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Machine Learning in Decision Support Systems: A Bibliometric Study of Intellectual Structures, Thematic Evolution, and Future Research Directions

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ABSTRACT

This study examines the intellectual structure and thematic evolution of research on machine learning (ML) in decision support systems (DSS), with particular attention to the financial management domain, through a bibliometric approach spanning 1993 to 2026. Data were retrieved from the Scopus database and analysed using performance analysis and science mapping methods, supported by VOSviewer to identify publication trends, collaboration networks, and co-occurrence patterns. The study reveals an annual growth rate of 13.88% in publications, reflecting sustained and accelerating scholarly interest. Collaboration networks remain fragmented, with China, India, and the United States occupying central positions. Thematic analysis indicates a transition from classical ML methods toward advanced integrations encompassing artificial intelligence, big data, and risk analytics. The findings provide strategic guidance for researchers and practitioners seeking to advance interpretable and ethically grounded ML-based DSS in financial decision-making environments. This study contributes a comprehensive bibliometric mapping of ML in DSS research, identifies persistent intellectual gaps, and proposes a structured agenda for future inquiry integrating explainable AI and cross-disciplinary collaboration.

Keywords: *Machine Learning, Decision Support Systems, Bibliometric Analysis, Artificial Intelligence, Big Data, Financial Management*

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INTRODUCTION

The accelerating digitisation of economic activity has fundamentally altered how organisations generate, process, and act on information. Decision support systems (DSS) emerged as a formal field of study in the 1970s precisely to bridge the gap between data abundance and actionable managerial insight, yet the statistical foundations underlying early DSS architectures were largely ill-equipped to handle the non-linear, high-dimensional data environments that define contemporary business (Shrestha and Ben-menahem, 2019). The subsequent rise of machine learning (ML) as a paradigm for data-driven computation has opened a qualitatively different design space for DSS, enabling systems that adapt, learn from historical patterns, and generate probabilistic predictions in real time. Dwivedi et al. (2021) document how the integration of artificial intelligence across decision-making domains has produced measurable gains in both efficiency and decision quality, particularly in environments characterised by high uncertainty and rapid informational change.

Within financial management, the practical implications of ML-enhanced DSS are especially pronounced. Applications spanning credit risk assessment, fraud detection, portfolio optimisation, and cash flow forecasting have demonstrated that algorithmic approaches can outperform rule-based systems across multiple performance dimensions (Garefalakis et al., 2026). This is not incidental: the financial sector operates at the intersection of massive data volumes, regulatory scrutiny, and irreversible decision consequences, precisely the conditions under which adaptive ML architectures provide maximum comparative advantage over conventional modelling approaches. The broader financial ecosystem has also been reshaped by macroeconomic forces including digitisation, globalisation, and the growing salience of environmental, social, and governance (ESG) criteria, each of which creates additional informational complexity that ML-enabled DSS is uniquely positioned to address (Wibowo et al., 2026).

Despite this momentum, the scholarly literature on ML in DSS remains intellectually fragmented. While individual studies document specific applications or methodological advances, no comprehensive bibliometric mapping has traced the structural evolution of this field as a whole, particularly in relation to the financial management subdomain. Studi bibliometrik in adjacent areas, including public financial management (Maulana et al., 2026), bounded rationality in decision-making (Azmi et al., 2026; Salwa et al., 2026), and finance-driven international business evolution (Yahya et al., 2026), consistently reveal that growth in publication volume does not automatically translate into intellectual coherence; instead, thematic fragmentation and uneven geographic collaboration tend to persist unless explicitly mapped and addressed. The same structural vulnerabilities are likely present in the ML-DSS literature, yet they have not been systematically diagnosed.

Bibliometric analysis offers a rigorous and scalable approach to this diagnostic task. By applying performance analysis and science mapping to the full corpus of Scopus-indexed publications on ML in DSS from 1993 to 2026, this study provides the first comprehensive portrait of how the field's intellectual architecture has developed across time. The analysis identifies dominant themes, maps collaboration networks, and traces the transition from classical ML methods toward more complex and contextually embedded frameworks. In doing so, it reveals persistent research gaps and formulates a structured agenda for future inquiry. This study contributes to the literature in three respects: it extends bibliometric methodology to a previously unmapped intersection of ML and DSS scholarship; it situates the field's evolution within the broader context of digital transformation and financial management challenges; and it identifies emerging themes, particularly explainable AI and ethical considerations, that represent high-priority directions for future work (Althaf et al., 2025; Dewanti et al., 2026; Kesuma, 2026; Rahma et al., 2026). The remainder of this paper is organised as follows. Section 2 reviews the theoretical and empirical literature on ML in DSS. Section 3 describes the bibliometric methodology. Section 4 presents and discusses the findings. Section 5 concludes.

LITERATURE REVIEW

The conceptual trajectory from rule-based DSS to ML-augmented decision architectures reflects a deeper epistemological shift in how organisations understand intelligence and adaptivity. Classical DSS frameworks, drawing on operations research and structured analytical models, presupposed a relatively stable decision environment in which expert knowledge could be formalised and encoded. Shrestha and Ben-menahem (2019) challenge this assumption directly, arguing that the emergence of AI-native organisational forms demands a reconceptualisation of decision structures that places adaptive learning, rather than pre-programmed expertise, at the core of system design. This theoretical reorientation has material implications for how ML is integrated into DSS: rather than functioning as a predictive subroutine embedded within a static decision model, ML enables the DSS itself to evolve in response to incoming data, effectively blurring the boundary between the decision system and the environment it is designed to navigate.

The translation of this theoretical argument into concrete system architectures has been enabled by parallel advances in deep learning, reinforcement learning, and ensemble methods, each of which addresses distinct limitations of earlier approaches. Deep learning models, particularly recurrent and convolutional architectures, have demonstrated superior performance in processing sequential and structured financial data, while reinforcement learning frameworks have proven effective in dynamic optimisation problems such as portfolio rebalancing and algorithmic trading (Garefalakis et al., 2026). Importantly, however, the interpretability deficit of these advanced models poses a practical constraint on their deployment in regulated industries. This concern has catalysed the development of explainable AI (XAI) frameworks, which seek to restore transparency without sacrificing predictive power (Zhuntyrbayev and Massalimova, 2026). The tension between model complexity and interpretability thus constitutes a foundational theoretical challenge for the field, one that has progressively moved to the centre of both academic debate and regulatory discourse.

The application of ML-enhanced DSS to financial management problems represents one of the most rapidly expanding subfields within the broader ML-DSS literature. The financial domain provides an especially demanding test environment for these systems: data arrive continuously, decisions are irreversible, and the cost of systematic errors can be catastrophic. Research has documented the application of ML-DSS across a wide spectrum of financial tasks, including credit scoring, fraud detection, market forecasting, liquidity management, and ESG risk assessment (Garefalakis et al., 2026; Irianto et al., 2025). Each of these applications exploits a distinct capability of ML: pattern recognition in high-dimensional feature spaces, real-time anomaly detection, non-linear forecasting under distributional shift, and multiobjective optimisation across competing financial criteria. Collectively, they suggest that ML-DSS has achieved sufficient maturity to serve as a primary analytical infrastructure for complex financial decision-making rather than merely a supplementary tool.

The intersection of ML-DSS with emerging financial paradigms, including digital finance, green finance, and sustainable investment, further amplifies the practical relevance of bibliometric inquiry into this field. Chandran and Chandran (2026) document a sharp increase in green finance publications, driven by the convergence of technological innovation, climate policy, and investor demand for ESG-aligned portfolios. This trajectory implies growing demand for ML-based DSS that can process non-financial data streams, including climate risk metrics and social impact indicators, alongside conventional financial variables. Similarly, Wibowo et al. (2026) demonstrate that financial management research has been increasingly reshaped by globalisation-induced complexity, creating demand for adaptive decision systems capable of integrating macro-level risk information with firm-specific financial dynamics. The bibliometric analysis presented in this study captures these convergent pressures and traces their imprint on the ML-DSS research frontier.

Bibliometric methodology has been extensively deployed in adjacent fields to diagnose intellectual structures, identify thematic clusters, and flag emergent research directions, providing important contextual benchmarks for the present study. In the domain of digital transformation, Althaf et al. (2025) and Ilmahdy et al. (2025) identify a consistent pattern in which early research concentrates on technical feasibility before progressively incorporating strategic and ethical dimensions; this trajectory closely mirrors what the present study finds in the ML-DSS context. Adelia et al. (2025) and Saputra et al. (2025) further document how bibliometric mapping in digital business and family firm digitalisation reveals persistent geographic concentration of scholarly output, a finding replicated in the ML-DSS co-authorship analysis below. In the decision sciences, bibliometric studies of decision-making styles (Dewanti et al., 2026), AHP applications (Maharani et al., 2026), and crisis management decision-making (Mawadah et al., 2026) each reveal that methodological pluralism and cross-disciplinary integration are hallmarks of maturing research fields, a benchmark against which the current state of ML-DSS scholarship can be evaluated.

Within the economics and governance domain, Korip et al. (2025) and Simangunsong et al. (2026) demonstrate that bibliometric analysis can detect not only the growth of a field but also its internal fault lines, specifically the gaps between dominant research clusters and underrepresented contextual applications. Maulana et al. (2026) and Yahya et al. (2026) extend this argument to financial management and international business, respectively, showing that bibliometric maps provide actionable intelligence for research prioritisation. The integration of ethics and behavioural considerations into financial decision-making, documented by Rahma et al. (2026) and Afifah et al. (2026), points toward a broadening of the DSS research agenda that the present study's thematic analysis both confirms and elaborates. Collectively, these benchmarks establish bibliometric analysis as an appropriate and validated methodology for mapping the ML-DSS field.

RESEARCH METHODOLOGY

This study adopts a quantitative bibliometric approach to systematically analyse and map the intellectual structure of research on ML in DSS. Bibliometric analysis has been widely validated as a method for evaluating the cumulative contribution of a research field through publication data, enabling the identification of thematic clusters, collaboration patterns, and evolutionary trajectories that would be inaccessible through conventional narrative review (Donthu et al., 2021). The approach is particularly well-suited to fields characterised by rapid growth and cross-disciplinary diffusion, both of which apply to ML-DSS research. Two complementary analytical procedures were employed: performance analysis, which assesses the productivity and impact of authors, institutions, and countries; and science mapping, which visualises the structural relationships among research entities through co-authorship, keyword co-occurrence, and citation networks (Cobo et al., 2011).

Data were retrieved from the Scopus database, selected for its comprehensive international coverage and rigorous quality standards relative to alternative sources. The search protocol combined the terms machine learning, decision support systems, and artificial intelligence in the title, abstract, and keyword fields, without language or document-type restrictions. The resulting dataset spans the period from 1993 to 2026, yielding 72 documents after a systematic cleaning procedure that removed duplicates, corrected metadata inconsistencies, and excluded records without sufficient bibliographic information. This cleaning procedure follows the protocol recommended by Zupic and Cater (2015) and is consistent with recent bibliometric studies in financial management contexts (Maulana et al., 2026; Korip et al., 2025). Analytical tools included VOSviewer for network construction and visualisation (van Eck and Waltman, 2010; Aria and Cuccurullo, 2017).

The science mapping component of the analysis encompasses three primary network types: co-authorship networks at both the author and country levels, which reveal collaboration structures and geographic concentration; keyword co-occurrence networks based on index terms, which identify thematic clusters and their inter-relationships; and term-based co-occurrence maps derived from title and abstract text, which capture implicit conceptual linkages that may not be reflected in formal keyword assignments. Overlay visualisations were additionally employed to trace the temporal evolution of research themes, enabling the identification of emerging topics and declining interests. Together, these complementary analytical layers provide a multi-dimensional portrait of the ML-DSS field that informs both the retrospective assessment and the prospective research agenda presented in the discussion.

RESULTS AND DISCUSSION

Publication Trends and Key Bibliometric Indicators

Table 1. Key Bibliometric Indicators of ML-DSS Research (1993–2026)

Indicator	Value
Time Span	1993–2026
Total Documents	72
Annual Growth Rate (%)	13.88%
Average Citations per Document	15.90

Total Authors	212
Single-Author Documents	12
Average Authors per Document	3.10

Source: Processed Data (2026)

Table 1 presents the key bibliometric indicators derived from the cleaned Scopus dataset. The 13.88% annual growth rate confirms that scholarly attention to ML in DSS has expanded at a rate substantially exceeding the average across most social science disciplines, reflecting the field's position at the confluence of two independently dynamic research streams. The average citation rate of 15.90 per document is particularly informative: it indicates that the literature has achieved sufficient maturity to generate a robust internal citation economy while remaining accessible to interdisciplinary scholars. This pattern is consistent with findings in adjacent bibliometric studies, which document similar citation densities in emergent technology-driven research fields (Donthu et al., 2021; Althaf et al., 2025). The predominance of multi-author documents, with an average of 3.10 authors per paper and only 12 single-author contributions, further corroborates the collaborative character of ML-DSS research, though the extent and quality of those collaborations requires closer examination through network analysis.

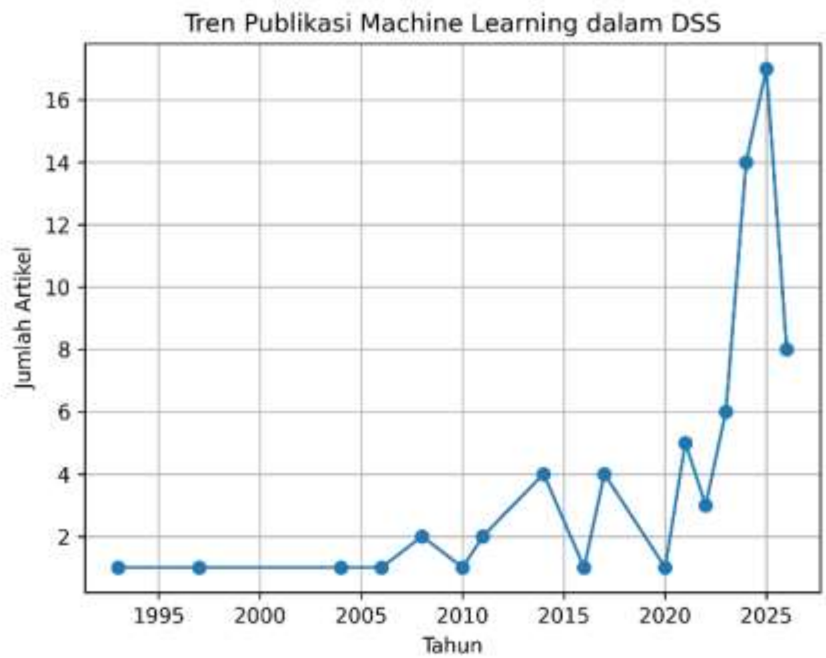

Figure 1. *Annual Publication Trends in ML-DSS Research (1993–2026)*

Figure 1 illustrates the temporal distribution of publications across the study period. Output remained modest and relatively stable through the early 2000s, reflecting the niche status of ML in decision computing at a time when computational infrastructure limited large-scale deployment. A pronounced inflection is observable from approximately 2018 onward, accelerating sharply between 2020 and 2025.

This trajectory is consistent with the broader diffusion of deep learning technologies, which reached commercial maturity during this period, and with the parallel expansion of cloud computing infrastructure that lowered the barrier to entry for ML-based application development. The slight decline visible in 2026 reflects the fact that data collection for the present study occurred mid-year; the underlying trajectory remains strongly positive when annualised. These dynamics mirror the publication growth patterns documented in related bibliometric studies of digital transformation (Althaf et al., 2025; Ilmahdy et al., 2025) and AI-enabled financial systems (Garefalakis et al., 2026), suggesting that ML-DSS is part of a coherent wave of technology-intensive research rather than an isolated bibliometric phenomenon.

4.2 Co-Authorship Analysis: Author Networks

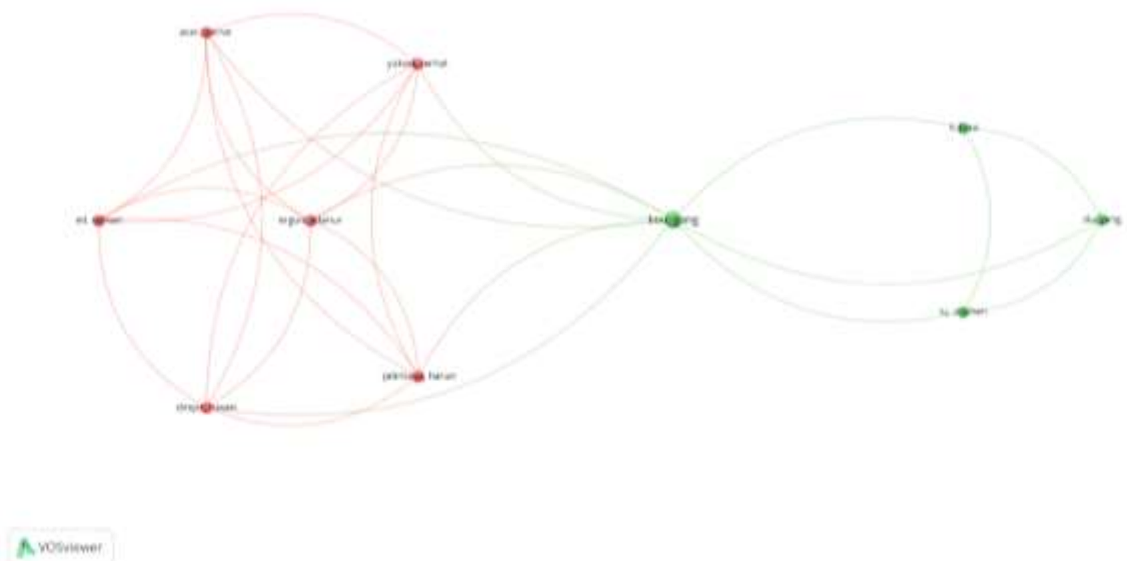

Figure 2. *Co-Authorship Network: Authors*

Table 2. Co-Authorship Cluster Analysis: Authors

Cluster Colour	Size & Density	Characteristics & Role
Red	Large cluster, dense interconnections	High-collaboration group forming the primary research network; inter-author links are intensive and structurally central.
Green	Small cluster, strong internal links	Represents a tightly connected but narrower collaboration cell; limited external linkages outside the group.

Source: Processed Data, VOSviewer (2026)

The co-authorship network at the author level, displayed in Figure 2 and summarised in Table 2, reveals a bimodal collaboration structure. The dominant red cluster aggregates the most productive authors and exhibits dense internal connectivity, consistent with the presence of established research teams working within a shared methodological paradigm. The smaller green cluster displays tighter but more insular linkage patterns, suggesting the existence of a secondary intellectual community whose integration with the broader field remains partial. Critically, the two clusters are connected only through a small number of bridging authors, implying that intellectual exchange across the network's main communities is mediated by a structurally fragile set of ties. This architecture mirrors patterns documented by Korip et al. (2025) and Adelia et al. (2025), who find that bibliometric co-authorship maps in emergent research domains frequently exhibit hub-and-spoke topologies that concentrate influence in small groups, potentially constraining the diversity of methodological approaches adopted across the field.

Co-Authorship Analysis: Country Networks

The country-level co-authorship network presented in Figure 3 and Table 3 confirms the geographic concentration of ML-DSS scholarship. China, India, and the United States emerge as the principal nodes, a pattern that reflects these nations' institutional investment in ML research infrastructure and their disproportionate representation in global computing science publication output. Hong Kong and the United Kingdom serve as cross-cluster connectors, facilitating knowledge flows between the East Asian and European research communities. Peripheral nodes, including Australia, the Netherlands, and Italy, display limited connectivity despite their individual research capacities, suggesting that language, funding, and institutional network effects may be impeding broader participation.

__Figure 3.__ Co-Authorship Network: Countries

Table 3. Co-Authorship Cluster Analysis: Countries

Cluster Colour	Size & Density	Primary Countries	Characteristics & Role
Blue	Small, limited connections	Czech Republic	Peripheral collaboration; limited integration with the central network.
Yellow	Medium, moderately connected	United States, Qatar	Early collaboration hubs with connections to multiple partner nations.
Green	Large, dense connections	China, India, Azerbaijan	Primary collaboration centres with intensive inter-node linkages.

Light Blue	Medium, cross-regional	Hong Kong	Bridge between Asian and European clusters.
Purple	Medium, international	United Kingdom	Facilitates global linkage across multiple clusters.
Red	Small, limited connections	Australia, Netherlands, Italy	Specialised collaboration with restricted network integration.

Source: Processed Data, VOSviewer (2026)

This geography of collaboration is directly relevant to financial management applications: the dominance of contexts characterised by large, technologically advanced economies means that contextual findings about ML-DSS performance may have limited generalisability to emerging market settings where data quality, institutional infrastructure, and regulatory environments differ substantially (Ruslianysah and Kesuma, 2026; Wibowo et al., 2026). Addressing this gap through deliberate cross-regional collaboration represents a clear priority for the field.

Keyword Co-Occurrence Analysis: Thematic Structure

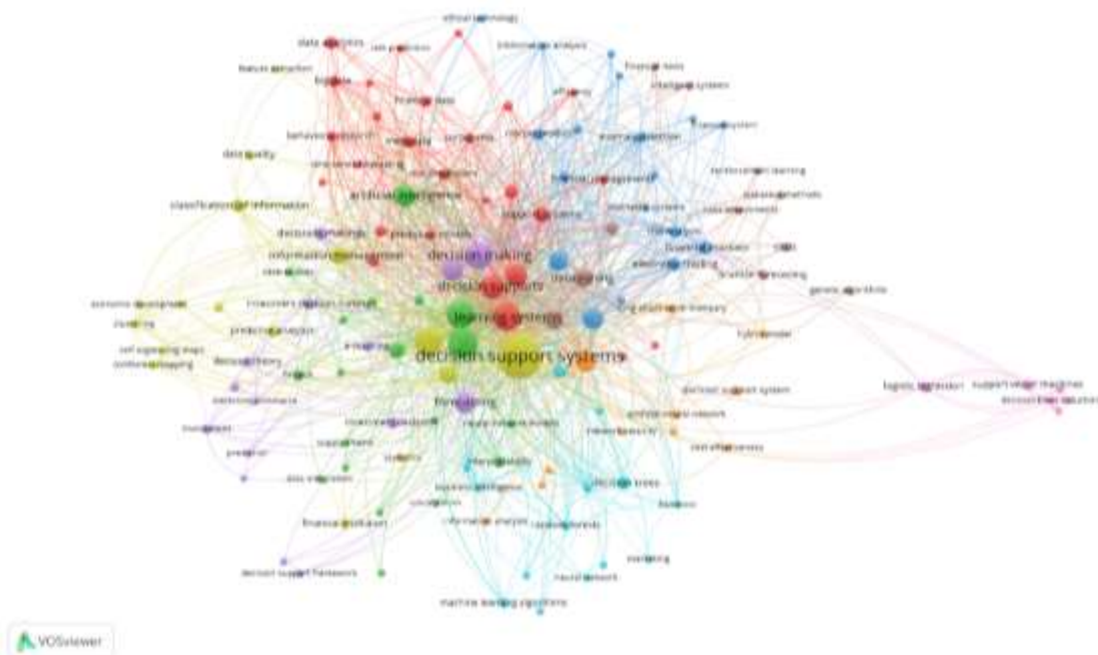

Figure 4. *Co-Occurrence Network: Author Keywords*

Table 4. Keyword Co-Occurrence Cluster Analysis

Cluster Colour	Size & Density	Core Keywords	Thematic Characteristics
Green	Very large, central node	decision support systems, learning systems, forecasting	Core research theme integrating DSS architecture and data-driven prediction.
Red	Large, dense connections	artificial intelligence, big data, data mining, machine learning	Primary technology cluster driving DSS advancement.
Blue	Large, broad connections	financial markets, anomaly detection, reinforcement learning	ML application in financial and dynamic system contexts.
Yellow	Medium	decision making, information management, classification	Decision process and information governance dimensions.
Purple	Small	investment, decision theory, forecasting, electronic commerce	Domain-specific economic and business applications.
Light Blue	Medium, dense	decision trees, random forests, neural networks	Core algorithmic approaches within ML methods.
Pink	Small, peripheral	support vector machine, logistic regression, decision tree induction	Classical ML classification methods, increasingly peripheral.

Source: Processed Data, VOSviewer (2026)

The keyword co-occurrence network, presented in Figure 4 and Table 4, reveals the multi-layered thematic architecture of the ML-DSS field. The centrality of decision support systems as a structural anchor, tightly coupled with artificial intelligence, big data, and machine learning, confirms that the field has achieved coherent conceptual integration around its core constructs. The blue cluster's linkage of financial markets, anomaly detection, and reinforcement learning is particularly instructive: it indicates that applications in dynamic financial environments have become a defining subcommunity within the broader ML-DSS research space, consistent with the argument that financial decision-making provides both demanding test conditions and high practical stakes for ML system development (Garefalakis et al., 2026; Mawadah et al., 2026). Conversely, the peripheral positioning of the pink cluster, which encompasses classical methods such as support vector machines and logistic regression, signals a progressive obsolescence of these approaches in favour of more architecturally sophisticated alternatives, a transition that the temporal overlay analysis below makes explicit.

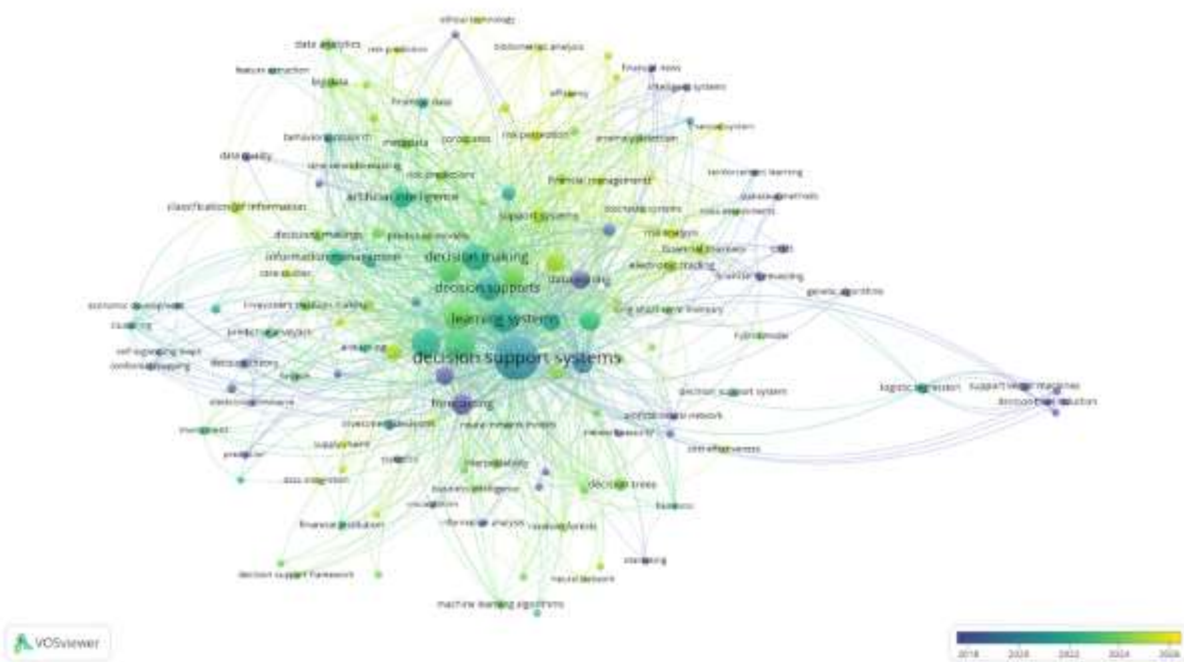

***Figure 5**. Keyword Co-Occurrence Overlay Visualisation (Temporal)*

Table 5. Temporal Evolution of Research Themes (Keyword Overlay)

Colour (Period)	Approximate Years	Core Keywords	Thematic Characteristics
Dark Blue	2018–2019	support vector machine, logistic regression, decision tree induction	Early classical ML methods and classification-focused inquiry.
Light Blue	2020–2021	decision trees, neural networks, anomaly detection, financial systems	Transition toward complex architectures applied to financial systems.
Green	2022–2023	decision support systems, data mining, artificial intelligence	Consolidation phase integrating ML into DSS as the primary framework.
Yellow	2024–2026	big data, data analytics, risk prediction, ethical technology, bibliometric analysis	Contemporary frontier: large-scale analytics, risk prediction, and ethical considerations.

Source: Processed Data, VOSviewer (2026)

The overlay visualisation in Figure 5 and Table 5 renders the field's temporal evolution with considerable clarity. The pre-2020 period was characterised by reliance on classical ML classification algorithms, reflecting the computational constraints and conceptual conservatism of early DSS-ML integration efforts. The 2020 to 2021 window marks a decisive methodological shift, coinciding with the widespread adoption of deep learning frameworks and the growing availability of financial data infrastructure. By 2022 to 2023, the field had consolidated around a shared intellectual core linking ML, AI, and DSS in a mutually reinforcing conceptual framework, suggesting the emergence of a dominant research paradigm (Aria and Cuccurullo, 2017). The most recent cluster, spanning 2024 to 2026, is the most diagnostically informative: the simultaneous emergence of big data analytics, risk prediction, ethical technology, and bibliometric analysis as co-occurring keywords indicates that the field is undergoing a dual transformation toward both greater technical sophistication and greater reflexive self-awareness about its own development trajectory (Rahma et al., 2026; Afifah et al., 2026). This is precisely the moment at which comprehensive bibliometric mapping, such as that undertaken in this study, provides maximum strategic value.

Text-Based Co-Occurrence Analysis: Conceptual Foundations

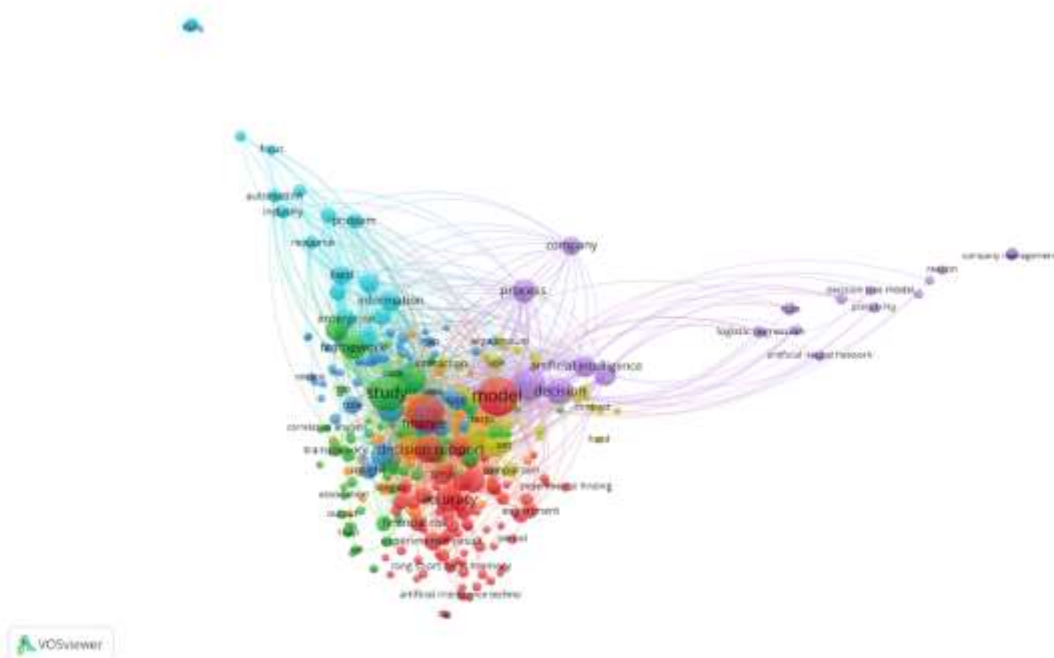

Figure 6. *Co-Occurrence Map Based on Text Data*

Table 6. Text-Based Co-Occurrence Cluster Analysis

Cluster Colour	Size & Density	Core Terms	Thematic Characteristics
Blue	Large, dense	information, system, enterprise, framework, resource, industry	Conceptual foundation: organisational and systemic contexts of DSS deployment.
Green	Medium	study, model, finance, analysis, use	Analytical orientation toward financial modelling and applied research.
Red	Large, dense	decision support, accuracy, experiment, result, performance	Evaluation and validation of DSS performance.
Yellow	Medium	decision, process, term, artificial intelligence	Bridge between systems architecture and AI application.
Purple	Small, linear	logistic regression, artificial neural network, decision tree model	Specific algorithmic methods within the technical core.
Light Blue	Small, limited	automation, problem, focus	Early-stage or specialised application contexts.

Source: Processed Data, VOSviewer (2026)

The text-based co-occurrence analysis, presented in Figure 6 and Table 6, complements the keyword network by surfacing conceptual linkages that emerge from the actual language of titles and abstracts rather than from formally assigned index terms. The dominance of system, information, enterprise, and framework in the blue cluster points to a consistent orientation in the literature toward DSS as an organisational-level artefact rather than a purely technical construct, underscoring the importance of institutional embeddedness in evaluating system performance. The red cluster's concentration of accuracy, experiment, result, and performance terms reflects a strong empirical tradition focused on quantitative validation, consistent with the ML field's broader culture of benchmark-driven evaluation. This emphasis on performance metrics, while methodologically rigorous, may also explain why interpretability and ethical considerations, captured in the more peripheral clusters, have historically received less sustained attention despite their practical importance in financial and governance applications (Zhuntyrbayev and Massalimova, 2026; Dewanti et al., 2026).

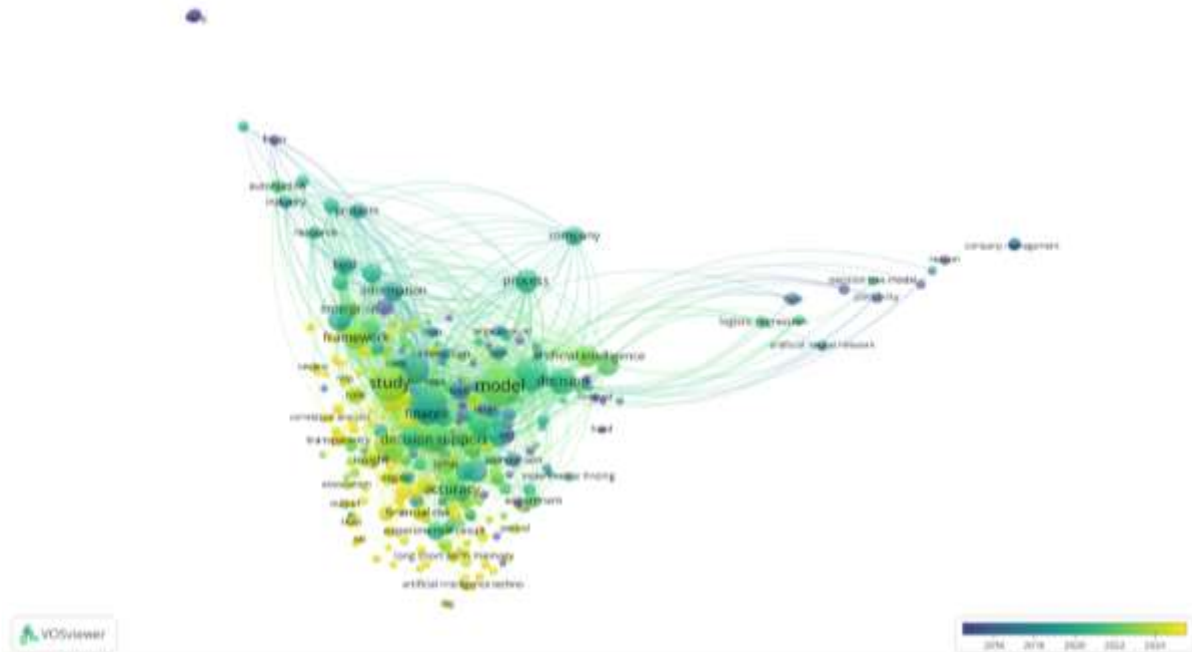

Figure 7. Text-Based Co-Occurrence Overlay Visualisation (Temporal) Source: VOSviewer (2026)

Table 7. Temporal Evolution of Research Themes (Text-Based Overlay)

Colour (Period)	Approximate Years	Core Terms	Thematic Characteristics
Dark Blue	2016–2018	decision tree model, logistic regression, artificial neural network, company management	Classical methods applied to basic organisational decision contexts.
Light Blue	2019–2020	artificial intelligence, process, company, information	Integration of AI into organisational processes and information flows.
Green	2021–2022	model, decision, system, enterprise, framework	Consolidation of DSS frameworks within enterprise contexts.
Yellow	2023–2024	decision support, accuracy, financial risk, experiment, performance	Emphasis on validation, financial risk modelling, and performance evaluation.

Source: Processed Data, VOSviewer (2026)

The temporal overlay of the text-based co-occurrence network in Figure 7 and Table 7 reinforces and extends the keyword-based temporal narrative. The progression from classical algorithmic methods in 2016 to 2018 through AI-enabled process integration and enterprise framework consolidation, and finally to performance-oriented financial risk evaluation in 2023 to 2024, describes a coherent developmental arc from technical feasibility to organisational embeddedness and performance accountability. This trajectory is consistent with technology adoption frameworks in the management literature, which predict that initial enthusiasm for a disruptive technology is followed by a consolidation phase in which the technology is institutionalised within existing organisational routines before a mature phase characterised by performance optimisation and governance scrutiny (Shrestha and Ben-menahem, 2019). The current positioning of ML-DSS research within this mature phase has important implications for the field's future direction: research priorities are likely to shift from pure performance maximisation toward interpretability, fairness, and regulatory alignment, themes that are already surfacing in the 2024 to 2026 yellow cluster and that will define the next generation of ML-DSS scholarship.

Synthesis: Intellectual Gaps and Research Priorities

Taken collectively, the four analytical layers, performance indicators, co-authorship networks, keyword co-occurrence, and text-based co-occurrence, converge on a coherent diagnosis of the ML-DSS field's intellectual strengths and structural vulnerabilities. The field's strengths are evident: sustained and accelerating publication growth, a robust internal citation economy, methodological pluralism spanning classical and advanced ML architectures, and a well-developed empirical culture centred on performance validation. Its vulnerabilities are equally clear. Geographic concentration in a small number of technologically advanced countries limits the contextual diversity of findings and impedes generalisability to emerging market settings where data environments, regulatory frameworks, and institutional capacities differ fundamentally (Rusliansyah and Kesuma, 2026; Chairani et al., 2026). Thematic fragmentation persists across collaboration clusters, with bridging linkages between major research communities remaining structurally fragile. Ethical and interpretability concerns, despite their clear practical importance, remain underrepresented in the formal structure of the literature relative to their centrality in practitioner and policy debates. Addressing these gaps through targeted collaboration, contextual diversification, and the deliberate integration of XAI and ethics research into the ML-DSS mainstream represents the most promising path toward a more coherent, impactful, and societally responsible research programme.

CONCLUSION

This study analyses the intellectual structure and thematic evolution of research on machine learning in decision support systems using bibliometric data from 1993 to 2026, encompassing 72 Scopus-indexed documents analysed through VOSviewer. The findings confirm a sustained annual growth rate of 13.88% and an average citation rate of 15.90 per document, reflecting a field that has achieved both quantitative momentum and scholarly influence. Co-authorship networks reveal a fragmented collaboration landscape dominated by Chinese, Indian, and American research communities, with peripheral participation from other national contexts. Thematic analysis identifies a clear evolutionary trajectory from classical ML classification methods toward architecturally advanced and contextually integrated frameworks incorporating artificial intelligence, big data, and risk analytics. The most recent publication cohort signals a further transition toward ethical technology, explainable AI, and reflexive bibliometric self-assessment as emerging research priorities. Across all analytical dimensions, the financial management domain emerges as a particularly active and consequential application context for ML-DSS integration.

For policymakers and financial institutions, this study highlights the urgency of developing governance frameworks that accompany ML-DSS deployment, particularly with respect to model interpretability, data bias mitigation, and accountability structures in high-stakes financial decisions. For researchers, the most productive frontier lies at the intersection of explainable AI, cross-regional collaboration, and the application of ML-DSS to emerging market financial environments where conventional system designs may require substantial contextual adaptation. This study contributes to the literature by providing the first comprehensive bibliometric mapping of the ML-DSS field, situating its evolution within the broader context of digital transformation and financial management research, and formulating a structured agenda for future inquiry. The principal limitation of the study is its reliance on a single database, Scopus, which may underrepresent research published in regional or non-English language outlets; future bibliometric analyses should consider multi-source triangulation to address this constraint.

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