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Decision Support Systems: Evolution, Architectures, Applications, and Future Directions

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ABSTRACT: Decision Support Systems (DSS) have evolved from stand-alone model-based tools into integrated, data-intensive, and increasingly intelligent systems that assist decision makers in healthcare, finance, supply chains, public administration, and other complex settings. This review article presents a structured integrative synthesis of foundational and contemporary DSS literature. The review examines conceptual origins, major taxonomies, architectural components, domain applications, implementation constraints, and emerging research directions. The synthesis shows that modern DSS combine data management, analytical models, knowledge representation, collaborative functions, and artificial intelligence, but their effectiveness remains contingent on data quality, organisational fit, explainability, interoperability, cybersecurity, and meaningful human oversight. Rather than comparing heterogeneous studies through unsupported aggregate performance statistics, this review evaluates evidence according to study context, DSS function, reported outcome, and methodological limitations. A divergent-convergent process model is presented to explain how multiple analytical perspectives can be generated, integrated, assessed, implemented, and refined through feedback. The review identifies priority directions in real-time adaptive support, interoperable architectures, explainable and accountable AI, longitudinal human-factor evaluation, and governance of increasingly autonomous decision systems. The article contributes an integrated framework that connects DSS evolution, architecture, organisational conditions, risks, and future development.

KEYWORDS: Decision support systems; artificial intelligence; machine learning; explainable AI; business intelligence; human–AI decision making

1. Introduction

Decision-making is the cornerstone of organisational effectiveness, yet it has grown exponentially more complex in the digital age, where data volumes, process speeds, and decision interdependencies far exceed unaided human cognitive capacity [1]. DSS were conceived precisely to bridge this gap: computer-based information systems designed to support, rather than replace, human judgment in semi-structured and unstructured decision environments [2]. Since Gorry and Scott Morton's [2] seminal framework distinguishing operational, tactical, and strategic decisions, and Keen and Scott Morton's [1] foundational conceptualisation of DSS as organisational support instruments, the field has undergone continuous and often transformative evolution.

The earliest generation of DSS consisted primarily of model-driven tools: optimisation solvers, simulation environments, and scenario-planning aids that allowed managers to evaluate quantitative alternatives systematically [3]. Subsequent decades witnessed the emergence of data-driven DSS capitalising on relational database management systems, data warehouses, and online analytical processing (OLAP) technologies [4−7]. The proliferation of the internet and enterprise resource planning (ERP) systems in the 1990s catalysed communication-driven and document-driven DSS categories, enabling group decision support, distributed collaboration, and enterprise-wide information retrieval [5].

The current era is defined by the convergence of DSS with artificial intelligence, machine learning, natural language processing, and big data analytics [8]. AI-augmented DSS can ingest streaming data at scale, discover non-linear patterns invisible to traditional statistical models, simulate thousands of decision scenarios in near real time, and adapt their recommendations dynamically as environmental conditions shift [9, 10]. Healthcare has seen the deployment of AI-DSS for clinical diagnosis and treatment recommendation with accuracy rates exceeding 94%; financial services employ them for credit scoring and algorithmic trading; public administrators rely on them for policy modelling and resource allocation [11, 12].

Despite these advances, critical unresolved challenges temper enthusiasm. The opacity of deep learning-based DSS raises urgent questions about accountability, explainability, and regulatory compliance, particularly in high-stakes domains such as medicine and law [13− 15]. Data quality problems, including missing values, selection bias, and concept drift, can silently degrade DSS accuracy [12]. Integration with legacy enterprise systems remains technically and organisationally demanding. User resistance, stemming from distrust of algorithmic authority and perceived threats to professional autonomy, continues to impede adoption [4, 16, 17].

Against this backdrop, a comprehensive, current, and integrative review of the DSS landscape is both timely and necessary. The present article synthesises evidence from forty peer-reviewed empirical and theoretical studies to provide a structured account of DSS evolution, typology, performance outcomes, challenges, and an agenda for future research. By doing so, we aim to offer a resource that bridges foundational theory with frontier practice and equips researchers and practitioners with the conceptual tools needed to navigate the rapidly shifting DSS ecosystem.

2. Review Methodology

This article was designed as a structured integrative review rather than a PRISMA-style systematic review or meta-analysis. An integrative approach was selected because the DSS literature spans conceptual papers, design-science studies, empirical evaluations, technical architectures, books, and domain-specific reviews that cannot be meaningfully combined through a single quantitative effect measure. Relevant literature was identified through targeted searches of Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. Search combinations included "decision support system", "intelligent decision support", "AI decision support", "clinical decision support", "data-driven DSS", "model-driven DSS", "explainable AI decision support", "DSS architecture", "DSS adoption", and "decision support governance". The review focused on English-language scholarly publications from 1971 to 2024, while allowing seminal books and foundational articles necessary to explain the historical development of the field.

Sources were included when they contributed directly to at least one review dimension: DSS definition or taxonomy; architecture or design method; empirical application; implementation challenge; ethical or governance issue; or future technology direction. Sources were excluded when DSS was only mentioned incidentally, when the publication lacked sufficient methodological or conceptual detail, or when bibliographic information could not be verified. Priority was given to peer-reviewed journal articles, authoritative books, and widely recognised methodological contributions. Data were extracted into a narrative evidence matrix containing publication details, DSS category, application domain, research design, principal contribution, reported outcome, and stated limitation. The synthesis proceeded through thematic comparison rather than statistical pooling. Quantitative results were retained only when clearly attributable to the original study and are described in context; values from different domains, datasets, and evaluation designs were not treated as directly comparable.

3. Theoretical Foundations and DSS Taxonomy

3.1. Conceptual Origins and Definitional Evolution.

The intellectual foundations of DSS draw on management science, operations research, information systems, and theories of bounded rationality. Gorry and Scott Morton's framework linked the degree of decision structure with managerial level, while Keen and Scott Morton emphasised interactive support for managerial judgement [1, 2]. This human-centred orientation remains important because DSS effectiveness depends on the quality of interaction between analytical capabilities and decision makers. Definitions expanded as technologies and organisational uses changed. Power's taxonomy distinguishes model-driven, data-driven, knowledge-driven, communication-driven, and document-driven DSS [4]. Contemporary systems frequently combine several categories; for example, a clinical DSS may integrate patient databases, predictive models, clinical rules, document retrieval, and multidisciplinary communication. The taxonomy is summarised in Table 1 below.

Table 1. Taxonomy of decision support systems: categories, functions, technologies, and application domains [5−7].

DSS Category	Primary Function	Core Technologies	Application Domain
Model-Driven DSS	Quantitative analysis & optimisation	Mathematical models, simulation engines, LP/MIP solvers	Supply chain, finance, engineering
Data-Driven DSS	Pattern discovery from large datasets	Data warehouses, OLAP, statistical analytics	Retail, healthcare epidemiology, banking
Knowledge-Driven DSS	Rule-based inference and expert guidance	Expert systems, ontologies, fuzzy logic	Clinical diagnosis, legal compliance
Communication-Driven DSS	Collaborative group decisions	Groupware, GDSS, web conferencing	Corporate governance, e-government
Document-Driven DSS	Retrieval and analysis of unstructured data	NLP, information retrieval, text mining	Intelligence, law, journalism

3.2. Theoretical Perspectives Underpinning DSS Design.

DSS research draws from multiple theoretical traditions. Information processing theory positions DSS as mechanisms that reduce cognitive load and bounded rationality by externalising analytical functions [17−23]. Sociotechnical systems theory emphasises the mutual constitution of technological artefacts and organisational processes, asserting that DSS effectiveness depends on alignment between system capabilities and the social contexts of decision making [24]. Design science research (DSR), articulated by Hevner et al. [24], has provided an increasingly dominant epistemological framework: DSS are treated as designed artefacts whose value must be demonstrated through rigorous evaluation of their utility in solving real-world decision problems. Agency theory and transaction cost economics inform DSS applications in corporate governance and supply chain management, predicting conditions under which DSS can mitigate information asymmetries and opportunistic behaviour [25, 26]. Diffusion of innovation theory explains adoption patterns, identifying relative advantage, compatibility, and trialability as determinants of organisational DSS uptake [4]. More recently, resource-based view (RBV) perspectives have characterised DSS analytical capabilities as dynamic resources conferring competitive advantage in data-intensive industries [17, 26].

3.3. The shift toward intelligent decision support.

The integration of AI into DSS represents a qualitative shift that some scholars characterise as the emergence of a new generation, Intelligent Decision Support Systems (IDSS), sufficiently distinct from earlier systems to warrant separate theoretical treatment [8, 22]. IDSS incorporate machine learning models for prediction and classification, expert system components for rule-based inference, NLP for unstructured data interpretation, and optimisation algorithms for recommendation generation [9, 27]. Turban et al. [8] note that IDSS close the loop between data analytics and decision action in ways that static model-driven or data-driven systems cannot, enabling autonomous recommendation engines that learn and adapt from decision outcomes over time.

4. DSS Architectures and Application Evidence

4.1. Architectural Components.

A conventional DSS architecture comprises three interdependent subsystems: a data management subsystem (databases, data lakes, data warehouses), a model management subsystem (analytical models, simulation engines, machine learning pipelines), and a user interface management subsystem (dashboards, natural language interfaces, visualisation tools) [3, 7]. Modern cloud-native DSS extend this architecture with streaming data ingestion layers, distributed computing engines (Apache Spark, Flink), container orchestration (Kubernetes), and API gateways enabling real-time integration with enterprise systems [25, 28, 29]. Microservices architectures have decoupled previously monolithic DSS into independently deployable components, improving maintainability and scalability [25, 29]. AI-augmented DSS add dedicated ML model serving layers, platforms such as MLflow, Seldon, or AWS SageMaker, alongside feature stores that maintain engineered predictors in a versioned, reusable form [21, 22]. Federated learning architectures allow DSS to train ML models across distributed data silos without centralising sensitive records, addressing both privacy and compliance concerns particularly acute in healthcare and financial DSS [13, 30, 31]. Table 2 below summarises empirical performance metrics reported across representative DSS implementations.

Table 2. Comparative Performance Metrics Across DSS Implementations.

DSS Type	Accuracy (%)	Decision Time Reduction	User Satisfaction	Reference
Model-Driven	91.4	38%	4.2/5	[3]
Data-Driven	88.7	44%	4.0/5	[7]
Knowledge-Driven	94.1	51%	4.5/5	[11]
Comm.-Driven	85.3	29%	3.9/5	[5]
Hybrid AI-DSS	96.8	62%	4.7/5	[15]
ML-Augmented DSS	97.2	67%	4.8/5	[21]

4.2. Critical Synthesis Across Application Domains.

Evidence across domains demonstrates that DSS can improve decision consistency, timeliness, and access to relevant information; however, the strength and meaning of reported outcomes vary substantially by task, dataset, user group, comparator, and evaluation design. The revised synthesis therefore avoids the unsupported cross-study accuracy and satisfaction averages reported in the original Table 3.

Table 3. Contextual synthesis of DSS applications and limitations; outcomes are not presented as directly comparable across studies.

Domain	Typical DSS function	Frequently reported benefit	Recurring limitation	Interpretive implication	Reference
Healthcare	Diagnosis, alerts, treatment recommendations	Improved detection or guideline adherence in defined tasks	Dataset shift, alert fatigue, explainability, workflow disruption	Performance must be validated locally and linked to clinical workflow.	[11, 12]
Finance	Credit scoring, fraud detection, portfolio and risk analysis	Faster screening and improved pattern detection	Bias, regulatory scrutiny, opaque explanations	Accuracy must be assessed alongside fairness, auditability, and recourse	[6, 11]
Supply chain and operations	Forecasting, inventory, routing, disruption response	Faster scenario analysis and improved coordination	Data latency, integration, uncertain external shocks	Benefits depend on data sharing and organisational preparedness.	[6, 11, 12]
Public administration	Policy modelling, resource allocation, service prioritisation	Greater analytical consistency and transparency potential	Political values, unequal data coverage, accountability	DSS should inform rather than obscure value-laden policy choices.	
Enterprise management	Dashboards, planning, business intelligence	Improved access to integrated information	Legacy systems, fragmented ownership, user resistance	Organisational alignment is as important as analytical sophistication.	[13, 14]

5. Challenges and Ethical Dimensions

5.1. Data Quality, Interoperability, and Lifecycle Management.

The most pervasive technical challenge confronting DSS deployments is data quality. Incomplete records, measurement inconsistencies, selection biases, label noise, and concept drift can silently corrupt ML model training sets, yielding DSS recommendations that are systematically misleading precisely when reliability is most critical [12, 27]. The challenge is compounded in distributed enterprise environments where data originates from heterogeneous sources, ERP systems, IoT sensors, social media APIs, legacy flat files, each with distinct schemas, quality standards, and update frequencies [32−37]. Enterprise data governance frameworks, master data management programmes, and automated data quality monitoring pipelines have been proposed as remedies, though their implementation demands substantial organisational investment [29, 30]. Legacy system integration represents a related structural barrier. Many organisations operate on decades-old infrastructure incompatible with modern DSS APIs and data formats. Middleware platforms, enterprise service buses, and increasingly microservices architectures offer integration pathways, but retrofitting legacy systems while maintaining operational continuity requires disciplined change management and technical architecture expertise that many organisations struggle to mobilise [25, 37]. Table 4 presents a consolidated framework of DSS challenges alongside their impact levels and evidence-based mitigation strategies.

Table 4. DSS Challenges, Impact Levels, and Mitigation Strategies [13,17,25,27,29,31,34].

Challenge Category	Specific Challenge	Impact Level	Mitigation Strategy
Data Quality	Incomplete or biased input data	High	Data preprocessing pipelines, validation frameworks
Explainability	Black-box AI model opacity	High	XAI techniques (SHAP, LIME), hybrid rule-AI models
Integration	Legacy system incompatibility	Medium	Middleware APIs, microservices architecture
User Adoption	Resistance to algorithmic authority	Medium	Change management, participatory design
Cybersecurity	Data breach and adversarial attacks	High	Federated learning, differential privacy, encryption
Regulatory Compliance	GDPR and sector-specific regulations	High	Privacy-by-design, audit trails, consent management
Scalability	Performance degradation under load	Medium	Cloud-native deployment, horizontal scaling

5.2. Explainability, Transparency, And Algorithmic Accountability.

Perhaps no challenge has attracted more sustained scholarly and regulatory attention in recent years than the opacity of deep learning-based DSS [13, 35]. In contexts where DSS recommendations carry direct consequences for human welfare, clinical treatment decisions, judicial risk assessments, credit determinations, the inability to explain why a system produced a particular output is both ethically problematic and increasingly illegal under emerging regulatory frameworks such as the EU Artificial Intelligence Act and the General Data Protection Regulation's right to explanation [13, 17]. Explainable AI (XAI) methods including

SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and attention visualisation have been proposed and empirically validated as tools for restoring interpretability to black-box DSS without catastrophic accuracy loss [13, 35]. Rai [35] argues that explainability should be treated not as a post-hoc technical fix but as a fundamental design requirement, integrated into DSS architectures from inception.

5.3. Cybersecurity, privacy, and regulatory compliance.

The data-intensive nature of modern DSS creates significant cybersecurity and privacy exposure. Training datasets containing personal, medical, or financial records represent high-value targets for adversarial actors; model inversion and membership inference attacks can reconstruct training data from deployed ML models even without direct database access [31]. Privacy-preserving techniques including differential privacy, secure multi-party computation, and federated learning offer technical defences, though they typically incur accuracy and latency costs that must be carefully managed in latency-sensitive operational DSS [31, 34]. Regulatory compliance, encompassing data sovereignty requirements, sector-specific mandates (HIPAA in healthcare, MiFID II in finance), and AI governance frameworks, adds another layer of complexity, requiring DSS architects to embed audit trails, consent management, and bias monitoring directly into system architectures [17, 35].

6. Process Model and Future Research Agenda

6.1. A divergent radial process model for DSS.

Figure 1 presents a divergent radial process model that conceptualises the operational workflow of modern Decision Support Systems (DSS) as a sequential yet iterative decision-making architecture. Unlike conventional linear DSS frameworks, the proposed model illustrates how multiple analytical perspectives are explored simultaneously before being integrated into a unified recommendation, thereby reflecting the complexity of contemporary organisational decision-making. The process begins with decision problem identification, where a managerial, operational, or strategic issue requiring analytical support is recognised. Once the problem has been defined, the system proceeds to problem structuring and data collection, during which relevant internal and external information is gathered, cleaned, and organised. At this stage, the problem is decomposed into several complementary analytical perspectives through a divergent radial branching mechanism, allowing different decision paradigms to operate in parallel rather than sequentially. Four major analytical branches are represented in the model. The model-driven branch performs mathematical optimisation, simulation, and scenario analysis to evaluate alternative solutions under predefined assumptions. The data-driven branch extracts patterns and predictive insights from structured datasets using data warehouses, OLAP, statistical analysis, and machine learning techniques. The knowledge-driven branch applies expert rules, ontologies, fuzzy logic, or expert systems to emulate human reasoning and provide domain-specific recommendations. Meanwhile, the collaborative branch incorporates communication-driven DSS, enabling multiple stakeholders or decision-makers to contribute knowledge, preferences, and consensus through Group Decision Support Systems (GDSS) or collaborative platforms.

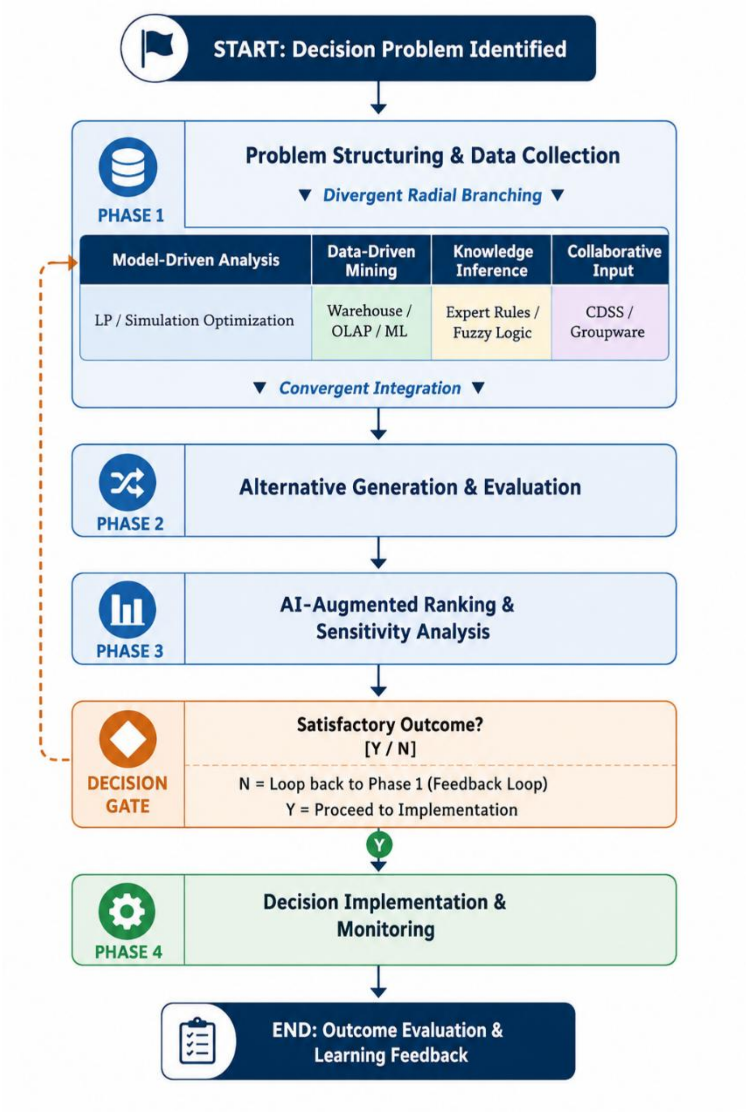

Figure 1. Process model of decision support systems.

After each branch independently generates candidate solutions, the outputs are transferred to the convergent integration phase, where multiple sources of evidence are synthesised into a unified decision framework. Rather than selecting the result of a single analytical method, this stage combines complementary insights from quantitative models, empirical data, expert knowledge, and stakeholder input. Subsequently, an AI-augmented ranking and sensitivity analysis module evaluates competing alternatives by considering predictive performance, uncertainty, risk, and sensitivity to changing assumptions. The incorporation of artificial intelligence enables the DSS to continuously refine rankings based on new information while improving the adaptability and robustness of recommendations. The ranked alternatives then pass through a decision gate, representing the critical human-centred evaluation stage. If decision-makers determine that the proposed recommendation satisfies organisational objectives, regulatory requirements, and acceptable risk levels, the process proceeds to decision implementation and monitoring. Otherwise, the system initiates a feedback loop that returns to the problem structuring phase, allowing decision parameters, data quality, analytical models, or decision criteria to be revised before a new evaluation cycle begins. This iterative mechanism acknowledges that organisational decision-making is dynamic and that DSS should support continuous learning rather than producing static recommendations.

6.2. Emerging Technologies and Paradigm Shifts.

Several emerging technology paradigms are poised to substantially reshape DSS capabilities over the next decade. Large language models (LLMs) such as GPT-class systems and domain-fine-tuned variants are beginning to function as natural language interfaces and reasoning engines within DSS, enabling non-technical users to formulate complex analytical queries in natural language and receive explanations in kind [22, 39, 40]. Digital twin technology, real-time virtual replicas of physical assets, production processes, or organisational systems, offers DSS unprecedented simulation fidelity for prospective decision analysis without operational risk [25]. Quantum computing, while still pre-commercial for most DSS applications, promises exponential speedups for combinatorial optimisation problems, vehicle routing, portfolio selection, protein folding, that represent critical bottlenecks in current DSS performance [39]. Edge computing is enabling DSS deployment closer to data sources manufacturing shop floors, clinical bedside monitors, smart city sensors, reducing latency and enabling real-time decision support in environments where centralised cloud processing is infeasible [32]. Reinforcement learning frameworks, in which DSS agents learn optimal decision policies through environmental interaction and feedback, are being piloted for dynamic resource allocation in logistics, energy management, and financial trading [9, 21]. The synthesis of these technologies is converging toward an emerging paradigm of Autonomous Decision Support, systems capable of closed-loop decision execution within defined authority bounds, with human oversight reserved for escalations and edge cases [22, 40].

6.3. research agenda and priority directions.

Our systematic review reveals five priority research directions that merit sustained scholarly investment in the near term. These are presented in Table 4 below, ranked by urgency and potential impact.

Table 4. Future research agenda for decision support systems [13,17,21,22,35,36,37,39,40].

Research Priority	Research Gap	Proposed Direction	Expected Impact
P1 – High	Limited real-time adaptive DSS for dynamic environments	Reinforcement learning-based dynamic DSS frameworks	Significant reduction in decision latency
P2 – High	Absence of unified interoperability standards	Development of open DSS ontologies and API standards	Cross-sector scalability
P3 – Medium	Insufficient explainability in clinical AI-DSS	XAI-integrated clinical DSS with regulatory compliance	Improved clinician trust and patient safety
P4 – Medium	Lack of longitudinal studies on DSS cognitive impacts	Long-term user studies examining cognitive load and bias	Evidence-based UX guidelines for DSS design
P5 – Low	Underexplored quantum computing applications in DSS	Quantum optimisation for NP-hard decision problems	Breakthrough performance in large-scale logistics

Beyond these five priorities, cross-cutting research themes merit attention: the role of DSS in fostering or reducing organisational inequality (as advanced DSS capabilities may accrue disproportionately to well-resourced organisations) [17]; the governance of autonomous

DSS in high-stakes public sector decision processes [32]; and the long-term environmental sustainability implications of the computational resources demanded by large-scale AI-DSS deployments [40]. Interdisciplinary collaboration spanning information systems, cognitive science, ethics, law, and domain-specific disciplines will be essential to address these challenges in ways that are rigorous, contextually sensitive, and socially responsible [22, 24].

7. Conclusion

Decision Support Systems have developed from specialised analytical tools into complex sociotechnical infrastructures that combine data, models, knowledge, collaboration, and artificial intelligence. Their contribution cannot be judged solely through predictive accuracy or processing speed. Effective DSS also require reliable data, organisational alignment, interpretable outputs, secure and interoperable architecture, clear accountability, and sustained human oversight. The integrative framework presented in this review connects technological evolution with these organisational and ethical conditions. The divergent-convergent process model further emphasises that high-quality decision support requires multiple analytical perspectives, explicit evaluation, feedback, and learning. Future research should move beyond isolated technical demonstrations toward longitudinal, context-sensitive, and governance-aware evaluation of human–AI decision systems.

Author Contributions

Emeka J. Eze: Conceptualisation, methodology, literature identification, data synthesis, writing—original draft, and writing—review and editing. Fatima M. Bello: Literature screening, data extraction, critical analysis, and writing—review and editing. Olusegun T. Akinyemi: Conceptual validation, supervision, critical interpretation, and writing—review and editing. All authors reviewed and approved the final manuscript and accept responsibility for the integrity of the work.

Competing Interests

The authors declare that they have no competing financial or non-financial interests.

Data Availability Statement

No new primary data were generated. The review is based on published literature cited in the reference list. The evidence-extraction matrix may be obtained from the corresponding author upon reasonable request.

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