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BEYOND TECHNOLOGY: UNPACKING ORGANIZATIONAL BARRIERS IN AI-DRIVEN FINANCIAL DECISION SUPPORT SYSTEMS - A SYSTEMATIC REVIEW AND BIBLIOMETRIC ANALYSIS

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ABSTRACT
This systematic literature review examines organizational barriers in AI-driven decision support systems (AIDSS) adoption within financial services through bibliometric and thematic analysis. Following PRISMA 2020 guidelines, 183 articles were screened, yielding 67 high-quality publications (2019-2024) for analysis. Keyword co-occurrence analysis using VOSviewer identified ten core concepts forming four distinct clusters: implementation challenges (barriers, implementation, systematic review, clinical decision support), financial sector applications (artificial intelligence, financial services, banking), organizational adoption dynamics (adoption, organizational), and healthcare sector transferability. Findings reveal a critical research-practice gap: while "artificial intelligence" dominated with 63 occurrences, "barriers" (23) and "adoption" (22) surpassed sector specific keywords, indicating a paradigm shift from technical capabilities toward organizational challenges. Temporal analysis shows emerging focus on organizational factors (average publication year 2024.00 vs. 2022.78 for financial services). However, absence of granular barrier constructs (culture, leadership, skills) and limited cross-sectoral knowledge transfer from healthcare CDSS literature represent conceptual underdevelopment. Results underscore that organizational readiness not technical sophistication constitutes the primary adoption constraint, requiring integrated change management strategies alongside technology deployment.

Key words: artificial intelligence; decision support systems; organizational barriers; financial services; bibliometric analysis

INTRODUCTION
Financial institutions are projected to invest USD 97 billion in artificial intelligence (AI) by 2027, making financial services the second-largest AI investment sector (World Economic Forum, 2025). However, 74% of organizations still struggle to generate and scale value from AI initiatives (Boston Consulting Group, 2024), highlighting challenges in adopting AI-Driven Financial Decision Support Systems (AI-DSS).

AI-DSS applications such as credit risk assessment, fraud detection, and portfolio management can automate 32–39% of banking tasks and increase efficiency by 34–37% (Accenture, 2024), while also improving forecasting accuracy and fraud detection performance (Siddiqui, 2025).

Existing research on AI adoption mainly focuses on technological capabilities (Černevičienė & Kabašinskas, 2024; Cao, 2021), user acceptance model (Hentzen et al., 2021; Meng et al., 2025), and regulatory issues (Mennella et al., 2024; Vatankhah et al., 2024). However, organizational mechanisms influencing AI-DSS implementation remain fragmented, with many challenges stemming from organizational and process-related factors rather than technology (BCG, 2024; McKinsey, 2024).

To address this gap, this study identifies organizational barriers to AI-DSS adoption in financial services and maps research developments through bibliometric analysis using VOSviewer, providing both theoretical insights and practical guidance for AI implementation.

METHOD
This study used a systematic literature review following PRISMA 2020 (Page et al., 2021) combined with bibliometric analysis using VOSviewer 1.6.19 (Van Eck & Waltman, 2010). A search through Consensus.app (October 5, 2025) yielded 183 articles (2019-2024). A three-stage selection process: (1) quality screening excluding 100 Tier 4 articles (unindexed/predatory journals), (2) title/abstract screening based on AI/ML criteria, financial services context, and organizational perspectives, yielded 83 potential articles, and (3) full-text assessment with a score of ≥6/10 points (journal quality, rigor, relevance, and citation impact), yielding 67 final articles. Data extraction included bibliographies and keywords (42 articles without keywords were manually extracted using standardized terminology). VOSviewer analysis included keyword co-occurrence (minimum 5 occurrences), temporal overlay, and network metrics. Organizational barriers were coded using Braun and Clarke's (2006) thematic analysis.

RESULTS AND DISCUSSION

Keyword co-occurrence analysis of 67 articles identified ten core concepts that shaped. The research landscape of AI-driven decision support systems adoption. The distribution of these keywords is divided into four clusters. different thematic (Table 1), with measurable network characteristics (Table 2).

Table 1. Distribution of Keywords by Research Cluster

Cluster	Colour	Keyword	Total Appearances	Average Year Publication	Thematic Interpretation
1	Red	barriers, implementation, systematic review, clinical decision support	43	2023.21	Implementation challenges and systematic methodological approaches
2	Green	artificial intelligence, financial services, banking	77	2022.85	AI applications in the context of the sector finance
3	Blue	adoption, organizational	27	2023.75	Adoption dynamics and factor organizational
4	Yellow	healthcare	6	2023.83	Health sector (transferability methodological)

Table 2. Keyword Network Metrics

Indikacor	Value	Interpretation
Total keywords analysis	10	Focus with coverage limited conseptual
Total appearances cumulative	153	Representation of research concentration the core concept
Average link of keywords	5	Moderate connectivity between concept
Average link of strength	26.3	Moderate intensity of association
Temporal range publication	2022.60 – 2024 .00	Up to date literature (range 1.4 years)
Number of cluster identified	4	Thematic fragmentation with limited integration
Centralized keywords	artificial intelligence (63 occurrences, link strength 83)	The dominance of AI discourse ascore technology

The keyword “artificial intelligence” dominates the network with 63 occurrences and the highest link strength, confirming its central role in AI-DSS research.

Table 3. Keyword Metrics in Co-occurrence Analysis

Keyword	Cluster	Occurrences	Amount links	Strength of total links	Average year publication
artificial intelligence	2	63	9	83	2023.17
barriers	1	23	7	50	2023.09
adoption	3	22	7	42	2023.5
implementation	1	9	6	19	2023.33
financial services	2	9	3	14	2022.78
clinical decision support	1	6	5	12	2023
healthcare	4	6	4	10	2023.83
banking	2	5	2	7	2022.6
organizational	3	5	4	10	2024
systematic review	1	5	5	13	2023.4

A key finding emerges from the prominence of the keywords “barriers” (23 occurrences; link strength 50) and “adoption” (22 occurrences; link strength 42), which appear more frequently than “financial services” (9 occurrences) and “banking” (5 occurrences). This pattern indicates a shift in research focus from technological capabilities toward implementation dynamics and adoption challenges. Such findings align with Kar and Kushwaha (2021), who argue that organizational barriers mrather than technological limitations are the primary determinants of successful AI adoption in business contexts. The dominance of barrier-related themes also reflects industry evidence showing that 74% of organizations struggle to scale value from AI investments, highlighting the practical relevance of research on adoption barriers (Boston Consulting Group, 2024).

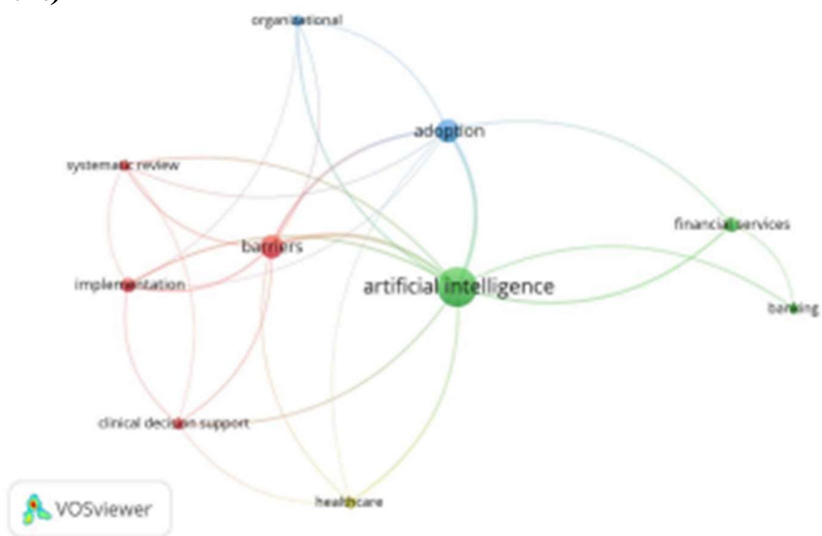

Figure 1. Data Overlay Results Using VOSviewer

The first cluster (red) includes “barriers”, “implementation”, “systematic review”, and “clinical decision support”. The presence of clinical decision support reflects conceptual similarities between healthcare CDSS and financial AI-DSS, particularly in high-risk decision environments and user trust requirements (Wang et al., 2023; Bertl et al., 2023; Abell et al., 2023).

The inclusion of “clinical decision support” is notable given the financial services focus. Studies by Wang et al. (2023), Bertl et al. (2023), and Abell et al. (2023) highlight implementation challenges of CDSS in healthcare that share similarities with financial AI-DSS, including high-risk decisions, trust requirements, and professional resistance. Strong links between “clinical decision support” and “barriers” (12) and “implementation” (19) further indicate cross-domain conceptual transferability (Abell et al., 2023).

The second cluster (green) combines “artificial intelligence”, “financial services”, and “banking” with 77 occurrences and the earliest average publication year (2022.85). Despite strong connections between AI and financial services, the relatively low frequency of “financial services” indicates a research paradox

The third cluster (blue) links “adoption” and “organizational”, indicating increasing attention to organizational factors in AI adoption. Previous studies emphasize that adoption barriers often stem from managerial perception, psychological factors, and organizational resistance rather than purely technical limitations (Marocco et al., 2024; Booyse & Scheepers, 2023).

The fourth cluster (yellow) contains only “healthcare” (6 occurrences; average year 2023.83), reflecting the separation of research domains. However, studies by Scott et al. (2024) and Pinsky et al. (2024) show that healthcare has developed substantial experience in large-scale CDSS implementation, offering insights potentially transferable to financial AI-DSS adoption.

Temporal analysis based on the average publication year per keyword (Table 3) shows that the field is recent and still developing, with a narrow range from 2022.60 (“banking”) to 2024.00 (“organizational”). Earlier keywords such as “banking” and “financial services” represent established topics, while the emergence of “organizational” reflects a shift toward organizational factors in AI adoption, supporting the argument that successful AI implementation requires broader organizational transformation (Agrawal et al., 2021).

The keyword “barriers” (2023.09) appears consistently across the period, indicating sustained attention to adoption challenges, as psychological, organizational, and ethical barriers often evolve more slowly than technological capabilities (Ivchyk, 2024).

Network metrics (Table 2) show moderate research integration, with an average of 5.0 links per keyword and link strength of 26.3, suggesting the field has not yet reached a mature research paradigm. The network is also hub-dominated, with “artificial intelligence” as the central node while keywords such as “banking” remain peripheral, indicating limited cross-domain integration. The absence of keywords such as “culture,” “leadership,” “change management,” “skills,” “trust,” and “ethics” further suggests limited conceptual granularity and the lack of a standardized taxonomy of barriers (Cubric, 2020).

Table 4. Comparison with Previous Bibliometric Studies

Aspect	This Study (2025)	Cubric (2020)	Lee et al. (2023)
Final number of articles	67	81 reviews	138

Aspect	This Study (2025)	Cubric (2020)	Lee et al. (2023)
Publication period	2019-2024	Until 2019	Until 2022
Sector focus	Financial services + transferable	Cross-sectoral	General organization
Number of main keywords	10	15	70 themes
Dominant theme	Barriers, adoption, organizational	Organizational, technological, environmental	70 diverse themes
Key findings	Shift to organizational factors (2024)	Equal emphasis 3 dimensions	Fragmented landscape
Network density	0.56 (moderate)	Not reported	Not reported

The comparison in Table 4 shows that this study was more focused (67 high-quality articles) resulting in concentration on fewer core concepts compared to comprehensive studies such as Lee et al. (2023) which identified 70 themes. This difference can be interpreted in two ways: positively as increasing research focus on crucial issues, or negatively as an indication that the literature base is not mature enough to explore nuances and sub-themes.

Theoretical and Practical Implications

The findings reveal a disconnect between research on AI technological capabilities and studies on organizational adoption. Many studies focus on algorithm performance or technical innovation while paying limited attention to organizational transformation required for successful implementation. The prominence of the "barriers" keyword indicates that AI adoption research often focuses on identifying obstacles rather than developing strategies for organizational capability building. The presence of healthcare-related studies within the barriers cluster also suggests opportunities for cross-sector learning. Healthcare AI systems face similar challenges, including user resistance, trust issues, and workflow integration problems. Lessons from healthcare implementation strategies may therefore help financial institutions accelerate AI adoption. For practitioners, the results highlight the importance of balancing technological investment with organizational readiness. Successful AI implementation requires leadership support, employee training, change management strategies, and transparent communication regarding AI capabilities and limitations.

CONCLUSION

This study analyzed organizational barriers to the adoption of AI-Driven Financial Decision Support Systems (AI-DSS) in financial services using a systematic literature review and bibliometric analysis of 67 publications from 2019–2024. The results identify four main research clusters: implementation challenges, financial sector applications, organizational adoption dynamics, and healthcare sector transferability.

The findings show a shift in research focus from technological capabilities toward organizational challenges. Keywords such as "barriers" and "adoption" appear more frequently than sector-specific terms, indicating that organizational readiness plays a more critical role than technological sophistication in AI implementation.

Overall, the study highlights the importance of organizational transformation, including leadership support, employee readiness, and change management, for successful AI-DSS adoption. Future research should explore more specific organizational factors and develop clearer frameworks to support effective AI integration in financial institutions.

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