

Artificial Intelligence and Machine Learning in Financial Services: A Systematic Literature Review based on the TCCM framework

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ABSTRACT

Purpose: *The literature on Artificial Intelligence (AI) and Machine Learning (ML) in financial services remains dispersed across finance, computer science, management, and law, with no single study integrating these strands. This paper performs a systematic review to consolidate this knowledge and propose further areas of research.*

Design/methodology/approach: *This study applies the Theory, Context, Characteristics and Methods (TCCM) framework (Paul and Rosado-Serrano, 2019) to synthesise the literature. Scopus served as the sole database; an initial pool of 550 records was reduced to a final sample of 37 papers through successive rounds of subject, document-type, language, and relevance screening.*

Findings: *The reviewed literature consists predominantly of publications in high-quality journals, with almost three-quarters in Q1/Q2 outlets across finance, economics, management, and law, confirming its multi-disciplinary nature. The geographic focus is mostly multi-country and developed-market, reflecting where digital financial infrastructure is most advanced. The underlying theories are almost entirely long-standing frameworks such as EMH and UTAUT rather than AI-native theories, indicating that AI/ML is more often used to re-examine existing theories than to generate new ones.*

Practical implication: *The results give researchers an aggregated map of theoretical, contextual, and methodological gaps, and offer financial institutions and regulators a guide to where AI/ML deployment and research is concentrated.*

Originality/value: *This is the first paper to apply the TCCM approach to systematise the scattered literature on AI/ML-based solutions in financial services.*

Keywords: Artificial intelligence; Machine learning; Deep learning; Financial services

1. Introduction

Artificial intelligence (AI) and Machine Learning (ML) have developed as some of the most transformative technologies, reshaping industries such as healthcare, manufacturing, transportation and communication (Bresnahan and Trajtenberg, 1995). The field of financial services is one such area where this change has been felt strongly. There has been a rapid increase in the applications of AI in recent years due to its ability to process vast amounts of information, detect patterns that the human eye cannot recognise, and continually improve through learning, making it a true game-changer in ways far beyond just computer science.

The adoption of AI/ ML in financial services spans the financial services sector, ranging from banking, insurance, asset management, trading and regulatory compliance and spans across both developed and developing markets worldwide.

Although there is exponential growth in this sector, the literature surrounding AI/ML in financial services remains fragmented, spanning across various disciplines like finance, computer science and management studies, without one study attempting to provide an overarching summary of the connections between all these threads. It is important for both researchers who aim to further explore these issues and practitioners in an increasingly AI-focused industry to understand the theories, contexts, characteristics, and methods that build this body of research.

By conducting an SLR on AI/ML in financial services, this paper serves several audiences at once: researchers looking to pinpoint where the literature still falls short, financial institutions assessing their own AI strategies, and regulators grappling with the implications of AI-driven decision-making in markets

To carry out such a scrutiny and analysis of the literature systematically, this study draws on the Theory, Characteristics, Context and Methods (TCCM) framework, developed by Paul and Rosado-Serrano (2019), which is well suited to producing a rounded, structured picture of a fragmented literature. Using this framework ensures that a comprehensive overview of the literature is achieved (Dewasiri et al., 2026; Singh, 2023). The literature review as a research method has been widely used in the past to untangle the intellectual development in the particular domain (Ganti & Singhania, 2025; Sardana et al., 2024; Khetan et al., 2025). In this way, this paper will first identify where the gaps in the literature are and to determine new avenues for research.

Through this research paper and the TCCM framework, we seek to answer the following questions:

RQ1. What does the existing literature reveal about where and in which sectors AI/ML in financial services research has concentrated?

RQ2. Which theories and techniques most frequently underpin research on AI/ML applications in financial services?

RQ3. How has existing research methodologically approached the study of AI/ML in financial services, in terms of research design and data type?

RQ4. What future research directions emerge from the theoretical, contextual, characteristic, and methodological gaps identified in this review?

2. Research Methodology:

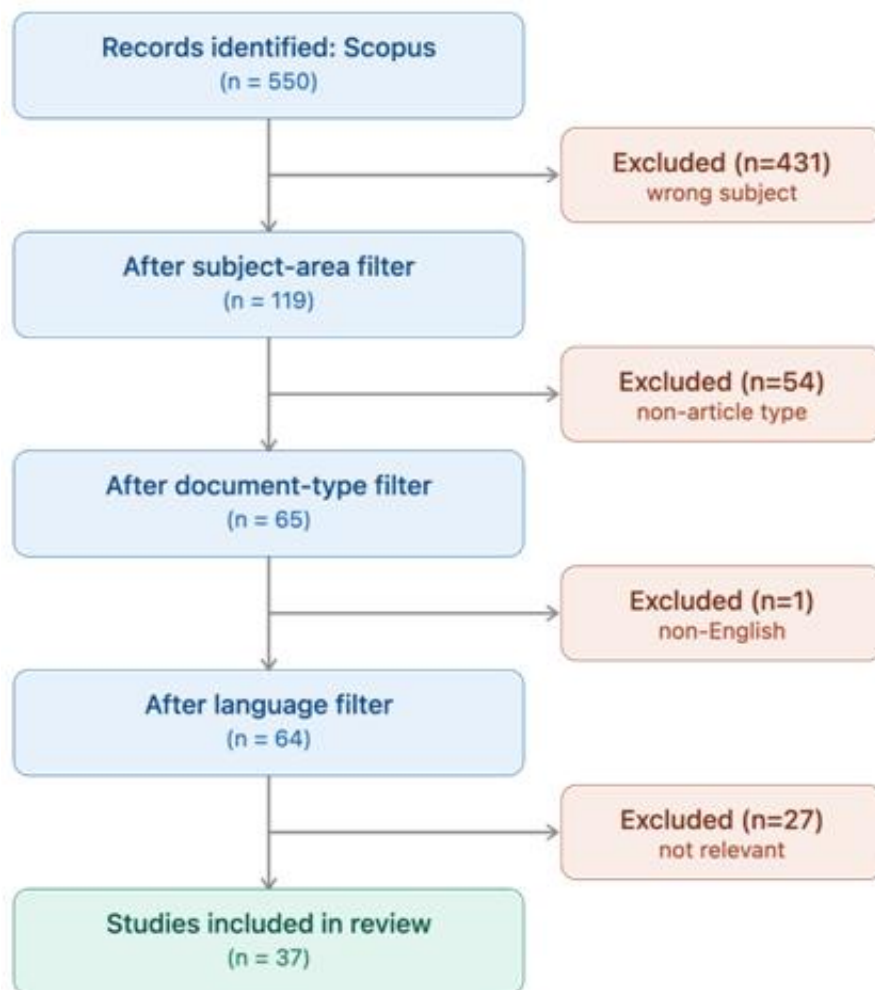
2.1 Defining the search string and database selection

The current set of studies regarding applications of AI/ML in finance can be found in disciplines ranging from finance to computer science and even management, without a single article connecting all these dots together. A systematic literature review (SLR) has become a tool to understand the complexity of the issue (Ganti & Singhania, 2025). A systematic literature review (SLR) seeks to synthesise findings from research studies in a systematic and replicable fashion (Davis et al., 2014). SLR is becoming more prevalent in business and finance research as well as in the context of consolidating rapidly growing research areas like that of AI/ML in finance (Hentzen et al., 2022). Given the rapid fragmentation of research in finance, computer science, and management studies, an SLR methodology was applied to synthesise the extant literature on the application of AI/ML in financial services (Sardana et al., 2024; Sardana & Singhania, 2024).

However, before conducting a literature search, the review required the formulation of a search string that could encompass all of the field without venturing into irrelevant areas. The Search String was formulated based on the identification of topics that are most pertinent to AI in Financial Services and using previous literature on such topics. Having considered these topics, the following search string was formulated: ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Networks" OR "Natural Language Processing" OR "Generative AI"). After the search string was developed, the subsequent step involved choosing the right database for this review. Now that the search string had been defined, it became necessary to know what source the search would be conducted on. Scopus was identified as the only database that could be used for this particular review since it covers a wide range of quality, peer-reviewed journals on business and finance (Chadegani et al., 2013).

A total of 550 papers emerged from this search on Scopus, which is a large enough sample but too large for this purpose, requiring several steps in the process of filtering and selecting the final list. Not all the results matched the topic of this study; hence, they had to be filtered first by fields of study, retaining those that belong to economics, econometrics, and finance, thereby getting 119 papers. The following filter was document type, since only articles and reviews were considered, and 65 papers remained after this filtration step. As for the fact that the review will be conducted in English, only papers published in English were kept, leaving 64 papers. Those 64 papers were examined thoroughly for their titles and abstracts being related to the research problem, culminating to a final selection of 37 papers for the review.

Figure 1. Article filtration and selection process



Source(s): The authors, based on the Scopus screening process described in Section 2.1

2.2 Study Method

Given the final batch of articles in hand, the subsequent problem was finding a way of analysing them in a manner that could make for an effective analysis and comparison of such a diverse collection of literature. In order to achieve this, the method used for carrying out the SLR was the TCCM model, proposed by Paul and Rosado-Serrano (2019), which makes it possible to analyse existing literature in a systematic, repeatable, and understandable manner (Snyder, 2019). It was found to be a very suitable model for this purpose, as it made it possible to analyse the literature using four interrelated aspects, namely: the theories that each article is based on, the context in which the research is carried out, the features of the literature, and the methods used by researchers. Thus, using these four aspects together, it was possible to systematically analyse a fragmentary collection of literature on the topic of AI/ML in the field of financial services, a task that SLR can successfully perform in any number of academic disciplines (Sardana & Shukla, 2025; Goswami et al., 2025).

3. Results and Analysis

3.1 Journal Outlet

The 37 studies included in this review were published across 29 distinct outlets. Table 1 summarises this, with around 75% ranked Q1 or Q2 by Scopus. The most recurrent one is The Journal of Risk and Financial Management, followed by the International Journal of Financial Studies, Journal of Behavioural Finance, Oxford Review of Economic Policy and Strategic Change. A smaller part of the studies was published in Q3- or Q4-ranked journals, or appeared in non-quartile-ranked publications, such as institutional working papers and preprint archives, which may be due to the relatively new status of AI/ML applications as a topic in the financial services industry.

The diverse range of these papers is what particularly stands out. The journals span finance (*Quantitative Finance*, *Borsa Istanbul Review*), economics and policy (*Oxford Review of Economic Policy*, *Central Bank Review*), management (*Strategic Change*, *IIMB Management Review*), and law (*Journal of Financial Crime*, *Law and Economics Yearly Review*). Additionally, the presence of explicitly multidisciplinary journals such as *Humanities and Social Sciences Communications* and *Forecasting* further underscores this trend. The dispersal highlights what has been mentioned above as fragmentation: AI/ML in financial services is being tugged at from various academic angles simultaneously by economists, management academics, computer scientists, and legal academics, none of which seem to be communicating with one another enough. It is exactly for this reason that an integrative review such as this one is necessary.

Table 1. Journal outlet (top 10)

Journal title	Count	Scopus
Journal of Behavioral Finance	2	Q1
Oxford Review of Economic Policy	2	Q1
Strategic Change	2	Q1
Borsa Istanbul Review	1	Q1
International Review of Economics and Finance	1	Q1
Journal of Sustainable Finance & Investment	1	Q1
Regional Science Inquiry	1	Q1
Research in International Business and Finance	1	Q1
Journal of Risk and Financial Management	4	Q2
International Journal of Financial Studies	2	Q2

Source(s): The authors

3.2 Theories

The question is which theories support the existing literature of AI/ML in financial services, and this is answered by Table 2. Every framework in the table predates AI and ML by decades, even centuries, which means that what is happening in terms of theory in this body of literature is not necessarily explaining AI per se but rather utilising AI as an advanced tool with which to test old theories about the market. One of the most prominent theoretical foundations throughout the entire body of literature that has been examined in this paper is that of the Efficient Market Hypothesis (EMH). It is mentioned in four out of 37 sources analysed in this paper, which constitutes 12.9%. It was formulated originally by Fama (1970) and states that asset prices adjust to all available information instantly and in such a way that there are no more opportunities for outperforming the market. The prevalence of EMH in this body of literature is quite evident – AI/ML literature on financial services, to a large extent, is an empirical study of EMH postulates (Wang et al., 2021; Chen and Hu, 2025).

The next two most-used frameworks are the Unified Theory of Acceptance and Use of Technology (UTAUT) and Modern Portfolio Theory (MPT); both are present in 2 studies (6.5%), and they help form the second part of the question, explaining in a clear breakdown, one emphasising how AI gets adopted and one how AI performs once it gets adopted. UTAUT

explains how AI gets adopted; a theory by Venkatesh et al. (2003), exploring how technology is chosen through concepts like performance expectancy and facilitating conditions. Morshed & Khrais (2026) apply it to show how trust and adoption of AI-powered predictive analytics emerge among financial institutions in the GCC region. The Mean-variance theory, also known as MPT and created by Harry Markowitz in 1952, falls under the category of performance theories: Ngo et al. (2023) and Mu et al. (2025) have utilised it to compare the performance of portfolio management strategies using reinforcement learning and machine learning with the classical efficient frontier.

This adoption-versus-performance split recurs throughout the rest of the table and is, in effect, the key that helps decode RQ2 further.

Table 2. Major theories used in the domain of AI/ML in financial services

Theory	Origin	Example citation	Meaning	Freq.	%
Efficient Market Hypothesis (EMH)	Fama (1970)	Wang et al. (2021); Chen and Hu (2025)	Market prices fully reflect all available information	4	12.9
Unified Theory of Acceptance and Use of Technology (UTAUT)	Venkatesh et al. (2003)	Morshed and Khrais (2026)	Performance expectancy and facilitating conditions drive adoption	2	6.5
Modern Portfolio Theory (MPT)	Markowitz (1952)	Ngo et al. (2023); Mu et al. (2025)	Diversification optimizes the risk-return trade-off (efficient frontier)	2	6.5
Acemoglu and Restrepo task-automation and labor-displacement theory	Acemoglu and Restrepo (2016, 2019)	Kouakou (2025)	Automation displaces labor unless offset by new task creation	1	3.2
Adaptive Markets Hypothesis (AMH)	Lo (2004)	Wang et al. (2021)	Market efficiency evolves as investor behavior adapts	1	3.2
Agency Theory	Jensen (1986)	Ho et al. (2022)	Self-interested managers may overinvest at shareholders' expense	1	3.2

Theory	Origin	Example citation	Meaning	Freq.	%
Behavioral Finance Theory	Shleifer and Vishny (1997); Thaler (1999); Shiller (2003)	Viebig (2019)	Investor irrationality drives systematic mispricing	1	3.2
Behavioral economics / cognitive bias theory (Prospect Theory)	Kahneman and Tversky (1979)	Bobrovska et al. (2023)	Loss aversion and biases distort trading decisions	1	3.2
Bounded rationality / satisficing theory	Simon (1955, 1957)	Bobrovska et al. (2023)	Cognitive limits bound rational decision-making	1	3.2
Corruption-and-debt theory	Cooray et al. (2017)	Barbier-Gauchard and Sofianos (2024)	Corruption raises public debt via weaker fiscal discipline	1	3.2
Diffusion of Innovation theory (DoI)	Rogers (1962)	Morshed and Khrais (2026)	Innovations spread through a population over time	1	3.2
Financial inclusion theory	Gabor and Brooks (2017)	Goncharenko and Miglionico (2019)	Digital technology widens access to banking services	1	3.2
General Purpose Technology (GPT) theory	Bresnahan and Trajtenberg (1995); Cockburn et al. (2019)	Bholat and Susskind (2021)	Productivity gains from GPTs materialize with a lag	1	3.2
Information asymmetry / adverse selection theory (Pecking Order Theory)	Myers (1984)	Ho et al. (2022)	Information gaps between managers and shareholders cause underinvestment	1	3.2

Theory	Origin	Example citation	Meaning	Freq.	%
Keynesian multiplier theory	Keynes (1936)	Ortega Peral et al. (2025)	Income growth raises demand for goods and services	1	3.2
Law of One Price	Cournot (1838)	Bobrovska et al. (2023)	Identical assets should trade at the same price	1	3.2
Modigliani and Miller (1958) perfect capital market theorem	Modigliani and Miller (1958)	Ho et al. (2022)	Capital structure is irrelevant under frictionless markets	1	3.2
Political economy of public debt theory	Stasavage (2003)	Barbier-Gauchard and Sofianos (2024)	Political and institutional factors drive debt fluctuation	1	3.2
Social Network Theory	Moreno (1934); Wasserman and Faust (1994)	Go et al. (2020)	Network centrality identifies influential nodes and keywords	1	3.2
Stakeholder Theory	Freeman (1984)	Ho et al. (2022)	Firms are a nexus of stakeholder relationships	1	3.2
Systematic risk / beta theory (CAPM)	Sharpe (1964)	Deep (2024)	Asset volatility relative to the market prices risk	1	3.2
Systemic risk and financial network theory	Acemoglu, Ozdaglar and Tahbaz-Salehi (2015)	Goncharenko and Miglionico (2019)	Network interconnectedness propagates financial shocks	1	3.2
Tobin's q theory of investment	Tobin (1969)	Ortega Peral et al. (2025)	Market valuation relative to replacement cost drives investment	1	3.2
Trade-off hypothesis	Preston and O'Bannon (1997)	Ho et al. (2022)	CSR spending trades off against investment efficiency	1	3.2

Source(s): The authors

There are also a small bunch of theories that explore how AI-driven automation shapes markets and labour, extending the adoption-versus-performance split into a third dimension: displacement. The task-automation and labour displacement theory advanced by Acemoglu and Restrepo (2016, 2019), according to which automation is beneficial to the economy only as it creates new tasks, forms the foundation for the theoretical framework developed by Kouakou (2025) concerning the relationship between adoption of AI technology and the development of financial markets and economic growth. Next to it stands the Adaptive Markets Hypothesis, Lo's (2004) evolutionary reinterpretation of EMH, which proposes that market efficiency is adaptive in nature, evolving together with the changing behaviour of investors, a notion applied by Wang et al. (2021) along with EMH.

The next segment of the table focuses on corporate finance and behavioural theory, addressing another aspect of RQ2: a substantial body of this literature is not concerned with markets but with corporations and their management. Agency Theory (Jensen, 1986), which depicts self-interested management that is likely to overinvest to its detriment, provides one theoretical foundation for the study conducted by Ho et al. (2022) of the impact of corporate social performance on investment inefficiency in China, research that will be shown in the next rows of the table, is based on no less than five theories. In contrast, there is a cluster of theories related to human behaviour in markets: Behavioural Finance Theory (Shleifer & Vishny, 1997; Thaler, 1999; Shiller, 2003), which posits that investors' irrationality leads to systematic mispricing, is applied by Viebig (2019) to the argument that machine learning algorithms can identify the market exuberance typical of behavioural finance. Bobrovska et al. (2023) build on the same behavioural tradition from another perspective by combining Prospect Theory (Kahneman and Tversky, 1979) and bounded rationality (Simon, 1955, 1957) to demonstrate how the integration of artificial intelligence in European Union financial markets is not just an issue of improving data quality, but rather addressing the loss-averse and cognitively constrained decision-making of humans.

Back again to Ho et al. (2022): another example would be the reliance of this article on Information Asymmetry theory (Myers, 1984), in which case underinvestment is an outcome of informational differences between the manager and the shareholder sides; furthermore, it uses the Modigliani-Miller (1958) capital-structure irrelevance theorem, which in this case is employed as a benchmark of frictionless markets. In a different context, Barbier-Gauchard and Sofianos (2024) employ Corruption-and-debt theory (Cooray et al., 2017) to claim that weaker fiscal discipline associated with corruption is one explanation of public debt dynamics forecasted by their machine learning model, which in turn is reconsidered in the political economy of public debt framework (Stasavage, 2003) in which debt variations can be attributed to politics and

institutions. Altogether, this leads us to the forth answer to RQ3: here theory is also applied in order to encode political and institutional realities into technical forecasting models.

The Theory of Diffusion of Innovation (Rogers, 1962) is again applied in Morshed and Khrais (2026) repeatedly as an adoption model to understand how AI-based prediction tools have diffused across GCC organisations. Financial inclusion theory (Gabor and Brooks, 2017) brings another shift of focus towards inclusivity: Goncharenko and Miglionico (2019) apply the theory to understand how AI and automation in Russia's banking sector affect the accessibility of financial services for different segments of the population. Very close in its focus is the Theory of General Purpose Technology (Bresnahan and Trajtenberg, 1995; Cockburn et al., 2019), which states that productivity gains from groundbreaking innovations come only after a certain delay; this is the approach used by Bholat and Susskind (2021) to dampen optimism regarding the potential rate at which AI can change UK financial services.

The Keynesian multiplier (Keynes, 1936) and Tobin's q investment theory (Tobin, 1969) are present in Ortega Peral et al. (2025), together offering an explanation of how government actions and investment into AI technology interact to affect financial market development. The Law of One Price (Cournot, 1838) is applied for the final time in Bobrovska et al. (2023) as the classical point of reference for spotting price distortions caused by AI. Social Network Theory (Moreno, 1934; Wasserman & Faust, 1994) is the basis for Go et al. (2020) and serves to map those keywords and research topics which are the most central in the AI-in-finance literature in general – another rare case when the theory is employed in a self-reflexive manner. Finally, three theories complement Ho et al.'s (2022) five-theory framework: Stakeholder Theory (Freeman, 1984); the Systematic risk/beta theory underlying CAPM (Sharpe, 1964), used by Deep (2024) to provide context to ensemble machine-learning predictions as regards classical risk factors in the asset pricing; Systemic risk and financial network theory (Acemoglu, Ozdaglar & Tahbaz-Salehi, 2015), used by Goncharenko and Miglionico (2019) to justify the possibility of propagation of AI-related risks rather than their isolation; and trade-off hypothesis (Preston & O'Bannon, 1997) suggesting a trade-off between the effectiveness of corporate investments and social expenditures.

Overall, these 24 theories answer RQ in three ways. First, the theoretical basis of the field is nearly completely borrowed, not native — there is no dominant theory specific to AI, because AI/ML is used as a tool for re-testing of already established financial, adoption, and behavioral hypotheses, not as a phenomenon that requires its own theoretical explanation. Second, borrowed theory can be easily categorized into clear families: market efficiency theory (EMH, AMH), adoption theory (UTAUT, DoI), performance/valuation theory (MPT, CAPM, Tobin's q), corporate governance and agency theory, behavioural theory – and there is one paper, Ho et al. (2022), using five different theories to explain one empiric question. Finally, and most important,

the use of established theories and absence of any truly novel theorization about the role of AI in finance is an issue in itself – it implies that the field has not generated any theory of AI-in-finance but rather used AI to test finance's theories.

3.3 Context Classification

Through the Countries table, one can see that this study still hasn't found a single geographical fit. The largest category is multicountry and global studies, with 12 of 37 papers; this suggests the research is more cross-border and focuses on global impact rather than specific countries (see Table 3). However, when research papers have chosen to base themselves on a particular country, the trend becomes much clearer: developed countries, the US, UK, EU, South Korea, Lithuania, and Germany form around 70% of all single-country research papers, whereas emerging and developing countries such as India, South Africa, and Brazil have only one paper each.

This imbalance in digital finance literature is not incidental. Boukherouaa et al. (2021), in their IMF paper on the use of AI and ML within financial services, they make the point that the use of such technology in finance has primarily taken place in developed nations, with the risk of creating an even larger digital divide between developed and developing financial systems. The underlying logic is straightforward: The type of AI/ML studies discussed above requires the previous existence of digitalised financial architecture, high-frequency transaction data, and computing capacity, which are unequally distributed around the world, favouring those markets that have already undergone thorough digitalisation (Gabor and Brooks, 2017). China is a partial exception in this regard; although it falls into the category of an emerging economy, it represents four of the reviewed studies, which is more than that of any other single economy except the US, more in line with its unique development trajectory of digital financial architecture rather than a representative example of an emerging market scenario. Additionally, markets in the Global South, arguably stand to gain from efficiencies and inclusive effects brought about by AI, yet are still under-researched within the literature in this field, making up one of the more feasible areas of future research highlighted through this review.

Table 3. Country classification of the studies

Country	Frequenc y	%	Example
Multi-country / Global	12	32.4	Ampountolas (2023); Viebig (2019)
United States	4	10.8	Deep (2024); Sirignano and Cont (2019)

Country	Frequency	%	Example
United Kingdom	3	8.1	Bholat and Susskind (2021); Buchanan and Wright (2021)
China	4	10.8	Chen and Hu (2025); Ho et al. (2022); Xu et al. (2025)
Europe (multi-country / EU bloc)	2	5.4	Barbier-Gauchard and Sofianos (2024); Bobrovska et al. (2023)
Russia	2	5.4	Goncharenko and Miglionario (2019); Yusupova et al. (2020)
Middle East (GCC multi-country)	2	5.4	Morshed and Khrais (2026); Yaseen and Al-Amarneh (2025)
South Africa	1	2.7	Dube et al. (2021)
India	1	2.7	Fatima and Chakraborty (2024)
South Korea	1	2.7	Go et al. (2020)
Lithuania	1	2.7	Maknickiene and Maknickas (2013)
Germany	1	2.7	Pamuk and Schumann (2023)
Brazil	1	2.7	Pinto et al. (2024)
N/A	2	5.4	Grigorova et al. (2025); Kouakou (2025)
Total	37	100.0	

Source(s): The authors

3.4 Characteristics

Dependent variables adopted by studies in the above literature represent what the researchers hope to explain through the use of AI/ML techniques in the area of finance, and price/return prediction takes a prominent place in this regard. Six out of the 37 papers use definitions of their dependent variables in terms of predicting some kind of movement in prices or returns — ranging from simple binary classifications of future abnormal low returns (Viebig, 2019) to the direction of future mid-price movements (Sirignano and Cont, 2019; Xu et al., 2025) — and making this the most numerous characteristic category and, effectively, the default test ground for whether AI can beat regular forecasting in the field. This makes it the largest cluster in the table and, by extension, the default testbed in the field to determine if artificial intelligence really

does perform better than conventional prediction methods. Right on its heels is a cluster of four papers that focuses not on markets but on people: AI adoption, its effects, and trust in AI-based finance tools (El Hajj and Hammoud, 2023; Yaseen and Al-Amarneh, 2025; Fatima and Chakraborty, 2024). And that division says something important on its own — there are a number of articles that do not focus as much on whether AI works but rather on whether financial institutions and their clients are willing to let it work. A third group of three articles concentrates on credit risk and distress prediction (Pinto et al., 2024; Pamuk and Schumann, 2023; Dube et al., 2021) and tries to see whether the use of AI/ML in one of the oldest questions in banking, namely, who will default, could do better than logistic regression.

Where the dependent variables represent what is to be predicted, the independent variables represent what is fed to the AI in order to predict these, and in this case, the trend is heavily laden with data on markets and prices. Seven papers construct their models directly out of historical prices, returns, and order flows; such as OHLC prices, adjusted close and volumes (Deep, 2024), depth of limit order books and historical order flows (Sirignano and Cont, 2019; Xu et al., 2025), and historical exchange rate time series (Maknickiene and Maknickas, 2013), indicating that the very technical core of this literature is all about training machines to read prices better than humans can. Coming a close second is another set of themes that have emerged from five different articles, and which, instead of focusing on market variables, look at the other end of the spectrum — the user and his attitude, trust and performance expectations (El Hajj and Hammoud, 2023; Fatima and Chakraborty, 2024; Yaseen and Al-Amarneh, 2025). This is almost identical to the division that we see in the dependent variables in the previous section, indicating that the study of AI/ML in financial services is actually two distinct paths, instead of one unified one. The third-biggest category, which is financial ratios and company fundamentals, is found in three papers (Dube et al., 2021; Pamuk and Schumann, 2023; Pinto et al., 2024), and they feed back directly into the credit risk dependent variables mentioned above, utilising between 24 and 74 financial ratios in their distress and default prediction models.

However, the control variables, mediation, moderation, and instruments are relatively less numerous compared to those explained above and contribute significantly towards explaining the nature of the relationships. The most numerous among the variables are control variables which are found in five separate papers, with their main goal being to control for alternative explanations of the AI/ML phenomenon in question. More specifically, such variables as gender and age (El Hajj and Hammoud, 2023), firm size and cash volatility (Ho et al., 2022) and institution size (Morshed and Khrais, 2026) are meant to ensure that an observed AI effect does not just represent a proxy of something else. Moderating variables, which appear in four different research papers, take the analysis one more step forward by trying to understand when and for whom the AI relationship exists: according to Fatima & Chakraborty (2024), age, gender, and

investment knowledge affect robo-advisors' adoption, whereas Yaseen & Al-Amarneh (2025) prove that the fairness perception serves as a moderator of the effect of trust on AI fraud detection adoption. The use of mediators, which has been limited in two other studies, attempts to understand the process underlying the relationship between AI and results, as opposed to simply understanding the environmental conditions – Chen and Hu (2025) demonstrate the role of technology features and legal context in mediating the influence of risks associated with generative AI on legal liability, suggesting that some research is attempting to go beyond “does it work” to “how does it work.”

Table 4. Dependent variables (grouped by main construct)

Main construct	Dependent variable(s)	Example citation(s)
Price / Return / Market-Movement Forecasting (n = 6)	1. Binary classification of abnormally low future returns 2. Ternary price movement ('up/down/flat') per 2-hour interval 3. Predicted asset prices/returns 4. Daily index/price forecasts 5. Direction of the next mid-price move	1. Viebig (2019) 2. Wang et al. (2021) 3. Deep (2024) 4. Ampountolas (2023) 5. Sirignano and Cont (2019); Xu et al. (2025)
AI/Technology Adoption, Perception and Trust (n = 4)	1. Perceived impact of AI/ML on financial markets 2. AI adoption 3. Behavioural intention to adopt robo-advisors 4. Evolvment of AI in financial services	1. El Hajj and Hammoud (2023) 2. Yaseen and Al-Amarneh (2025) 3. Fatima and Chakraborty (2024) 4. Todri and Papajorgji (2024)
Credit Risk, Default and Financial-Distress Prediction (n = 3)	1. Binary default flag 2. Corporate credit rating class 3. Binary financial distress classification	1. Pinto et al. (2024) 2. Pamuk and Schumann (2023) 3. Dube et al. (2021)

Main construct	Dependent variable(s)	Example citation(s)
Portfolio Performance and Risk Metrics (n = 2)	1. Portfolio metrics: E(R), Std(R), Sharpe, Sortino, max drawdown 2. Predicted future exchange rate values	1. Ngo et al. (2023) 2. Maknickiene and Maknickas (2013)
Market Turbulence / Systemic Crisis Prediction (n = 2)	1. Binary market turbulence indicator 2. Turbulence/crisis indicator (S&P 500 and VIX)	1. Petropoulos et al. (2021) 2. Petropoulos and Siakoulis (2021)
Corporate Investment Behavior (n = 1)	Investment inefficiency	Ho et al. (2022)
Legal Liability Classification (n = 1)	Legal liability (contractual/tort)	Chen and Hu (2025)
Household Financial-Market Participation (n = 1)	Household participation in risky markets	Mu et al. (2025)
Macro-Financial Market Development Index (n = 1)	Financial market index	Ortega Peralas et al. (2025)
Insider-Trading Stock-Price Impact (n = 1)	MSFT price change, trade-to-disclosure window	Tregub and Wagner (2024)
Sovereign Debt / Macro-Fiscal Prediction (n = 1)	Public debt-to-GDP ratio	Barbier-Gauchard and Sofianos (2024)
Operational and Predictive Performance Metrics (n = 1)	Predictive accuracy	Morshed and Khrais (2026)

Source(s): The authors

Table 5. Independent variables (grouped by main construct)

Main construct	Independent variable(s)	Example citation(s)
Market/Price Inputs (n = 7)	1. Historical price/return series (scaled) 2. OHLC prices, Adjusted Close, Volume 3. Limit order book depth and order-flow history 4. Raw OHLCV data 5. Price-to-book ratio 6. Historical exchange-rate time series	1. Ampountolas (2023) 2. Deep (2024) 3. Sirignano and Cont (2019); Xu et al. (2025) 4. Wang et al. (2021) 5. Viebig (2019) 6. Maknickiene and Maknickas (2013)
AI Adoption Drivers (Attitude, Trust, Firm Factors) (n = 5)	1. AI/ML adoption level, attitude, firm size 2. Trust, anxiety, performance expectancy, preference for human advisors 3. Seven Likert-scale constructs (transparency, trust, usefulness, ease of use, etc.) 4. AI usage, reasons for (non-)use, perceived risks, regulatory perceptions 5. Type of predictive model	1. El Hajj and Hammoud (2023) 2. Fatima and Chakraborty (2024) 3. Yaseen and Al-Amarneh (2025) 4. Todri and Papajorgji (2024) 5. Morshed and Khrais (2026)
Financial Ratios and Firm Fundamentals (n = 3)	1. Industry performance indices (factor analysis) 2. 74 financial metrics, screened for validity 3. 24 financial ratios (from a pool of 41)	1. Dube et al. (2021) 2. Pamuk and Schumann (2023) 3. Pinto et al. (2024)
Text/Sentiment-Derived Indicators (n = 2)	1. NLP sentiment index from central bank speeches 2. Google Trends monthly search-volume indices	1. Petropoulos and Siakoulis (2021) 2. Petropoulos et al. (2021)
Portfolio Construction Method (n = 1)	Portfolio construction method	Ngo et al. (2023)

Main construct	Independent variable(s)	Example citation(s)
Corporate Social/Governance Performance (n = 1)	Corporate Social Performance	Ho et al. (2022)
AI System Failure Factors (n = 1)	Data leakage, erroneous decisions, technical failures	Chen and Hu (2025)
Household Demographic and Wealth Indicators (n = 1)	21 indicators across 5 dimensions (demographics, wealth, etc.)	Mu et al. (2025)
Macroeconomic/Investment Indicators (n = 1)	Log of estimated private AI investment	Ortega Peralas et al. (2025)
Market and Trade-Level Indicators (n = 1)	S&P 500 change over trade-to-disclosure period	Tregub and Wagner (2024)
Macroeconomic, Institutional and Political Indicators (n = 1)	566 economic, financial, institutional and political variables	Barbier-Gauchard and Sofianos (2024)

Source(s): The authors

Table 6. Control, moderating, mediating and instrumental variables (grouped by type)

Variable type	Variable(s)	Example citation(s)
Control (n = 5)	1. Gender, age group 2. Firm size (log of total assets), cash volatility, firm age, tangible fixed assets 3. Institution size (total assets, USD billions) 4. Long-term interest rates (OECD data) 5. Crisis-probability cutoff (cost function, 5x false-positive penalty)	1. El Hajj and Hammoud (2023) 2. Ho et al. (2022) 3. Morshed and Khrais (2026) 4. Ortega Peralas et al. (2025) 5. Petropoulos et al. (2021)
Moderator (n = 4)	1. Age, gender, investment knowledge (multi-group analysis) 2. State ownership (SOE vs. non-SOE) 3. Government functioning index 4. Fairness perception moderates trust-to-adoption link	1. Fatima and Chakraborty (2024) 2. Ho et al. (2022) 3. Ortega Peralas et al. (2025) 4. Yaseen and Al-Amarneh (2025)

Variable type	Variable(s)	Example citation(s)
Mediator (n = 2)	1. Technology characteristics (security, reliability, quality); legal environment 2. Fairness perception mediates bias-to-adoption effect	1. Chen and Hu (2025) 2. Yaseen and Al-Amarneh (2025)
Instrumental (n = 1)	Lagged CSP differential, industry-median CSP score	Ho et al. (2022)

Source(s): The authors

3.5 Methods

The methodology in this body of literature is predominantly empirical; 26 out of 37 reviewed articles use primary data analysis, and the vast majority of these (22 articles), which are empirical and quantitative in nature, completely overshadowing the other four articles (empirical and mixed), nine articles (non-empirical and qualitative), and two articles (non-empirical quantitative) studies making the rest of the field. Forecasting models constructed using statistical, machine learning, and mixed models architectures is the most common approach within this mainstream empirical-quantitative family (Wang et al., 2021; Deep, 2024; Maknickiene and Maknickas, 2013; Ampountolas, 2023), while second place is taken by statistical and machine learning classification models which were mainly developed for credit and distress prediction (Pamuk and Schumann, 2023; Grigorova et al., 2025; Dube et al., 2021), and the third position is held by a less popular, yet methodologically distinctive family which uses natural language processing in combination with econometric modelling to extract sentiments signals from text. (Petropoulos et al., 2021; Petropoulos and Siakoulis, 2021). Such a focus on quantitative and model-based techniques stems from the fact that most of the research on AI/ML in finance takes place in the presence of structured and voluminous data. This is what accounts for the clustering of qualitative research papers reviewed in this paper (Bholat and Susskind, 2021; Milana and Ashta, 2021; Goncharenko and Miglionico, 2019) around questions related to institutions, laws, and regulations in which the core topic is inherently more difficult to translate into a data set.

Table 7. Trends in research design (Methods, grouped by type/design)

Type of paper / Design	Research technique(s)	Example citation(s)
Empirical Quantitative technique types) (14	1. Forecasting models (statistical/ML/hybrid) (n=4) 2. Statistical / ML classification models (n=3) 3. Primary survey (cross-sectional, structural model) (n=2) 4. NLP + econometric model (n=2) 5. Panel data / ML prediction models (n=1) 6. Text mining / social network analysis (n=1) 7. Panel regression / econometric model (n=1) 8. Panel / microdata econometric model (n=1) 9. Portfolio / time-series models (n=1) 10. Panel data / GMM econometric model (n=1) 11. Credit-risk / statistical model (n=1) 12. High-frequency data / ML model (n=2) 13. Web-scraped data / econometric model (n=1) 14. Valuation / statistical model (n=1)	1. Wang et al. (2021); Deep (2024); Maknickiene and Maknickas (2013); Ampountolas (2023) 2. Pamuk and Schumann (2023); Grigorova et al. (2025); Dube et al. (2021) 3. Yaseen and Al-Amarneh (2025); Fatima and Chakraborty (2024) 4. Petropoulos et al. (2021); Petropoulos and Siakoulis (2021) 5. Barbier-Gauchard and Sofianos (2024) 6. Go et al. (2020) 7. Ho et al. (2022) 8. Mu et al. (2025) 9. Ngo et al. (2023) 10. Ortega Peralas et al. (2025) 11. Pinto et al. (2024) 12. Sirignano and Cont (2019); Xu et al. (2025) 13. Tregub and Wagner (2024) 14. Viebig (2019)
Empirical / Mixed (4 technique types)	1. Quantitative survey (SEM) + qualitative content analysis (n=1) 2. Quantitative survey + qualitative literature synthesis (n=1) 3. Primary survey + secondary institutional data (n=1) 4. Primary survey (integrative quant/qual) (n=1)	1. Chen and Hu (2025) 2. El Hajj and Hammoud (2023) 3. Morshed and Khrais (2026) 4. Todri and Papajorgji (2024)

Type of paper / Design	Research technique(s)	Example citation(s)
Non-empirical Qualitative technique types) / (8	1. Conceptual / narrative review (n=2) 2. Conceptual / editorial synthesis (n=1) 3. Narrative literature review + industry survey synthesis (n=1) 4. Doctrinal legal / policy review (n=1) 5. Theoretical / mathematical derivation (no data) (n=1) 6. Narrative/systematic literature review (n=1) 7. Systematic review (PRISMA/PICOC-guided) (n=1) 8. Descriptive/conceptual case-study review (n=1)	1. Singh (2023); Bobrovska et al. (2023) 2. Bholat and Susskind (2021) 3. Buchanan and Wright (2021) 4. Goncharenko and Miglionico (2019) 5. Kouakou (2025) 6. Milana and Ashta (2021) 7. Vasquez-Serpa et al. (2025) 8. Yusupova et al. (2020)
Non-empirical Quantitative technique types) / (2	1. Systematic review + bibliometric science mapping (n=1) 2. Bibliometric / co-citation network analysis (n=1)	1. Herrmann and Masawi (2022) 2. Jankova (2021)

Source(s): The authors

4. Conclusion

This review aimed to answer four key research questions regarding AI/ML research in the domain of financial services, and the data obtained in the course of the study above has provided answers to each of the questions raised. Regarding the focus area of AI/ML research (RQ1), the analysis of journal outlets and countries demonstrates that this research domain is truly multidisciplinary in terms of journal outlets used (ranging from finance, economics, management, and law), but very geographically skewed, featuring multiple-country and developed single-country studies, with China being the sole exception. In terms of the theories underpinning the research (RQ2), the review identifies an area that draws heavily upon external theories developed decades ago, such as the Efficient Markets Theory and UTAUT, as opposed to an AI-specific theoretical framework, where the use of AI/ML is merely another technique used to answer already asked questions. In relation to the methodology applied in approaching this research (RQ3), there exists a preponderance of empirical, quantitative research, where the

vast majority of research is based on forecasting models, classification models, and most recently natural language processing (NLP)-based sentiment analysis. In contrast, the remaining qualitative/conceptual research focuses on institutional/regulatory issues that resist assessment. Collectively, these results have also answered RQ4, with the most obvious directions for future research lying exactly within the gaps revealed by the imbalance, including the underrepresentation of developing and emerging markets, the virtual lack of AI-driven theory development, and the relatively small amount of qualitative and experimental research compared to the well-established quantitative research approach.

Some implications of these findings can be drawn for policy purposes. In developed countries, where research and applications of AI/ML are most prominent, authorities and financial institutions should concentrate on developing policies on explainability and liability, as AI usage in all these studies relies greatly on trustworthiness rather than just its technical performance. In light of the importance of the availability of digital finance and data for AI/ML research and implementation as identified in this review, the implications for regulatory bodies and institutions focused on development in under-represented markets indicate a need to make a deeper foundational investment for the efficiency and inclusiveness benefits of AI to be realised.

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