer-reviewed journal articles or conference proceedings addressing managerial AI implementation, decision support modeling, or explainable governance, yielding an initial pool of 148 candidate records that were deduplicated, screened by title and abstract, and narrowed after full-text eligibility checks to 20 core verified studies synthesized in this review.

Following study selection, extracted evidence was coded inductively using thematic synthesis across five operational constructs—Artificial Intelligence, Information Systems, AI Integration, Intelligent Decision Support, and Decision-Making Systems—and mapped to observable technical and organizational indicators as detailed in Table 2. Coding consistency was preserved through cross-author verification comparing literature themes directly against the prototype workflow and dashboard requirements (Saffiera et al., 2026; Jonathan et al., 2025).

Table 2: Operational Variables and Synthesized Indicators

Variable Construct	Synthesized Observable Indicators
Artificial Intelligence (AI)	Machine learning capability, rule-based logic, automation, prediction, pattern recognition
Information Systems (IS)	Multi-source data processing, storage, interoperability, real-time delivery
AI Integration	Workflow embedding, API connectivity, modular architecture, data governance
Intelligent Decision Support	Recommendation quality, speed, accuracy, XAI rationale transparency
Decision-Making Systems	Decision effectiveness, managerial responsiveness, human-in-the-loop review

III. RESULTS AND DISCUSSION

The thematic synthesis confirms that AI integration in enterprise information systems delivers measurable strategic value only when aligned with organizational readiness, people capabilities, and clear governance rules (Jöhnk et al., 2020; Hradecky et al., 2022; Palade & Căruțaşu, 2023). Table 1 highlights how conceptual and empirical scholarship converges on four pillars: socio-technical embedding, managerial trust, readiness maturity, and human-AI collaboration (Qazi & Ullah, 2025; Saffiera et al., 2026). Similarly, empirical industry evidence demonstrates that readiness factors significantly moderate downstream productivity and forecasting accuracy (Heimberger et al., 2025; Shinkarev et al., 2025).

Table 2 presents the operational variables and their synthesized indicators used to translate these conceptual themes into an actionable system blueprint. Rather than deploying standalone analytics scripts, organizations require an end-to-end sequential workflow beginning with structured problem formulation, automated multi-criteria evaluation, explainable output visualization, and human decision review—consistent with domain implementations in enterprise planning, public governance, and education (Ashok, 2025; Lizar et al., 2025; Jonathan et al., 2025).

To operationalize Table 2 into an applied architectural reference, Figures 2 through 5 present the resulting AI-Integrated Decision Support System prototype. First, Figure 2 illustrates the overarching sequential pipeline from user input through data processing, AI engine execution, recommendation output, and human-in-the-loop decision review (Qazi & Ullah, 2025). Second, Figure 3 clarifies the underlying System Architecture and AI Integration mechanisms—illustrating the four-stage data processing flow (input ingestion, Weighted Sum Model and constraint analysis, transparent visualization, and feedback recalibration) alongside bilingual localization and UI clarity.

Third, Figure 4 displays the Decision Dashboard interface used to monitor cumulative decision volume, AI recommendation accuracy trends, and category distribution; notably, the captured interface depicts the baseline clean-state configuration (`0` logged decisions and `0%` accuracy) prior to longitudinal live deployment, underscoring why post-implementation usage logs must populate

accuracy recalculations dynamically over time (Banerjee, 2026; Saffiera et al., 2026). Finally, Figure 5 illustrates the Decision Input Workflow screen (`Define Decision Problem`), enabling managers to define problem titles, select business or educational categories, choose an analytical AI engine (such as Multi-Criteria Analysis / AHP), and submit context before downstream engine processing.

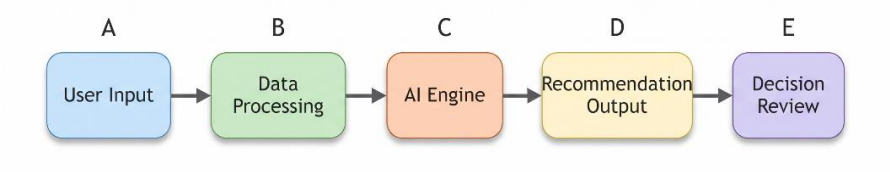

Figure 2: Application Workflow for AI-Based Intelligent Decision Support

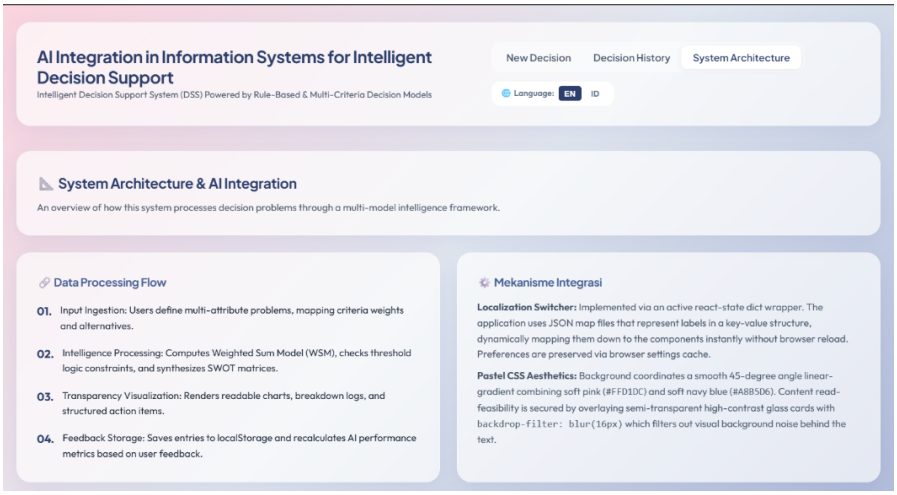

Figure 3: System Architecture and AI Integration Layer

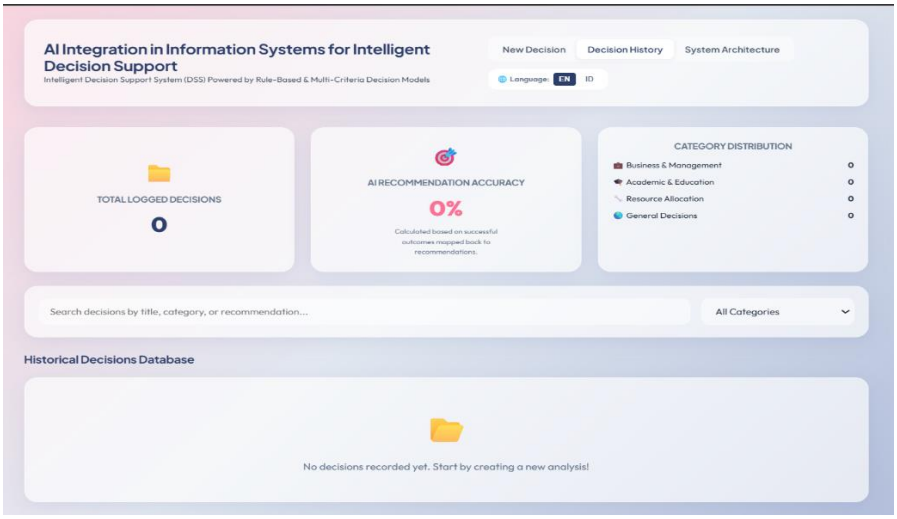

Figure 4: Decision Dashboard Interface (Initial Clean-State Configuration)

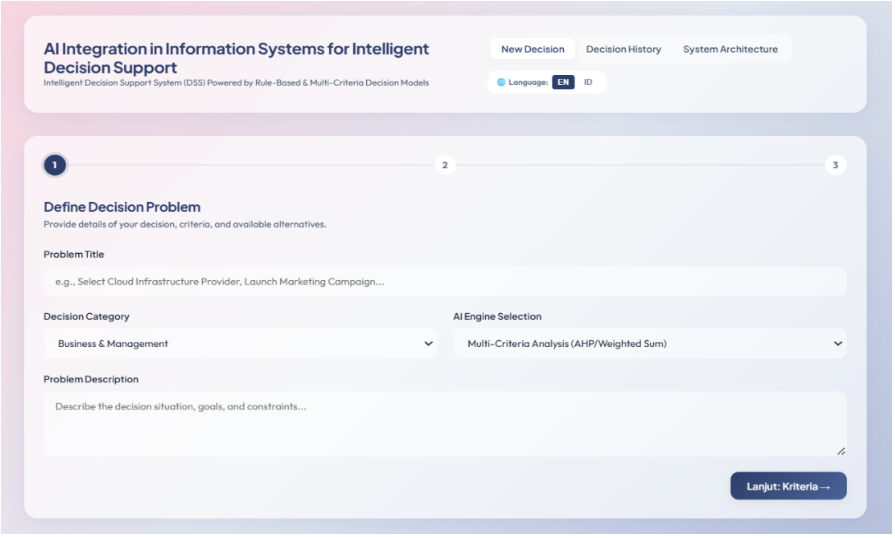

Figure 5: Interactive Decision Input Workflow Screen

IV. CONCLUSIONS

This study concludes that integrating Artificial Intelligence within Information Systems substantially strengthens Intelligent Decision Support and enterprise Decision-Making Systems when embedded seamlessly inside operational workflows (Collins et al., 2021; Soori et al., 2026). Synthesized evidence across 20 peer-reviewed studies demonstrates that technical analytical speed alone is insufficient; sustainable value depends equally on organizational readiness, data governance, model explainability, and structured human-in-the-loop validation (Ågerfalk et al., 2022; Saffiera et al., 2026; Uren & Edwards, 2022).

By aligning the conceptual chain (Figure 1), operational indicators (Table 2), and verified prototype screens (Figures 2–5), this research provides practitioners and academic system designers with a cohesive reference architecture for building transparent decision support platforms. Practically, managers should evaluate organizational readiness and establish clear feedback loops before scaling automated recommendations (Jöhnk et al., 2020; Muhyi et al., 2025). Future empirical research should conduct longitudinal field trials using live organizational datasets to measure post-deployment recommendation accuracy, user trust calibration, and return on decision latency.

REFERENCES

Ågerfalk, P. J., Conboy, K., Crowston, K., Eriksson Lundström, J. S. Z., Jarvenpaa, S., Mikalef, P., & Ram, S. (2022). Artificial intelligence in information systems: State of the art and research roadmap. Communications of the Association for Information Systems, 50(1), 420–438. https://doi.org/10.17705/1cais.05017

Alsaigh, R., Mehmood, R., & Katib, I. A. (2023). AI explainability and governance in smart energy systems: A review. Frontiers in Energy Research, 11, 1071291. https://doi.org/10.3389/fenrg.2023.1071291

Ashok, P. P. K. (2025). Embedding AI in ERP workflows: A new paradigm for intelligent decision support. International Journal of Computer Engineering & Technology, 16(4), 104–115. https://doi.org/10.34218/ijcet_16_04_007

Banerjee, A. (2026). An artificial intelligence-driven decision support framework for intelligent information systems management and operational optimization. Journal of Intelligent Decision Making and Information Science, 3(6s), 1916–1931. https://doi.org/10.59543/jidmis.v3.1585

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. International Journal of Information Management, 60, 102383. https://doi.org/10.1016/j.ijinfomgt.2021.102383

Donmez, S., Celikel, A. T., Sarica, Y. P. S., & Develi, E. İ. (2025). Understanding AI adoption at organizations: Literature review of TOE framework. Pressacademia. https://doi.org/10.17261/pressacademia.2025.1994

Heimberger, H., Horvat, D., Jäger, A., & Schultmann, F. (2025). Exploring AI adoption in manufacturing: An empirical study on effects of AI readiness. International Journal of Production Economics, 297, 109733. https://doi.org/10.1016/j.ijpe.2025.109733

Hradecky, D., Kennell, J. S., Cai, W., & Davidson, R. (2022). Organizational readiness to adopt artificial intelligence in the exhibition sector in Western Europe. International Journal of Information Management, 65, 102497. https://doi.org/10.1016/j.ijinfomgt.2022.102497

Jöhnk, J., Weißert, M., & Wyrtki, K. (2020). Ready or not, AI comes — An interview study of organizational AI readiness factors. Business & Information Systems Engineering, 63(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Jonathan, G. M., Yalew, S. D., Gebremeskel, B. K., & Watat, J. K. (2025). AI adoption in the public sector: Organizational readiness and the pursuit of public value. Complex Systems Informatics and Modeling Quarterly, 45, 43–70. https://doi.org/10.7250/csimq.2025-45.03

Khilji, N. K., Safaei, M., Alamassi, S., Mamani, N. U. Q., Al-Shaybani, A., & Khalitovna, I. I. (2026). Next-generation decision support systems: Integrating artificial intelligence, machine learning, big data analytics, and intelligent information systems. Computer and Decision Making, 3(1S), 275–286. https://doi.org/10.1922/comdem.v3i1s.18608

Lizar, Y., Guci, A., & Sunadi, J. (2025). Artificial intelligence–based information systems to support educational decision-making. AL-TA LIM, 32(3), 256–263. https://doi.org/10.15548/jt.v32i3.904

Muhyi, H. A., Sukmadewi, R., Chan, A., & Kahfi, A. A. (2025). Organizational readiness for artificial intelligence with systematic mapping study in public and private sectors. Sosiohumaniora, 26(3), 483–494. https://doi.org/10.24198/sosiohumaniora.v26i3.56493

Palade, M., & Căruțaşu, G. (2023). Organizational readiness for artificial intelligence adoption. Scientific Bulletin of the Politehnica University of Timişoara Transactions on Engineering and Management, 7(1–2), 30–35. https://doi.org/10.59168/fdms6321

Putchakayala, R., & Yallavula, R. (2025). The intelligent governance core: A multi-layer AI framework for predictive compliance and autonomous digital analytics. International Journal of AI, BigData, Computational and Management Studies, 6(1). https://doi.org/10.63282/3050-9416.ijaibdcms-v6i1p117

Qazi, A., & Ullah, S. (2025). Human–AI collaboration in intelligent decision support systems. Multidisciplinary Research in Computing Information Systems, 5(9), 691–702. https://doi.org/10.71465/mrcis134

Saffiera, C. A., Sase, T., Aini, Q., Manongga, D. H. F., & Agustian, H. (2026). Explainable AI supporting responsible human AI interaction in intelligent decision support systems. Journal of Orange Technology, 3(1), 13–24. https://doi.org/10.68012/jot.v3i1.105

Shinkarev, A. A., Yadryshnikova, M., Loginovskiy, O. V., Lazareva, S. A., & Gubin, V. M. (2025). Evolution of usage and application of machine learning and artificial intelligence in the development of enterprise information systems and in decision support systems. Bulletin of the South Ural State University. Series: Computer Technologies, Automatic Control, & Radioelectronics, 25(4), 17–42. https://doi.org/10.14529/ctcr250402

Soori, M., Jough, F. K. G., Dastres, R., & Arezoo, B. (2026). AI-based decision support systems in Industry 4.0, a review. Journal of Economy and Technology, 4, 206–225. https://doi.org/10.1016/j.ject.2024.08.005

Uren, V. S., & Edwards, J. S. (2022). Technology readiness and the organizational journey towards AI adoption: An empirical study. International Journal of Information Management, 68, 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102588