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Research Article

A Scalable Human Centered Artificial Intelligence Architecture for Decision Support Systems in Large Scale Digital Transformation Ecosystems

Aziz Azindani [1]*, Ismi Kusumaningroem [2], and Ilham Akhsani [3]

[1] Politeknik Baja Tegal, Indonesia, Email: aziz.azindani@pbjt.ac.id
[2] Politeknik Baja Tegal, Indonesia, Email: ismi@pbjt.ac.id
[3] Politeknik Baja Tegal, Indonesia, Email: ilham@pbjt.ac.id
* Corresponding Author: email : aziz.azindani@pbjt.ac.id

Abstract: Artificial Intelligence (AI)-based Decision Support Systems (DSS) have become a central component of digital transformation initiatives across various industries. While prior studies have primarily emphasized technical aspects such as accuracy, performance, and computational efficiency, less attention has been given to the integration of human-centered principles and scalable architectural design. This study aims to examine how AI-based DSS can be enhanced through the combined application of Human-Centered Artificial Intelligence (HCAI) principles and scalable AI architecture. Using a qualitative, literature-based research methodology, this study systematically analyzes peer-reviewed publications indexed in Scopus to identify key dimensions influencing the effectiveness and sustainability of AI-driven DSS. The findings indicate that technical capabilities alone are insufficient to ensure successful adoption and long term impact. Instead, transparency, explainability, ethical governance, and user empowerment core elements of HCAI are critical for fostering trust and user acceptance. Furthermore, scalable architectural principles, including modularity, interoperability, and adaptability, are essential for enabling AI-based DSS to operate reliably in large-scale and dynamic environments. This study contributes a unified conceptual framework that bridges technical scalability and human-centered design, offering theoretical insights and practical guidance for developing trustworthy, scalable, and sustainable AI-based Decision Support Systems in digital transformation contexts.

Keywords: Artificial Intelligence; Decision Support Systems; Human-Centered Artificial Intelligence; Scalability; Trustworthy AI.

1. Introduction

Largescale digital transformation has become a strategic imperative for organizations seeking to enhance competitiveness, efficiency, and adaptability in an increasingly complex and datadriven environment. Advances in emerging technologiesparticularly Artificial Intelligence (AI)have fundamentally reshaped how organizations collect, process, and utilize information to support managerial decisionmaking. Within this context, Decision Support Systems (DSS) have evolved from conventional rulebased and descriptive tools into intelligent, adaptive systems capable of handling large volumes of heterogeneous data and generating actionable insights in real time (Lu et al., 2025; Zhang et al., 2025).

AIbased DSS play a critical role in enabling organizations to automate analytical processes, detect patterns within big data, and support timely and accurate decisions across various operational and strategic domains. By leveraging machine learning, predictive analytics, and knowledgebased models, AIenhanced DSS allow organizations to move beyond static and linear decisionmaking models toward more dynamic, datadriven, and nonlinear approaches (Daoud et al., 2025; Salgado-Reyes et al., 2024). This shift is particularly important in digital transformation initiatives, where rapid market changes and increasing uncertainty demand high levels of responsiveness and adaptability.

Previous studies have demonstrated that the integration of AI into DSS significantly improves decision quality and organizational performance. Empirical evidence indicates that

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AIenhanced DSS can achieve decision accuracy levels of up to 92%, compared to approximately 80% in traditional DSS, highlighting the substantial performance gains enabled by intelligent decision support (Lu et al., 2025). Although AIdriven systems may require longer processing times due to complex data analysis and model computation, such tradeoffs are generally acceptable in contexts where decision accuracy, reliability, and strategic impact are critical.

Beyond decision accuracy, AIbased DSS contribute to digital transformation by improving operational efficiency through process automation and optimization. AIdriven analytics reduce manual workloads, lower operational costs, and enhance resource utilization, particularly in dataintensive environments such as finance, healthcare, and supply chain management (Bertl et al., 2023; Patjoshi et al., 2025). Furthermore, the use of hybrid predictive models and business knowledge graphs enhances transparency and interpretability, addressing longstanding concerns regarding the opacity of AIbased decisionmaking processes (Patolia, 2025).

AIbased DSS also support organizational collaboration and innovation through AIdriven knowledge management systems. These systems facilitate knowledge sharing, organizational learning, and crossfunctional collaboration, which are essential for sustaining digital transformation initiatives in complex and largescale projects (Ahmed et al., 2025). Leadership and organizational readiness play a crucial role in ensuring that AIenabled decision support tools are effectively adopted and aligned with strategic objectives.

Despite these benefits, the implementation of AIbased DSS presents several challenges that must be carefully managed. Ethical considerations and data privacy issues remain major concerns, particularly regarding the responsible use of sensitive and personal data in automated decisionmaking processes (Bertl et al., 2023; Salgado-Reyes et al., 2024). In addition, organizations must invest in workforce upskilling to ensure that employees possess the technical and analytical competencies required to effectively interact with AIdriven systems (Ahmed et al., 2025; Daoud et al., 2025). The complexity of integrating AI technologies with existing legacy systems further underscores the need for systematic and wellplanned implementation strategies (Zhang et al., 2025).

In summary, AIbased Decision Support Systems represent a foundational component of contemporary digital transformation efforts. While their potential to enhance decision quality, operational efficiency, and organizational competitiveness is well established, successful implementation depends on addressing ethical, technical, and humanrelated challenges. Understanding the strategic role of AIdriven DSS is therefore essential for organizations seeking to leverage digital transformation as a sustainable source of competitive advantage.

Decision Support Systems (DSS) have long been recognized as an essential component in enhancing managerial and organizational decision making processes. Since their early development, DSS have evolved alongside advances in information technology, data management, and computational methods, enabling decision-makers to handle increasingly complex and data-intensive problems. Contemporary DSS development is largely driven by the need to improve decision accuracy, system performance, and computational efficiency in response to growing volumes of data and the rising complexity of organizational environments (Lausberg & Krieger, 2021).

In recent years, the primary focus of DSS research and implementation has shifted toward technical optimization. Advances in machine learning and data analytics have enabled DSS to generate more accurate and reliable predictions, particularly in industrial and operational contexts. For example, the integration of machine learning algorithms such as Random Forest, Naïve Bayes, and Support Vector Machines has demonstrated substantial improvements in predictive performance. In the canning industry, Random Forest models achieved prediction accuracy levels of up to 90% in estimating production losses, highlighting the effectiveness of algorithm-driven DSS in supporting operational decision-making (Mallioris et al., 2024).

Beyond accuracy, computational efficiency has become a critical concern in modern DSS development. The increasing availability of big data and heterogeneous data sources has encouraged the adoption of advanced data collection, storage, processing, and visualization techniques. Industrial DSS now frequently leverage big data analytics and multi-source data fusion to enhance real-time decision-making capabilities and system scalability (Duan, 2025). These technological advancements enable organizations to process large volumes of structured and unstructured data more efficiently, thereby supporting faster and more informed decisions.

Despite these technical advancements, several challenges persist in the practical deployment and adoption of DSS. One of the most significant issues relates to user acceptance and real-world implementation. DSS developed for specific domains such as real estate and social work often struggle to align technical outputs with the nuanced and context dependent needs of human decision-makers. In the real estate sector, DSS have been widely explored for valuation, investment analysis, and risk assessment; however, their practical application remains limited due to complexity, usability concerns, and insufficient integration with decision-makers' workflows (Lausberg & Krieger, 2021).

Similar challenges have been observed in social work and public service contexts, where predictive and algorithm based DSS raise concerns regarding transparency, interpretability, and professional judgment. While predictive algorithms have the potential to support decision making in child welfare and family services, their adoption is often hindered by ethical considerations, trust issues, and resistance from practitioners who remain cautious about over reliance on automated systems (Gillingham, 2019). These findings suggest that technical excellence alone is insufficient to guarantee the successful implementation of DSS.

Consequently, future DSS development must move beyond a predominantly technical orientation and address human centered and organizational factors that influence system acceptance and effectiveness. While improvements in accuracy and computational efficiency remain essential, greater attention is required to ensure that DSS are usable, interpretable, and aligned with the real world decision contexts they are intended to support. Addressing these challenges is critical for advancing DSS from technically sophisticated tools into practically valuable systems that can be effectively integrated into organizational decision making processes.

2. Literature Review

Decision Support Systems in Digital Transformation

AI Based Decision Support Systems in Strategic Decision Making

Decision Support Systems (DSS) have become a central component of digital transformation initiatives, particularly through the integration of Artificial Intelligence (AI) technologies. Modern AI based DSS leverage big data analytics, machine learning, and advanced computational techniques to process large volumes of structured and unstructured data, enabling organizations to generate optimized performance outcomes and actionable business insights (Rakshitha et al., 2025). By transforming raw data into strategic knowledge, AI-driven DSS enhance managerial capabilities in complex and dynamic decision environments.

Empirical evidence highlights the strategic value of AI based DSS in improving organizational performance and competitiveness. In a qualitative study of Morocco's automotive industry, (Mantouzi & Youssef, 2025) demonstrated that AI driven DSS significantly improve resource allocation, organizational responsiveness, and innovation capacity. These improvements enable organizations to better align strategic objectives with operational execution, ultimately strengthening long-term performance in highly competitive markets.

In manufacturing and industrial contexts, AI based DSS increasingly integrate Internet of Things (IoT) technologies, big data analytics, and cyber physical systems to support real time and near real time decision making. Such systems utilize industrial sensors and edge computing architectures to optimize production processes, detect anomalies, and enhance decision accuracy under time critical conditions (Hameed et al., 2025). The convergence of AI, IoT, and advanced analytics thus represents a key enabler of data-driven strategic decision-making within digital transformation frameworks.

Challenges of Large Scale Decision Support Systems

Despite their strategic benefits, large scale AI based DSS face significant technical and organizational challenges. One major issue lies in the complexity of managing, updating, and maintaining very large and geographically distributed data repositories and program cores. As DSS scale in size and functionality, design limitations, system errors, and operational hazards become increasingly difficult to anticipate and control, leading to elevated risks in system reliability and performance (Koukoutsis et al., 2020).

Data-related challenges further complicate large scale DSS implementation. Ensuring data quality, consistency, and security across heterogeneous sources remains a critical concern, particularly for technology driven enterprises seeking to sustain competitive advantage through data centric strategies (Rakshitha et al., 2025). Moreover, the effective deployment of AI-based DSS requires the establishment of a data-driven organizational culture that supports evidence-based decision-making and continuous learning.

In security sensitive domains, such as cyber forensics and cybersecurity, AI based DSS introduce additional ethical and operational challenges. Issues related to data privacy, ethical decision-making, and the availability of robust training datasets are particularly prominent, as inaccuracies or biases in AI models may lead to severe legal and operational consequences (Bhardwaj & Choudhary, 2024). These challenges highlight the need for transparent, accountable, and ethically grounded DSS design.

Overall, the literature suggests that while AI based DSS play a crucial role in enabling strategic decision making and driving digital transformation, their effectiveness depends on the ability to address large scale system complexity, data governance, and ethical considerations. A balanced approach that integrates technical innovation with organizational readiness and governance mechanisms is therefore essential to ensure the sustainable impact of DSS in digital transformation initiatives.

Human-Centered Artificial Intelligence (HCAI)

Principles of Human CCentered Design in Artificial Intelligence

Human Centered Artificial Intelligence (HCAI) represents a paradigm shift in AI development that emphasizes the alignment of intelligent systems with human values, needs, and ethical principles. Unlike technology-centered approaches that prioritize performance and automation, HCAI focuses on empowering users and ensuring that AI systems augment, rather than replace, human decision making. Core principles of HCAI include user empowerment, ethical governance, transparency, accountability, and privacy protection (Schmager et al., 2024; Usmani et al., 2023).

User empowerment in HCAI is achieved through user-centric design approaches that actively involve stakeholders throughout the AI lifecycle. Ethical guidelines play a crucial role in this process by ensuring fairness, accountability, and responsible data usage, particularly in sensitive domains such as public services and healthcare (Schmager et al., 2024). These principles aim to mitigate risks associated with algorithmic bias and opaque decision-making while fostering trust between users and AI systems.

Inclusivity and empathy are also fundamental to HCAI design. Integrating diverse user perspectives helps ensure that AI systems respect human rights and avoid reinforcing existing social inequalities. (Sahoo & Saurav, 2025) emphasize that inclusive AI design requires deliberate attention to representation, bias mitigation, and contextual understanding of users' lived experiences. By embedding empathy into system design, AI developers can create systems that are more responsive to human needs and societal expectations.

Interdisciplinary collaboration further strengthens the HCAI framework. Effective human AI collaboration relies on shared decision making models in which users retain meaningful control over AI outputs. Collaboration between computer scientists, designers, ethicists, and domain experts enables the development of AI systems that are not only technically robust but also socially and ethically grounded **(Usmani et al., 2023)**. Such interdisciplinary efforts contribute practical design recommendations that enhance usability, interpretability, and user trust.

Explainability, Transparency, and Trustworthiness in AI Systems

Explainability, transparency, and trustworthiness are widely recognized as critical enablers of Human-Centered AI. Explainable Artificial Intelligence (XAI) seeks to make AI decision-making processes understandable to users, which is particularly important in high-stakes domains such as healthcare, security, and public administration (Benois-Pineau & Petkovic, 2023; Krejcar et al., 2026). Techniques such as counterfactual explanations and causal modeling improve interpretability by clarifying how specific inputs influence AI outputs, thereby aligning system behavior with human reasoning (Krejcar et al., 2026).

Transparency refers to the degree to which AI systems, models, and decision logic are accessible and comprehensible. It is often viewed as an overarching concept encompassing explainability, interpretability, and predictability. Transparent AI systems enable users to better understand system limitations and decision rationales, which contributes to perceived reliability (Grimmelikhuijsen, 2023). However, transparency alone is insufficient; without meaningful explanations, users may still struggle to develop trust in AI-generated outcomes (Atf, 2025).

Trustworthiness in AI extends beyond technical performance metrics to include ethical, social, and contextual dimensions. Trustworthy AI systems are expected to demonstrate robustness, reliability, fairness, accountability, explainability, and privacy protection (Donati et al., 2025). Trust is not static; it evolves dynamically based on user experiences, system behavior, and contextual factors. (Hepworth et al., 2021) highlight that trust in human machine teaming environments depends on continuous feedback, transparency mechanisms, and adaptive system behavior.

Empirical studies further suggest that explainability is positively correlated with perceived trustworthiness, although the strength of this relationship varies across contexts and user groups (Atf, 2025). This reinforces the view that trust in AI is user-relative and domain-dependent rather than universally determined. Consequently, designing trustworthy AI systems requires moving beyond checklist based compliance toward a holistic, human-centered understanding of trust (Donati et al., 2025; Rosário & Dias, 2025).

Overall, the literature underscores that HCAI provides a comprehensive framework for designing AI systems that are ethically responsible, socially inclusive, and aligned with human values. Explainability, transparency, and trustworthiness are not merely technical features but foundational design principles that shape how humans perceive, interact with, and rely on AI systems in real world contexts.

Scalable AI Architecture

Scalability in Artificial Intelligence Systems

Scalability in Artificial Intelligence (AI) systems refers to the capability of an architecture to handle increasing volumes of data, users, and computational workloads without significant degradation in performance. As AI adoption expands across industries such as healthcare, manufacturing, smart infrastructure, and large scale networks, scalability has become a fundamental architectural requirement rather than an optional feature (Freeda et al., 2025; Wajdi et al., 2025). Scalable AI systems must efficiently manage resource allocation, optimize computational processes, and leverage cloud-based and distributed computing infrastructures to meet growing operational demands (Mishra, 2024).

The literature highlights several core challenges in achieving AI scalability, including efficient utilization of computing resources, architectural complexity, and system heterogeneity. In large scale communication networks, scalability issues arise from increasing data traffic, model complexity, and real-time processing requirements, which necessitate advanced architectural strategies and distributed AI solutions (Freeda et al., 2025; Kanchibhotla et al., 2024). Empirical studies further indicate that organizations that successfully integrate scalable AI architectures into their projects can achieve significant operational and strategic impacts, particularly when scalability is addressed early in the system design phase (Wajdi et al., 2025).

Modularity as a Design Principle for Scalable AI

Modularity is widely recognized as a key architectural principle for managing complexity in large scale AI systems. By decomposing complex systems into smaller, independent modules, modular architectures reduce system complexity, enhance maintainability, and promote component reuse (Biggar et al., 2022; Maikantis et al., 2020). In AI contexts, modularity enables developers to update, replace, or optimize specific components such as data ingestion, model training, or inference without disrupting the overall system architecture.

Research on software architecture reconstruction demonstrates that modular refactoring techniques can improve system structure and scalability by isolating tightly coupled components and enhancing architectural clarity (Maikantis et al., 2020). In cyber-physical and robotic systems, modular control architectures support rapid adaptation to diverse application requirements, facilitating scalability across multiple deployment scenarios (Biggar et al., 2022). These findings suggest that modularity not only supports scalability but also strengthens system robustness and long-term sustainability.

Interoperability in Scalable AI Ecosystems

Interoperability refers to the ability of AI systems to exchange information and operate seamlessly with other systems across heterogeneous environments. In scalable AI architectures, interoperability is essential for integrating AI components with external platforms such as Internet of Things (IoT) devices, cyber physical systems, and enterprise information systems (Nilsson et al., 2024; Vernadat, 2023). Without interoperability, scalable AI systems risk becoming isolated silos that limit data sharing and cross domain collaboration.

The literature identifies major interoperability challenges, including inconsistent data standards, fragmented communication protocols, and incompatible device ecosystems (Khanna & Bhusri, 2025; Vernadat, 2023). To address these issues, researchers propose modular and interoperable architectural frameworks that support real time orchestration and consistent data access across systems (Nilsson et al., 2024). In IoT enabled environments, unified data frameworks and standardized interfaces have been shown to enhance interoperability and scalability, particularly in domains such as healthcare and smart infrastructure (Khanna & Bhusri, 2025; Palanivel Rajan & Abirami, 2023).

Adaptability in AI System Architectures

Adaptability is another critical dimension of scalable AI architectures, referring to a system's ability to adjust to changing environments, requirements, and operational conditions. Adaptive AI systems leverage learning mechanisms and feedback loops to evolve over time without requiring extensive manual intervention (Mishra, 2024). This capability is particularly important in dynamic environments where system requirements and external conditions frequently change.

Empirical studies illustrate the role of adaptability in real world applications. For example, AI-enabled self learning buildings continuously collect environmental data and autonomously adjust operational parameters to optimize energy consumption and user comfort, demonstrating high levels of architectural adaptability (Maksoud et al., 2022). Such adaptive capabilities allow AI systems to remain effective over time, even as contextual factors evolve, thereby reinforcing scalability from a long-term perspective.

Synthesis of Scalable AI Architecture Research

Overall, the literature suggests that scalability in AI systems is a multidimensional concept that encompasses architectural scalability, modularity, interoperability, and adaptability. Scalable AI architectures require deliberate design choices that balance performance, flexibility, and system complexity. Modular designs facilitate maintainability and evolution, interoperable frameworks enable cross system integration, and adaptive mechanisms ensure long term relevance in dynamic environments (Freeda et al., 2025; Mishra, 2024; Nilsson et al., 2024).

Despite significant progress, challenges remain in harmonizing these architectural principles within unified AI frameworks, particularly in large scale, heterogeneous, and real time systems. Future research is therefore needed to develop integrated architectural models that systematically address scalability while supporting interoperability, adaptability, and sustainable system evolution.

3. Research Method

Research Design

This study adopts a qualitative research design based on a systematic literature-based analysis to examine the integration of AI driven Decision Support Systems (DSS), Human Centered Artificial Intelligence (HCAI) principles, and scalable AI architectures within the context of digital transformation. A qualitative approach is appropriate given the conceptual, architectural, and human-centric nature of the research focus, which emphasizes theoretical synthesis rather than empirical measurement.

The methodology aims to develop a conceptual and analytical understanding of how scalable AI architectures and human centered principles can enhance the effectiveness, trustworthiness, and sustainability of AI based DSS.

Data Sources and Selection Criteria

The primary data sources for this study consist of peer reviewed scientific publications indexed in Scopus, including journal articles, conference proceedings, book chapters, and review papers. The literature selection focused on publications addressing AI based Decision Support Systems and digital transformation, with particular attention to studies on Human Centered AI, such as user empowerment, explainability, transparency, and trustworthiness. In addition, the selected works discuss scalable AI architectures, including aspects of scalability, modularity, interoperability, and adaptability. To ensure relevance to current technological and methodological developments, only publications released between 2020 and 2026 were considered. Furthermore, the study included only research published in reputable international venues with clear methodological and theoretical contributions, and limited the selection to final-stage publications to ensure the reliability and maturity of the analyzed findings.

Data Collection Procedure

The data collection process involved a systematic review and extraction of relevant literature based on predefined thematic categories derived from the research objectives. Each selected publication was examined to identify conceptual definitions and theoretical frameworks related to AI based Decision Support Systems, architectural principles supporting AI scalability such as modularity, interoperability, and adaptability and human-centered design principles, including ethical guidelines, user empowerment, and inclusivity. In addition, the review captured challenges and limitations associated with large scale AI systems and the implementation of Decision Support Systems. All key findings and conceptual insights were systematically documented and organized to support comparative and integrative analysis.

Data Analysis Technique

The study employs a thematic analysis approach to synthesize insights across the selected literature. The analysis began with thematic coding, in which findings from the reviewed publications were categorized into major themes, including AI driven Decision Support Systems in digital transformation, human centered AI principles, explainability, transparency, and trust in AI systems, as well as scalable AI architectures encompassing scalability, modularity, interoperability, and adaptability. These coded themes were then subjected to comparative analysis across various domains such as industry, healthcare, the Internet of Things, and cyber physical systems to identify recurring patterns, conceptual alignments, and divergences. Finally, the results of the thematic analysis were conceptually integrated to develop a coherent analytical framework that links the effectiveness of AI-based Decision Support Systems with Human-Centered AI principles and scalable architectural design. This analytical process enables the identification of relationships between technical architectures and human centered considerations in AI-enabled decision-making systems.

Research Framework Development

Based on the synthesized findings, this study develops a conceptual research framework that illustrates the interconnections between AI based Decision Support System capabilities such as data analytics, automation, and decision accuracy Human Centered AI dimensions, including user empowerment, explainability, ethical governance, and trust, and scalable AI architecture principles encompassing modularity, interoperability, and adaptability. This framework serves as an analytical lens to explain how scalable and human centered AI architectures can support sustainable, effective, and trustworthy decision making processes within digital transformation initiatives.

Validity and Rigor

To ensure methodological rigor, this study applies several strategies, including source triangulation by integrating evidence from multiple domains and publication types, theoretical consistency by grounding the analysis in established concepts from Decision Support Systems, Human-Centered AI, and software architecture literature, and transparency of method through explicit documentation of literature selection and analysis procedures. These measures enhance the credibility and analytical validity of the research findings.

Scope and Limitations

This research is limited to conceptual and literature-based analysis and does not include empirical validation through experiments, surveys, or case studies. Consequently, the findings provide theoretical and architectural insights rather than quantitative performance evaluation. Future research may extend this work by empirically testing the proposed framework in real-world organizational or industrial DSS implementations.

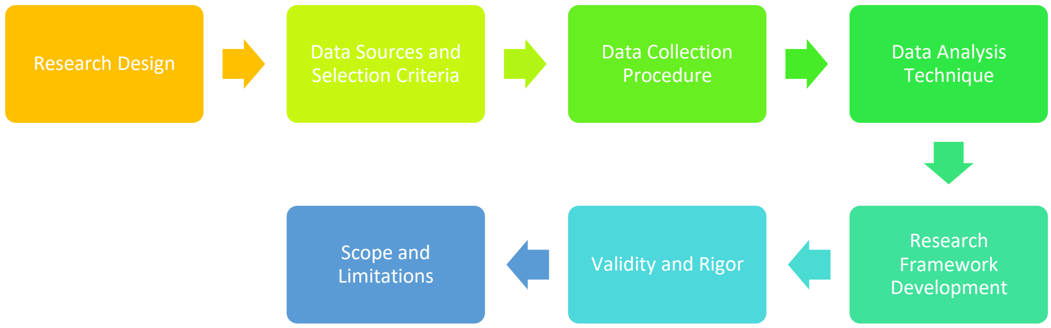

Figure 1. Research Methodology Flowchart.

4. Results and Discussion

Results

Overview of Research Findings

This section presents the results of the literature-based thematic analysis conducted to examine the integration of AI based Decision Support Systems (DSS), Human Centered Artificial Intelligence (HCAI) principles, and scalable AI architecture in the context of digital transformation. The results synthesize findings from the selected Scopus indexed literature and are structured to highlight key dimensions, dominant themes, and their relationships. The outcomes are summarized through a thematic table and a conceptual graphical representation to provide a clear and structured understanding of the research findings.

Thematic Results of Literature Analysis

Table 2. Key Thematic Dimensions of AI-Based DSS in Digital Transformation.

Thematic Dimension	Core Focus	Key Contributions Identified in Literature
AI-Based DSS Capabilities	Data-driven decision-making, automation, optimization	Improved decision accuracy, real-time analytics, enhanced organizational responsiveness
Human-Centered AI (HCAI)	User empowerment, ethics, inclusivity	Transparency, explainability, fairness, accountability, user trust
Scalability	Performance under growth	Efficient handling of increasing data, users, and computational demands
Modularity	Architectural flexibility	Easier maintenance, component reuse, independent subsystem evolution
Interoperability	Cross-system integration	Seamless data exchange with IoT, cyber-physical systems, and enterprise platforms
Adaptability	System evolution	Learning from environmental changes and continuous system optimization

Table 1 summarizes the primary thematic dimensions identified through the thematic analysis of the selected literature. The results indicate that AI based DSS capabilities form the technical foundation of digital transformation by enabling advanced analytics and automation. However, the literature consistently emphasizes that technical performance alone is insufficient. HCAI principles emerge as a critical dimension to ensure that AI-driven decisions remain transparent, explainable, ethical, and aligned with human values.

In addition, the findings highlight that scalability-oriented architectural principles namely modularity, interoperability, and adaptability are essential for sustaining AI-based DSS in large-scale and dynamic environments. These dimensions collectively support the long-term viability, trustworthiness, and practical applicability of AI driven decision making systems.

Graphical Representation of the Research Results

Introduction to the Diagram

To further illustrate the relationships among the identified thematic dimensions, a conceptual diagram is used to visualize how AI based DSS, HCAI principles, and scalable AI architecture interact within digital transformation initiatives. This graphical representation emphasizes the integrative nature of the research findings and supports the interpretation of the thematic results.

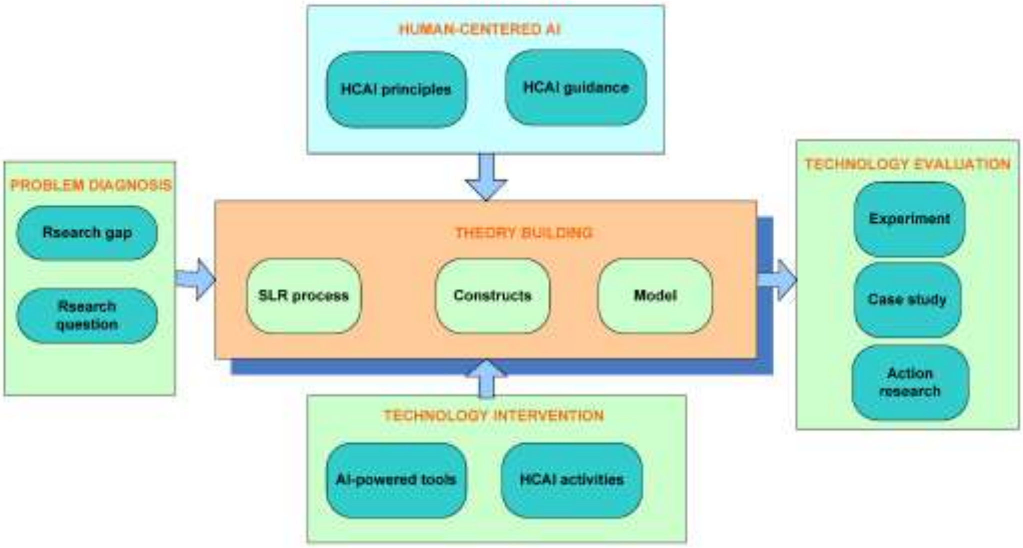

Figure 2. Integrated Conceptual Model of AI-Based Decision Support Systems.

The diagram illustrates AI-based DSS as the central decision making engine, supported by two interdependent pillars. The first pillar represents Human Centered AI, encompassing explainability, transparency, ethical governance, and user empowerment. These elements ensure that AI-driven decisions are interpretable, trustworthy, and aligned with human values.

The second pillar represents Scalable AI Architecture, which includes scalability, modularity, interoperability, and adaptability. This architectural foundation enables AI based DSS to operate effectively in complex, data intensive, and evolving environments. The interaction between these pillars demonstrates that effective digital transformation requires a balance between technical robustness and human centered design, rather than prioritizing one over the other.

Discussion

Interpretation of the Results

The results demonstrate that the effectiveness of AI based DSS in digital transformation is not solely determined by algorithmic accuracy or computational performance. Instead, the findings confirm that human centered principles and scalable architectural design play a decisive role in determining system acceptance, sustainability, and strategic impact.

The thematic results presented in Table 1 indicate that while AI based DSS capabilities provide essential analytical power, their real world applicability depends on the integration of HCAI principles. This aligns with the literature emphasizing that transparency, explainability, and ethical considerations are critical for fostering trust and user acceptance in AI-driven systems. Without these elements, AI based DSS risk resistance from users and limited organizational adoption.

Relationship Between Architecture and Human-Centered Design

The graphical representation further clarifies that scalable AI architecture and HCAI principles function as complementary enablers rather than independent components. Modularity and interoperability allow AI based DSS to integrate seamlessly with existing systems, such as IoT and cyber-physical infrastructures, while adaptability ensures long term relevance in dynamic environments. These architectural features directly support human centered goals by enabling systems to remain understandable, controllable, and responsive to user needs over time.

Implications for Digital Transformation and DSS Design

The discussion highlights that successful digital transformation initiatives require a holistic design approach that integrates AI based DSS capabilities, human centered principles, and scalable architecture. Organizations that focus exclusively on technical optimization may achieve short-term efficiency gains but face long-term challenges related to trust, usability, and system evolution.

From a research perspective, the results suggest that future studies should move beyond isolated technical evaluations and adopt integrative frameworks that address both architectural scalability and human centered governance. From a practical standpoint, the findings provide guidance for system designers and decision makers to prioritize modular, interoperable, and transparent AI based DSS that support sustainable and trustworthy decision making.

5. Comparison

Compared to prior studies that predominantly emphasize the technical optimization of AI based Decision Support Systems such as improvements in prediction accuracy, computational efficiency, and system performance this study adopts a more integrative perspective by explicitly combining human centered AI principles with scalable architectural design. Existing research on DSS and scalable AI architectures largely focuses on algorithmic efficiency, data processing scalability, and system interoperability, often treating human factors as secondary considerations. In contrast, the findings of this study highlight that technical excellence alone is insufficient to ensure the effectiveness and sustainability of AI driven DSS within digital transformation initiatives.

Furthermore, while previous studies on Human Centered Artificial Intelligence primarily concentrate on ethical guidelines, explainability, and user trust at the interaction or interface level, they frequently overlook the architectural constraints that influence system scalability and long-term adaptability. This research bridges that gap by demonstrating how modularity, interoperability, and adaptability at the architectural level directly support human centered objectives such as transparency, user empowerment, and trustworthiness. By integrating these dimensions into a unified analytical framework, this study extends existing literature and offers a holistic view of AI-based DSS that aligns technical scalability with human values, thereby contributing a more comprehensive foundation for the design and implementation of sustainable, trustworthy decision support systems.

6. Conclusion

This study has examined the role of AI based Decision Support Systems (DSS) within digital transformation by integrating perspectives from Human Centered Artificial Intelligence (HCAI) and scalable AI architecture. Through a systematic, literature based qualitative analysis, the research demonstrates that the effectiveness and sustainability of AI-driven DSS depend not only on technical performance but also on human-centered design principles and robust architectural foundations.

The findings indicate that while AI based DSS enhance decision accuracy, automation, and analytical capabilities, their successful adoption requires transparency, explainability, ethical governance, and user empowerment. Human centered principles play a critical role in fostering trust and acceptance, particularly in complex and high stakes decision-making environments. At the same time, scalable architectural features such as modularity, interoperability, and adaptability enable AI-based DSS to operate reliably under increasing data volumes, system complexity, and evolving operational conditions.

By synthesizing these dimensions into a unified conceptual framework, this study contributes to the existing literature by bridging the gap between technical scalability and human-centered AI design. The results suggest that digital transformation initiatives that prioritize only algorithmic optimization risk limited long-term impact, whereas integrative approaches that align architectural scalability with human values offer greater potential for sustainable and trustworthy decision support.

Despite its contributions, this study is limited by its reliance on conceptual and literature based analysis without empirical validation. Future research is encouraged to empirically test the proposed framework through case studies, experimental implementations, or longitudinal evaluations across different organizational contexts. Such efforts would further validate the practical applicability of human centered, scalable AI based DSS and support the development of resilient decision making systems in the evolving digital landscape.

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