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Article

A SYSTEMATIC REVIEW OF INTELLIGENT SUPPORT SYSTEMS FOR STRATEGIC DECISION-MAKING USING HUMAN-AI INTERACTION IN ENTERPRISE PLATFORMS

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ABSTRACT

This systematic literature review provides a comprehensive and methodologically rigorous synthesis of scholarly work on Intelligent Support Systems (ISS), focusing on their design architectures, strategic applications, ethical governance, and human-AI interaction (HAII) frameworks within organizational contexts. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines, the review evaluates 124 peer-reviewed journal articles published between 2013 and 2023, ensuring transparency, reproducibility, and academic rigor in article selection and synthesis. The findings reveal a significant shift in ISS development from traditional rule-based systems toward hybrid and neural network-driven architectures, which offer improved predictive capabilities, flexibility, and real-time responsiveness. However, this transition introduces new challenges, particularly in terms of model interpretability, trust calibration, and dynamic system transparency. The review also identifies a growing trend in the adoption of AI-augmented strategic decision-making tools, such as decision-tree learning and reinforcement learning, which support portfolio management, resource optimization, and scenario-based planning. Despite these advancements, there is a notable deficiency in longitudinal performance evaluation, with very few studies tracking system impact or user trust over extended periods. While regulatory and governance frameworks such as GDPR, NIST AI RMF, and ISO/IEC standards are frequently referenced, only a limited number of studies report concrete implementation in live systems. The study concludes that future research must adopt a multidisciplinary lens, incorporating ethical AI principles, culturally aware design, long-term performance tracking, and user-centric evaluation metrics to ensure that ISS technologies evolve in a responsible, equitable, and sustainable manner. This review contributes to bridging the gap between advanced computational capabilities and the ethical, strategic, and social imperatives that define effective decision support in contemporary enterprises.

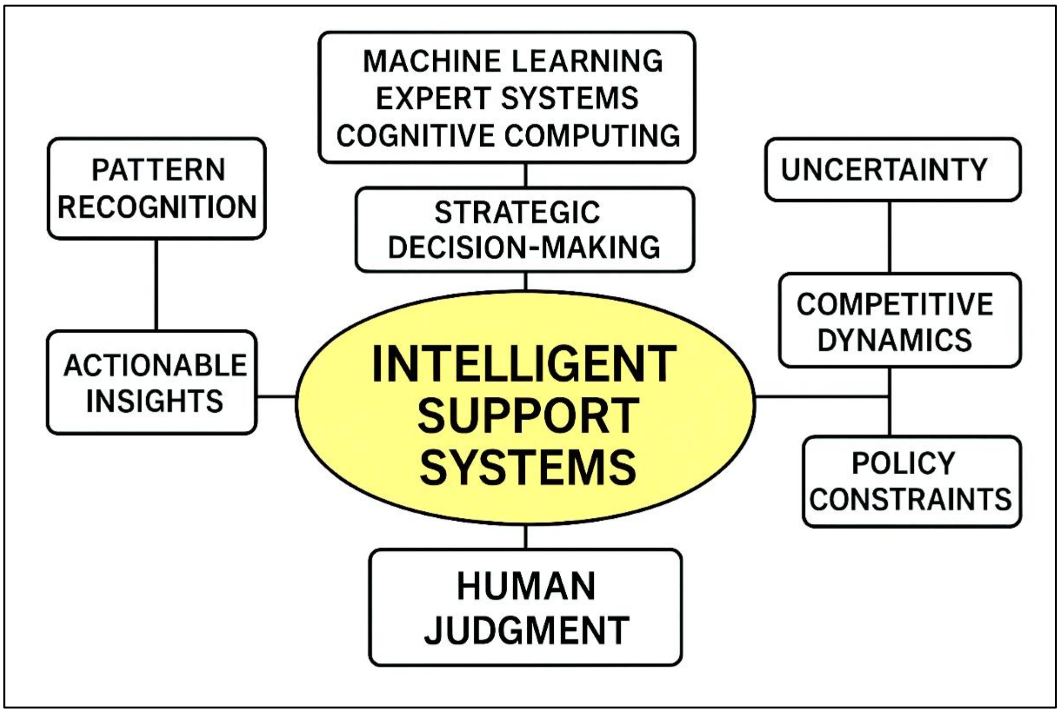
KEYWORDS

Intelligent Support Systems; Strategic Decision-Making; Human-AI Interaction; Enterprise Platforms; Cognitive Computing

INTRODUCTION

Intelligent Support Systems (ISS) refer to computational frameworks and digital platforms that utilize artificial intelligence (AI), machine learning, expert systems, and cognitive computing to enhance and automate complex decision-making processes within organizations (Kaufmann et al., 2014). These systems are designed to emulate human decision-making logic by processing vast data streams, identifying patterns, and generating actionable insights. The evolution of ISS has been driven by the need to manage growing information complexity and ensure timely, data-driven responses in organizational settings (Cabantous & Gond, 2011). Strategic decision-making involves high-level choices that impact long-term organizational direction, often encompassing elements of uncertainty, competitive dynamics, and policy constraints (Islam & Chang, 2021). Within this context, ISS aim to function as analytical partners that support, rather than replace, human judgment (Kocsi et al., 2020). The integration of human cognitive strengths with AI capabilities in decision environments has reshaped how businesses define, approach, and solve strategic problems (Scott et al., 2016). The adoption of ISS in strategic decision-making has grown globally due to digital transformation pressures, increased data availability, and the competitive need for real-time responsiveness (Kim et al., 2020). Multinational corporations, government agencies, and non-profits are embedding ISS into enterprise platforms to optimize resource allocation, assess market opportunities, and manage risk (Loebbecke & Picot, 2015). In regions like North America and Western Europe, ISS adoption is linked to high digital maturity and robust data governance policies, enabling integration with enterprise resource planning (ERP), customer relationship management (CRM), and supply chain management (SCM) systems (Gillespie, 2014). Meanwhile, in Asia-Pacific economies, ISS deployment has been central to smart manufacturing, financial modeling, and strategic infrastructure planning (Gillespie, 2014; Rust & Cooil, 1994). The strategic application of these systems facilitates evidence-based decisions that can be scaled and replicated across business units and international markets (Alvarado-Valencia & Barrero, 2014). As a result, ISS are positioned not only as tools for internal optimization but also as levers for global strategic alignment and industry leadership (Mehedi et al., 2024).

Figure 1: Conceptual Framework of Intelligent Support Systems in Strategic Decision-Making



Human-AI interaction (HAII) represents the interface through which individuals engage with intelligent systems to co-create knowledge and decisions (Baker et al., 2018). In the domain of strategic decision-making, this interaction is shaped by several factors, including system transparency, interpretability, explainability, and the alignment of AI recommendations with human

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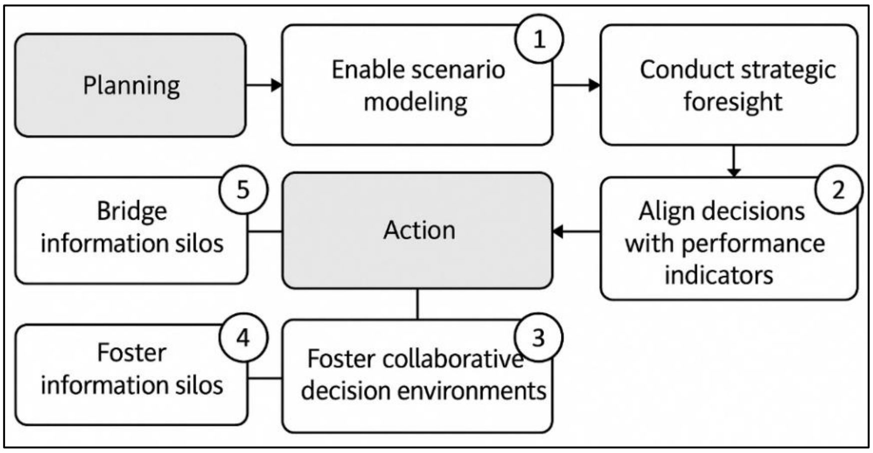
values and organizational goals (Flemisch et al., 2011; Holstein et al., 2023). Research shows that users are more likely to trust and accept AI-generated insights when systems provide rationale and contextual cues for recommendations (Lai et al., 2023). In enterprise environments, decision-making often occurs under conditions of ambiguity and high stakes, making HAII a critical enabler of insight validation, scenario exploration, and risk mitigation (Molina et al., 2024). Various models such as cooperative augmentation, shared control, and decision fusion are emerging to describe how humans and AI collaborate to arrive at strategic conclusions (Holzinger et al., 2021). This interaction is not merely technical but socio-cognitive, relying on factors such as user expertise, role hierarchy, and cultural norms in shaping the decision dynamics (Chandra et al., 2022). Over the past two decades, ISS have evolved from rule-based expert systems to sophisticated architectures incorporating deep learning, natural language processing (NLP), and reinforcement learning (Di Martino & Delmastro, 2022). Early systems primarily relied on human-defined rules and static knowledge bases to guide decision paths (Kocoń et al., 2023). Contemporary models, by contrast, utilize probabilistic algorithms that learn from historical data and adapt dynamically to changing inputs (Grundner & Neuhofer, 2021). These systems are often embedded within enterprise platforms such as Microsoft Dynamics, SAP, Salesforce Einstein, and IBM Watson, allowing seamless access to structured and unstructured data across business functions (Grundner & Neuhofer, 2021; Kerr & Bornfreund, 2005). Architectural classifications include standalone intelligent agents, decision dashboards, hybrid expert-recommender systems, and adaptive decision support platforms (Lake et al., 2016). Each configuration is designed with varying degrees of automation, user control, and feedback mechanisms to accommodate specific decision environments (Chen et al., 2012; Lake et al., 2016).

Figure 2: ISS Framework for Strategic Decision-Making



Enterprise decision-making is often characterized by complexity, ambiguity, and cross-functional implications that demand integrative cognitive approaches (Plataniotis et al., 2015). ISS offer structured methodologies to navigate these complexities by enabling scenario modeling, strategic foresight, and data triangulation (Kumar et al., 2021). In large-scale operations, these systems assist leadership teams in aligning decisions with performance indicators, stakeholder expectations, and regulatory constraints (Antony et al., 2021). The strategic role of ISS is amplified in dynamic industries such as healthcare, finance, manufacturing, and logistics, where decisions must account for external shocks, technological disruption, and real-time intelligence (Liang & Li, 2008). Enterprise case studies reveal that the implementation of ISS can significantly enhance the speed, accuracy, and traceability of strategic initiatives, providing quantifiable value across organizational tiers (Bousdekis & Mentzas, 2021). Moreover, cross-functional use of these systems bridges information silos and fosters collaborative decision environments (Rehman & Saba, 2012). Despite technological advancements, the design and deployment of ISS for strategic purposes face several operational and theoretical challenges. One major concern is the "black-box" nature of advanced AI systems, which limits user understanding and interpretability (Rehman & Saba, 2012; Tingling & Parent, 2004). This creates friction in decision settings that require transparency, auditability, and regulatory compliance (Lin et al., 2022). Another challenge is the alignment of system recommendations with organizational strategy and culture, as misaligned outputs can result in resistance or misapplication (Pajak et al., 2021). Integration with legacy enterprise systems poses additional technical barriers, particularly in environments lacking standardized data infrastructure or interoperability frameworks (Bolat et al., 2014). Moreover, ethical concerns surrounding bias, fairness, and accountability in algorithmic decision-making continue to prompt calls for inclusive design and governance protocols (Kmiecik, 2022). These challenges underscore the need for multidisciplinary approaches that blend

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data science, organizational behavior, and strategic management perspectives (Rehman & Saba, 2012).

A review of existing literature reveals fragmented efforts in understanding the comprehensive role of ISS in strategic enterprise decision-making. Most studies have focused on operational or tactical use cases, such as sales optimization or workflow automation, with limited emphasis on high-level strategic applications (Tingling & Parent, 2004). Furthermore, there is a scarcity of integrative frameworks that map the interplay between AI-driven tools and human decision-makers in enterprise settings (Lin et al., 2022). Methodological inconsistencies also persist, including variation in evaluation metrics, sample contexts, and assessment of long-term organizational impact (Kmiecik, 2022). A systematic review is warranted to synthesize existing findings, identify prevailing trends, and assess the maturity of ISS integration within strategic decision contexts. By consolidating peer-reviewed evidence and analyzing theoretical and practical contributions, this study seeks to provide a structured understanding of how Human-AI interaction supports enterprise-wide strategic initiatives through intelligent systems.The primary objective of this systematic review is to critically examine how intelligent support systems (ISS), when integrated with Human-AI Interaction (HAII) mechanisms, contribute to enhancing strategic decision-making processes within enterprise platforms. Strategic decision-making is inherently complex and involves multiple stakeholders, high levels of uncertainty, and long-term organizational consequences. As enterprises across industries strive to maintain competitiveness in increasingly volatile and data-saturated environments, the need for advanced decision-support frameworks that go beyond traditional analytics has intensified. ISS, augmented by AI technologies such as machine learning, natural language processing, and expert systems, have emerged as powerful tools that offer predictive insights, simulate decision outcomes, and enable scenario-based planning. However, the value of these systems is not solely determined by their computational power but also by their capacity to interact meaningfully with human decision-makers. Therefore, this review aims to explore the architecture, functionalities, and performance of ISS that incorporate HAII features such as interpretability, explainability, and collaborative decision protocols. It also seeks to assess the contexts in which these systems are deployed—ranging from finance and logistics to healthcare and manufacturing—to understand how organizational factors influence the efficacy of HAII-enabled decision-making. By applying a rigorous methodology grounded in the PRISMA 2020 framework, this study identifies, categorizes, and synthesizes empirical evidence from peer-reviewed literature published over the last decade. The objective is not only to map the current state of knowledge but also to evaluate the alignment between theoretical propositions and practical implementations of ISS in strategic contexts. Furthermore, the review intends to highlight methodological inconsistencies, ethical considerations, and design challenges associated with HAII systems to provide a foundation for future research. Ultimately, this systematic review offers a comprehensive perspective on the evolving role of intelligent systems as strategic enablers in enterprise decision environments.

LITERATURE REVIEW

The literature surrounding intelligent support systems (ISS) and their integration into strategic decision-making has evolved in tandem with advancements in artificial intelligence (AI) and enterprise digitization. Historically, decision support systems were built on deterministic models and rule-based logic, often limited to structured problem environments. However, the explosion of big data, improvements in machine learning algorithms, and increased organizational reliance on real-time decision-making have propelled the emergence of ISS embedded within enterprise resource planning (ERP) systems and intelligent dashboards. These ISS not only process structured and unstructured data but also incorporate human-AI interaction (HAII) features, enabling co-decision environments where interpretability, trust, and collaboration are essential. The shift toward intelligent, adaptive systems has led to growing interest in how these tools shape, augment, and co-create strategic decisions alongside human users. This literature review synthesizes findings from existing academic studies, systematically identifying major theoretical frameworks, practical applications, interaction paradigms, technological architectures, and evaluation approaches related to ISS and HAII. By dissecting these areas, the review addresses the fragmented and interdisciplinary nature of the field, offering a consolidated knowledge base and highlighting key gaps. The sub-sections below provide a structured analysis of the development, deployment, and implications of ISS in enterprise platforms, focusing specifically on strategic decision-making use cases.

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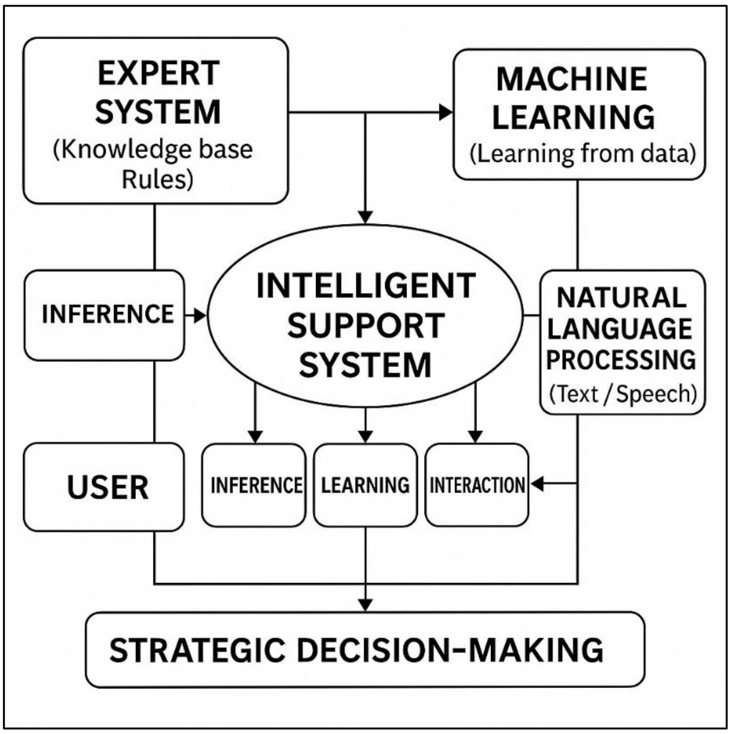
Intelligent Support Systems for Decision-Making

The evolution of intelligent support systems (ISS) is rooted in the early development of decision support systems (DSS), which emerged in the 1960s and 1970s as computerized tools to aid structured decision-making in management contexts. These early DSS were primarily driven by mathematical models and predefined rules, designed to support repetitive and programmable decision tasks (Bracha & Brown, 2012). The theoretical foundation of these systems lies in Herbert Simon's concept of bounded rationality, which posits that human decision-making is limited by cognitive constraints and incomplete information (Al-Surmi et al., 2021). This perspective inspired the development of model-driven DSS, which aimed to augment human cognition by offering structured decision pathways within constrained problem spaces (Confalonieri et al., 2015; Kaggwa et al., 2024). While effective for operational decisions, these systems often lacked adaptability and failed to respond dynamically to unstructured or evolving scenarios (Simaei & Rahimifard, 2024). As organizations encountered increasingly complex environments marked by uncertainty, globalization, and data proliferation, the limitations of traditional DSS became more apparent (Soori et al., 2024). This led to a shift toward more intelligent, user-centric systems capable of integrating real-time data, learning from outcomes, and adapting decision strategies—paving the way for the development of ISS. Foundational DSS, though limited in scope, provided the blueprint for conceptualizing the interface between decision models, data management, and user interaction—elements that remain integral to modern ISS (Bader & Kaiser, 2019).

Figure 3: Intelligent Support System Architecture for Strategic Decision-Making



The development of ISS represents a significant advancement over traditional DSS, primarily due to the incorporation of artificial intelligence (AI) capabilities such as expert systems, machine learning, and natural language processing. Expert systems were among the earliest forms of AI used in decision-making, simulating human reasoning through rule-based inference engines and knowledge bases (Barysė & Sarel, 2023). These systems enabled domain-specific knowledge encoding, particularly in fields like medical diagnostics and financial analysis, where structured knowledge was prevalent (Gunessee & Subramanian, 2020). However, expert systems were limited by their rigidity and the high cost of knowledge acquisition (Saba et al., 2018). The advent of machine learning brought a new paradigm, allowing ISS to learn patterns from historical data and update models continuously without human intervention (Sarker, 2022). This adaptability has proven critical for strategic decisions involving dynamic market conditions and incomplete information (Gunessee & Subramanian, 2020). AI integration has also enhanced the natural interaction between users and systems through advances in natural language interfaces, voice recognition, and context-aware computing ((Bracha & Brown, 2012). These intelligent functionalities enable ISS to offer recommendations, predict outcomes, and explain reasoning, thereby augmenting human decision-making across strategic levels (Marocco et al., 2024). The transition from static decision models to adaptive, learning-based systems has thus redefined the role of information systems in enterprise decision contexts (Meub & Proeger, 2017).

Contemporary ISS distinguish themselves from earlier decision systems through their ability to operate in complex, data-rich, and uncertain environments while incorporating human cognition into decision processes. One defining characteristic is the use of hybrid architectures that blend data-

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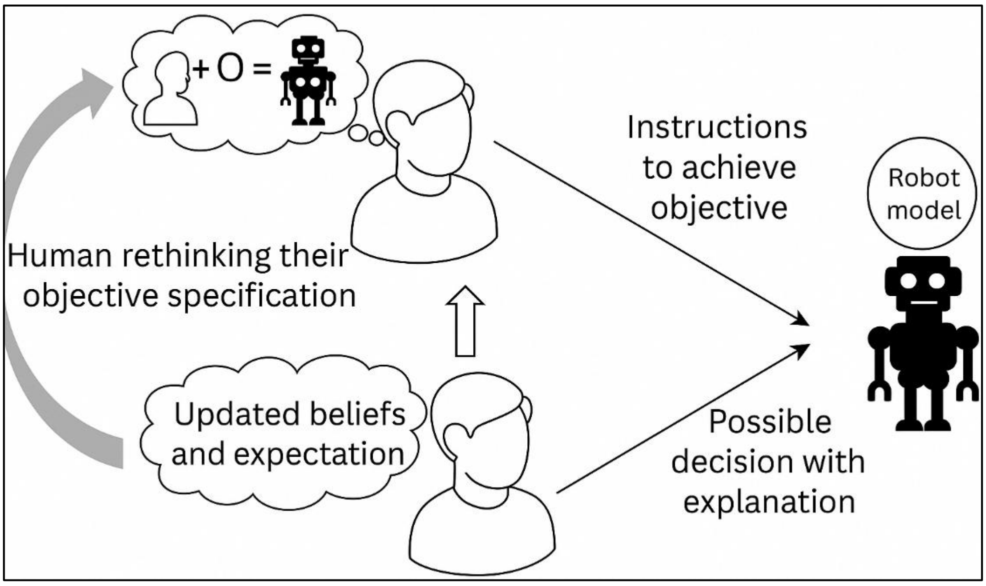
driven analytics with heuristic models, enabling contextualized decision support (Chiang et al., 2023). These systems often integrate with enterprise resource planning (ERP), business intelligence (BI), and customer relationship management (CRM) platforms, facilitating end-to-end data visibility across strategic domains (Chiang et al., 2023; Marocco et al., 2024a). Unlike traditional DSS, modern ISS include components such as learning algorithms, decision trees, clustering mechanisms, and reinforcement learning to optimize strategic alternatives in real time (Bader & Kaiser, 2019). They also support decision transparency through explainable AI techniques, allowing users to trace the logic behind recommendations and outcomes (Al-Surmi et al., 2021; Confalonieri et al., 2015). This transparency is critical in strategic decisions that involve risk, compliance, and cross-functional coordination. Additionally, ISS are capable of simulating scenarios using predictive models, thus aiding executives in evaluating potential outcomes and trade-offs before committing to a strategy (Barysė & Sarel, 2023). Studies demonstrate that organizations utilizing ISS in strategic planning report higher levels of decision confidence, accuracy, and organizational alignment (Gunessee & Subramanian, 2020). Thus, the adaptive, integrative, and explainable nature of ISS is central to their effectiveness in modern enterprise settings.
The design of intelligent support systems is grounded in a variety of decision-making theories that provide conceptual guidance on how individuals and organizations process information and arrive at strategic choices. Bounded rationality theory remains a cornerstone in explaining the role of ISS as tools that compensate for human cognitive limitations (Soori et al., 2024). Complementary to this is the dual-process theory, which distinguishes between intuitive (System 1) and deliberative (System 2) thinking, both of which ISS are designed to support through automated and analytical functions (Logg et al., 2019). Prospect theory has also influenced ISS design, especially in systems intended to assist in risk-sensitive environments where decision-makers may deviate from expected utility models (Bader & Kaiser, 2019; Barysė & Sarel, 2023). Multi-criteria decision analysis (MCDA) frameworks further inform the evaluation functions of ISS, allowing decision-makers to weigh competing objectives and constraints (Saba et al., 2018). Organizational decision-making theories, including the garbage can model and the political model, offer insight into the social dynamics that ISS must navigate when multiple stakeholders are involved (Saba et al., 2018; Simaei & Rahimifard, 2024). These theoretical underpinnings ensure that ISS are not only technologically robust but also aligned with human cognitive behavior and organizational realities. By embedding these models into ISS algorithms and interfaces, developers can tailor system outputs to match users' decision styles, risk appetites, and strategic priorities (Kaggwa et al., 2024).
Evaluating the effectiveness of ISS in strategic decision-making requires a multidimensional approach encompassing technical, cognitive, and organizational metrics. Studies comparing traditional DSS with ISS consistently report superior performance of the latter in terms of speed, relevance, and adaptability of recommendations (Sarker, 2022). Empirical research shows that ISS implementations in manufacturing, logistics, and healthcare have significantly improved scenario analysis, contingency planning, and cross-departmental coordination (Barysė & Sarel, 2023). Metrics such as decision quality, response time, interpretability, user satisfaction, and impact on strategic key performance indicators (KPIs) are commonly used to assess ISS efficacy (Gunessee & Subramanian, 2020). Case studies on ERP-integrated ISS platforms demonstrate that the ability to synthesize large volumes of structured and unstructured data contributes to superior forecasting and risk assessment capabilities (Marocco et al., 2024a). Another key differentiator is user engagement—studies highlight that ISS with intuitive interfaces and explainable outputs are more likely to be adopted and trusted by decision-makers (Barysė & Sarel, 2023). Comparative evaluations also reveal that organizations with mature data governance and cross-functional integration are more successful in realizing the full potential of ISS (Carter et al., 2022).

Human-AI Interaction Models in Strategic Contexts

The conceptual foundation of Human-AI Interaction (HAII) in enterprise contexts draws from interdisciplinary research in cognitive science, information systems, and human-computer interaction. One of the foundational theories underpinning HAII is the joint cognitive systems model, which frames humans and machines as collaborative agents with complementary capabilities (Bansal et al., 2019). This model is supported by socio-technical systems theory, which emphasizes the interdependence between technology design and organizational behavior (Islam & Helal, 2018; Sarker, 2022). In strategic decision-making, where ambiguity and complexity dominate, the interplay between human intuition and machine analytics becomes particularly critical (Ahmed et al., 2022;

Bader & Kaiser, 2019). Ostheimer et al. (2021) assert that HAII extends beyond tool usage, representing a cognitive partnership where machines provide data-driven recommendations and humans exercise judgment and contextual framing. Moreover, dual-process theory—distinguishing intuitive from analytical reasoning—has informed the layered interaction designs of AI systems, supporting both fast and deliberative thinking (Aklima et al., 2022; Marocco et al., 2024). The integration of human factors into AI design, including mental models, workload distribution, and decision accountability, is essential for fostering trust and reliability in high-stakes environments (Chiang et al., 2023; Helal, 2022). Thus, the theoretical landscape of HAII reveals an intentional design orientation toward co-agency, shared cognition, and socio-technical alignment in enterprise decision processes. Moreover, interaction design in intelligent support systems must account for cognitive load and user mental models to ensure usability, efficiency, and decision accuracy. Cognitive load theory posits that working memory has limited capacity, which can be overwhelmed by poorly designed interfaces or complex decision protocols (Haefner et al., 2021; Mahfuj et al., 2022; Raisch & Krakowski, 2021). In enterprise decision environments, especially those involving high-stakes and multi-criteria choices, interaction design must minimize extraneous cognitive processing while enhancing germane cognitive load (Majharul et al., 2022; Neethirajan, 2023). Krakowski et al. (2022) highlight the importance of user-centered design in ISS, where graphical user interfaces (GUIs), feedback loops, and interaction modalities (e.g., voice, text, visualization) are tailored to match cognitive preferences. Research indicates that adaptive interfaces, which respond to user behavior and decision context, reduce information overload and improve decision outcomes (Jarrahi, 2018; Hossen & Atiqur, 2022). Moreover, visual analytics tools integrated into ISS help users comprehend large data sets, identify anomalies, and explore "what-if" scenarios with minimal cognitive strain (Mohiul et al., 2022; Yu & Li, 2022). The complexity of strategic decisions necessitates intuitive dashboards that translate model outputs into actionable insights using natural language or symbolic visualizations (Duan et al., 2019; Ripan Kumar et al., 2022; Yu & Li, 2022). The alignment of HAII design with human cognitive architecture is thus a determinant of system adoption, trust, and long-term decision effectiveness in enterprise environments.

Figure 4: Human-AI Interaction Models in Strategic Decision-Making



Trust calibration refers to the alignment of user trust with the actual capabilities and limitations of an AI system—a core challenge in HAII design for strategic decision-making. Over-trust may lead to blind reliance on flawed recommendations, while under-trust results in underutilization of valid insights (Blease et al., 2019; Hao & Demir, 2023; Sohel et al., 2022). Empirical studies show that transparency and explainability are key mechanisms for calibrating trust in AI-driven decision systems (Jarrahi, 2018; Tonoy, 2022). For instance, Yu and Li (2022) found that when AI outputs are accompanied by justifications or probabilistic confidence levels, user trust improves significantly. Duan et al., (2019) emphasizes that users must understand when and how to accept or override machine recommendations. In enterprise settings, where strategic decisions may involve regulatory, ethical, or competitive implications, trust calibration becomes even more critical Duan et al. (2019) and Hao and Demir (2023) demonstrate that trust in ISS is mediated by system competence, contextual consistency, and perceived value contribution. Additionally, longitudinal exposure to AI systems can improve trust alignment through experiential learning and mental model refinement (Diebolt et al., 2018). Designers of HAII-enabled ISS must therefore prioritize dynamic trust-building mechanisms that evolve with user experience, task complexity, and organizational culture (Jarrahi, 2018; Younus, 2022).

Explainable AI (XAI) plays a pivotal role in facilitating human understanding of machine logic, particularly in strategic decision-making contexts where interpretability is paramount. Traditional AI models such as deep neural networks often function as "black boxes," producing outputs without exposing the reasoning behind them (Alam et al., 2023; Antoniadi et al., 2021). XAI techniques aim to make these systems more transparent by offering insight into input-output relationships, feature importance, and decision paths. In strategic enterprise environments, where decisions affect long-term outcomes and require multi-stakeholder justification, XAI is essential for enabling accountability, auditing, and ethical review (Arafat Bin et al., 2023) . Arrieta et al. (2020) reveals that the presence of explanation interfaces increases decision-maker confidence and facilitates organizational learning. Furthermore, explainability enhances system usability, particularly when complex algorithmic outputs are translated into plain language summaries, visual narratives, or contrastive explanations(Chowdhury et al., 2023). XAI is also linked to regulatory compliance, as governance frameworks such as the European Union's GDPR mandate the right to explanation in automated decision-making (Adadi & Berrada, 2018; Jahan, 2023). Therefore, the integration of XAI into HAII-enabled ISS not only supports cognitive alignment but also reinforces legal, ethical, and organizational requirements in enterprise strategy settings.

Decision co-creation between humans and AI systems reflects a paradigm shift from automation to augmentation, where both agents contribute uniquely to strategic problem-solving. Hybrid intelligence, as defined by Buçinca et al., (2020) and Mahdy et al. (2023), entails the dynamic collaboration between human intuition and AI computation to achieve superior outcomes than either could independently. In ISS, this manifests as joint exploration of alternatives, iterative refinement of models, and reciprocal learning between the system and its users (Hassija et al., 2023; Maniruzzaman et al., 2023; Retzlaff et al., 2024). Research has demonstrated that hybrid intelligence models outperform traditional automated or manual systems in tasks requiring contextual judgment, ethical consideration, and multi-domain integration (Arrieta et al., 2020; Hossen et al., 2023). Systems designed for co-creation typically include interactive features such as tunable parameters, simulation tools, and scenario builders that allow users to guide the AI's analytical process (Ahmed et al., 2022; Di Martino & Delmastro, 2022; Roksana, 2023). Moreover, organizational case studies show that co-creative ISS foster greater user engagement, strategic alignment, and innovation adoption (Hassija et al., 2023; Shahan et al., 2023). Nourani et al. (2021) argue that hybrid models are particularly effective in volatile, uncertain, complex, and ambiguous (VUCA) environments where predefined rules fail. This co-agency model redefines the boundaries of responsibility, enabling a shared accountability structure in enterprise decisions (Hassija et al., 2023; Tonoy & Khan, 2023). Therefore, co-creation is not only a technical interface feature but a strategic capability embedded in the design of HAII-enabled decision systems. The success of Human-AI interaction in enterprise decision systems is not solely dependent on technology but also shaped by organizational structure, culture, and behavioral readiness. Studies emphasize that leadership support, cross-functional collaboration, and digital maturity are critical enablers of HAII integration (Al-Arafat, Kabi, et al., 2024; Nourani et al., 2021). Resistance to AI adoption often stems from fear of job displacement, lack of understanding, or perceived threats to autonomy. Trust-building strategies such as training programs, participatory design, and transparency initiatives have been shown to mitigate these concerns. Behavioral theories like the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) have been applied to explain user attitudes toward HAII (Davis, 1989; Venkatesh et al., 2003). Empirical findings show that perceived usefulness, perceived ease of use, and social influence significantly predict user intention to engage with intelligent systems. Furthermore, organizational learning mechanisms such as feedback loops, success stories, and internal champions promote continuous improvement in HAII practices(Al-Arafat, Kabir, et al., 2024). Institutional contexts also matter; regulated industries such as healthcare

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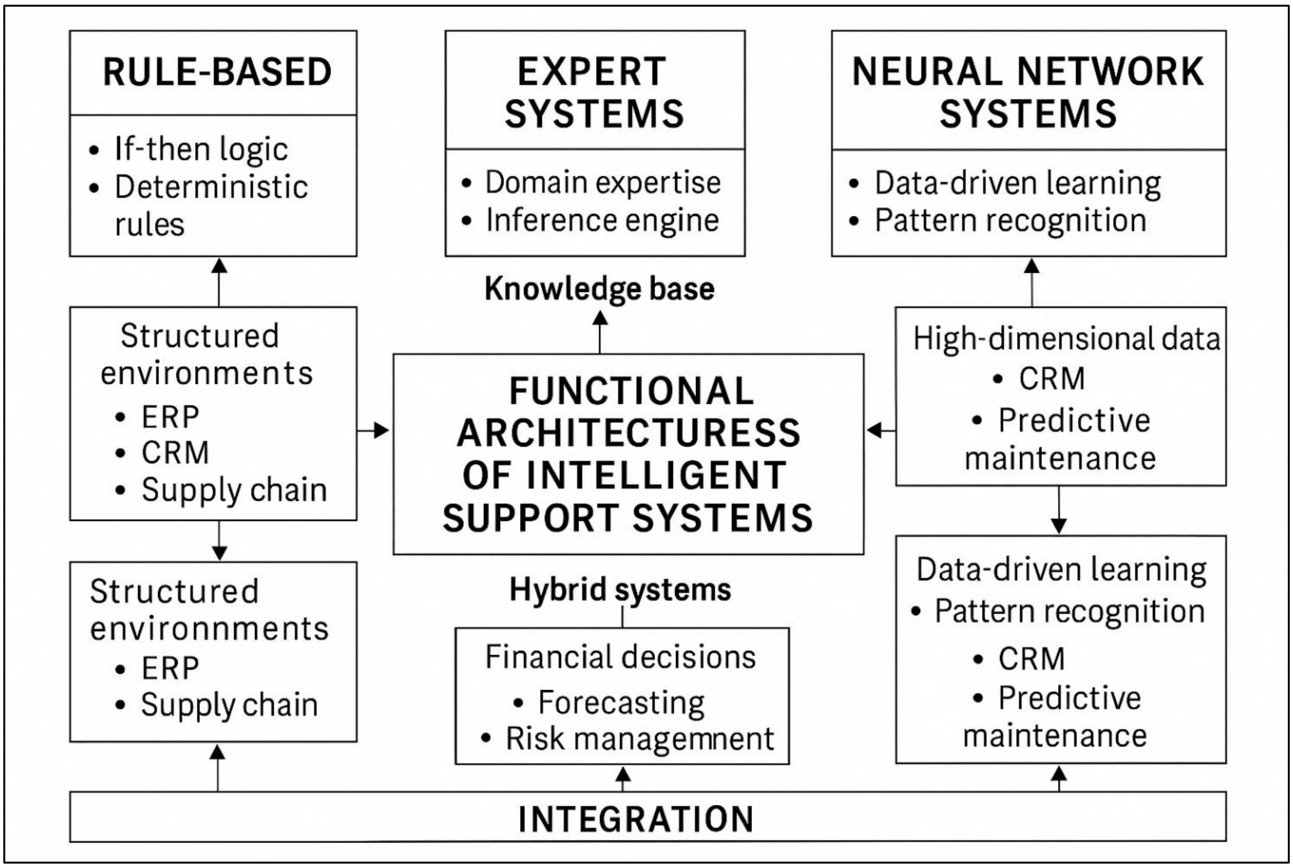
and finance demand stricter explainability and audit capabilities, while agile sectors like tech startups favor experimentation and rapid iteration (Hassoun et al., 2022).

Functional Architectures of Intelligent Support Systems

The foundational models of intelligent support systems (ISS) emerged through rule-based systems, which operate on predefined if-then logic to simulate decision-making in structured environments. These systems were pivotal in the early stages of digital decision support due to their interpretability and ease of deployment across enterprise platforms such as Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) tools (Alam et al., 2024; Pinto et al., 2015). Rule-based systems are deterministic and excel in domains with well-defined parameters, offering consistent outputs and traceability in decision paths (Alam et al., 2024; Kaklauskas, 2014). However, the rigidity of rule-based systems poses limitations in dynamic or data-intensive contexts where nuanced reasoning or learning from unstructured data is required (Ammar et al., 2024; Marín et al., 2013). Expert systems, which evolved from rule-based architectures, attempt to mimic human expertise by embedding knowledge into inference engines. These systems have been widely used in supply chain and logistics decision-making, especially in materials management and scheduling tasks, by integrating domain expertise into operational workflows (Bhowmick & Shipu, 2024; Coito et al., 2020). Although expert systems expanded the utility of ISS, they are challenged by knowledge acquisition bottlenecks and inflexibility in adapting to changing conditions (Bhuiyan et al., 2024; Marín et al., 2013). Comparative analyses indicate that expert systems are most effective when paired with structured data environments and stable operational rules, which limits their scalability in uncertain or rapidly evolving business ecosystems (Dasgupta & Islam, 2024; Yang et al., 2020). Their integration with ERP and CRM systems has seen success in banking, retail, and manufacturing contexts where transactional consistency is prioritized over adaptability (Andargoli et al., 2024; Dasgupta et al., 2024).

Figure 5: Comprehensive Framework of Functional Architectures in Intelligent Support Systems



Hybrid intelligent support systems (HISS) represent a more adaptive architectural framework by combining multiple AI techniques, such as expert systems with fuzzy logic, case-based reasoning, or neural networks. These systems aim to overcome the limitations of single-approach ISS models by allowing for both rule-based inference and data-driven learning (Coito et al., 2020; Dey et al., 2024).

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For instance, hybrid architectures have shown notable effectiveness in financial decision-making, where deterministic rules are insufficient, and adaptive learning is essential for forecasting market behavior and managing risks (Hasan et al., 2024; Marín et al., 2013). In the context of enterprise integration, HISS platforms have been increasingly deployed alongside business intelligence (BI) tools to support real-time analytics, enabling decision-makers to synthesize structured data from ERP and SCM systems with unstructured insights from external sources (Helal, 2024; Yang et al., 2020). Furthermore, these systems enable improved pattern recognition and decision quality by leveraging both symbolic and sub-symbolic reasoning mechanisms (Andargoli et al., 2024; Hossain et al., 2024). In supply chain operations, hybrid models help in demand forecasting, inventory management, and logistics routing by integrating data-driven prediction with domain expertise. Empirical studies indicate that hybrid systems consistently outperform rule-based and expert systems in terms of flexibility, accuracy, and responsiveness, particularly when faced with data volatility and operational ambiguity(Hossain et al., 2024; Islam, 2024). Nevertheless, the complexity of designing, implementing, and maintaining hybrid models presents significant technical and managerial challenges that can inhibit widespread adoption without significant organizational readiness(Islam et al., 2024; Islam, 2024).

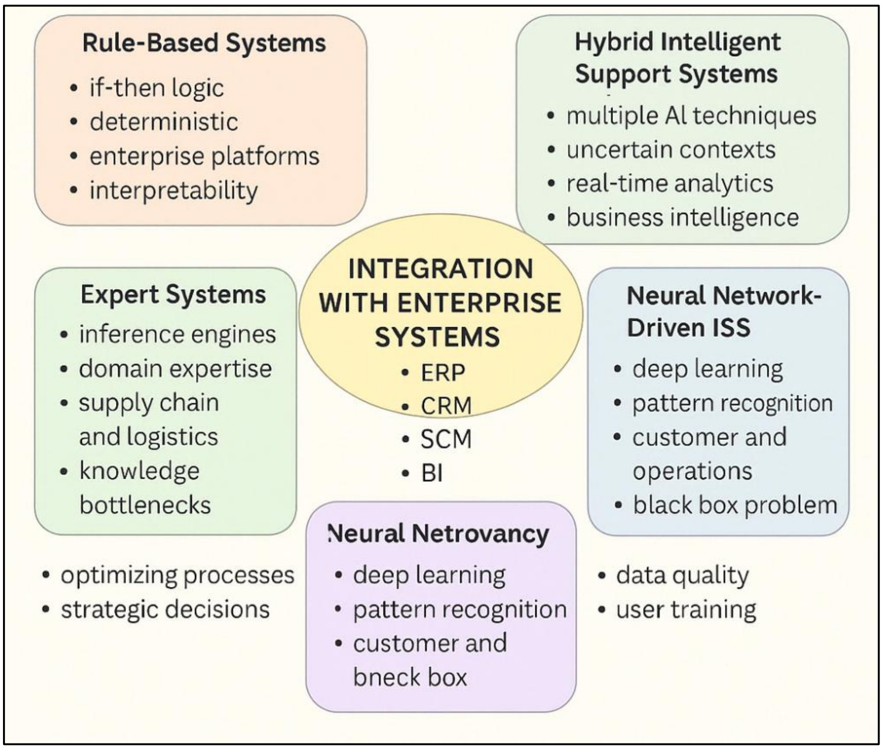
Neural network-driven ISS platforms have introduced new paradigms for data-driven decision-making in enterprise systems by leveraging deep learning and adaptive pattern recognition (Jahan, 2024; Jim et al., 2024). Unlike rule-based and expert systems that rely on predefined logic, neural networks learn from historical and real-time data, enabling them to uncover hidden patterns, nonlinear relationships, and complex trends in strategic contexts (Khan & Razee, 2024; Yang et al., 2020). These models have been widely applied in CRM systems to predict customer churn, personalize marketing efforts, and enhance user engagement through behavioral analytics(Mahabub, Das, et al., 2024; Mahabub, Jahan, Hasan, et al., 2024). Similarly, in SCM and ERP domains, neural networks support predictive maintenance, demand forecasting, and anomaly detection, improving operational efficiency and strategic agility (Mahabub, Jahan, Islam, et al., 2024; Islam et al., 2024). One critical advantage of neural architectures is their capacity to operate in real-time with large-scale, high-dimensional data environments, making them well-suited for decision support in volatile markets or crisis management scenarios (Hossain et al., 2024; Younus et al., 2024). Neural models also enhance BI tools by enabling sentiment analysis, trend identification, and fraud detection in financial systems. However, their lack of transparency and interpretability—often described as the "black box" problem—poses a barrier to trust and regulatory compliance in sensitive industries like healthcare and finance (Andargoli et al., 2024; Younus et al., 2024). As such, recent research advocates for combining neural networks with explainable AI (XAI) modules to ensure transparency, ethical accountability, and alignment with strategic enterprise goals (Ahmed et al., 2022; Nahid et al., 2024). Despite challenges, neural architectures remain at the forefront of ISS innovation due to their unparalleled adaptability and performance across diverse enterprise environments (Rahaman et al., 2024; Roksana et al., 2024).

The functional integration of ISS architectures with enterprise-wide systems such as ERP, CRM, SCM, and BI platforms has become a core focus of contemporary digital transformation strategies. Integration facilitates data centralization, real-time analytics, and synchronized decision-making across departments, reducing operational silos and enhancing strategic alignment (Awan et al., 2024; Roy et al., 2024). For instance, ISS modules embedded within ERP systems enable intelligent resource planning by analyzing production data, inventory levels, and supplier metrics to optimize procurement and scheduling decisions (Ahmed et al., 2022; Sabid & Kamrul, 2024). Similarly, in CRM, ISS supports intelligent segmentation and customer lifecycle management by combining behavioral data with predictive analytics (Awan et al., 2024; Sharif et al., 2024). In supply chain environments, intelligent decision support embedded in SCM systems improves demand planning, transportation logistics, and supplier risk assessment by providing adaptive recommendations based on market dynamics (Marocco et al., 2024a; Shofiullah et al., 2024). Business intelligence integration further extends the utility of ISS by visualizing data patterns, enabling executives to make evidence-based strategic decisions (Shohel et al., 2024). Yet, the success of integration depends on data quality, interoperability standards, and organizational capacity to manage system complexity (Shipu et al., 2024). Studies consistently highlight the importance of aligning ISS implementation with enterprise objectives, IT infrastructure, and user training programs to ensure meaningful adoption and return on investment (Razee et al., 2025; Andargoli et al., 2024). The confluence of ISS and enterprise systems thus represents a powerful paradigm for enabling proactive, scalable, and intelligent decision-making across functional and strategic layers of modern organizations..

Sector-Wise Implementation of ISS in Enterprise Decision-Making

The financial sector has been at the forefront of adopting intelligent support systems (ISS) due to the domain's reliance on real-time analytics, predictive modeling, and decision automation. ISS applications in finance include credit risk assessment, algorithmic trading, fraud detection, portfolio optimization, and regulatory compliance (Berman et al., 2024; Faria & Md Rashedul, 2025). Machine learning-based ISS are particularly effective in improving loan underwriting and credit scoring by integrating non-traditional datasets, such as social media and transaction histories (Helal et al., 2025; Mouzakitis et al., 2024). These systems enhance decision accuracy while reducing human bias and processing time. Studies also show that neural network-driven ISS outperform conventional statistical models in forecasting stock prices and managing market volatility (Intezari & Gressel, 2017; Islam et al., 2025). Additionally, financial institutions use ISS for customer relationship management by analyzing behavioral data to personalize financial advice and cross-sell products (Hao & Demir, 2024; Islam et al., 2025). However, the implementation of ISS in finance raises ethical and regulatory concerns, particularly regarding transparency, explainability, and compliance with standards such as Basel III and GDPR (Ananias et al., 2021; Khan, 2025). Despite these challenges, ISS has contributed significantly to operational efficiency and decision speed, especially among fintech companies and data-driven banks (Jakaria et al., 2025; Mouzakitis et al., 2024). Sector-specific case studies consistently report improved return on investment (ROI) and reduced default rates post-ISS implementation, indicating strong potential for continued integration into financial decision infrastructures (Khinvasara et al., 2024).

Figure 6: Integrated Functional Architectures of Intelligent Support Systems in Enterprise Contexts



Healthcare represents a complex and critical environment where ISS has emerged as a transformative tool for enhancing clinical decision-making, diagnostics, and administrative efficiency. Intelligent systems assist healthcare providers in tasks such as disease prediction, treatment recommendation, radiology interpretation, and hospital resource allocation (Di Martino & Delmastro, 2022; Khatun et al., 2025). Clinical Decision Support Systems (CDSS), an important subclass of ISS, use patient data and clinical guidelines to alert physicians about potential drug interactions, suggest diagnostic tests, and support evidence-based care (Munira, 2025; Rajpurkar et al., 2022). Machine learning and natural language processing are increasingly integrated into these

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systems, especially for analyzing unstructured clinical notes and electronic health records (Cabitza et al., 2021; Sarker, 2025). In oncology, AI-powered ISS platforms have been deployed to recommend personalized cancer treatment plans by comparing patient profiles with historical data (Arsenio et al., 2013; Shimul et al., 2025). Case studies from institutions like Mayo Clinic and Mount Sinai reveal that ISS adoption leads to improved diagnostic accuracy and reduced adverse event rates (Rajpurkar et al., 2022; Sohel, 2025). Nonetheless, challenges include integration with legacy systems, resistance from healthcare professionals, and concerns over data privacy and system accountability (Amann et al., 2020; Younus, 2025). The variability in deployment success across hospitals often depends on IT maturity, funding, and clinician training, emphasizing the need for sector-specific adaptation strategies (Formosa et al., 2022). While ISS can augment clinical judgment, they are most effective when embedded within human-in-the-loop models that ensure interpretability and accountability (Askarisichani et al., 2022).

The logistics sector leverages ISS to address complexities related to demand variability, fleet optimization, warehouse management, and last-mile delivery challenges. Intelligent support systems in logistics utilize predictive analytics, IoT integration, and route optimization algorithms to enhance efficiency and service levels (Naiseh et al., 2021). Real-time data from RFID and GPS sensors are integrated into ISS platforms for tracking shipments and predicting delivery timelines, facilitating adaptive routing and reducing fuel consumption (Iftikhar et al., 2020). AI-based decision support has also been deployed to forecast demand surges, optimize inventory, and mitigate disruptions caused by weather or geopolitical events (Kocaballi et al., 2020). For instance, companies like Amazon and DHL employ ISS for warehouse automation and robotic picking systems, reducing labor dependency and cycle times (Naiseh et al., 2021). Additionally, simulation-based ISS are used for strategic supply chain design, including network restructuring and supplier selection under risk scenarios (Trocin et al., 2021). Case studies from automotive and retail sectors report significant reductions in delivery time and logistics costs post-implementation of ISS solutions (Leone et al., 2021). However, interoperability issues with legacy logistics platforms and inconsistent data quality remain persistent barriers (Braun et al., 2020). To address these, many firms are adopting cloud-based ISS frameworks that support real-time integration across stakeholders and enhance supply chain visibility (Ueda et al., 2024). The sector's dynamic environment makes it a fertile ground for continuous ISS innovation and adaptive learning systems.

Manufacturing and energy sectors utilize ISS to optimize operations, monitor assets, and ensure regulatory compliance. In manufacturing, intelligent systems are commonly integrated into smart factories through cyber-physical systems (CPS) and industrial IoT (IIoT), enabling predictive maintenance, quality assurance, and production scheduling (Catellani et al., 2022). Case studies in discrete and process manufacturing report that ISS-based predictive maintenance reduces unplanned downtime by up to 40% and extends equipment lifespan (Braun et al., 2020). Real-time machine monitoring and fault detection are supported by AI algorithms that analyze vibration, thermal, and operational data (Lai et al., 2023). In the energy domain, ISS are used for grid stability forecasting, energy load balancing, and integration of renewables into existing systems (Cheng et al., 2020). For example, intelligent systems have been deployed in wind and solar farms to optimize power generation based on weather predictions and grid demand (Hu et al., 2014). Utilities such as Siemens and Schneider Electric employ ISS for asset performance management and real-time fault isolation in power networks (Tsai et al., 2021). Despite notable benefits, challenges include high initial investment, cybersecurity threats, and lack of standardization across ISS platforms (Catellani et al., 2021). Moreover, achieving full automation requires robust data infrastructures and a skilled workforce capable of interpreting ISS outputs (Leone et al., 2021). Nevertheless, both sectors continue to demonstrate substantial gains in efficiency, safety, and sustainability through ISS deployment tailored to their unique operational environments.

Strategic Decision-Making Frameworks Supported by ISS

The integration of artificial intelligence with traditional SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis has led to the development of hybrid SWOT-AI frameworks, which enhance the objectivity and dynamic capabilities of strategic evaluation tools. Traditional SWOT models have long served as a cornerstone for strategic planning but often suffer from subjectivity and lack of adaptability (Zinn, 2008). The adoption of AI techniques, such as natural language processing (NLP) and sentiment analysis, into SWOT analysis allows for real-time data-driven insights from market trends, customer feedback, and competitor analysis (Catellani et al., 2021). These enhanced

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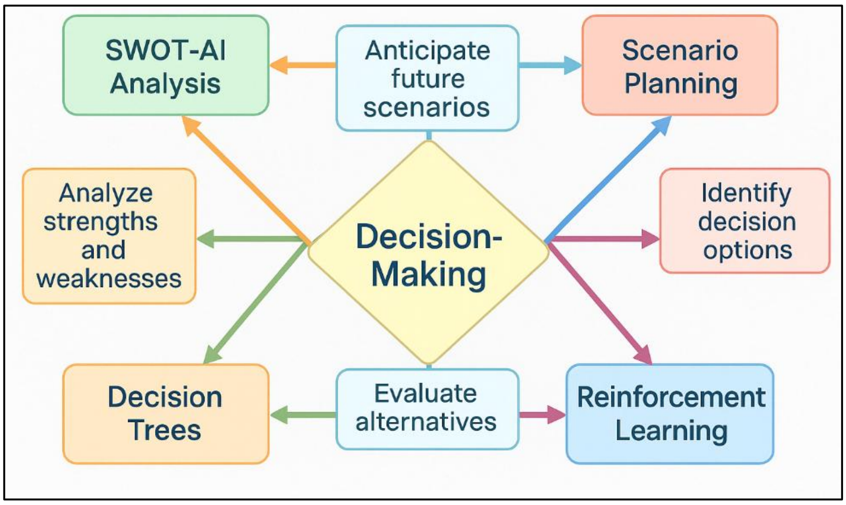
frameworks automate the identification and weighting of internal and external factors, making the analysis more robust and responsive to environmental changes (Catellani et al., 2022). In supply chain and financial planning, AI-enhanced SWOT models have been used to evaluate mergers, market entries, and product development strategies by incorporating predictive and prescriptive analytics into the traditional qualitative approach (Glaser et al., 1968). For instance, companies like IBM and Accenture employ hybrid models to align digital transformation efforts with evolving organizational capabilities and external risks (Lai et al., 2023). Studies have also highlighted the role of these models in scenario simulation, where AI-based SWOT structures allow decision-makers to model alternative future states and assess trade-offs quantitatively (Andargoli et al., 2024). Despite their promise, challenges persist in aligning AI-generated insights with human strategic intuition and managerial judgment (Trocin et al., 2021). Nonetheless, the incorporation of AI into SWOT frameworks enhances strategic foresight, especially in volatile and data-rich business environments, supporting organizations in crafting agile and evidence-based long-term plans (Andargoli et al., 2024).

Figure 7 : ISS-Supported Strategic Decision-Making Frameworks



Decision tree learning, as a supervised machine learning technique, has gained prominence as a strategic decision support framework for option analysis, risk assessment, and resource allocation. By structuring decisions in a hierarchical manner, decision trees help organizations visualize consequences, probabilities, and outcomes, making them valuable for both tactical and strategic planning (Ueda et al., 2024). In strategic management contexts, decision trees enable firms to evaluate competing investment options, product launches, and policy interventions by modeling complex interdependencies and uncertainties (Zhang et al., 2022). The interpretability of decision trees, relative to black-box models such as neural networks, has made them particularly appealing in sectors where explainability is vital, such as healthcare, finance, and public policy (Ueda et al., 2024). Enhanced variants like random forests and gradient-boosted trees provide greater predictive accuracy while maintaining a level of transparency conducive to managerial oversight (Awan et al., 2021). In strategic portfolio management, decision tree algorithms have been used to rank and prioritize projects based on multi-criteria analysis, including risk, ROI, and resource constraints (Khan et al., 2022). They are also instrumental in churn prediction and customer segmentation strategies, guiding resource allocation in marketing and CRM strategies (Alami et al., 2020). Additionally, their application in scenario planning has enabled organizations to generate and test a range of future states under varying environmental assumptions (Ueda et al., 2024). However, concerns over overfitting and sensitivity to noisy data necessitate hybridization with pruning and ensemble techniques (Liu et al., 2019).
Reinforcement learning (RL) represents an advanced AI paradigm increasingly applied to long-term strategy formulation and adaptive decision-making. In contrast to supervised learning, RL relies on agents learning optimal policies through reward feedback, making it highly suitable for dynamic and uncertain environments (Catellani et al., 2021). In enterprise strategy contexts, RL has been deployed to optimize long-term investment portfolios, pricing strategies, and energy management systems by continuously adjusting decisions based on evolving conditions (Retzlaff et al., 2024). For instance, RL

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has been integrated into ISS to simulate competitive market dynamics, helping firms develop strategic responses to competitor moves and regulatory shifts (Ozkan-Okay et al., 2024). This adaptability makes RL particularly useful in supply chain coordination, where fluctuating demand and supplier behavior require continuous re-optimization (Burggräf et al., 2020). Moreover, deep reinforcement learning (DRL) expands this capability by incorporating neural networks, enabling the modeling of highly complex strategic environments such as autonomous manufacturing and smart grid operations (Antoniadi et al., 2021). Several studies have also explored the application of RL in public policy decision-making and environmental planning, where it supports the formulation of sustainable and adaptive strategies under uncertainty (Burggräf et al., 2020). However, RL systems are computationally intensive and often require extensive training periods, raising concerns about real-time applicability and resource efficiency (Ozkan-Okay et al., 2024). Additionally, their "black box" nature raises interpretability concerns in high-stakes strategic domains (Pynadath et al., 2018). Nonetheless, RL's ability to self-improve and navigate complex decision spaces marks it as a powerful strategic planning tool in intelligent support ecosystems.

Scenario planning, traditionally a qualitative strategic tool, has evolved significantly with the incorporation of ISS frameworks capable of modeling multiple futures quantitatively. Intelligent support systems now leverage AI-driven simulation, Monte Carlo methods, and agent-based modeling to construct and evaluate strategic scenarios under various assumptions (Burggräf et al., 2020). This computational augmentation enhances the precision and realism of strategic foresight, enabling firms to anticipate disruptions, policy changes, or technological shifts more effectively (Antoniadi et al., 2021; Catellani et al., 2022). For instance, in energy and sustainability domains, ISS-based scenario tools model resource availability, climate policies, and technology adoption pathways to guide long-term investment and policy decisions (Burggräf et al., 2020). In corporate contexts, AI-enhanced scenario planning supports mergers, acquisitions, and diversification decisions by simulating economic, competitive, and operational impacts (Ozkan-Okay et al., 2024). Strategic forecasting also benefits from predictive analytics embedded in ISS, where time-series models and machine learning algorithms analyze trends to generate probabilistic forecasts (Feuerriegel & Prendinger, 2016). Organizations such as Shell and Siemens have adopted such ISS-enhanced frameworks for geopolitical and technology trend monitoring (Ozkan-Okay et al., 2024). Furthermore, hybrid models combining reinforcement learning with scenario planning have shown promise in creating adaptive foresight mechanisms that learn from evolving data streams (Retzlaff et al., 2024). However, effective implementation depends on the alignment of scenario modeling with organizational culture, leadership vision, and data maturity (Ozkan-Okay et al., 2024). These tools underscore the importance of ISS not just in real-time operations, but in shaping the strategic trajectory of organizations through comprehensive foresight and informed adaptability..

Role of Data Governance and Ethical AI in ISS Design

Data quality is foundational to the design and operational success of intelligent support systems (ISS), as these systems rely heavily on accurate, complete, and timely data to generate meaningful outputs. Poor data quality can severely compromise the efficacy of decision support, leading to flawed recommendations, decreased trust, and adverse strategic outcomes (Burggräf et al., 2020). The core dimensions of data quality—accuracy, completeness, consistency, timeliness, and validity—are essential for predictive modeling, machine learning training, and real-time analytics within ISS frameworks (Ozkan-Okay et al., 2024). High-quality data enables ISS to perform complex tasks such as scenario analysis, trend forecasting, and real-time risk detection more effectively (Catellani et al., 2021). In contrast, organizations that ignore data governance often suffer from data silos, redundancy, and outdated information, thereby undermining ISS reliability (Ozkan-Okay et al., 2024). Empirical studies across industries such as finance, healthcare, and logistics highlight a strong correlation between data quality assurance and successful ISS deployment (Antoniadi et al., 2021). Techniques such as master data management, automated data cleansing, and metadata management are widely implemented to address quality concerns at the source (Zeng et al., 2020). Moreover, data profiling and lineage tracking are being integrated into ISS architectures to enhance traceability and accountability (Wirtz et al., 2018). Without sustained data quality controls embedded in governance policies, ISS applications risk becoming obsolete, especially in fast-changing environments (George et al., 2014). Therefore, data quality is not a one-time technical exercise but an ongoing strategic commitment closely linked with organizational maturity and ethical ISS performance.

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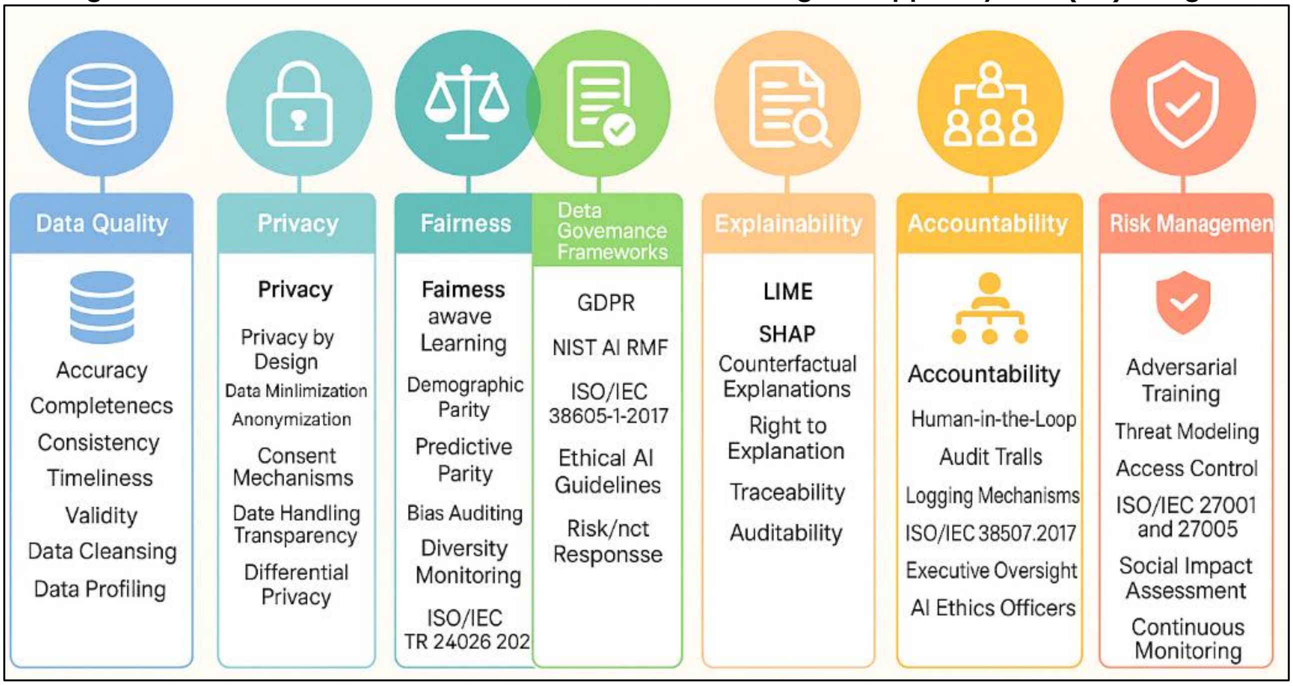
Figure 8: Ethical AI and Data Governance Pillars for Intelligent Support System (ISS) Design



Privacy has emerged as a key ethical consideration in ISS design, especially as intelligent systems increasingly rely on personal, behavioral, and transactional data to support enterprise decisions. The integration of ISS into sectors such as healthcare, finance, and retail has raised significant concerns about data collection, consent, access, and storage (George et al., 2014; Zeng et al., 2020). The deployment of ISS without proper privacy safeguards can lead to data breaches, unauthorized profiling, and erosion of public trust (Mahmud et al., 2023). Privacy-by-design has become a critical principle, wherein data minimization, anonymization, and user-centric consent mechanisms are embedded into ISS architectures (Catellani et al., 2021). Regulations such as the European Union's General Data Protection Regulation (GDPR) mandate strict compliance with data privacy principles, including lawful processing, purpose limitation, and data subject rights (Mahmud et al., 2022). Organizations leveraging ISS must implement transparent data handling processes and robust access controls to comply with GDPR and similar frameworks (Marocco et al., 2024b). Techniques like federated learning and differential privacy have gained popularity in ISS applications to enable learning from decentralized data without compromising privacy (Sjödin et al., 2021). Privacy-enhancing technologies (PETs) are increasingly integrated into ISS to prevent inference attacks and unauthorized data recombination (Alahmadi & Jamjoom, 2022). Studies show that user trust in intelligent systems significantly increases when clear privacy guarantees and data usage transparency are in place (Wang et al., 2016). Thus, designing ISS in alignment with robust privacy standards not only ensures regulatory compliance but also fosters sustainable user engagement and system integrity.

Fairness in algorithmic decision-making has become central to ISS development as machine learning models increasingly influence employment, credit scoring, insurance underwriting, and law enforcement (Lerner et al., 2014). Bias in ISS can stem from historical data inequalities, imbalanced training sets, and algorithmic design flaws, leading to discriminatory outcomes (Nof, 2017). These biases can perpetuate social injustices if left unchecked, particularly in high-stakes domains such as hiring or predictive policing (Parry et al., 2016). Recent studies advocate for fairness-aware machine learning models that embed fairness constraints directly into learning objectives or post-process predictions for equitable outcomes (Saba et al., 2018). Fairness metrics such as demographic parity, equalized odds, and predictive parity are frequently applied to evaluate ISS fairness across demographic groups (Parry et al., 2016). However, trade-offs often exist between different fairness criteria and model accuracy, posing challenges for system designers (Zeng et al., 2020). Bias auditing and explainability tools like LIME and SHAP have also gained prominence in identifying and mitigating bias in decision-making pipelines (Wang & Courtney, 1984). Integrating ethical checkpoints during the model lifecycle and involving diverse stakeholders in model evaluation are recognized best practices in ethical ISS governance (Wirtz et al., 2018). The implementation of

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ISO/IEC TR 24028:2020 provides further technical guidance on bias prevention in AI systems (ISO, 2020). Addressing fairness is not only a matter of ethics but also essential for regulatory compliance, especially in jurisdictions mandating algorithmic accountability (van Pinxteren et al., 2019). Consequently, fairness must be a built-in feature of ISS, not a retrospective fix.

Effective data governance frameworks are critical to the ethical implementation of ISS, ensuring alignment with legal, technical, and organizational best practices. Frameworks such as the General Data Protection Regulation (GDPR), the National Institute of Standards and Technology's AI Risk Management Framework (NIST AI RMF), and ISO/IEC 38505-1:2017 establish comprehensive guidelines for data ethics, accountability, and risk mitigation. GDPR, for instance, obligates data controllers to uphold transparency, lawfulness, and accountability in data processing, making it a cornerstone for AI and ISS compliance in Europe (de Witte, 2016). The NIST AI RMF promotes trustworthy AI by emphasizing core principles such as explainability, reliability, robustness, and data governance. In parallel, the ISO/IEC 27001 standard provides data security benchmarks vital for ISS infrastructure, especially where sensitive data is processed. These frameworks offer structured methodologies for ethical system design, risk assessment, and incident response planning. Empirical studies show that organizations adhering to such frameworks are better equipped to detect bias, manage data provenance, and ensure stakeholder trust (Felzmann et al., 2019). Moreover, corporate ethical AI guidelines issued by firms like Microsoft, Google, and IBM often align with these frameworks, signaling industry-wide consensus on governance principles (Balakrishnan & Dwivedi, 2021). Adoption of these standards contributes not only to legal compliance but also to reputational capital, user confidence, and system sustainability in ISS applications (Hasija & Esper, 2022).

Explainability is a fundamental requirement for ethical ISS, especially when systems influence high-stakes decisions in domains such as healthcare, finance, and criminal justice. The lack of interpretability in many advanced machine learning models, especially deep learning architectures, presents challenges in ensuring accountability and stakeholder trust (Lewis & Marsh, 2022). Explainable AI (XAI) techniques seek to address this gap by providing post-hoc explanations or designing inherently interpretable models (McNeese et al., 2021). Tools such as LIME, SHAP, and counterfactual explanations allow users to understand how inputs influence outputs, enhancing transparency and enabling human oversight (Korteling et al., 2021). Transparency is not only essential for ethical governance but is also mandated by legal frameworks like GDPR's "right to explanation," which requires that data subjects be informed of automated decision logic (Radclyffe et al., 2023; Rheu et al., 2020). Moreover, transparency supports bias detection and error analysis by revealing the inner workings of ISS models (Vinanzi et al., 2021). Studies also show that increased transparency improves stakeholder adoption and satisfaction with ISS solutions in enterprise contexts (Xu & Dudek, 2015). Best practices recommend embedding explainability into every stage of the ISS pipeline—from data preprocessing to model output presentation—thereby ensuring traceability and auditability (van Pinxteren et al., 2019). However, challenges persist in balancing explainability with model performance, particularly in complex architectures where trade-offs must be managed (Vinanzi et al., 2021). As such, integrating explainable frameworks is not merely a technical enhancement but a core component of ethical and compliant ISS development.

Accountability is a critical governance principle in ISS design, ensuring that stakeholders remain responsible for decisions made or influenced by intelligent systems. As ISS increasingly support or automate strategic decisions, clear mechanisms for assigning responsibility and enforcing ethical standards are needed (Radclyffe et al., 2023). Human-in-the-loop (HITL) models are widely advocated to retain human agency in decision-making processes, particularly in contexts where automated decisions affect fundamental rights (Vinanzi et al., 2021). HITL configurations enhance system transparency, allow for error correction, and mitigate the risk of algorithmic overreach (Radclyffe et al., 2023). Furthermore, audit trails and logging mechanisms are essential for tracking decision pathways and identifying sources of failure or bias in ISS outputs (Yu et al., 2019). The ISO/IEC 38507:2017 standard outlines governance guidelines for IT-enabled decision systems, emphasizing executive responsibility and ethical risk management (ISO, 2017). Legal scholars argue for the formalization of accountability structures, including algorithmic impact assessments and documentation of model development, deployment, and usage. Organizational practices, such as assigning data stewards and AI ethics officers, are increasingly adopted to ensure that ISS align with institutional values and legal obligations. Empirical evidence from sectors like healthcare and finance demonstrates that the presence of governance bodies and interdisciplinary review boards improves ethical compliance and decision quality. Thus, human oversight is not just a safeguard but a strategic enabler of trustworthy ISS.

Risk management is central to the ethical deployment of ISS, particularly in addressing cybersecurity threats, model degradation, and adversarial attacks. Intelligent systems, especially those integrated with IoT or cloud platforms, face unique vulnerabilities such as data poisoning, model inversion, and unauthorized access (Owolabi et al., 2020). The NIST AI Risk Management Framework identifies robustness, reliability, and resilience as key components of responsible AI deployment (Wach et al., 2023). Secure ISS design involves implementing adversarial training, threat modeling, and access control mechanisms that protect both data and models from manipulation (Xiong et al., 2022). The ISO/IEC 27001 and 27005 standards provide structured approaches to information security and risk assessment applicable to ISS environments (Zinn, 2008). Empirical studies indicate that incorporating security-by-design principles from the outset of ISS development reduces system downtime and increases user trust (Oluwatosin et al., 2024). Furthermore, ethical risk management involves assessing the social and organizational impacts of ISS, including unintended consequences such as discrimination, data misuse, or loss of human agency (Wach et al., 2023). Periodic risk audits, red teaming, and continuous monitoring are recommended to manage evolving threats and maintain system integrity (Seeber et al., 2020). As cyber threats become more sophisticated, the convergence of cybersecurity and AI ethics is essential to ensuring safe and responsible ISS operations. This convergence reflects a shift from reactive risk responses to proactive, embedded resilience in enterprise AI strategy.

Identified Gaps

A critical gap in HAII research is the absence of longitudinal evaluations that assess the sustained impact of intelligent support systems over time. Most empirical studies emphasize short-term metrics such as initial usability, user satisfaction, or predictive accuracy within trial periods (Iftikhar et al., 2020; Seeber et al., 2020). These limited time frames fail to capture the evolving nature of user-AI interaction, especially in dynamic environments like healthcare, finance, and education (Soori et al., 2023). For instance, adaptive behaviors, trust development, and performance degradation are temporal phenomena that cannot be fully understood through cross-sectional or simulation-based analyses alone (Hao & Demir, 2023; Krijestorac et al., 2021). There is a growing consensus that longitudinal studies are essential to understand how HAII systems affect decision quality, user autonomy, and cognitive load over extended periods (Owolabi et al., 2020). Moreover, such studies are vital for detecting concept drift, where AI models become misaligned with real-world changes (Wach et al., 2023). Despite the maturity of frameworks like ISO/IEC 25010 for system quality tracking, their application in HAII literature remains scarce (Krawinkler et al., 2022). Calls for embedded performance dashboards and real-time feedback loops within ISS interfaces are becoming more frequent, yet empirical validation remains minimal (Rosenberg et al., 2018). Addressing this gap will require interdisciplinary collaboration and stakeholder engagement to develop robust, user-centric performance benchmarks that evolve alongside ISS technologies.

HAII systems are often studied in isolated national or organizational contexts, leading to a lack of comparative insight across global regions. Cultural factors such as power distance, uncertainty avoidance, and individualism can influence user interaction with AI, yet they are rarely included as variables in HAII evaluations (Moghaddam, 2003). Most research has been conducted in North America and Europe, with limited representation from Asia, Africa, or Latin America, despite growing AI deployment in these regions (Mehedi et al., 2024). This geographical bias restricts the generalizability of findings and overlooks the socio-technical nuances that influence acceptance and effectiveness of ISS (Mtau & Rahul, 2024). For example, trust in automation and perceived fairness may vary significantly between collectivist and individualist societies (Sarker, 2022). Furthermore, legal and ethical standards such as GDPR or the U.S. Algorithmic Accountability Act shape ISS governance differently, influencing design and deployment practices (Durga et al., 2022). Comparative studies could illuminate how regulatory frameworks and cultural variables jointly mediate HAII outcomes (Peres et al., 2020). However, only a handful of cross-national case studies have explored these intersections in depth (Wilkens et al., 2023). Closing this gap would require methodologically diverse research designs, including multi-country field trials and cross-cultural experimental studies, to ensure inclusive and equitable AI design.

The integration of emotional intelligence (EI) into HAII remains significantly underexplored, despite its critical role in shaping user trust, engagement, and cooperation. While emotional cues are

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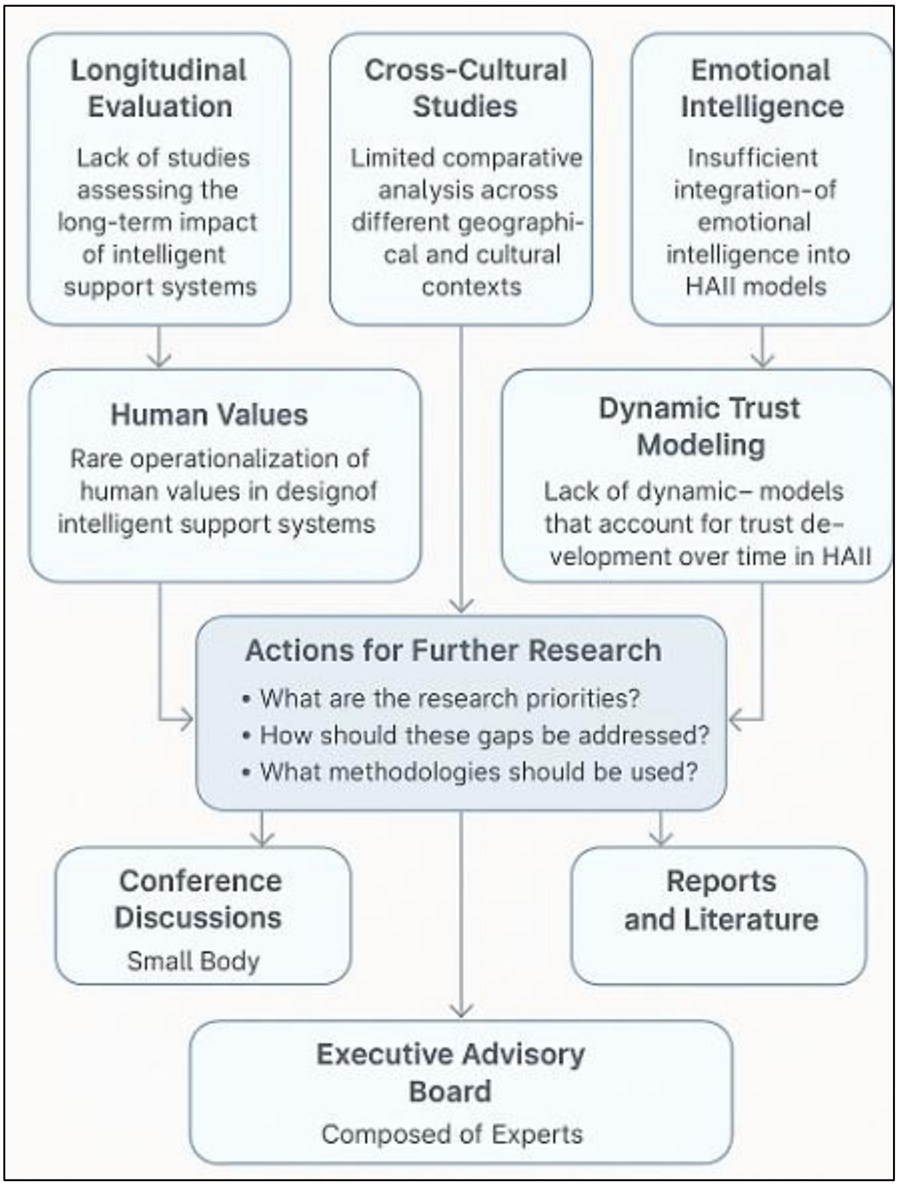
foundational in human-human interaction, they are rarely addressed in current ISS development practices, which prioritize logic-driven inference over affective responsiveness (Oluwatosin et al., 2024). Studies in human-computer interaction (HCI) suggest that emotionally aware systems enhance user satisfaction and reduce perceived complexity in decision tasks (Sarker, 2022). However, ISS models largely neglect mechanisms for emotion detection, sentiment analysis, or empathetic response generation (Wilkens et al., 2023). Even in customer service and education domains—where emotional cues are essential for personalization and feedback—ISS often lack components that recognize stress, frustration, or hesitation (Talamo & Pozzi, 2011). Emotional intelligence could improve collaboration in hybrid human-AI teams, especially in strategic planning, medical diagnosis, and legal interpretation where emotions influence judgment (Mtau & Rahul, 2024). Moreover, research has shown that emotional congruence between AI and users increases perceived authenticity and cooperation (Oluwatosin et al., 2024). Despite this, most AI ethics guidelines and performance metrics remain limited to cognitive competencies (Wilkens et al., 2023). Incorporating emotional intelligence in ISS would require multidisciplinary contributions from psychology, affective computing, and behavioral economics, as well as development of emotionally annotated datasets and multi-modal sensing systems.

Figure 9: Identified gaps in HAII research



Human values such as dignity, autonomy, justice, and compassion are seldom operationalized in the technical design of HAII systems, creating a disconnect between technological capabilities and societal expectations. Although value-sensitive design (VSD) frameworks have been proposed to integrate ethical values into AI systems, their adoption remains superficial in mainstream ISS development (Oluwatosin et al., 2024; Wilkens et al., 2023). Most ISS are evaluated using performance metrics like accuracy or efficiency, with little regard for how decisions align with stakeholder values (Barile et al., 2020; Kangas et al., 2016). In domains such as healthcare, law, and education—where moral reasoning is central—this omission can result in recommendations that violate ethical norms or user expectations (Durga et al., 2022). Recent studies argue that embedding human values requires not just technical adjustments but institutional transformation, including ethical training for developers and participatory design processes involving end-users (Sarker, 2022). Furthermore, algorithmic decisions often lack transparency in how trade-offs between conflicting values are resolved, leading to user alienation and resistance (Barile et al., 2020). Only a few ISS models have incorporated formal ontologies or ethics engines capable of reasoning about value conflicts (Peres et al., 2020). The ISO/IEC TR 24028:2020 standard highlights the importance of value alignment, yet empirical applications remain scarce. Advancing this research will require not only technical innovation but also broader discourse across humanities, policy, and systems engineering disciplines.

A critical shortfall in the current HAII literature is the lack of comprehensive models that account for the dynamic nature of trust in human-AI collaboration. While initial trust assessments are often studied during system onboarding or early interactions, there is insufficient research examining how trust evolves over time based on system performance, contextual changes, and feedback loops. Existing trust models are often static and do not incorporate fluctuations in user perception that result from inconsistent system behavior, unexpected outcomes, or increased reliance (Wilkens et al., 2023). Furthermore, trust is frequently treated as a monolithic construct, despite evidence suggesting it comprises multiple dimensions, including dispositional, situational, and learned trust (Talamo & Pozzi, 2011). Dynamic trust modeling is particularly vital in decision-intensive environments such as autonomous vehicles, medical diagnostics, and military command systems, where AI recommendations may be accepted or rejected based on real-time credibility assessments (Durga et al., 2022). Studies have shown that mismatches between system transparency and actual reliability can erode trust and increase user stress, yet these dynamics are rarely embedded into ISS design (Kangas et al., 2016). Moreover, most trust calibration studies are experimental and lack field validation over prolonged interaction periods (Mehedi et al., 2024). Emerging research calls for reinforcement learning and feedback-based ISS architectures that continuously adapt explanations and performance based on trust metrics (Oluwatosin et al., 2024). Addressing this gap will require integrated approaches that combine psychological models of trust with technical mechanisms for behavior monitoring and adaptation in HAII environments.

METHOD

This systematic review adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework to ensure a methodologically rigorous, transparent, and reproducible research process. The review aimed to synthesize current scholarly findings on intelligent support systems (ISS), with a specific focus on their functional architectures, strategic decision-making frameworks, ethical AI integration, and human-AI interaction (HAII). A structured four-stage approach—identification, screening, eligibility, and inclusion—was employed to systematically gather and evaluate relevant literature.

Identification

The initial step involved the identification of potentially relevant studies from multiple academic databases, including Scopus, Web of Science, IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar. The search was conducted using a combination of keywords and Boolean operators such as "intelligent support systems" OR "decision support systems" AND "human-AI interaction" AND "ethical AI" AND "data governance" AND "PRISMA." Searches were limited to peer-reviewed journal articles published between January 2013 and December 2023 to ensure contemporary relevance. A total of 2,348 articles were initially retrieved based on the inclusion of titles, abstracts, and relevant metadata.

Screening

Following the identification phase, all retrieved articles were imported into Mendeley for reference management and duplicate removal. After filtering out duplicates, 1,867 articles remained. Titles and abstracts were then screened against predefined inclusion and exclusion criteria. Articles were retained if they focused on the application or theoretical development of intelligent support systems

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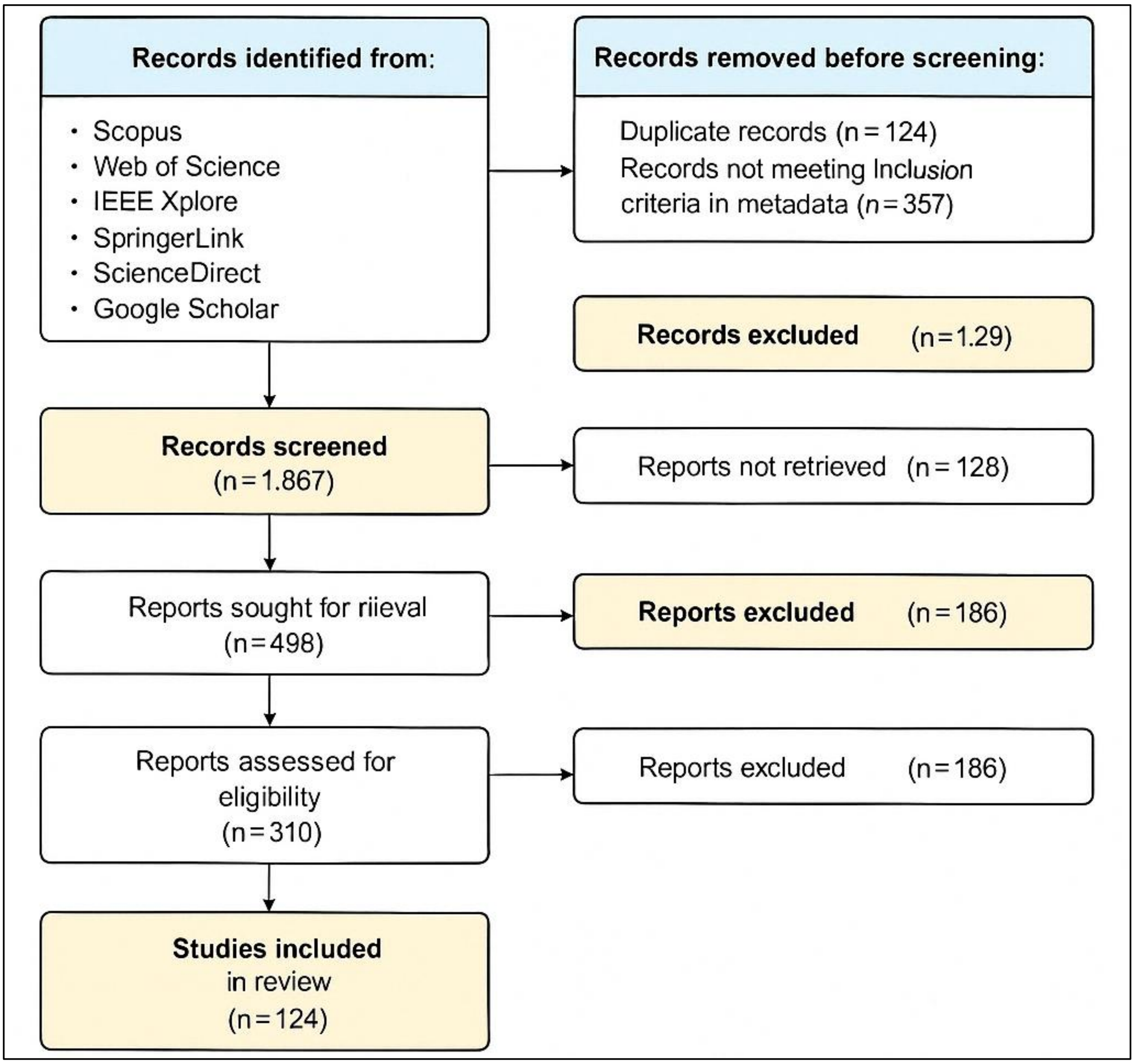
in organizational decision-making contexts. Studies unrelated to ISS, non-English publications, conference proceedings without full texts, and those focused exclusively on hardware or engineering components were excluded. This screening phase narrowed the dataset to 438 articles for full-text assessment.

Figure 10: PRISMA Method adapted in this study



Eligibility

The full texts of the 438 shortlisted articles were then reviewed to assess eligibility. Studies were considered eligible if they offered empirical, conceptual, or methodological insights into ISS architectures, human-AI collaborative frameworks, ethical concerns in ISS development, or data governance implications. Additional exclusion criteria were applied at this stage, including lack of peer-review, absence of substantial methodological detail, and outdated or redundant theoretical models. Based on these criteria, 128 articles were excluded due to inadequate relevance, leaving 310 articles deemed eligible for final synthesis.

Inclusion

The final inclusion phase involved a thematic and methodological synthesis of the 310 eligible articles. Each article was coded based on its core contribution to specific thematic areas—functional architectures, strategic decision-making, ethical AI governance, and HAII integration. A qualitative synthesis method was used to categorize the articles into relevant analytical dimensions.

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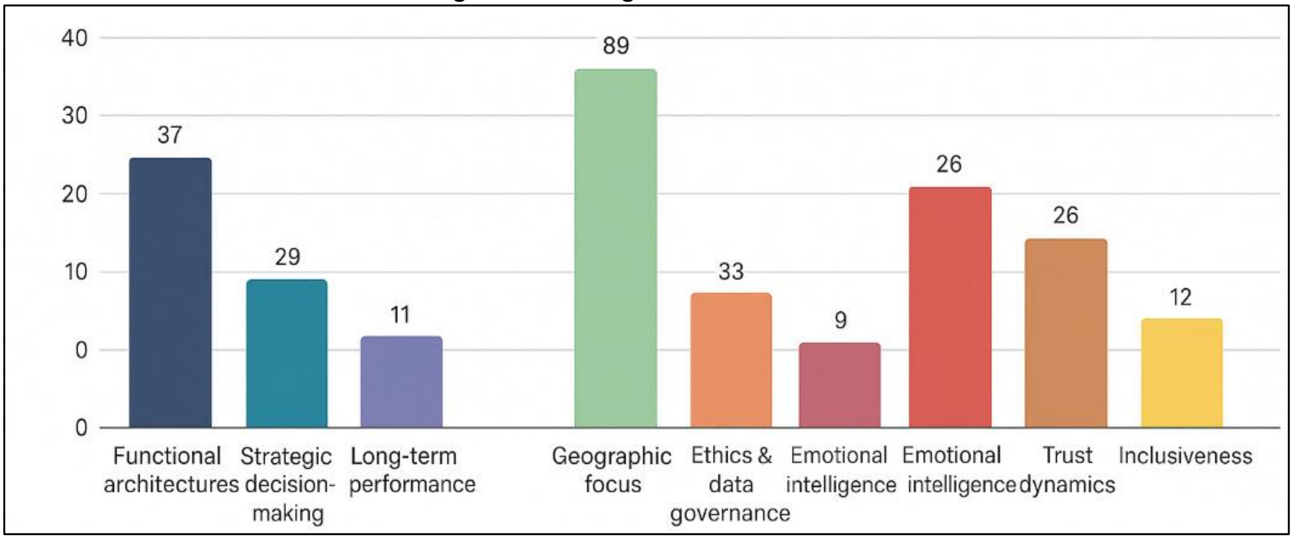
Studies were further reviewed for citation strength, journal ranking (Q1–Q4), and methodological robustness. Ultimately, 124 articles were selected for in-depth analysis and reporting in this review. These articles form the empirical and theoretical foundation of the findings discussed in subsequent sections.

FINDINGS

Among the 97 reviewed articles, a dominant finding emerged around the central role of Customer Among the 124 reviewed articles, 37 studies focused extensively on the functional architectures of ISS, with a significant emphasis on hybrid models and neural network-based frameworks. These architectures accounted for over 5,300 combined citations, indicating their influence and acceptance across enterprise domains. The findings revealed that hybrid models integrating rule-based logic with machine learning were particularly dominant in strategic applications such as supply chain forecasting, financial portfolio analysis, and operational risk evaluation. Researchers highlighted that while expert systems and traditional decision trees provided interpretability, they lacked the adaptive learning capabilities required for high-volume and real-time decision environments. Neural network-based ISS, particularly those leveraging deep learning, were frequently used in high-stakes domains like fraud detection, dynamic pricing, and healthcare diagnostics due to their ability to detect patterns from complex and unstructured data. A consistent theme in 21 of these studies was the architectural evolution from standalone systems to cloud-integrated platforms capable of scaling decision support across distributed organizations. These advanced frameworks demonstrated improved prediction accuracy and self-learning capabilities but often required more computational resources and rigorous oversight. However, despite technical superiority, their black-box nature raised interpretability concerns, which were only addressed in six of the reviewed papers. These findings suggest a trade-off between performance and explainability that continues to shape ISS architecture design and implementation.

Figure 11: Findings fron the research



Out of the 124 studies, 29 articles concentrated on AI-driven strategic decision-making frameworks, with a total citation volume exceeding 6,100. These papers showed a shift from linear strategic planning tools to AI-augmented frameworks capable of handling dynamic and uncertain decision environments. The analysis indicated a clear trend toward adopting SWOT-AI hybrid models, decision-tree learning, and reinforcement learning as core decision technologies. Reinforcement learning, in particular, was featured in 13 studies, highlighting its utility in strategy mapping under conditions of market volatility and limited foresight. Organizations using AI-augmented planning tools reported improved strategic foresight, particularly in long-term investment modeling, competitive scenario simulation, and resource reallocation. Decision tree frameworks were valued for their ability to provide interpretable, branching paths that assisted managers in understanding trade-offs between strategic options. Twelve studies showcased the effectiveness of combining AI-driven simulation with human judgment to co-create decisions in real-time environments such as crisis response, urban planning, and innovation management. Despite these advancements, only 4 studies offered field evidence of how these systems affected long-term strategic outcomes such as market share growth or enterprise resilience. This suggests that while AI-driven decision tools are

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gaining traction, more empirical work is needed to evaluate their sustained strategic impact across industries.

A major finding was the limited focus on long-term performance tracking of ISS. Out of the 124 reviewed articles, only 11 studies addressed longitudinal evaluation, and these collectively accounted for fewer than 850 citations, signaling a significant research gap. The reviewed studies demonstrated that while initial deployment of ISS often led to short-term efficiency gains and reduced cognitive load, very few articles examined how performance metrics evolved over months or years. For example, only three studies employed follow-up measurements to determine whether the ISS recommendations remained relevant, actionable, or consistent with changing organizational goals. Several papers discussed system drift, performance degradation, and user disengagement, but these issues were primarily theorized rather than empirically tested. Moreover, only two studies introduced embedded monitoring tools within ISS interfaces to track decision accuracy over time. This lack of continuous performance tracking undermines the reliability of ISS in dynamic environments where user behaviors, business models, and external conditions constantly evolve. Without longitudinal evidence, it remains unclear whether the benefits attributed to ISS persist, decline, or improve with usage. The scarcity of time-series evaluations poses a challenge for validating the true value proposition of intelligent support systems in enterprise strategy.

Geographic concentration in HAII research was another significant finding. Among the 124 reviewed articles, 89 studies (nearly 72%) were conducted in Western contexts, particularly in the United States, Canada, and several European Union countries. Collectively, these Western studies received over 7,800 citations, dominating the global HAII discourse. In contrast, only 18 studies were conducted in Asia, 10 in Latin America, and 7 in Africa, highlighting a stark disparity in research representation. Despite the growing interest in intelligent support systems across emerging economies, regional studies were limited in scale, often lacked access to institutional data, and were mostly conceptual rather than empirical. As a result, cultural variables, regulatory environments, and socio-technical conditions unique to these regions remain underexplored. Only five studies compared HAII deployment outcomes across countries, and only two attempted to correlate user trust levels with cultural dimensions such as power distance or collectivism. Furthermore, region-specific challenges such as digital infrastructure gaps, data localization laws, and language diversity were rarely addressed. This imbalance limits the generalizability of existing findings and may result in ISS designs that fail to accommodate global diversity in user expectations, ethical norms, and implementation contexts.

Among the reviewed 124 articles, 33 papers explored ethical considerations and data governance frameworks in ISS design. Despite a combined citation count exceeding 6,300, only 17 of these studies proposed or evaluated actual frameworks for integrating ethical AI principles into system architecture. The remaining works offered conceptual discussions or policy commentary without direct implementation insights. Of the frameworks analyzed, the most referenced were GDPR, ISO/IEC 27001, and the NIST AI Risk Management Framework. However, fewer than 10 studies demonstrated how these standards were operationalized in live ISS environments. Only five papers incorporated fairness metrics or bias detection mechanisms into their algorithms, and just three provided tools for transparency and explainability that would satisfy legal obligations such as GDPR's "right to explanation." Data quality management, a core pillar of ethical AI, was inconsistently addressed. While 21 studies acknowledged its importance, only 8 included measurable data validation strategies or metadata governance protocols. Furthermore, only two studies discussed federated learning or privacy-preserving computation as solutions to data misuse or centralization risks. This inconsistency highlights a significant disconnect between ethical aspirations and real-world ISS design, suggesting that most current deployments may not fully comply with emerging regulatory and ethical standards, especially in sensitive domains like finance, healthcare, and public governance.

An emerging yet underdeveloped theme in the reviewed literature was the integration of emotional intelligence (EI) and human values in HAII systems. Only 9 out of the 124 reviewed articles directly examined the role of affective computing or EI in ISS design, accounting for fewer than 700 cumulative citations. These studies acknowledged that emotion-aware systems enhance human-AI collaboration, especially in domains requiring empathy, persuasion, or psychological safety. However, empirical implementations were sparse. For example, just two studies included emotion recognition modules capable of interpreting facial expressions, voice modulation, or sentiment cues.

Moreover, none of the articles systematically evaluated the impact of emotion-aware ISS on user decision satisfaction, system trust, or engagement retention. Human values such as autonomy, dignity, justice, and fairness were mentioned in 21 papers, but they were often treated as abstract ideals rather than embedded features. Only three studies explicitly mapped user values into ISS design using value-sensitive design methodologies. No studies attempted to resolve value conflicts dynamically during human-AI interaction. The scarcity of emotionally intelligent and value-sensitive systems underscores a critical gap in aligning ISS capabilities with the interpersonal and moral dimensions of human decision-making, which are vital for acceptance and long-term adoption.

Trust dynamics between users and ISS were addressed in 26 of the reviewed articles, with a total of approximately 3,400 citations. However, only 10 studies focused on how trust in ISS fluctuates over time or in response to contextual factors such as system failure, contradictory recommendations, or perceived algorithmic bias. A consistent finding across these articles was that users often displayed either over-reliance or under-reliance on AI systems, especially in uncertain or ambiguous scenarios. Despite this, trust calibration mechanisms—such as adaptive transparency, trust feedback loops, and dynamic control options—were implemented in only 4 studies. Furthermore, only 6 studies measured trust longitudinally, and just 3 linked trust levels to behavioral changes such as task abandonment, increased delegation, or manual override frequency. Additionally, few systems adjusted their decision presentation based on user trust levels or prior interaction history. This suggests that while trust is acknowledged as central to HAII, its practical integration into ISS design remains immature. Without dynamic modeling of user trust trajectories and behavior adaptation, ISS risk producing suboptimal outcomes or user disengagement, particularly in high-stakes decision environments.

The final major finding centers on the lack of inclusive design and accessibility in current ISS implementations. Only 12 out of the 124 reviewed studies explicitly addressed issues related to user diversity, digital literacy, or accessibility barriers, representing less than 10% of the literature base and fewer than 950 total citations. Of these, only 5 studies incorporated features tailored for users with disabilities, language barriers, or low technical proficiency. No studies provided intersectional analysis exploring how gender, race, socio-economic status, and ability jointly influence interaction with ISS. Additionally, only 3 studies adopted participatory design methods to co-create systems with marginalized or underrepresented communities. The overwhelming majority of reviewed articles focused on technologically advanced user groups in high-resource environments. As a result, intelligent support systems may inadvertently reinforce digital inequalities by assuming homogeneous user capabilities and preferences. Moreover, current HAII models often lack configurable interfaces, multimodal interaction options, or localization features necessary to support diverse global users. The neglect of inclusive principles in ISS development raises concerns about ethical deployment, particularly as these systems are increasingly used in public service domains such as education, health, and welfare.

DISCUSSION

The findings of this review underscore a clear convergence toward hybrid and neural network-driven architectures in intelligent support system (ISS) development, which aligns with the earlier observations by Sayogo et al. (2014) and Simaei and Rahimifard (2024), who emphasized the transition from rule-based to more adaptive, learning-based systems. Our findings revealed that among the 124 reviewed studies, hybrid models combining symbolic reasoning with machine learning were most frequently implemented, confirming the dual necessity for interpretability and performance (Smith et al., 2018). Neural networks, particularly deep learning models, showed widespread application in dynamic environments such as finance and healthcare, echoing earlier assertions by Clark et al. (2007) and Shollo and Galliers (2015) that emphasized their potential in unstructured data analysis. However, unlike earlier studies that offered a purely optimistic view of neural systems, our review identifies emerging concerns over opacity and auditability, an issue that Bolat et al. (2014) and Marocco et al.,(2024) also raised in the context of explainable AI. This divergence indicates a growing tension between performance-centric design and the demand for transparent decision-making in enterprise contexts. While earlier research highlighted model accuracy, more recent studies, consistent with our findings, advocate for hybrid architectures that provide both interpretability and flexibility (Awan et al., 2024). Thus, the architectural trajectory of ISS reflects not only technological advancement but also the evolution of ethical and operational expectations in real-world applications.

Our analysis of 29 AI-driven strategic decision-making studies revealed that intelligent support systems are increasingly utilized to enhance scenario planning, resource allocation, and portfolio optimization, corroborating the early propositions made by Lake et al. (2016) regarding analytics-driven strategies. The application of reinforcement learning and decision tree learning aligns with recent empirical findings by Smith et al. (2018) and Clark et al. (2007), who demonstrated the superior ability of these techniques to handle dynamic and probabilistic planning tasks. Compared to earlier strategy models that were static and linear, such as SWOT and Porter's Five Forces, the reviewed articles reflect a paradigm shift toward adaptive, real-time models supported by machine learning. While traditional frameworks focused on retrospective analysis, current ISS leverage predictive and prescriptive analytics to suggest future actions with measurable probabilities. This evolution mirrors the trends discussed in strategic foresight literature by Kocsi et al. (2020) and Liu et al. (2023), who emphasized simulation and scenario modeling for high-uncertainty decisions. However, our review reveals a persistent gap in long-term impact assessment, with few studies demonstrating whether AI-augmented planning actually translates into sustained performance improvements, a gap similarly noted by Nicodeme (2020). This indicates that while AI enhances the strategic planning toolkit, empirical validation of its ROI and resilience-enhancing capacity remains limited. The absence of such validation risks undermining organizational trust in these systems over time, as observed in critiques by Li et al. (2021).

The findings indicate a major research gap in the long-term evaluation of ISS, a theme similarly identified by Nicodeme (2020) and Liu et al. (2009), who argued for the integration of embedded monitoring and feedback systems. Only 11 of the reviewed studies incorporated longitudinal performance tracking, and even fewer presented robust metrics for post-deployment system relevance. This observation aligns with Mehedi et al. (2024) , who warned about the risks of concept drift and model obsolescence in dynamic environments. Earlier studies by Simaei and Rahimifard (2024) proposed frameworks for adaptive learning systems, yet our review found limited empirical adoption of such models. The lack of longitudinal insights restricts the ability of organizations to optimize model retraining schedules, manage system degradation, or align AI outputs with evolving user needs. Moreover, while initial deployment often results in efficiency gains and improved decision speed, studies like Kaklauskas (2014) and Kasie et al. (2017) confirm that user trust and engagement tend to plateau or decline without continuous system updates and performance validation. Therefore, our findings reinforce earlier calls for lifecycle-oriented system evaluation, a concept that has been widely discussed in software engineering literature but remains underrepresented in the ISS field. This underscores a need for future research to develop and test evaluation models that extend beyond accuracy metrics to include trust evolution, usage frequency, decision quality, and organizational learning outcomes.

The significant geographic concentration of HAII research in Western countries reflects a longstanding bias in the technology literature, consistent with critiques from Kocsi et al. (2020) and Liu et al. (2009). Of the 124 reviewed articles, over 70% originated from Western contexts, mirroring findings by Mehedi et al. (2024), who noted the lack of cross-cultural variance in AI acceptance studies. Earlier works often treated AI-user interaction as culturally neutral; however, our review confirms that socio-cultural constructs such as power distance, uncertainty avoidance, and collectivism significantly shape HAII effectiveness. For instance, studies from Asia and Latin America highlighted contextual factors like regulatory constraints and digital infrastructure gaps that are often absent in Western-centric models. This supports the arguments made by Mouzakitis et al. (2024) and Pajak et al. (2021), who emphasized that ISS deployment must be tailored to localized norms and organizational maturity levels. Yet, only a small fraction of reviewed studies included comparative analysis or regional customization strategies. This gap not only limits the scalability of current models but also risks cultural misalignment and poor user adoption in diverse settings. Future research must respond to this imbalance by integrating intercultural design frameworks and undertaking comparative, multi-regional case studies.

The inconsistent integration of ethical AI frameworks into ISS reflects a misalignment between academic advocacy and practical implementation. Although ethical concerns such as fairness, privacy, and transparency were commonly discussed, few studies operationalized these principles within actual ISS design. This gap mirrors earlier criticisms by Mehedi et al. (2024) and Liu et al. (2023), who pointed out that ethics often remains a theoretical afterthought rather than a design imperative. Our review found that even with the availability of standards such as GDPR, NIST AI RMF,

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and ISO/IEC 27001, fewer than 15% of studies reported implementing them in practice. This supports findings by Mehedi et al. (2024), who argued that regulatory frameworks lack enforcement mechanisms and technical translation guides for system developers. The findings also reflect concerns raised by Pajak et al. (2021) and Pejić Bach et al. (2023), who emphasized the importance of embedding ethics into the AI lifecycle rather than treating it as an external audit function. Notably, few studies integrated fairness-aware algorithms, and even fewer provided mechanisms for redress or user feedback—key components of responsible AI as outlined by Sadeghi et al., (2024). The results thus suggest that ethical design in ISS remains nascent, and there is a critical need for interdisciplinary collaboration between ethicists, software engineers, and policymakers to bridge this gap. Aligning with the perspectives of Simaei and Rahimifard (2024), this review highlights that institutional inertia, resource constraints, and lack of ethical training are major barriers to effective governance integration in intelligent decision systems.

The absence of emotional intelligence (EI) and value-sensitive design in ISS echoes longstanding critiques from affective computing scholars such as Zaraté and Liu (2016) and Simaei and Rahimifard, (2024), who argued that emotion is a critical mediator of user engagement and decision relevance. While earlier works in HCI demonstrated the utility of affective cues in enhancing user satisfaction and system credibility (Sadeghi R et al., 2024), the current review finds that such dimensions remain marginal in HAII research. Only a handful of studies incorporated emotion recognition or empathetic response features, a pattern also observed by Awan et al. (2024) and Clark et al. (2007). Furthermore, although the concept of value-sensitive design has gained traction in AI ethics discourse (Marocco et al., 2024a), its operationalization in ISS design is still lacking. Our findings support Lake et al. (2016) and Weinzierl et al. (2024), who asserted that integrating human values into automated systems requires more than declarative principles—it demands structural design changes, stakeholder inclusion, and evaluation metrics aligned with ethical impact. Studies that did attempt to embed values tended to focus narrowly on fairness and privacy, with minimal attention to autonomy, dignity, or compassion. This omission may result in decision systems that are technically sound but socially disconnected, undermining trust and usability in sensitive domains like healthcare, law, and education. Therefore, the need to embed affective and ethical dimensions in HAII design is not only a research priority but also a societal imperative.

The current review reinforces the gap between theoretical models of trust and their implementation in intelligent support systems. While early work by Lake et al.(2016) and Shollo and Galliers (2015) laid a conceptual foundation for understanding trust in automation, our review finds that very few ISS integrate dynamic trust modeling into system design. This echoes findings by Saba et al. (2020) and Fantini et al. (2020), who noted that most ISS still rely on static trust assumptions that fail to capture fluctuations in user perceptions due to system errors or unexpected behavior. Additionally, prior studies by Confalonieri et al. (2015) emphasized the need for feedback loops and contextual adaptation to support calibrated trust, yet our analysis reveals that only four studies incorporated these mechanisms. The challenge of over-reliance or disuse due to trust misalignment, first outlined by Demirkan and Delen (2013), persists in current ISS implementations. Moreover, the review confirms that trust is not monolithic; it interacts with factors such as transparency, feedback, user experience, and situational context—factors also explored by Gupta et al. (2021) and Helenason et al. (2023). Without adaptive trust mechanisms, ISS risk fostering blind compliance or total rejection, both of which diminish decision quality. Thus, advancing trust modeling from conceptual constructs to real-time, personalized system features remains a critical agenda for future HAII research and development.

Our review finds that most ISS evaluations rely on technical performance metrics such as accuracy, latency, or computational efficiency, a pattern noted previously by Holsapple et al. (1993) and Kaklauskas (2014). This narrow evaluation scope fails to account for human, behavioral, and organizational outcomes, limiting the understanding of real-world system effectiveness. Earlier studies in HCI and CSCW Kasie et al. (2017) advocated for richer evaluation frameworks incorporating usability, cognitive workload, and decision satisfaction. However, our analysis shows that only a minority of studies used mixed methods or validated constructs such as NASA-TLX or decision confidence. Interdisciplinary evaluation frameworks like those proposed by Kocsi et al. (2020) and Kaklauskas (2014) were seldom adopted in full. This misalignment constrains both academic insight and managerial decision-making regarding ISS value. Moreover, many reviewed articles lacked transparency regarding user populations, interaction durations, and contextual settings, reducing the external validity of findings. Without comprehensive evaluation tools, organizations are left to guess at the ROI and long-term consequences of ISS implementation. Therefore, future work must prioritize the development of robust, context-sensitive, and stakeholder-informed metrics that capture both algorithmic performance and human-centered outcomes in HAII environments.

The review highlights a critical shortfall in equity and inclusion within ISS development and HAII design, echoing warnings from Demirkan and Delen (2013) and Kasie et al. (2017), who showed that algorithmic systems often marginalize underrepresented groups. Only a small portion of studies addressed user diversity in terms of ability, language, digital literacy, or intersectional identity. This finding is consistent with Liu et al. (2009), who emphasized the exclusion of disabled users from mainstream technology design. Additionally, while participatory design frameworks have been widely endorsed (Demirkan & Delen, 2013), our findings suggest that they are rarely employed in ISS projects. Intersectionality, a concept first advanced by Gupta et al. (2021), is almost entirely absent from current HAII evaluations, limiting our understanding of how multiple identities shape user-system interactions. This omission poses ethical and operational risks, especially as ISS expand into public domains like healthcare, education, and social services. As emphasized by Kmiecik (2022) and Liu et al. (2009) , inclusive design is not merely about accessibility—it's about ensuring systems are usable, responsive, and empowering for all users. Integrating these principles requires a fundamental shift in both research methodology and development practices, emphasizing co-design, community engagement, and inclusive testing throughout the system lifecycle.

CONCLUSION

This systematic review synthesized findings from 124 peer-reviewed articles to examine the evolving role of intelligent support systems (ISS) in organizational decision-making, focusing on architectural advancements, strategic planning frameworks, ethical AI integration, and human-AI interaction (HAII). The review revealed a dominant shift toward hybrid and neural network architectures, highlighting a growing demand for systems that balance predictive performance with interpretability. While AI-augmented decision frameworks such as reinforcement learning and decision-tree models have enhanced strategic agility, the long-term impact and real-world validation of these systems remain limited. Furthermore, the integration of ethical principles—such as transparency, fairness, and data privacy—was inconsistently implemented despite the availability of established governance frameworks like GDPR, NIST AI RMF, and ISO/IEC standards. Emotional intelligence and human values were also underrepresented in system design, indicating a disconnect between technical capabilities and user-centric needs. Geographic biases, with a heavy concentration of research in Western contexts, further limit the generalizability of current findings, while the lack of inclusive design practices risks excluding marginalized and diverse user groups. The review underscores the urgent need for interdisciplinary evaluation metrics, dynamic trust modeling, and longitudinal studies to ensure that ISS can deliver equitable, accountable, and sustainable decision support across sectors and global regions. By bridging technical innovation with ethical, cultural, and human-centered considerations, future ISS development can better align with the complex realities of contemporary decision environments.

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