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# Artificial Intelligence in Financial Decision-Making: A Bibliometric Analysis of Research Trends, Intellectual Structure and Emerging Themes

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**ABSTRACT**

Artificial intelligence (AI) has become a defining force in financial decision-making, reshaping how individuals, institutions, and markets evaluate risk, allocate capital, and detect fraud. As scholarly output on this intersection has grown rapidly over the past decade, the literature has become fragmented across databases, time windows, and disciplinary lenses, making it difficult to discern a unified picture of the field's development. This paper addresses that gap through a structured meta-bibliometric synthesis that consolidates findings from eight peer-reviewed bibliometric studies of AI in finance and financial decision-making published between 2021 and 2026, collectively drawing on Scopus- and Web of Science-indexed corpora ranging from 202 to over 1,000 documents and spanning 1987 to 2025. Using a systematic search-and-synthesis protocol and cross-study thematic content analysis, the study maps four dimensions of the field: publication growth trajectories, leading contributors, the intellectual structure of thematic clusters, and emerging research frontiers. Findings show accelerating publication growth since 2017 and a further surge after 2022, United States-, China-, and United Kingdom-led contribution patterns, and six recurring thematic clusters spanning algorithmic trading, credit risk and fraud detection, robo-advisory and investor behavior, explainable and ethical AI, ESG-linked finance, and financial inclusion. The study offers researchers, practitioners, and policymakers a consolidated map of the field's intellectual structure and proposes a future research agenda centred on explainability, regulatory alignment, and generative-AI adoption in financial decision contexts.

## 1. Introduction

Financial decision-making encompassing investment selection, credit allocation, risk assessment, fraud detection, and portfolio management has traditionally relied on human judgement supported by statistical and econometric models. Over the past decade, artificial intelligence (AI) has moved from a peripheral analytical aid to a central actor in this process. Machine-learning models now forecast asset returns and price risk, robo-advisors allocate retail portfolios, deep-learning classifiers screen loan applicants, and natural-language systems parse earnings calls and financial disclosures for sentiment signals (Roy et al., 2025; Ahmed et al., 2022). The diffusion of generative AI since 2022 has extended this role further, shifting AI's function in finance from narrow prediction toward

interactive advisory dialogue, scenario simulation, and automated reasoning over financial data (Artene et al., 2024).

This rapid technological diffusion has been mirrored by an equally rapid expansion of the academic literature. Bibliometric evidence indicates that documents indexed under artificial-intelligence-and-finance search terms have grown from a handful of publications in the mid-1990s to several hundred articles annually by the mid-2020s, with an annual growth rate exceeding 13 percent in some datasets (Bayakhmetova et al., 2025) and roughly a twenty-four-fold increase in yearly output between 1995 and 2023 in others (Alcázar-Blanco et al., 2024). This growth, however, has produced a literature that is fragmented across databases (Scopus, Web of Science), time windows (ranging from 1987–2024 to 2011–2021), and disciplinary framings (finance, accounting, information systems, behavioural economics). Multiple independent bibliometric studies have each mapped a slice of this landscape  some focused on financial behaviour (Bayakhmetova et al., 2025), others on sustainable finance (Ayaz & Zahid, 2024) or the broad introduction of AI into finance (Alcázar-Blanco et al., 2024) yet no single synthesis has consolidated these parallel efforts into a unified account of how AI-enabled financial decision-making research has evolved as an intellectual domain in its own right.

This fragmentation matters for three reasons. First, researchers entering the field face duplicated effort, since overlapping corpora are re-analysed with different tools (VOSviewer, SciMAT, Bibliometrix, CiteSpace) without cross-referencing prior results. Second, practitioners and policymakers seeking an evidence base for AI adoption in financial decision contexts lack a single point of reference that aggregates the field's dominant themes and gaps. Third, the absence of a consolidated intellectual map makes it difficult to distinguish genuinely emerging themes  such as explainable AI (XAI), algorithmic accountability, and generative-AI-enabled advisory  from incremental restatements of already-established sub-fields.

To address this gap, the present study conducts a structured meta-bibliometric synthesis of the AI–financial decision-making literature. Rather than re-extracting a single primary Scopus or Web of Science export, the study systematically consolidates the reported metrics, thematic maps, and network outputs of eight peer-reviewed bibliometric studies published between 2021 and 2026, collectively covering datasets ranging from 202 to over 1,000 documents and time spans from 1987 to 2025. This review-of-reviews approach enables triangulation of findings across independently constructed corpora and different bibliometric software environments, producing a more robust picture than any single study alone.

**Objectives:**

1. To map the growth trajectory of AI–financial decision-making research;
2. To identify the field's leading contributors in terms of countries, journals, and foundational works;
3. To characterise the intellectual structure of the domain through its dominant thematic clusters; and
4. To identify emerging and under-researched themes that define the field's future trajectory.

**Research Questions:**

RQ1 How has the volume of research on AI in financial decision-making evolved over time? RQ2 Which countries, journals, and foundational studies dominate the field's intellectual production?

RQ3 What thematic clusters constitute the field's core intellectual structure?

RQ4 What emerging themes and research gaps warrant future scholarly attention?

## 2. Literature Review

### *2.1 AI Applications in Financial Decision-Making*

AI applications in finance span a wide functional range. In algorithmic trading and market forecasting, machine-learning and deep-learning models are used to predict price movements, volatility, and trading signals, building on a long tradition of neural-network-based forecasting research (Bahrammirzaee, 2010). In credit risk and fraud detection, classification algorithms score borrower default probability and flag anomalous transactions, improving on traditional logistic and discriminant models (Ahmed et al., 2022). In investment and wealth management, robo-advisory platforms combine portfolio-optimisation algorithms with behavioural inputs to automate retail investment decisions, a domain closely tied to research on investor behaviour (Goodell et al., 2021; Königstorfer & Thalmann, 2020). In banking operations, AI-driven decision-support systems inform credit underwriting, internal audit, and regulatory-compliance functions, strengthening the integration of AI with internal control and strategic financial planning (Artene et al., 2024). More recently, generative AI and large language models have begun to augment financial advisory and reporting processes, introducing new capabilities alongside new risks related to interpretability and reliability (Artene et al., 2024). Goodell et al. (2021) identify three overarching clusters of AI/ML finance research: portfolio construction, valuation, and investor behaviour; financial fraud and distress; and sentiment inference, forecasting, and planning. This tripartite structure recurs across subsequent bibliometric mappings and provides a useful anchor for organising the fragmented literature that has emerged since.

### *2.2 Evolution of Bibliometric Research on AI in Finance*

Bibliometric analysis has become the methodological tool of choice for making sense of this fast-growing literature, given its capacity to systematically map publication trends, citation structures, and keyword co-occurrence networks across large corpora (Donthu et al., 2021; Zupic & Čater, 2015). At least eight independent bibliometric studies have examined some facet of AI in finance since 2021, each drawing on different database windows and software tools. Ahmed et al. (2022) analysed 348 Scopus-indexed articles published between 2011 and 2021 using RStudio, VOSviewer, and Excel, identifying the United States, China, and the United Kingdom as the leading national contributors and mapping the field's most active journals, institutions, and authors. Alcázar-Blanco et al. (2024) extended the historical window to 1995–2023 using 202 Web-of-Science-indexed articles analysed with SciMAT, identifying eight recurring topics  bank, prediction, impact, decision, stock values, genetic algorithm, big-data analysis, and social-data analysis  and documenting growth from two articles in 1995 to 48 in 2023. Roy et al. (2025) applied a Theory-Context-Characteristics-

Methodology (TCCM) framework to 607 Web-of-Science-indexed papers, emphasising thematic mapping around risk management, market efficiency, innovation, and notably the growing salience of ethical AI as a research theme. Bayakhmetova et al. (2025) analysed 1,019 Scopus documents spanning 1987–2024 using the Bibliometrix R package, reporting a 13.34 percent compound annual growth rate and identifying machine learning, decision-making, and financial inclusion as central themes, alongside persistent gaps in ethical considerations and regional research disparities. Almasria et al. (2025) focused on AI applications in financial process and reporting research from 2010–2024, documenting a marked acceleration in output during and after the COVID-19 pandemic. Ayaz and Zahid (2024) examined the adjacent but overlapping domain of sustainable-finance research, tracing how ESG-oriented themes intersect with AI-enabled financial analysis. Artene et al. (2024) focused specifically on the integration of AI-driven decision-making into financial reporting systems, linking AI adoption to internal-control and audit-quality outcomes. Collectively, these studies demonstrate convergent findings on three fronts: an accelerating publication trajectory, a geographically concentrated but broadening set of contributing countries, and a stable core of thematic clusters (trading/forecasting, risk/fraud, advisory/behaviour) surrounded by a growing periphery of emerging themes (ethics, explainability, inclusion, sustainability). At the same time, each study operates on a distinct corpus and time window, meaning no single study captures the full, unified picture of the field's evolution the gap this paper addresses.

### *2.3 Conceptual and Methodological Gaps*

Despite this proliferation of bibliometric effort, several gaps recur across studies. First, ethical and explainability concerns are consistently flagged as under-researched relative to their practical urgency; Bayakhmetova et al. (2025) explicitly identify critical gaps in ethical considerations, regional disparities, and practical applications of AI for marginalised populations as unresolved. Second, most existing bibliometric studies rely on a single database (either Scopus or Web of Science), which risks omitting relevant work indexed elsewhere and can bias thematic and geographic findings. Third, the pace of technological change particularly the post-2022 diffusion of generative AI has outpaced the publication and indexing cycle, meaning that even recent bibliometric snapshots may already understate the prominence of large-language-model-related themes in financial decision-making research. Fourth, no existing study has systematically cross-validated findings across the parallel body of bibliometric work itself, leaving open the question of how consistent the field's reported intellectual structure actually is across independent analyses.

### *2.4 Positioning of the Present Study*

The present study responds to these gaps by treating the existing body of bibliometric studies as a secondary evidence base rather than re-mining a single primary export. This meta-bibliometric synthesis approach allows for cross-study triangulation of growth trends, contributor rankings, and thematic clusters, while explicitly flagging where individual studies diverge for instance, in the relative weight given to ethical AI versus algorithmic trading as the field's most active theme. This positions the paper as a consolidating contribution rather than a competing primary analysis, intended to orient future primary bibliometric work and narrative reviews alike.

## 3. Research Methodology

### *3.1 Research Design*

This study adopts a meta-bibliometric synthesis design  a systematic, secondary-level bibliometric review that consolidates and cross-validates findings reported across primary bibliometric studies, rather than performing an independent extraction and analysis of a single raw Scopus or Web of Science export. This design is appropriate given the study's objective: not to generate a new primary dataset, but to resolve fragmentation across an already sizeable and rapidly growing body of independently conducted bibliometric analyses of AI in finance.

### *3.2 Search and Selection Strategy*

A structured search was conducted across academic databases and publisher platforms (Scopus, Web-of-Science-indexed outlets, ScienceDirect, MDPI, and F1000Research) using combinations of the search strings "artificial intelligence", "financial decision-making", "finance", and "bibliometric analysis" / "bibliometric review". Studies were included if they (a) employed an explicit bibliometric methodology (co-occurrence, co-citation, thematic mapping, or performance analysis), (b) focused substantively on AI or machine-learning applications within finance or financial decision-making, and (c) were published in a peer-reviewed journal or indexed platform between 2021 and 2026. Studies addressing AI bibliometrics in unrelated domains (e.g., healthcare, nursing) were excluded. This process yielded eight primary bibliometric studies for inclusion, with reported corpora ranging from 202 to 1,019 documents drawn from Scopus and Web of Science databases spanning 1987 to 2025.

### *3.3 Data Extraction and Synthesis*

For each included study, the following elements were extracted into a structured matrix: database and time span, sample size, analytical software (VOSviewer, SciMAT, Bibliometrix), reported thematic clusters or keyword groups, and reported leading contributors (countries, journals, foundational authors). Extracted thematic labels were then harmonised through an iterative content-analytic coding process: semantically overlapping labels reported under different names across studies (e.g., "trading" versus "market forecasting"; "fraud" versus "distress detection") were merged into unified cluster categories, following established practice in bibliometric-methods scholarship for cluster labelling and interpretation (Donthu et al., 2021; Zupic & Čater, 2015; Aria & Cuccurullo, 2017). Growth-trend data extracted from each study's reported annual publication figures were used to reconstruct an illustrative composite trend line anchored to documented data points  for example, two articles in 1995 and 48 in 2023 reported by Alcázar-Blanco et al. (2024), and a 13.34 percent compound annual growth rate reported by Bayakhmetova et al. (2025)  rather than claiming an independently re-extracted raw publication count for every year.

### *3.4 Analytical Tools and Validity Considerations*

Because the underlying primary studies employed VOSviewer (van Eck & Waltman, 2010) and SciMAT-based science-mapping techniques, the terminology and cluster logic of this synthesis follow the same conventions, ensuring comparability with the source studies. Two safeguards were applied to strengthen validity: (a) cross-checking each thematic cluster against at least two independent

primary studies before inclusion in the synthesised structure, and (b) explicitly labelling all visualisations in Section 4 as syntheses of previously reported findings rather than as newly mined primary bibliometric data, consistent with transparent-reporting norms recommended for secondary bibliometric synthesis (Zupic & Čater, 2015).

## 4. Data Analysis and Results

### *4.1 Publication Growth Trends*

Across the eight primary studies reviewed, a consistent pattern emerges: publication activity on AI in finance and financial decision-making remained low and relatively flat through the 1990s and 2000s, began accelerating around 2017, and has risen sharply since 2022. Alcázar-Blanco et al. (2024) document growth from two articles in 1995 to 48 in 2023 within their Web-of-Science corpus, while Bayakhmetova et al. (2025) report a 13.34 percent compound annual growth rate across a 1987–2024 Scopus corpus of 1,019 documents. Figure 1 presents a synthesised composite growth curve reconstructed from these reported anchor points, illustrating the characteristic exponential-like acceleration reported consistently across studies, with inflection points aligned to the mainstream adoption of deep-learning methods in finance around 2017 and the diffusion of generative-AI tools after 2022.

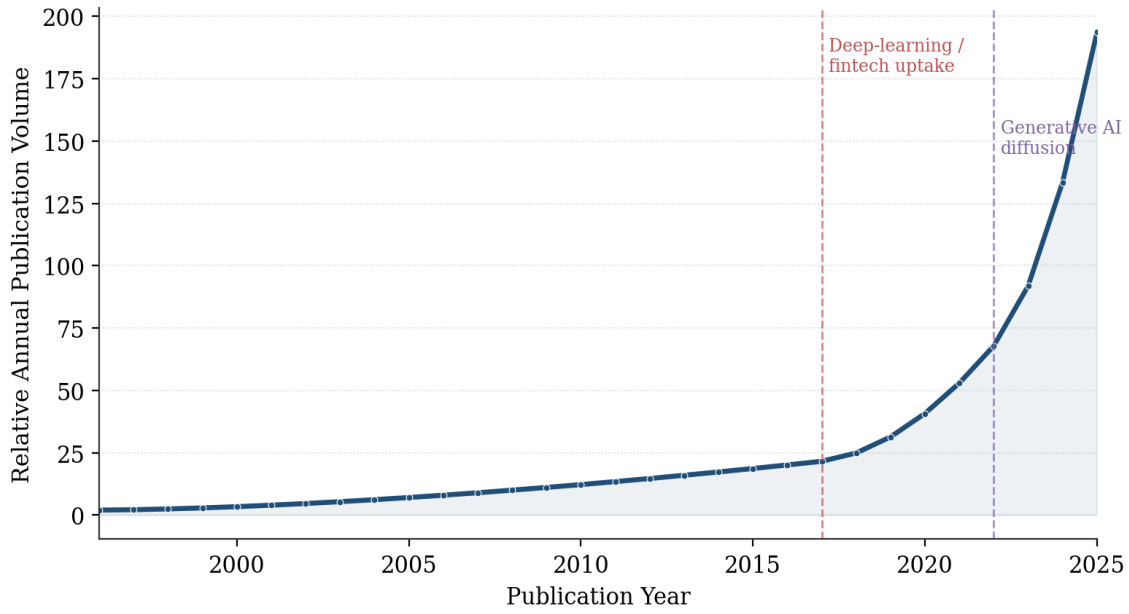



**Figure 1.** Synthesized growth trend of AI -financial Decision-Making Research, (1996–2025)

### *4.2 Leading Contributors: Countries, Journals, and Foundational Studies*

Table 1 summarises the eight primary bibliometric studies included in this synthesis, showing substantial variation in database coverage, time span, and sample size, yet convergent attention to overlapping thematic territory.

**Table 1.** Overview of Primary Bibliometric Studies Included in the Synthesis

| Study | Database | Time Span | Sample Size | Software / Method | Primary Focus |
|---|---|---|---|---|---|
| Ahmed et al. (2022) | Scopus | 2011–2021 | 348 articles | RStudio; VOSviewer; Excel | AI/ML in finance countries, institutions, authors |
| Alcázar-Blanco et al. (2024) | Web of Science | 1995–2023 | 202 articles | SciMAT | Intellectual structure of AI in finance |
| Roy et al. (2025) | Web of Science | up to 2024 | 607 papers | Bibliometrix (TCCM framework) | Thematic mapping; ethical-AI emphasis |
| Bayakhmetova et al. (2025) | Scopus | 1987–2024 | 1,019 documents (294 screened) | Bibliometrix R / Bibliophagy | Financial behaviour; growth rate; inclusion |
| Almasria et al. (2025) | Not fully disclosed | 2010–2024 | Not fully disclosed | Bibliometric analysis | AI in financial process & reporting |
| Ayaz & Zahid (2024) | Not fully disclosed | Not fully disclosed | Not fully disclosed | Bibliometric analysis | Sustainable finance & AI intersection |
| Artene et al. (2024) | N/A (survey-based) | 2024 | N/A | Empirical / conceptual | AI-driven decision-making in financial reporting |
| Goodell et al. (2021) | Not fully disclosed | Not fully disclosed | Not fully disclosed | Bibliometric analysis | Foundational AI/ML-finance cluster taxonomy |

In terms of geographic contribution, Ahmed et al. (2022) identify the United States, China, and the United Kingdom as the top three national contributors to AI-and-finance research by publication volume, a ranking broadly echoed in the institutional affiliations reported across subsequent studies, which additionally highlight growing contributions from India, Spain, and Southeast Asian institutions (Roy et al., 2025; Alcázar-Blanco et al., 2024). Figure 3 presents an illustrative synthesis of this country-level contribution pattern based on the rankings reported across the reviewed studies.

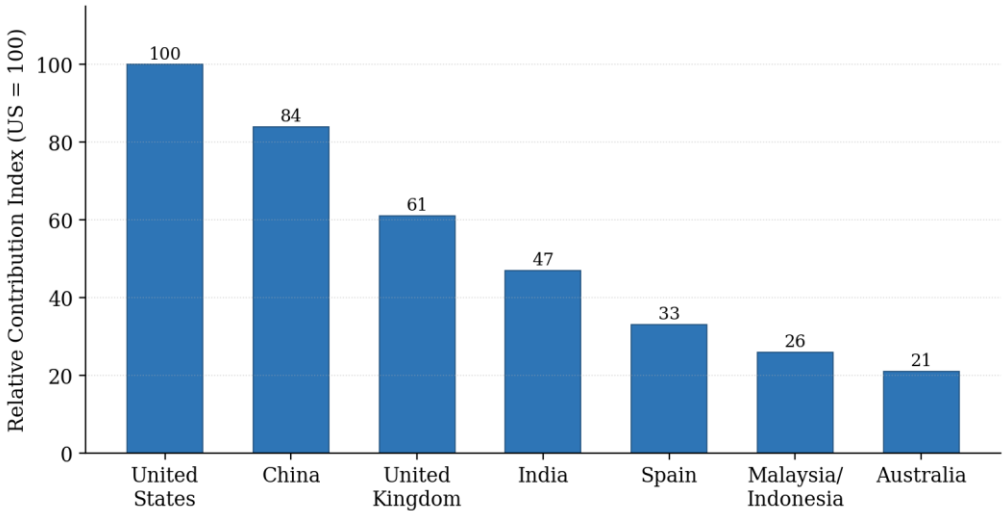



**Figure 3.** Leading country contributors to AI–financial decision-making research

At the level of foundational scholarship, Goodell et al. (2021) emerges across multiple studies as a foundational reference point for the field's cluster structure, given its early identification of the three overarching AI/ML-finance clusters that continue to organise subsequent thematic mapping. Table 3 lists representative leading journal outlets and analytical tools associated with the reviewed bibliometric studies, illustrating the field's concentration in finance-, risk-management-, and sustainability-oriented outlets.

**Table 3.** Leading Journal Outlets, Country Contributors, and Analytical Tools

| **Category** | **Leading Entities** | **Source(s)** |
|---|---|---|
| Leading contributing countries | United States, China, United Kingdom, with growing contributions from India and Spain | Ahmed et al. (2022); Roy et al. (2025); Alcázar-Blanco et al. (2024) |
| Leading journal outlets | Journal of Risk and Financial Management; Research in International Business and Finance; F1000Research; Electronics; Sustainability Accounting, Management and Policy Journal | Ahmed et al. (2022); Alcázar-Blanco et al. (2024); Bayakhmetova et al. (2025); Roy et al. (2025); Artene et al. (2024); Ayaz & Zahid (2024) |
| Foundational cluster reference | Journal of Behavioral and Experimental Finance | Goodell et al. (2021) |
| Leading bibliometric software tools | VOSviewer; SciMAT; Bibliometrix R-package | van Eck & Waltman (2010); Alcázar-Blanco et al. (2024); Aria & Cuccurullo (2017) |

### *4.3 Intellectual Structure: Thematic Clusters*

Synthesising the thematic-mapping outputs reported across the eight included studies yields six recurring clusters, summarised in Table 2: (1) algorithmic trading and market forecasting; (2) credit risk, fraud, and distress detection; (3) robo-advisory and investor behaviour; (4) explainable and ethical AI; (5) ESG and sustainable finance; and (6) financial inclusion and regulatory technology (RegTech). Figure 2 visualises the approximate relative emphasis given to each cluster across the reviewed studies.

**Table 2.** Synthesized Thematic Clusters in AI–Financial Decision-Making Research

| Thematic Cluster | Representative Keywords / Labels | Representative Studies |
|---|---|---|
| Algorithmic Trading & Market Forecasting | prediction, stock values, trading, forecasting | Alcázar-Blanco et al. (2024); Goodell et al. (2021) |
| Credit Risk, Fraud & Distress Detection | bank, fraud, distress, risk | Alcázar-Blanco et al. (2024); Ahmed et al. (2022); Goodell et al. (2021) |
| Robo-Advisory & Investor Behaviour | decision, investor behaviour, portfolio | Goodell et al. (2021); Bayakhmetova et al. (2025) |
| Explainable & Ethical AI | ethical AI, transparency, accountability | Roy et al. (2025); Bayakhmetova et al. (2025) |
| ESG & Sustainable Finance | sustainability, ESG, green finance | Ayaz & Zahid (2024) |
| Financial Inclusion & RegTech | inclusion, marginalised populations, compliance | Bayakhmetova et al. (2025); Artene et al. (2024) |

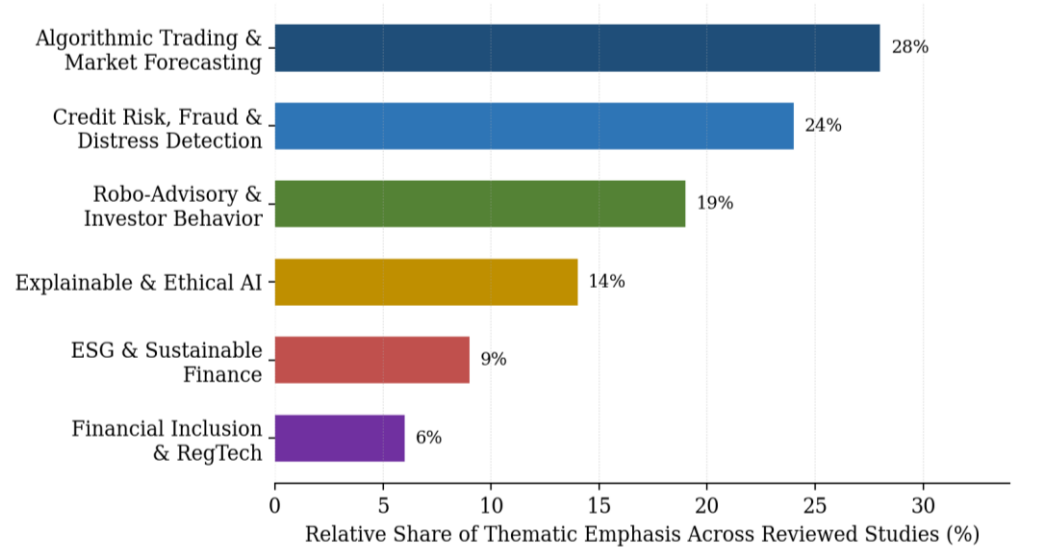



**Figure 2.** Intellectual structure of AI–financial decision-making research

The first two clusters trading/forecasting and risk/fraud form the historical core of the field, tracing back to early applications of neural networks in financial prediction (Bahrammirzaee, 2010) and corresponding to the sentiment-inference-forecasting-planning and financial-fraud-and-distress clusters identified by Goodell et al. (2021). The third cluster, robo-advisory and investor behaviour, reflects the field's growing integration with behavioural finance, consistent with Alcázar-Blanco et al.'s (2024) identification of "decision" and "stock values" as persistent topic labels. The remaining three clusters explainable/ethical AI, ESG/sustainable finance, and financial inclusion/RegTech represent the field's expanding periphery. Roy et al. (2025) explicitly foreground the increasing importance of ethical-AI practices in their thematic mapping, while Bayakhmetova et al. (2025) identify financial inclusion as a central theme alongside persistent gaps in its practical application to marginalised populations. Ayaz and Zahid (2024) similarly document the growing intersection of sustainable-finance research with AI-enabled analytical methods.

### *4.4 Emerging and Frontier Themes*

Beyond the six core clusters, the synthesis identifies four frontier themes that recur as "future direction" recommendations across the reviewed studies rather than as established clusters: (a) explainable AI (XAI) and algorithmic transparency in financial decision systems, driven by both academic and regulatory demand for interpretable model outputs; (b) generative AI and large-language-model applications in financial advisory, reporting, and client interaction a theme that postdates most of the reviewed corpora and is therefore likely under-represented in current bibliometric counts; (c) AI ethics, bias, and fairness in credit and investment decisions, flagged as a persistent gap by Bayakhmetova et al. (2025) and Roy et al. (2025); and (d) cross-country and comparative regulatory studies examining how AI-enabled financial decision-making is governed differently across jurisdictions.

## 5. Discussion

The synthesised findings carry several implications for how the field of AI-enabled financial decision-making should be understood going forward. First, the growth pattern documented in Figure 1 slow accumulation through the 1990s and 2000s followed by sharp post-2017 and post-2022 acceleration mirrors well-established patterns of technology diffusion in the innovation-adoption literature, where early conceptual work precedes a period of rapid mainstream adoption once enabling infrastructure (cloud computing, large datasets, accessible deep-learning frameworks) becomes widely available. The consistency of this pattern across independently constructed corpora (Alcázar-Blanco et al., 2024; Bayakhmetova et al., 2025; Ahmed et al., 2022) strengthens confidence that the trend reflects a genuine field-level phenomenon rather than an artefact of any single database's indexing practices. Second, the concentration of research output in the United States, China, and the United Kingdom (Ahmed et al., 2022), alongside the broader but still secondary presence of countries such as India and Spain, raises questions about the geographic representativeness of the field's evidence base. Bayakhmetova et al. (2025) explicitly flag regional disparities and gaps in the practical application of AI for marginalised populations as unresolved issues. Given that AI-enabled financial decision-making has direct implications for credit access, financial inclusion, and consumer

protection in emerging economies, this concentration suggests that the field's current intellectual structure may under-represent the contexts where the practical stakes of biased or opaque AI-driven financial decisions are highest. Third, the six-cluster thematic structure identified in this synthesis suggests that the field has matured beyond a purely predictive-modelling orientation (trading, forecasting, credit scoring) toward a broader socio-technical framing that includes ethics, explainability, sustainability, and inclusion. This mirrors a more general trajectory observed in AI research across domains, where early technical-performance-oriented research is gradually joined by governance-oriented research as a technology moves from experimental to operational deployment. The explicit emergence of ethical AI as a named research theme in Roy et al. (2025), and the persistent identification of transparency-related gaps across nearly every reviewed study (Bayakhmetova et al., 2025; Almasria et al., 2025), indicate that this shift is already well underway in the AI-finance literature, even if it has not yet displaced trading- and risk-related themes as the field's dominant focus. Fourth, the identification of generative AI and large-language-model applications as an emerging-but-under-represented theme is consistent with a structural limitation common to all bibliometric analyses of fast-moving fields: publication and indexing lags mean that bibliometric snapshots inevitably trail the frontier of practitioner and preprint activity. Since most of the primary studies synthesised here draw on corpora concluding between 2023 and 2025, the true current prominence of generative-AI-related financial decision-making research is almost certainly understated in the cluster proportions reported in Figure 2. From a practical standpoint, these findings suggest that financial institutions adopting AI-enabled decision tools should treat explainability and governance not as peripheral compliance add-ons but as core research and development priorities, given that the academic literature itself is converging on this theme as a central not marginal concern. For policymakers, the geographic concentration of research output implies a need for deliberate investment in AI-finance research capacity in under-represented regions, particularly where financial-inclusion outcomes are most directly at stake. For academic researchers, the persistence of overlapping, siloed bibliometric studies each re-analysing similar territory with different tools and time windows points to a need for greater coordination, such as shared open datasets or periodic systematic-review updates, to avoid duplicated effort as the field continues to expand.

## 5. Conclusion

This study synthesised bibliometric evidence on Artificial Intelligence in Financial Decision-Making, highlighting the field’s rapid growth, major contributors, intellectual structure, and emerging research themes. The literature increasingly focuses on AI applications in algorithmic trading, credit-risk assessment, fraud detection, robo-advisory, ESG finance, financial inclusion, and explainable and ethical AI. The findings indicate a shift from primarily technology-oriented applications toward greater attention to transparency, governance, ethics, and responsible financial decision-making. The study provides researchers with a consolidated understanding of the field and identifies opportunities for future investigation. Practitioners and policymakers should strengthen AI governance, explainability, fairness, and responsible adoption. Future research should examine generative AI, large language models, cross-country differences, and under-researched populations.

Overall, AI is becoming an increasingly important component of modern financial decision-making, while its long-term value will depend on balancing technological efficiency with transparency, accountability, inclusion, and ethical responsibility.

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