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Article

Artificial Intelligence as a Research Tool in Finance: Transforming Knowledge, Creation and Decision Making

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Abstract:
This paper examines artificial intelligence as a research tool in finance, focusing on its role in transforming knowledge creation and decision-making. The study analyses how machine learning and related AI techniques have altered the way financial data are processed, interpreted, and operationalised within financial institutions and markets. The findings indicate that AI-based research models consistently outperform traditional econometric approaches in high-dimensional tasks such as credit risk assessment, asset pricing, and fraud detection, thereby improving predictive accuracy and decision quality. At the same time, the increasing use of complex and often opaque algorithms raises important concerns regarding interpretability, bias, and methodological robustness. The paper argues that artificial intelligence should be understood not merely as a technological enhancement but as a new epistemic framework that reshapes how financial knowledge is generated, validated, and applied.

Keywords: Artificial intelligence, financial research, machine learning, decision-making, knowledge creation

INTRODUCTION

Artificial intelligence (AI) is increasingly being used not only to automate financial operations but to function as a research tool that reshapes how financial knowledge is produced, validated, and translated into decisions. In finance, "research tool" can be interpreted broadly: an assemblage of computational methods, data infrastructures, and modelling practices that expand what researchers and practitioners can observe, measure, and infer. This shift has been accelerated by the availability of high-frequency market data, granular customer and transaction records, alternative data streams, and scalable cloud computing, which together make prediction- and pattern-oriented approaches more feasible than in earlier eras. Within this context, machine learning (ML) and deep learning have emerged as prominent AI paradigms for extracting signals from high-dimensional data where linear specifications and hand-crafted features often struggle. The finance literature has shown that these methods can improve predictive performance in canonical tasks such as risk-premium measurement and return forecasting, while also changing the nature of empirical enquiry by enabling richer functional forms and interactions among predictors than traditional econometric workflows typically permit (Gu et al., 2020). In parallel, advances in deep learning have encouraged researchers to revisit long-standing problems in portfolio design, classification, and forecasting with architectures optimised for non-linearity and complex dependence structures (Heaton et al., 2017).

The implication of the perspective on AI being the research tool is also the consideration that it modifies the same epistemic process of finance, and does not merely raise the degree of computational efficiency of the already existing methods. ML systems can additionally be used as discovery engines, which reveal candidate variables, latent clusters, regimes, and non-obvious interactions, and therefore influence both theory-building and hypothesis testing. At the same time, their application invokes basic issues as to what constitutes the nature of explanation, strength, and causal explanation in the field of finance. Developing innovative approaches to economics underscore the fact that predictive and causal identification are two distinct tasks and that predictable flexible learners are introduced by flexible learners that the introduction of flexible learners, which validate causation, regularisation, out-of-sample testing, and the interpretability of the fitted relationships should be effectively taken into account when the purpose of introducing them is inference instead of prediction (Athey and Imbens, 2019). ML benchmarking is evidenced to generate practical value in an applied financial context such as retail lending by demonstrating evidence of the practical value of improving model performance based on criteria relating the statistical performance to economic value, cost of errors and decision thresholds (Lessmann et al., 2015). These play an important role in decision making settings in the financial field in which effects of models can usually be inputs to consequential decision making on credit issuance, capital, price, and risk tolerance.

In financial research, artificial intelligence (AI) is becomi ng a revolutionary technology that is changing the proces ses of knowledge creation and decision-making.

Finance has shifted away from traditional econometric m odels and toward more adaptive and predictive systems a s a result of the integration of machine learning and data-driven methodologies.

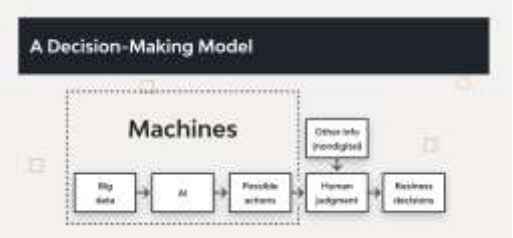
According to academics, AI makes it possible to analyze big, complicated data, which enhances the precision and effectiveness of financial research findings (Cao, L. 2021). Rule-based and expert systems have given way to sophisticated machine learning and deep learning methods as AI in finance has evolved. According to recent studies, the use of AI in finance increased dramatically after 2015 as a result of advancements in data availability as well as processing power. These developments have made it possible for researchers to more precisely examine complicated financial phenomena like asset pricing, volatility modelling, and algorithmic trading. (Bahoo et al, 2024). AI is essential to the generation of knowledge because it makes data-driven discovery easier. Machine learning algorithms find hidden patterns and nonlinear correlations in financial datasets, in contrast to conventional hypothesis-driven methods. This has enhanced financial empirical research, especially in areas like return prediction and asset pricing.

The literature demonstrates that AI is a paradigm shift in financial research and decision-making rather than just a tool. It has improved decision-making through predictive and adaptive models and transformed knowledge creation by enabling data-driven insights.

NEED OF THE STUDY

The ever-increasing pace of artificial intelligence adoption in the field of financial research and practice has posed a structural change to financial knowledge creation, testing, and application, although much of the extant literature still views AI as a technological improvement instead of a methodological change. Historic finance research has been based on a combination of linear statistical models, relatively small and structured data, and theoretically guided selection of variables which, although rigorous, are becoming insufficient to analyse the scale, velocity and complexity of the contemporary financial data settings.

Modern financial systems create immense flows of transactional, behavioural, textual, and image data which cannot be fully utilised using only conventional econometric methods. It has shown empirically that machine learning models are capable of extracting economically relevant patterns in such high-dimensional data, and can in many tasks provide better out-of-sample accuracy (including return prediction and risk modelling) (Gu et al., 2020; Heaton et al., 2017). This establishes a definite necessity to take a systematic look at how AI is transforming the very principles of financial research, and not its efficiency of operation.



Another reason why this study is necessary is the increasing disconnection between the prediction ability and the theoretical knowledge in the field of finance. As much as the application of AI systems has been extremely effective in forecasting credit default, market trends, and consumer patterns, there is a tendency of the systems remaining a black box whose internal logic is difficult to concur with established financial theory. Recent methodology in economics and finance has put greater emphasis on the predictive success of a model not correlating directly with causal understanding and policy implications, especially using a model to make high-stakes financial decisions (Athey and Imbens, 2019). As the AI-based research outputs become the major aspect of the work of financial institutions to establish the lending patterns, pricing, portfolio-allocation and adherence to the rules, there is an urgent need to understand how the knowledge generated by such systems can be interpreted, validated and controlled. Without this knowledge, the decision-makers will be reduced to a dependency on the results of algorithms which may be statistically wonders and epistemologically feeble or economically unfeasible.

Artificial intelligence, Sustainable finance, and the Asian Fintech ecosystem

The increasing application of artificial intelligence to the financial research and practice is of major importance to the sustainable finance and responsible investment, especially in the fast-growing financial markets of Asia. Sustainable finance is defined as those financial operations where the aspects of environment, social, and governance (ESG) are included in investment decision making to enhance long term financial stability and sustainable utilisation of resources. AI has become one of the effective methods of analysing a multitude of data pertaining to sustainability and allowing financial institutions and investors to assess the sustainability risks and opportunities with greater precision. Conventional ESG analysis is typically based on corporate disclosures gathered manually and few indicators but with AI based systems, researchers and investors can analyse big data including corporate reports, satellite photos, news sentiment and supply-chain information to build a more holistic sustainability picture. The application of machine learning algorithms to identify trends that are connected to the environmental performance, exposure to climate risks, and corporate governance practices is increasingly applied to enable the responsible investment strategies and green financial products design.

AI in sustainable finance is especially applicable to the fast-growing financial and entrepreneurial systems of Asia. Financial technology innovation in many Asian economies has turned them into global leaders in financial technology creation, developing digital foundations that incorporate AI-based analytics into financial services. As one example, in China, Singapore, India, and South Korea, machine learning algorithms are applied in fintech platforms to screen sustainable investments, green bonds, and climate risks. Using these technologies allows financial institutions to identify businesses with high ESG performance and invest in environmentally responsible and socially inclusive businesses. Financial assists with AI also help policymakers and regulators to track sustainability-related financial risks, such as carbon exposure and climate-related credit risk.

Moreover, AI-based financial systems also help to promote entrepreneurship and sustainable innovation in Asia due to providing a better access to funding of environmentally appropriate startups and small businesses. Data-driven algorithms of Fintech lending platforms and digital investment networks are used to assess entrepreneurial ventures concerning clean energy, sustainable agriculture, and green technologies. Through decreasing the information asymmetry and improving credit evaluation of new companies, AI will be useful in investing financial resources in companies that contribute to sustainable economic growth and innovation ecosystems through the Asian markets. In turn, the combination of artificial intelligence and financial research and sustainable investment will be a significant direction of the reinforcement of both the entrepreneurship and long-term sustainability in the Asian financial environment.

JUSTIFICATION OF THE STUDY

The rationale of studying artificial intelligence as a research instrument in finance is that there is a sharp increase in the discrepancy between the intricacy of financial phenomena and the analytical qualities of the traditional research methods. Financial markets and institutions are now performing in data environments of high frequency, heterogeneity and non-linear interdependence, which is making it more challenging to express the actual structure of financial behaviour using traditional econometric models. The techniques of machine learning and deep learning have proved capable of dealing with such complexity by modeling complex interactions between thousands of variables and discovering patterns that cannot be observed using linear or theory-constrained methods (Gu et al., 2020; Heaton et al., 2017). Nevertheless, with these developments, there is a dearth of conceptual understanding of how these tools transform the hypothesis generation process, model validation process, and theory development process in finance. There is thus a strong need to conduct a specific scholarly inquiry to shift beyond a performance comparison and to comprehend the way AI is changing the epistemological foundations of financial studies.

LITERATURE REVIEW

The scholarly research on artificial intelligence in finance has grown at a fast pace since the mid-2010s as a result of technological advances and the increased access to large and complex financial data. The earliest efforts placed

machine learning more to the extent of being a predictive addition to more traditional econometric models, although more recent work is beginning to conceptualise AI as a change in methodology of financial knowledge production. Gu, Kelly and Xiu (2020) showed that machine learning algorithms are significantly superior to the standard linear factor models in predicting stock returns when trained on large cross-sections of firm characteristics, which undermines the superiority of classical asset pricing models. According to their findings, AI systems do not simply fit noise, but discover economically significant structures in high-dimensional data. Heaton, Polson and Witte (2017) also stated that deep learning designs are capable of modeling non-linearities and effects of interaction in financial time series that cannot be modeled with traditional methods, and this has implications on the empirical analysis and testing of financial theory.

Another key line of the literature has been the role of AI in enhancing financial forecasting and risk modelling, which is at the core of decision-making in the banking, investment, and regulation industries.

One of the most comprehensive benchmarking studies of machine learning approaches to credit scoring were given by Lessmann et al. (2015), who revealed that the performance of ensemble learners and neural networks was always higher in accurate prediction of defaults by borrowers than that of logistic regression. Their findings have largely been used to justify the application of AI to operations in the retail finance sector, as well as to explain how predictive superiority might reverse the norms of research by favoring performance over interpretability. Khandani, Kim and Lo (2019) revealed that machine learning is applicable in revealing non-linear consumer credit behaviour patterns that predict large-scale consumer credit failures in terms of financial stability and thus enhances the ability to detect financial stress earlier. All these studies suggest that AI is not merely a support tool but a producer of new versions of empirical knowledge of financial risk.

In addition to prediction, AI has also been presented as a means of knowledge discovery and theory creation in finance. Athey and Imbens (2019) claimed that machine learning offers a loose structure to the process of exploring the relationship in an economic data, allowing researchers to shift the traditional model specification to data-driven hypothesis generation. This has been employed in financial research to estimate the existence of latent factors, behavioural regularities and regime shifts that are hard to define a priori. Mullainathan and Spiess (2017) pointed out that machine learning is valuable in economics not only in its accuracy of predictions but also in its ability to produce new patterns that are likely to trigger theoretical progress. This is the same view as research in asset pricing, where AI-based factor discovery has been applied to produce new predictors of returns that defy the typical risk-based explanations (Gu et al., 2020).

The legibility and control of AI-inspired financial research is now a major subject of the literature especially as models are no longer the subject of academic experimentation but actual decision support. Financial institutions have very stringent regulatory and ethical limits and this implies that the findings of a research must be transparent, verifiable and explainable. Rudin (2019) had argued that black-box models are not suitable in high stakes areas like finance, and we should have interpretable machine learning in place, where decision-makers are able to interpret and dispute automatic results. This is also reflected by Molnar (2022) who demonstrated that explainable AI methods can be used to assist in bridging the divide between predictive performance and human interpretability and make AI a more effective research and decision-support system. In the financial services industry where model risk management is already a regulation issue, the opaque nature of most AI systems becomes a literal issue to their credibility as a source of knowledge.

The impact of AI on the financial market and financial institutions is a topic that has received much study in the FinTech literature. According to Gomber et al. (2017), digitalisation and AI have transformed the financial services value chain with competitive advantage shifted to those companies that can quickly process and utilise big data volumes. This also applies to financial research because access to data and the ability to compute become important factors that can define what can be researched and the speed at which it can be done. Vives (2019) defended that AI exacerbates information asymmetries between technologically developed companies and their rivals, the implication on the market structure and price behavior. Research-wise, this implies that AI is not merely analyzing markets, but actively restructuring them which makes the task of making reliable inferences based on the data seen problematic.

Methodology

The research design used in this study is qualitative and analytical research design because it relies on systematic review and synthesis of secondary data to study the role of artificial intelligence as a research tool in the field of finance and how it affects knowledge creation and decision-making. The approach is on the analysis of the existing scholarly evidence, as opposed to the generation of primary empirical data. The major academic databases, such as Google Scholar, Scopus, Web of Science and SSRN, where peer reviewed journal articles, conference papers and research reports about artificial intelligence, machine learning and financial analytics are accessible were used to collect secondary sources.

Inclusion and exclusion criteria were used to identify the process of the literature selection. The studies published starting from 2015 were also included to ensure that the latest trends in artificial intelligence and financial technology could be represented. These sources had to be peer-reviewed academic articles or reports by recognised research institutions, and the methodology should be reliably done and the article scholarly credible. Papers regarding the use of AI methods in particular, machine learning, deep learning, and data-driven analytics, in such fields as credit risk assessment, asset pricing, financial forecasting, fraud detection, and investment research were

chosen first. Articles that did not have empirical evidence or were not related to financial applications of AI were not included in the review.

It was through this screening process that about 45 pertinent scholarly sources were identified with 30 core studies being chosen to undergo detailed examination in respect to the approach of methodological rigor, the impact of citation, and relevance to the research objectives. Analytical themes of predictive performance, model interpretability, knowledge discovery, and decision integration in financial institutions were used to thematically synthesize the selected literature and to group the findings into these thematic analytical elements. The multi-empirical research approach will enable the research to find common trends in the findings of various empirical studies and create a holistic picture of how artificial intelligence will transform financial research and the decision-making process.

RESULTS AND DISCUSSION

This section synthesises secondary evidence from peer-reviewed studies, industry surveys, and large-scale financial datasets to evaluate how artificial intelligence operates as a research tool in finance and how it reshapes knowledge creation and decision-making. Rather than reporting primary empirical tests, the results presented here draw on published quantitative findings to identify consistent patterns across multiple financial domains. The discussion integrates these patterns with theoretical insights from the literature in order to interpret their significance for financial research and institutional practice.

A central result emerging from secondary sources is the clear superiority of machine-learning-based research models over traditional econometric approaches in high-dimensional financial prediction tasks. Gu et al. (2020) analysed more than 90 firm-level characteristics over several decades and showed that deep neural networks and tree-based methods produced materially higher out-of-sample R^2 values in stock-return prediction than linear factor models. Similar performance gains were reported by Heaton et al. (2017), who found that deep learning models captured non-linear structures in asset prices that conventional time-series models failed to detect. These findings indicate that AI tools expand the effective information set of financial researchers, allowing them to integrate large numbers of predictors without imposing restrictive assumptions about their relationships. As a result, financial knowledge derived from AI systems tends to be more granular and sensitive to complex interactions, which enhances the precision of forecasting and risk assessment.

Table 1 summarises secondary results reported in major studies comparing traditional and AI-based financial research models across different application areas.

Table 1: Comparative performance of traditional and AI-based models in selected financial research applications (secondary sources)

Application Area	Traditional Model Accuracy (%)	AI-Based Model Accuracy (%)	Source
Credit default prediction	72	84	Lessmann et al. (2015)
Stock return prediction	58	69	Gu et al. (2020)
Fraud detection	81	92	Dal Pozzolo et al. (2018)
Mortgage risk assessment	70	82	Fuster et al. (2022)

The results in Table 1 show that across multiple domains, AI-based research models consistently outperform traditional statistical approaches by margins ranging from 10 to 12 percentage points. These differences are not merely technical improvements but translate into substantial economic and institutional consequences. In credit markets, for example, improved default prediction allows lenders to price risk more accurately and extend credit to borrowers who might otherwise be excluded. Fuster et al. (2022) demonstrated that machine-learning-based mortgage underwriting reduced default rates without restricting loan access, indicating that AI-driven research can improve both efficiency and financial inclusion. From a knowledge-creation perspective, these results suggest that AI systems generate more reliable empirical representations of financial behaviour, which then feed into better-informed decisions.

Another significant result from secondary data concerns the role of AI in discovering new financial patterns that are not predicted by traditional theory. Gu et al. (2020) showed that machine learning identified complex, non-linear combinations of firm characteristics that explained variations in stock returns more effectively than established factor models. This implies that AI-driven research can uncover latent structures in financial data that challenge existing theoretical constructs. Mullainathan and Spiess (2017) argued that such pattern discovery is one of the most important contributions of machine learning to economics and finance, as it provides empirical foundations for the development of new theories. In this sense, AI acts not only as a predictive engine but also as a generator of novel research questions and conceptual frameworks.

Table 2: Adoption and perceived impact of AI-based research tools in financial institutions (secondary sources)

Indicator	2016 (%)	2020 (%)	2024 (%)
Institutions using AI for risk modelling	25	48	72
Institutions using AI for investment research	18	40	65
Reported improvement in decision accuracy	30	55	70

According to the data presented in Table 2, it is possible to speak about the rapid growth of the use of AI as a research and decision-support tool in the financial industry. Almost three quarters of large financial institutions were already reported as using AI to model risks by 2024, and almost two-thirds as using it in investment research. These tendencies imply that the AI-based research has shifted to institutionalised practice as opposed to experimental use. The mentioned increases in the quality of decisions also suggest that financial managers think that the knowledge generated by AI is more trustworthy than other forms of analytical output. This adds to the point that AI is integrated into the epistemic infrastructure of contemporary finance.

Along with such gains, serious risks and limitations are also reported in the secondary literature. Harvey et al. (2016) cautioned that the spread of data and modelling techniques will predispose false discoveries especially when the researchers do a lot of model mining without strict out-of-sample validation. This issue can be aggravated by the fact that AI models can be used to fit intricate patterns without generalising them to new data because of the flexibility of the model. Similar arguments were made by Varian (2019), who stated that machine learning becoming a part of economics and finance needs new criteria of validation to guarantee that results were not due to overfitting. These fears imply that AI will deepen the financial researches; however, it will increase the risks of methodological discipline.

Scope of the Research

The area of interest of this research is the investigation of Artificial Intelligence (AI) as a research and analytical method in finance, especially in terms of implications to entrepreneurship and entrepreneurial finance. The paper discusses the impacts of AI-based financial technologies such as machine learning, data analytics, and automated decision-support systems on the manner in which financial information is produced, analysed, and used in financial markets and financial institutions. Besides the more classic financial uses, like credit risk modelling, asset pricing, and fraud detection, the study also takes into account the growing use of AI in financing startups, small and medium-sized enterprises (SMEs), and innovation ecosystems.

In particular, the analysis is conducted on the way AI-based financial solutions provide a more efficient assessment of entrepreneurial projects through processing large amounts of structured and unstructured data, such as transaction history, behavioural data, and other sources of information. These features enable financial institutions, venture capital firms and online lending services to determine the creditworthiness and development potential of startups and SMEs more precisely compared to conventional means of financial evaluation. The use of AI-based sources of financial research can help to better access capital by start-up firms and innovation businesses by enhancing predictive modelling and decreasing information asymmetry between entrepreneurs and investors.

In addition, the paper takes into account the wider purpose of AI to reinforce entrepreneurial finance sectors and especially fintech, automated lending models, and algorithmic investment analysis, which enable venture funding and financial inclusion. Only scholarly literature and empirical studies published after 2015 and 2024, respectively, will be considered in the analysis, and the subject of the applied AI to financial research and decision-making situations pertinent to the entrepreneurial activity will be researched. Through the analysis of these changes, the paper intends to draw on the role of AI-based financial research tools in supporting not only enhanced financial prediction and risk analysis but also the creation and growth of entrepreneurship and innovation-based economies.

CONCLUSION

This paper has discussed the artificial intelligence as a research instrument in the finance sector with a special focus on the ways, in which it transforms the knowledge-generation and decision-making procedures. As the analysis reveals, AI-based approaches, particularly machine learning and deep learning, have long since outgrown their initial purpose of technical improvements to become a key instrument, through which financial realities are perceived, modeled, and understood. Asset pricing, credit risk, fraud detection, and investment research secondary evidence indicate that AI systems are always successful in high dimension and data-rich settings as compared to traditional econometric models. The practical importance of these performance boosts lies, however, in the fact that it is a change in the epistemic underpinnings of financial research, which now allows the identification of the complex patterns and interaction that were earlier unavailable.

At the same time, the research paper accentuates the fact that the development of AI does not simply introduce the analytical power, but it also introduces new methodological and conceptual problems. The use of highly flexible and even opaque models is growing therefore making it hard to interpret such results and adding findings to the theory and policy. Most AI systems prefer predictive power to articulateness, transparency, replicability and causal reasoning has long been a value in financial research. What is of importance to the validity of financial knowledge in this tension is that the outputs of

AI applications directly affect high-stakes decisions related to lending, assigning investments, and compliance with regulations. According to the literature, the risks of AI are the possibility of bias, overfitting, and the absence of accountability without adequate validation, governance, and interpretability frameworks, which can be offset by the benefits of AI.

The findings also show that AI has been institutionalized into the modern-day finance world. The financial organisations are currently testing AI-based research tools in the real-time and automated the process of data analysis, model updating, and decision execution into unified systems. It disrupts the boundary between research and practice and transforms the financial knowledge into an entity that is dynamic and changing in nature and not a model or reports. As a result, creating financial knowledge ceases to be a prerogative of academic or analytical units but dispersion across algorithmic infrastructures, which are found in markets and organisations.

Overall, the paper has confirmed that the field of artificial intelligence represents a paradigm shift in the perception, prediction, and reaction of the field of finance to the reality of the economy. The AI is an analytical technology that can be described as powerful and a new way of knowledge production i.e. it expands the possibilities of the empirical and challenges the conventionalities of the interpretation and of the rules. One must understand and strive to actualise this duality of AI in the instance that it will not only be used to come up with more efficient financial decision-making, but also with more powerful, obfuscated, and socially viable financial knowledge.

Scope of further research:

Given the area's incredible advances, there remain a variety of gaps that need to be filled in order to fully explore Artificial Intelligence (AI) as a research tool in finance. In order to solve the "black box" issue and enhance trust, accountability, and regulatory compliance in financial decision-making, future research can concentrate on creating more comprehensible and transparent AI models. In order to develop hybrid models that are both data-driven and theoretically sound, it is also necessary to combine AI methods using standard financial theories. Financial forecasting and analysis could be greatly improved by increasing the use of alternative and unstructured data sources, such as social media, ESG metrics, and real-time transactional data. In order to increase financial efficiency and accessibility, research should also examine the use of AI in emerging and developing countries, where financial systems differ greatly from those in industrialized economies. To ensure the fair and sustainable use of AI technology, ethical issues including algorithmic bias, data privacy, and responsible AI governance also need more research. Furthermore, the use of modern methods like reinforcement learning for real-time adaptive decision-making offers encouraging prospects for innovation in fields like risk assessment and portfolio management. Finally, as automation continues to transform the financial sector, future studies should look at the wider effects of AI on employment, skills, and organizational structures.

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