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Human–AI Collaboration in Financial Decision-Making: A Comprehensive Bibliometric Analysis (2015–2025)

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Abstract
Human-AI collaboration has led to transformative innovations in financial decision-making in areas like investment analysis, fraud detection, financial literacy, cognitive assessment and behavioural finance, and remarkable growth has been witnessed. However, there is insufficient evidence of an accompanying robust bibliometric record unifying co-authorship patterns, country collaborations, evolutions of keywords, and changes of fields. The methodology taken by the study is bibliometric, based on data sourced from the Dimensions database, from 2015 to 2025, and by utilising visualisation tools, to delineate intellectual domains and forge new thematic groups, and facilitate academic collaborations, such as VOSviewer software. The study focuses on 7,742 articles in the commerce and management disciplines, with an additional 5,165 for information systems research, and 2681 for economics literature. The United States, China and Europe in general present evidence of strong governance of published articles and collaborative relationships. Furthermore, keywords also indicate clusters of convergences of cognitive decline with manipulation through technology in economics and progress of AI-based applications, as enhanced diagnostic accuracy in the analysis of financial strategies, paving pathways for interdisciplinary collaborations and to guide cross-disciplinary expertise. Research indicates opportunities such as continued investigation of the ethical implications of artificial intelligence in finance, additional development of models of hybrid intelligence that incorporate multiple forms of cognition in decision-making, and ways to translate complex data in finance so artificial intelligence can make sense of it. The paper proposes possibilities for future research related to the broad area of ethical AI in finance, hybrid intelligence models, and AI explainability in finance.

Keywords: Human–AI collaboration, financial decision-making, bibliometric analysis, behavioural finance, Dimensions database, and VOSviewer software.

1. Introduction
The integration of Artificial Intelligence (AI) into financial decisions has revolutionised analytical, behavioural, and operational frameworks within financial systems around the world. From algorithmic trading (Al-Mansour, 2020) to Robo-advisory services (Jung et al., 2018), from credit scoring (Khandani et al., 2010) to individualised financial planning (Sironi, 2016), the financial industry is rapidly moving towards hybrid human–AI systems. In recent years, there has been a greater focus on AI's potential to augment human judgment rather than to supplant it (Shrestha et al., 2019). Decision-making in finance, other than being aligned with uncertainty and cognitive biases, is tuned to context through risk tolerance differences and bounded rationality. Therefore, AI's use to support and augment human intelligence and judgment in hybrid intelligence is valuable in the future. This area of study has received much greater attention in the last ten years. However, literature is dispersed among behavioural finance, medical cognition, AI diagnostics, psychology, economics, and computer science. A complete bibliometric review is needed to integrate these various knowledge traditions and understand their developing structures.

This study analyses publications from Dimensions (2015–2025), focusing on:
- Human–AI collaboration
- Hybrid intelligence
- Financial decision-making
- Cognitive impairment in financial tasks
- AI-assisted diagnostic accuracy

The visual bibliometric maps provided (co-authorship, country collaboration, research categories, keyword clusters) support a detailed meta-level evaluation of the global research landscape.

2. Literature Review

2.1 Human–AI Collaboration: Conceptual Foundations and Hybrid Intelligence

The concepts of human–AI collaboration have moved from being focused on automation towards a perspective that promotes augmentation and hybrid intelligence, and where humans and AI operate collaboratively on cognitive tasks (Shrestha et al., 2019; Dellermann et al., 2019). In earlier viewpoints, Brynjolfsson and McAfee (2017) suggested that AI would take over analytical roles that involve routine decision-making and analysis. However, newer research suggests that hybrid machine-human teams led to better decision-making outcomes than either type of agent worked alone in uncertain environments (Jarrahi, 2018; Wilson & Daugherty, 2018). Jarrahi (2018) highlighted that, while AI can support human decision-making skills in complex digital decision environments, humans offer contextualisation and ethical judgement.

The research areas of finance extensively utilise hybrid intelligence models that include the benefits of human intuition and creativity, social understanding, and their computational efficiency (Dellermann et al., 2021; Topol, 2019; Winkelhaus & Grosse, 2020; Raisch & Krakowski, 2021). These studies argue that in situations of uncertainty, ethical issues, and complex trade-offs, humans remain collaborators with AI tools.

2.2 AI in Financial Decision-Making: Applications and Technological Developments

Due to the adoption of AI in the field of finance, the financial decision-making process has changed drastically. Use of Machine learning techniques has enhanced performance in various domains of finance, such as credit risk assessment (Khandani et al., 2010; Moscato et al., 2021), market forecasting (Marioni, 2021), portfolio optimisation (Moghar & Hamiche, (2020), and fraud detection (Ngai et al., 2011). Nowadays, Deep learning algorithms are frequently used for high-frequency trading pattern identification, to spot price anomalies, and help in risk analysis in blockchain transactions (Henrique et al., 2019).

2.3 Behavioural Finance and Cognitive Biases in Decision-Making

Research in behavioural finance has demonstrated that financial decisions are more driven by heuristics, emotions, and biases than rational thought (Tversky & Kahneman, 1974; Galli, 2011). The most common biases which influence investors' investment decisions include overconfidence, anchoring, mental accounting and herding (Barber & Odean, 2001; Furnham & Boo, 2011; Thaler, 1999; Bikhchandani et al., 1992). As per the Neurofinance literature, an investor's propensity to take risks is heavily influenced by neural networks, an individual’s emotional response, and their personality traits (Kuhnen & Knutson, 2005). Recently, several studies have also explored psychological factors of financial decision-making such as stress, impulsiveness, and emotional states (Loewenstein et al., 2001; Pompian, 2011).

AI can help in mitigating the above-illustrated irrationality and bias in decision-making by co-creating rules of engagement for advisory service platforms Galli2015; Sanders et al., 2018). Algorithms that identify large data sets are able to detect behavioural predispositions and disrupt patterns of behaviour based on irrational stimulus, showcasing the necessity of the AI-human interplay in behavioural finance.

2.4 Cognitive Impairment, Decision Vulnerability, and AI Diagnostic Integration

A significant interdisciplinary advance is the merging of neuropsychology with financial decision research. An important interdisciplinary shift is that neuropsychology is starting to merge with the research on financial decision making. Cognitive decline due to age affects some judgment, risk perception, and financial capacity (Marson, 2013; Agarwal et al., 2009). For example, Boyle et al. (2012) found that declines in executive functions increased temporal discounting and vulnerability to exploitation, while Lichtenberg (2016) found that fraud prevalence has increased among adults with cognitive vulnerabilities. Another area of progress are the ways in which diagnoses using artificial intelligence (AI)—for example, MRI-based diagnosis of Alzheimer's disease (Moradi et al., 2015), models for prediction of cognitive impairment (Esteva et al., 2017), deep learning and detection of neurodegenerative signals (Goenka & Tiwari, 2021). —now offer new forms of tools to assess decision-making capacity. In addition, studies indicate that some digital biomarkers can predict the earliest stages of cognitive decline, which will allow for the types of proactive interventions to be conducted to preserve financial safety (Kourtis et al., 2019). These intersections help to explain the observations of considerable cluster fusion in the bibliometric analysis of cognitive impairment and ageing, behavioural vulnerability, and financial decision making.

2.5 Global Trends in AI–Finance Research and International Collaboration

Research on science metrics indicates that both the United States and China are the top countries in terms of contributions to AI research across a range of disciplines (Zgurovsky, 2025). Europe is also an important contributor to AI, particularly when it comes to ethical AI applications and ethics frameworks, for the finance industry and beyond (Floridi & Cowls, 2022). As well, countries like India, Singapore, Japan, and South Korea are becoming emerging actors in fintech and retail banking in AI across Asia, due to the rapid digital transformation trend and business-friendly regulations (Das et al., 2025; Gai et al., 2018).

Partial to India's digital infrastructure efforts—from UPI and Aadhar-enabled payments to the expanded digital payments systems from India Stack—have set the foundation for future research on financial inclusion, digital literacy, and AI-based risk analytics (Sahay et al., 2020). In some way, this commencement positions India as an emerging actor in an international bibliometric collaborative space.

2.6 Ethical, Regulatory, and Explainability Challenges in Financial AI

As the influence of artificial intelligence grows in large financial decisions, issues around transparency, responsibility, bias, and data privacy become more relevant. Explainable A.I. (X.A.I.) helps to develop trust in the outputs of algorithms, especially in the areas of financial advice and lending decisions (Guidotti et al., 2018; Ribeiro et al., 2016). Regulators emphasise a coordinated ethical approach to the adoption of AI, particularly with respect to the EU's GDPR and the prospective EU AI Act (Floridi, 2021). Algorithmic bias can negatively impact vulnerable populations and worsen disparities with regard to access to credit and evaluation of risk (O'Neil, 2016). Researchers call for human oversight, algorithm audits, and the use of more interpretable ML for automated decision making (Ivanov, 2023; Dwivedi et al., 2021).

Despite the increased interest in this type of research, several important gaps still exist, such as: limited bibliometric mapping connecting elements of finance, AI, psychology, and cognitive neuroscience; limited exploration of hybrid human-AI decision making systems in developing countries; inadequate attention to cross-cultural differences in AI augmentation and trust; under exploration of XAI in financial advising and evaluation of risk; and a lack of evidence of use of AI/advisory decision support models in Human-AI collaborations. This research attempts to fill these gaps through an extensive interdisciplinary bibliometric review that covers AI, financial decision-making, behavioural sciences, and neurocognitive studies.

3. Methodology

3.1 Data Source

The dataset was collected from **Dimensions.ai** using the search string:
"Human–AI collaboration" OR "hybrid intelligence" OR "financial decision-making"
Publication type: Article
Journal List: PubMed, UGC Group I/II
Publication years: **2015–2025**
The final dataset included:

- **7,742** publications in Commerce, Management & Tourism
- **5,165** in Information & Computing Sciences
- **2,681** in Economics
- **1,649** in Psychology
- **1,459** in Human Society

(and related categories)

3.2 Tools Used

- **VOSviewer** for network mapping (co-authorship, keywords, authors, countries)
- **Dimensions database** for metadata extraction
- **Microsoft Excel & Python** for pre-processing

3.3 Inclusion/Exclusion Criteria

- Peer-reviewed journal articles
- Full metadata available
- Publications focused on AI, hybrid intelligence, decision-making, financial behaviours, cognitive function, behavioural biases, or machine learning applications

4. Results

4.1 Co-authorship Network Analysis

The co-authorship network shows multiple interconnected clusters, with **Han, S. Duke**, **Boyle, Patricia A.**, **Lichtenberg, Peter A.**, **Bennett, David A.**, and **Boyle, Patricia** serving as high-density nodes (refer to Figure 1). These authors are mostly associated with research on:

- cognitive impairment
- financial exploitation
- decision capacity
- dementia-related financial behaviour

This indicates a strong interdisciplinary bridge between **neuroscience, psychology, and financial decision-making**.
Such works include:

- Boyle et al. (2012) “Poor decision making is a consequence of cognitive decline”
- Wood & Lichtenberg, (2017) “Fraud susceptibility in older adults”

This suggests that **financial decision-making research is not solely economic or behavioural, but increasingly medical and cognitive**.

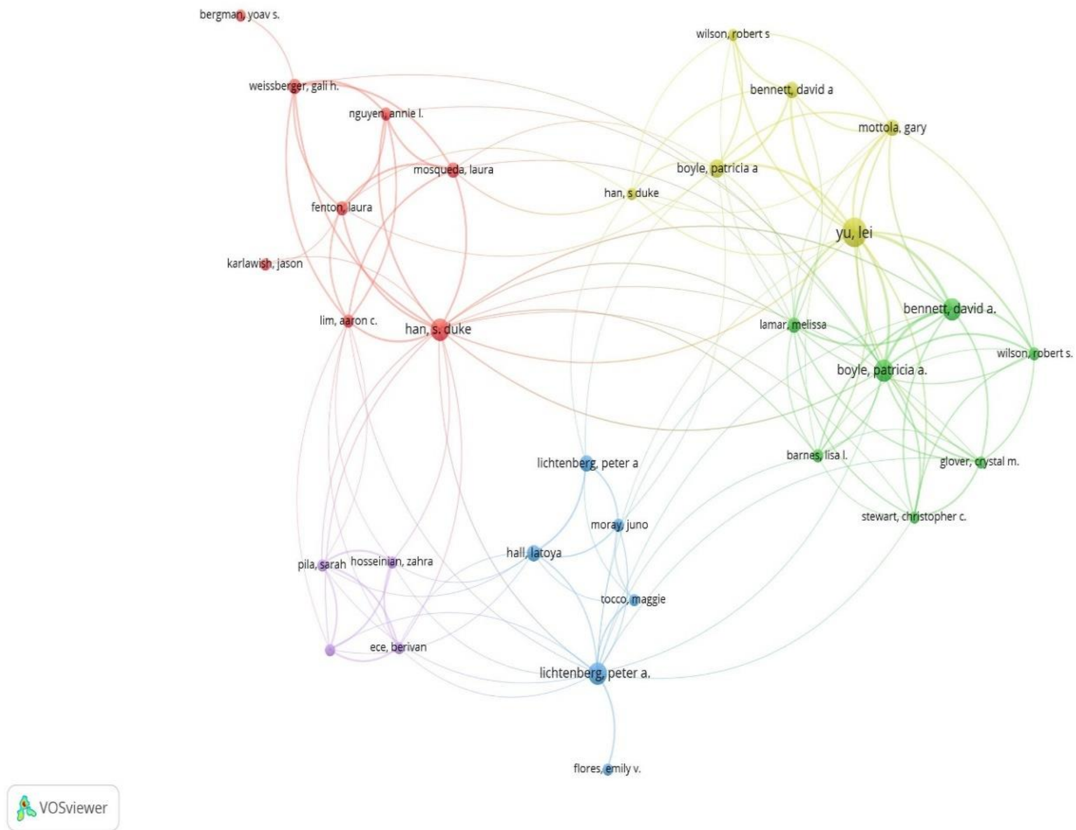

Figure 1: Co-authorship Network Analysis (sources: generated by VOSviewer)

4.2 Country Collaboration Network

The United States is the largest contributor with extensive global links. China, Germany, the Netherlands, Australia, and Japan are forming strong secondary hubs, and India, South Korea, Malaysia, and Saudi Arabia are emerging as growth regions. The dominance of the U.S. and China aligns with previous bibliometric findings that these nations lead in AI research (Zgurovsky, 2025; Dwivedi et al., 2021) (refer to Figure 2). India's growing node reflects expanding interest in AI in fintech, supported by national initiatives such as:

- **AI for All (NITI Aayog)**
- **Digital India Programme**
- **Unified Payments Interface (UPI) & Aadhaar-linked digital finance**

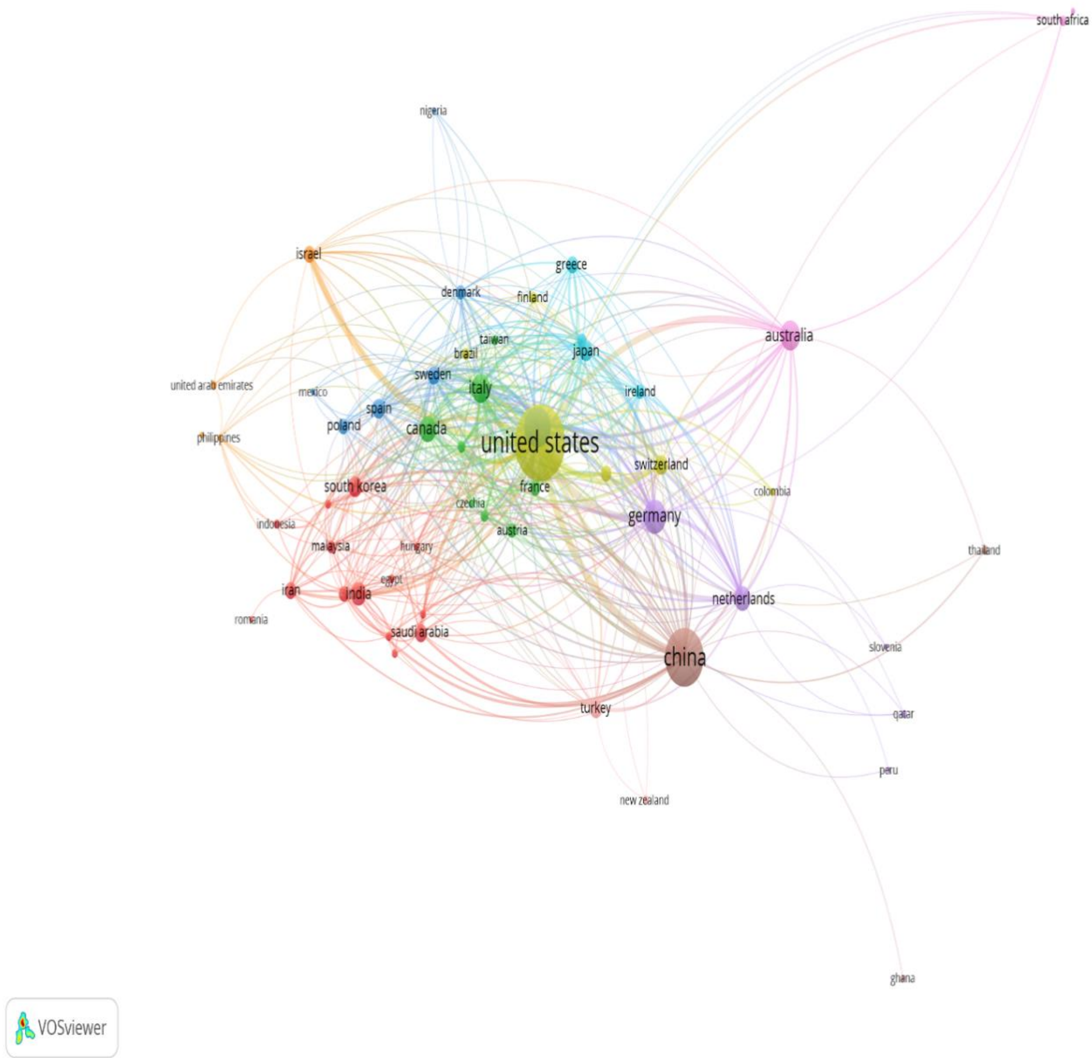

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Figure 2: Country Collaboration Network (sources: generated by VOSviewer)

4.3 Keyword Co-occurrence Network

Five major clusters were identified.

Cluster 1 (Green): Behavioural Finance & Literacy

- *financial literacy, investment decision, decision-making, investor, loss aversion, personality trait*

This aligns with literature exploring behavioural biases such as anchoring, herding, and overconfidence (Barberis, 2018).

Cluster 2 (Blue): Cognitive Impairment & Financial Exploitation

- *dementia, memory, depression, cognitive impairment, financial exploitation, ageing*

This unexpected but powerful connection shows that **decision-making research overlaps with medical cognition studies**.

Cluster 3 (Red): AI, Machine Learning & Diagnostics

- *deep learning, diagnostic accuracy, random forest, ethical considerations*

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These terms indicate a rapid shift toward **AI-driven medical diagnostics** that could influence financial capacity assessments.

Cluster 4 (Purple & Yellow): Demographics and Social Factors

- *age, adult, older adult, woman, poverty, empowerment*

Therefore, from the above analysis, the key highlights are that Human–AI collaboration research in financial decision-making is **highly interdisciplinary**, integrating behavioural finance, machine learning, psychology, and biomedical sciences (refer to Figure 3).

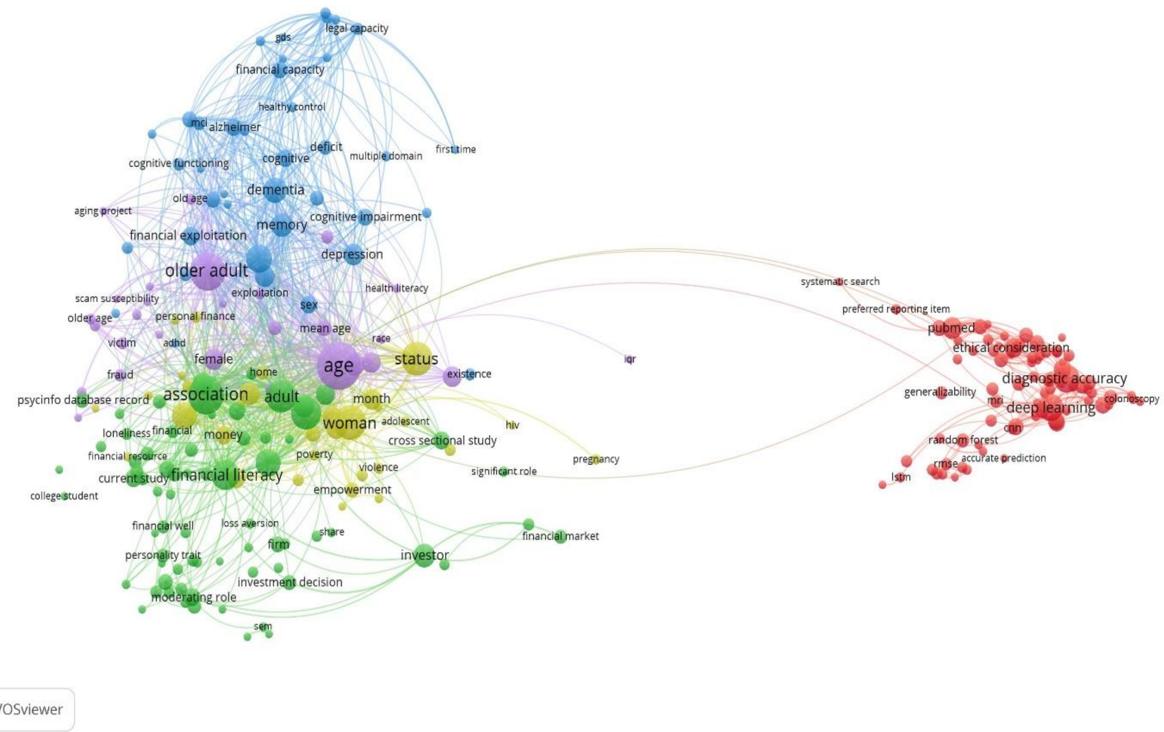

Figure 3: Keyword Co-occurrence Network (sources: generated by VOSviewer)

4.4 Research Category Publication Volume

Publication distribution:

Category	Publications
Commerce & Management	7,742
Information & Computing Sciences	5,165
Engineering	2,700
Economics	2,681
Psychology	1,649
Human Society	1,459
Biomedical Sciences	1,218

This confirms that **AI–finance decision-making research is not dominated by economics**, but distributed across multiple disciplines (refer to Figure 4).

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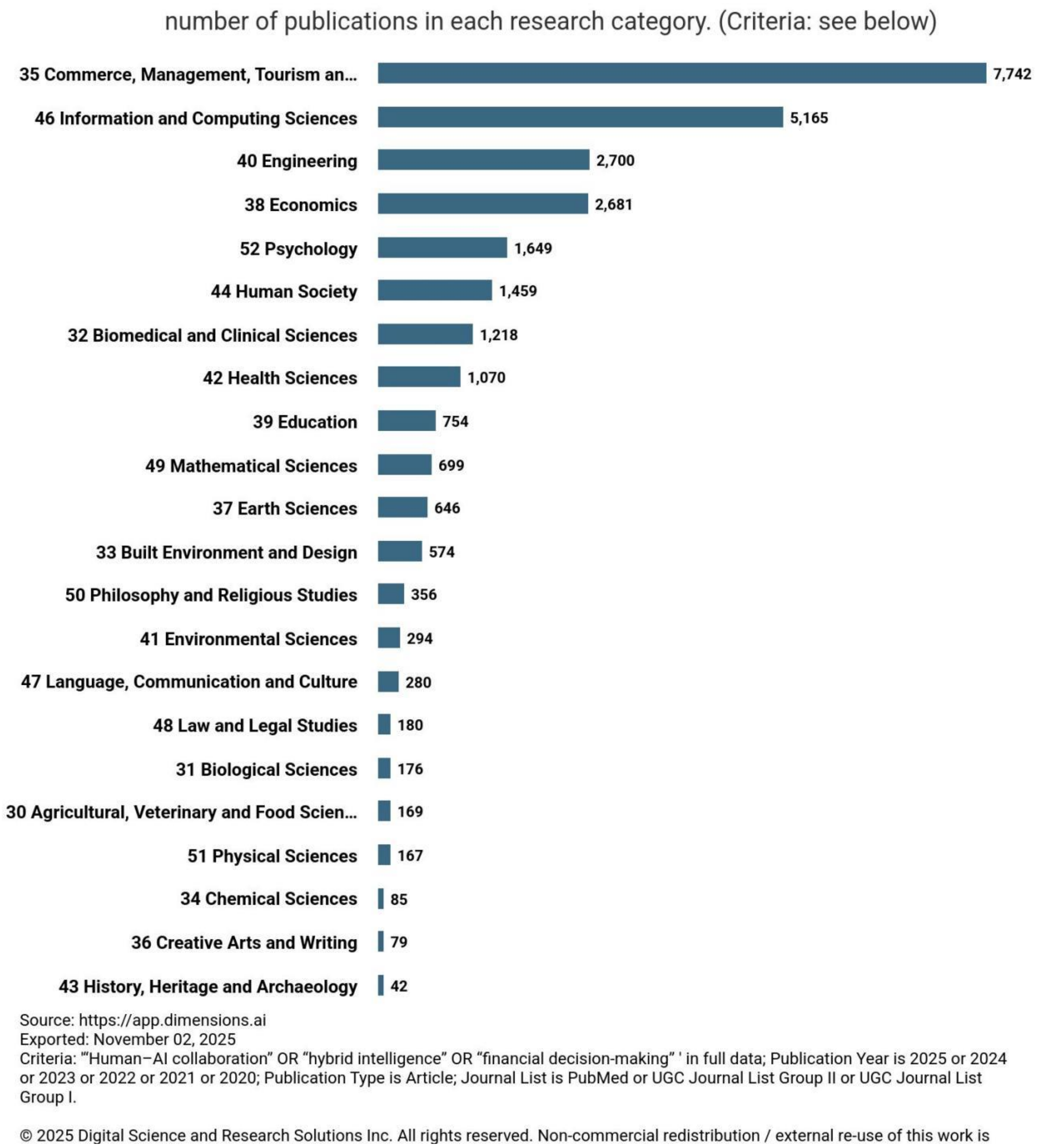

Figure 4: Research Publication in each Category (generated by Dimension.ai database)

4.5 Author Collaboration Networks (Advanced map)

This network highlights emerging authors in **hybrid intelligence, deep learning, computational modelling**, and **AI applications in finance (**refer to Figure 5)

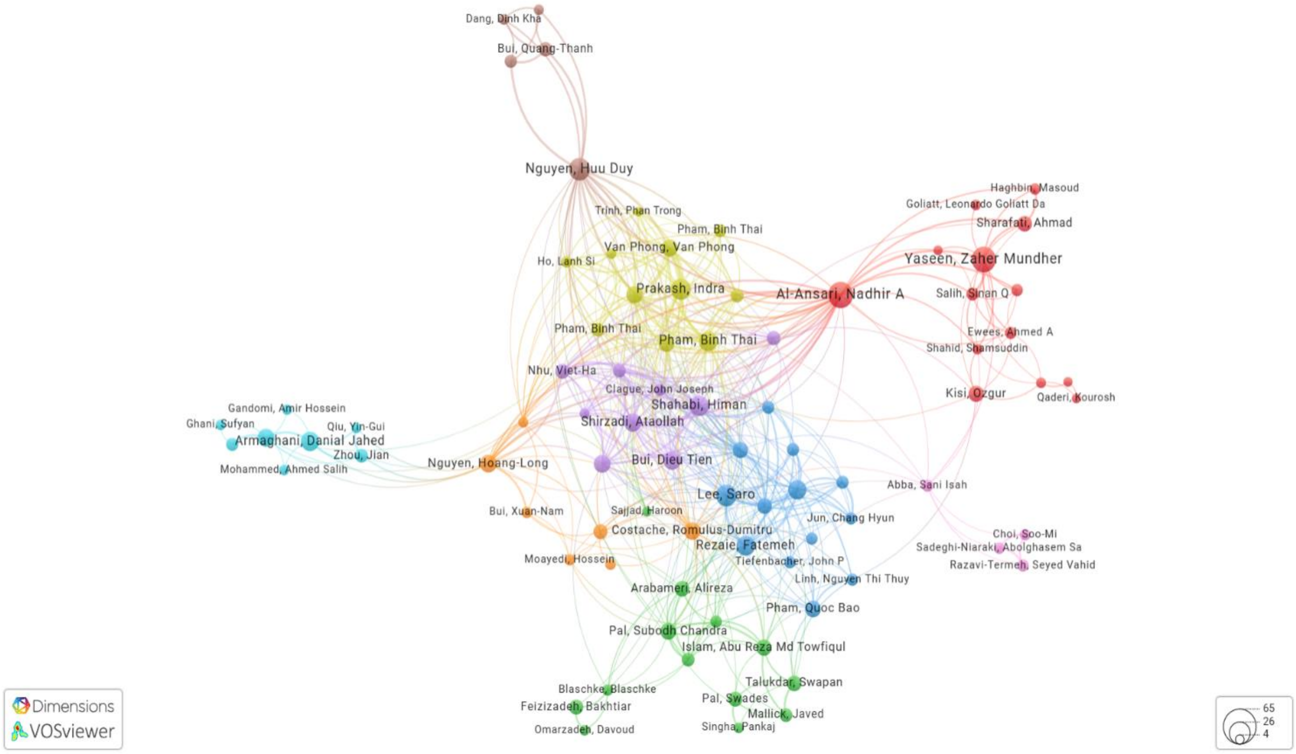

Figure 5: Author Collaboration Networks (Advanced map) (sources: generated by VOSviewer)

The major clusters represent collaborations in:

- **machine learning algorithm improvement**
- **computational modelling of decision behaviour**
- **AI-driven risk assessment**
- **hybrid human–AI modelling**

4. Discussion

4.1 Interdisciplinary Expansion of the Field: The bibliometric mapping indicates that the area of research on Human–AI collaboration in financial decision-making has developed into an emerging interdisciplinary topic that integrates finance, behavioural science, cognitive neuroscience, and artificial intelligence. The co-author network (Figure 1) shows dense clusters that centre around researchers such as Duke Han, Patricia Boyle, and David Bennett, who study cognitive ageing, financial capacity, and neuropsychological vulnerability (Boyle et al., 2012; Lichtenberg et al., 2015). The centrality of these authors suggests that financial decision-making research is further integrating medical and/or neurocognitive perspectives beyond just behavioural finance. The co-occurrence mapping diagram of keywords (Figure 3) provides additional evidence to support a shift towards an interdisciplinary approach. It suggests that fields of study such as financial literacy, investment behaviour, and risk perception relate to terms which include dementia, memory, cognitive impairment and ageing. This indicates an emerging awareness that financial decisions are not solely based on an economic rationalist and/or behavioural bias (Barberis, 2018), but are also grounded in cognitive health, mental capacity, and fraud risk, particularly in an ageing population. Parallel to this is an increase in

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terms associated with machine learning, particularly, deep learning, diagnostic accuracy, and random forest. This provides further evidence of concurrent accumulation of knowledge in AI-based diagnosis, Algorithmic Modelling, and Automated Decision Support Systems. This trajectory of knowledge accumulation over time precedes longer temporal trajectories of technology that enable the propulsion of AI-informed practices in finance, and, in practice, has been about improving the accuracy of decisions, reducing outliers, and automating investment functions (Khandani et al., 2010; Al-Mansour, 2020).
Ultimately, these observations demonstrate and relate evaluative patterns of dual transformation evident in the field, a culmination of both technology disruption and human-centred vulnerabilities.

4.2 Global Research Leadership and Emerging Regions:
The country collaboration network (Figure 2) clearly shows that the United States and China are the dominant players, which fits in line with the global patterns evident in AI research (Zgurovsky, 2025; Dwivedi et al., 2021). Their leadership is a combination of significant national investment, advanced digital ecosystems and existing, mature AI research communities. Additionally, closer collaboration is apparent within European countries like both Germany and the Netherlands.
Developing regions such as India, Malaysia, Saudi Arabia, and South Korea shape emerging clusters. India's rise in particular has been facilitated by programs such as Digital India, Aadhaar, UPI-based fintech innovations, and various national AI initiatives, such as "AI for All". These developments explain India's increasing contributions to fintech, behavioral finance, AI-based credit scoring, and digital payments. Yet, many emerging markets have limited research into ethical AI, explainable AI (XAI), and hybrid intelligence models to consider their socio-cultural values and norms.

4.3 Emerging Themes in Human–AI Research: The analysis identifies four emerging themes related to emerging economies:
(a) Hybrid intelligence models: An increasing number of studies point to the combined use of human judgment and AI predictive tools to enhance accuracy, mitigate bias, and improve financial planning (Shrestha et al.,2019). These models aim to retain human judgment while leveraging AI's analytic capacities.
(b) Cognitive decline, susceptibility, and decision-making: More research is directed at understanding the effects of cognitive decline, also related to ageing, on an individual's financial ability/competency, susceptibility to financial risk-taking or financial exploitation, and decision-making (Boyle et al.,2012; Lichtenberg, 2016). This is likely another reason for the apparent weighting of psychologists in the co-author network.
(c) AI Diagnostic Accuracy and Predictive Modelling: There is an increasing reliance on machine learning approaches (i.e., deep learning and ensemble models) to analyse financial behaviours, detect fraud, and forecast the risks of financial product use for consumers (Khandani et al., 2010). The presence of technical terms provides further evidence of rising interest in related modelling and automated systems.
(d) Behavioural Finance and Investors' Thoughts: Traditional behavioural biases such as loss aversion, overconfidence, or anchoring are still influential areas of inquiry (Barberis, 2018). AI-driven decision tools are frequently incorporated to mitigate bias and increase investor decision outcomes.
4.4 Research Gaps and Future Directions: Even though there has been considerable advancement, several gaps still exist: Explainable AI (XAI) has not received widespread

attention, and transparency is a major requirement for regulatory acceptance in finance. Despite countries having quite different experiences with digital adoption and differing financial cultures, there is not much research that compares national perspectives. Although ethical issues, such as model bias and related issues of fairness and data privacy, require further research. Human readiness—laser perhaps AI literacy, trust in automation, etc.—is underdeveloped in many economies. Hybrid human–AI frameworks, articulating where the accuracy of AI meets human intuition, remain poorly articulated and require further testing in real applications. Each gap presents an opportunity for future research. In particular, in regard to contextualising AI/machine learning for finance solution designs and developing them to accommodate differing cultural ease, ethics and behaviour adaptability.

5. Conclusion

This bibliometric review gives an extensive insight into worldwide scholarly trends in human–AI collaboration in financial decision-making between 2015 and 2025. The results show an expanding and interdisciplinary field more quickly than others, which brings together behavioural finance, cognitive psychology, machine learning, and decision science. The prominence of the United States and China, in addition to developing countries like India, indicates the global relevance of AI-driven innovations in the field of finance. Co-authorship and keyword networks shed light on two primary intellectual streams, whereby scholars assess human vulnerabilities, cognitive degradation, and behavioural biases (e.g., Boyle et al., 2012; Wood & Lichtenberg, 2017), while the other focuses on AI-diagnostics, predictive analytics, and algorithmic efficiency (e.g. Khandani et al., 2010; Al-Mansour, 2020). This bifurcation indicates that future financial decision-making will not be solely dependent on technology, but will also be predicated on the manner in which humans will engage with, depend on and evaluate the insight of AI. As AI tools are widely adopted in financial planning, investment, and risk management, it becomes essential to consider ethical issues like transparency, fairness, and accountability (Dwivedi et al., 2021). Hybrid models that integrate human intuition with algorithmic accuracy offer a promising approach, delivering quick decision solutions that are both data-driven and context-aware. Thus, the present research maps key themes, identifies major scholarly groups and highlights new research directions. Future research should concentrate on cross-cultural comparisons, explainable AI, and empirical evaluations of human-AI decision systems. These initiatives will contribute to ensuring that AI in financial decision-making develops ethically, inclusively, and with a deeper understanding of human behaviour.

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