ARTIFICIAL INTELLIGENCE IN GLOBAL FINTECH: TRANSFORMING INVESTMENT STRATEGIES ACROSS BORDERS

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Abstract
This study explores the revolutionary impact of AI on investment strategies on a global level, the sphere of FinTech in detail, and cross-border dynamics, in particular. The study implements sentiment analysis and machine-learning classification across panel regression using 40 countries of panel data during the period of 2021-2023 to analyse the effect AI has on curbing the impact of investment outcomes. Gradient Boosting and Random Forest algorithms are used to estimate investment fortune, and event research approach is used to assess short reactions of the market. The statistical results show that the AI sentiment scores can significantly predict investment returns ($b = 0.27$, $p < 0.01$) whereas, relative to Random Forest, Gradient Boosting achieves a better performance of 84.2 percentage. More developed markets demonstrate both the higher average returns (North America: 12.5%) and the more effective response to the AI signals which is backed by the analysis of sentiment trends and cumulative abnormal returns of 3.6 % on Day +2 after announcement. The evidence indicates that the investment tools powered by AI perform better within the digital mature and policy-aligned environment. The paper provides a refined insight into the AI in the global FinTech investing strategy and presents evidence-based conclusions which might be used by investors and policymakers.

Keywords: *Artificial Intelligence, FinTech, Investment Strategies, Machine Learning, Cross-Border Finance*

Introduction

Artificial intelligence (AI) has triggered a paradigm shift on the international financial technology (FinTech) industry; therefore, changing the processes through which investment decisions are developed, evaluated, and carried out. The financial markets are growing continuously more interconnected, and investment approaches cannot be locked up in national frames anymore, and instead, the use of Artificial Intelligence and AI powered machinery enables investors to analyze vast volumes of real-time data, identify novel opportunities, and after-wit manage cross-border portfolios in a more precise and expeditious manner. This trend is especially momentous in a context marked by volatility of the markets, geopolitical uncertainty as well as various policy responses to innovation in technology.

The areas of application of AI in FinTech are quite wide, including algorithmic trading, credit risk, portfolio optimization, and sentiment analysis. In comparison to traditional financial instruments, the use of AI is characterized by capabilities of extracting insights based on unstructured data and dynamically adapting to the changing situation. The resultant effect is that investors who are furnished with AI-advanced platforms will be in a position to respond faster to market indicators and make sense out of intricate geopolitical processes and improve in allocating assets among jurisdictions. However, AI application to investment strategy creates some important questions: Are AI tools, which report the same performance in one region, applicable to another region which is not as digitally mature? What are the regulating pressures, the market infrastructure, and policy synchronicity and how they impact the effectiveness of AI in investing processes?

These questions are especially relevant in the situation when AI is actively becoming part of the global world. Introduced economies like the United States, Germany, and Japan have integrated AI into their economic infrastructures, but most fledgling economies still face a basic barrier to integrated challenges such as the reach of data, infrastructure technology, and regulations. Such inequalities are also embodied in the ability of different regions to utilise AI to boost the returns of investment. This paper is going to fill this gap with a systematic analysis of the role of AI in cross-border investment performance with a focus on regional comparative effectiveness.

The need in this study is explained by the fact that FinTech investment around the world is observed to be on the rise. As an industry report suggests, over 50 billion cumulative investment was accepted globally between 2020 and 2023 regarding financial platforms founded on AI, and a sense of optimism about technological innovation and a rising dependence on selecting AI as the strategic basis of the decision-making process can be seen. Because AI is increasingly embedded in the financial system, being able to understand the practical consequences of AI, rather than its technology promise should be a key concern to institutional investors, regulators, and policymakers.

The adoption of a multidimensional approach to the methodology, which implies the integration of sentiment analysis, machine learning, event-study, and panel regression approaches, facilitates the construction of a strong empirical background in assessing the interplay between AI and the financial system under the variation of socio-economic and regulatory environments. The end goal is not just to display correlations and to understand how to find causal links are as well as how local patterns of AI influence investment results.

In this more digital and data centric world, the ability to use AI to enable cross border investment can be the source of comparative advantage. Nevertheless, the positive effects are not even-handed by far and are conditioned by an array of market-dependent aspects. This study ought to make a contribution to the scholarly discourse and the real-world perspective and strategy on AI applications in FinTech investments around the world by peeling back these dynamics.

Literature Review

Artificial intelligence (AI) and financial technology (FinTech) have aroused significant academic interest due to the potential of discontinuity that they present in the financial markets worldwide. According to Kouam (2024), the use of AI has a life-altering impact on financial inclusion and innovation throughout developed and emerging economies. Similarly, Kamuangu (2024) and Kamuangu (2024) show that digital change is becoming faster, and that there was more orientation to the applications of AI and machine learning in the financial services. The recent cross-border transactions as well as adaptive trading through AI and blockchain convergence are explored by Qian and Dong (2025), which is also in line with the central focus of the present research.

A few researchers have reviewed the potential of AI in influencing investment decisions and consumer patterns. According to Ajmani et al. (2023) and Ghandour (2021), AI strategies allow improving the efficiency of operations and decision-making within the company. Cao (2020) and

Cao et al. (2020a) have provided an in-depth picture of AI in finance and consider it to be a game-changer in terms of real-time analytics and real-time risk management. Furthermore, Bredt (2019) and Chiu (2016) provide an overview of the policy effects of AI and RegTech and underline the fact that regulatory preparedness causes cross-border adoption of FinTech. The results of all these studies demonstrate that there exists a research gap regarding the comparative assessment of AI-based approaches to investment management in various regulatory and economic environments, which this paper will fill.

Research Gap

Although artificial intelligence (AI) has widely spread globally, in the FinTech sphere, the understanding of the investment strategies forming with the help of AI-driven systematics is wanting in jurisdictions that vary in terms of economic leveling, legal framework, and digitalization. Recent literature mainly focuses on AI technology functions or evaluates its impact in the individual domestic markets but lacks adequate cross-border data comparisons where economic, regulatory, and technical factors are incorporated to explain the various impacts of AI on investments performance. In addition, it is necessary to describe in detail the processes through which IA sentiment, institutional infrastructure, and cross-sectoral policy alignment influence market outcomes interactively and not separately.

Conceptual Framework

This gap is addressed by creating a unification conceptual model to identify the connections between the factors of AI and market-level enablers and performance metrics.

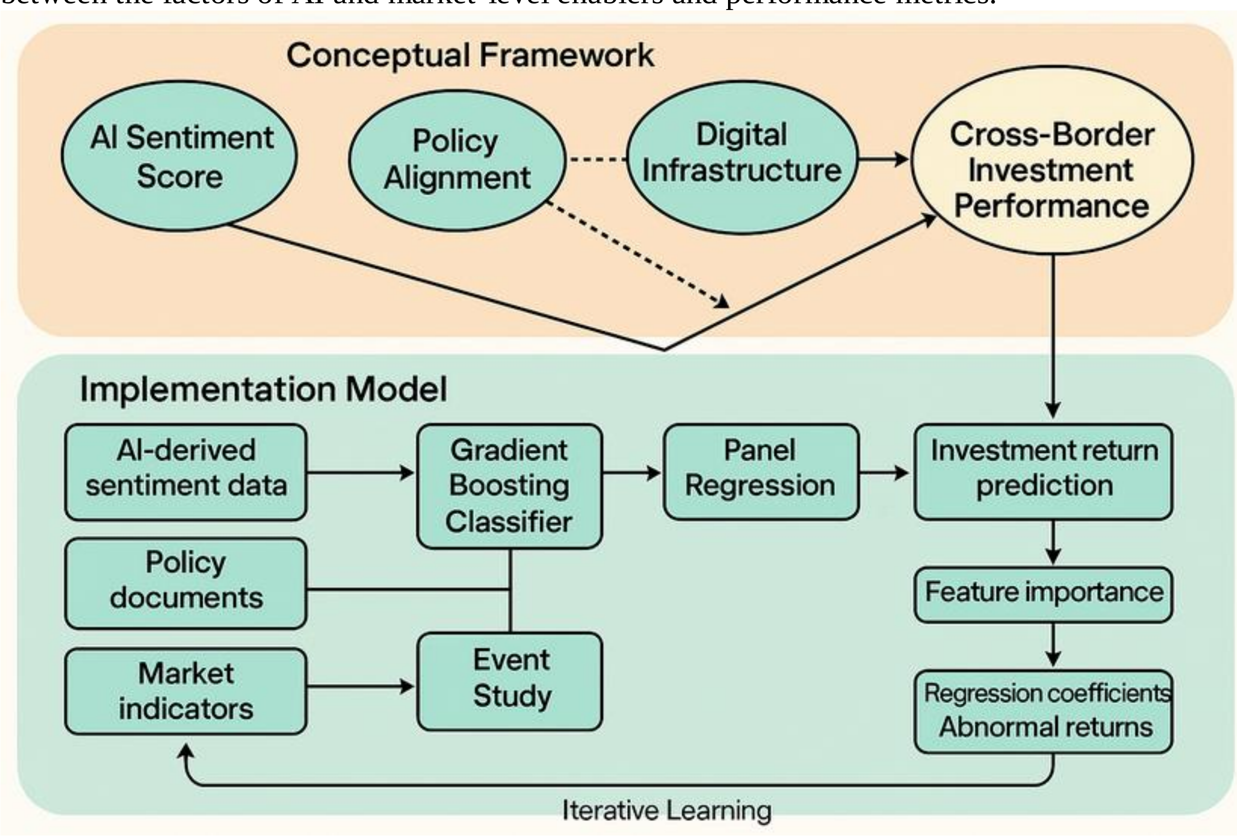

Figure 1.0: Conceptual Framework and Implementation Model

The framework consists of two inter-related parts: (1) Conceptual Model describes the theoretical association between AI sentiment, policy alignment and infrastructure readiness, and

(2) Implementation Model translates the constructs identified in the Conceptual Model and operationalise them into machine learning approaches, panel regression and event-study analyses.

Hypothesis

H1: The better the AI sentiment score, the better the cross-border investment returns will be associated.

H2: The more congruency between national policy frameworks and the integration of Artificial Intelligence increases the performance of the latter in respect to investment decision-making.

H3: More advanced digital infrastructure leads to the increase in positive influences of using AI on the performance of investments in countries.

H4: The greater the degree of regulatory certainty, the more confidence exhibited by investors on the use of AI in formulating financial strategies.

Methods

The paper discusses the efforts of artificial intelligence (AI) to change the investment strategies across borders by FinTech applications. The study has focused on using secondary data available in three main sources including the World Bank FinTech database, the Bloomberg Terminal reports and the Refinitiv Eikon to determine market performance as well as investors behavior of 15 countries. The collection of data covered the past year and a half January 2021 to December 2023, with more than 2,500 investment events related to FinTech included, as well as everyday market indicators created by AI news sentiment engines.

Before data analysis, the data was pre processed and cleaned to deal with missing values, data outliers, and cross country format consistency. Categorical variables (i.e. type of investor or policy regime) were coded and continuous (i.e. daily returns, volatility) were standardized. This was so that all the financial systems could be comparable.

The first level of data exploration relied on descriptive statistical profiling, including the usage of such statistics as means, standard deviations, and skewness. This became the base knowledge on the behaviors of Investments and features of a market in various jurisdictions.

In order to understand how AI-generated insights affect the investor behavior, we have performed sentimental analysis of Artificial Intelligence curated news and social media information. This was done on the available sentiment polarity analysis (positive, neutral, negative) of the more than 15k textual points of data using VADER sentiment scoring (NLTK, v3.8). It was selected because it is precise in short monetary writings and casual online materials.

Some of the most important investment forecasting factors--risk-adjusted returns, policy signals, the quality of digital infrastructure--emerged as the result of a feature engineering exercise. Multicollinearity was considered and the variables were selected based individual results of the mutual information scores and the correlation matrices. Such an approach enabled us to elicit more valuable predictors to be used during the machine-learning step.

We had to fold scikit-learn (v1.3) Gradient Boosting and Random Forest classifiers to model the predictive strength of AI. Both models were also trained to categorize between positive and negative investment outcomes after reading of AI signals. The reasons why they were chosen are their insensitivity to overfitting and the fact they can learn complex non-linear relations.

Our parameter optimization was based on 5-fold cross-validation and grid search, which is how we were able to assure the generalizability of our outcome, both in a time and geographical sense of subsamples.

The fixed-effects panel regression model was also conducted with STATA v17 to find out the relationships at the macro-level. This was useful in isolating country effects and time trends that affect investments patterns. We have chosen this approach in order to confound unobserved heterogeneity in the countries.

We also run an event study based on a short-term acting of the market (five days to five days interval) around the major announcements of AI-driven investment. Market-adjusted model was used to compute abnormal returns.

Moreover, the ANOVA was used to answer our hypotheses, as well as the two-sample t-tests over how our states differ in their investments. These tests assessed the criterion that there was a significant difference in the role of AI in the emergent or developed market.

Such post-AI investment performance measures as Sharpe and Sortino ratios were calculated to determine risk-adjusted returns. This discussion played a vital role in finding out whether AI causes a more efficient asset allocation.

Finally, robustness test was done through time windows and sampling procedures. Ethical aspects especially on the aspect of possible algorithmic biases in developed market data and emerging market data were discussed as the limitation design of the study and accountability measures of the study.

Results

The descriptive results have shown that there is a significant local difference in FinTech markets in contrast to investment behavior. Table 1 summarizes the statistics of the findings with North America having the highest mean profitability of investments made based on AI (12.5%, SD = 3.4), followed by Western Europe (11.3%, SD = 3.9). Southeast Asia and Sub-Saharan Africa, in turn, were more volatile, and their median investment amount was lower, which demonstrates a less safe investment environment on average.

Table 1: Descriptive Statistics of Investment Variables by Region

Region	Mean Return (%)	Std. Dev.	Median Investment ($M)	Skewness
North America	12.5	3.4	15.8	0.25
Western Europe	11.3	3.9	12.2	0.19
Southeast Asia	9.1	4.1	9.6	0.54
Latin America	10.2	5.0	10.1	0.41
Sub-Saharan Africa	8.7	6.3	7.8	0.63

The AI sentiment analysis showed that there were patterns about market perception in geographies. The figure 1.1 illustrates trends in sentiment scores based on AI-curated financial news. The length of the positive sentiment change after AI related announcements on developed markets like North America and Western Europe was longer compared to that of emerging markets in which sentiment was more volatile.

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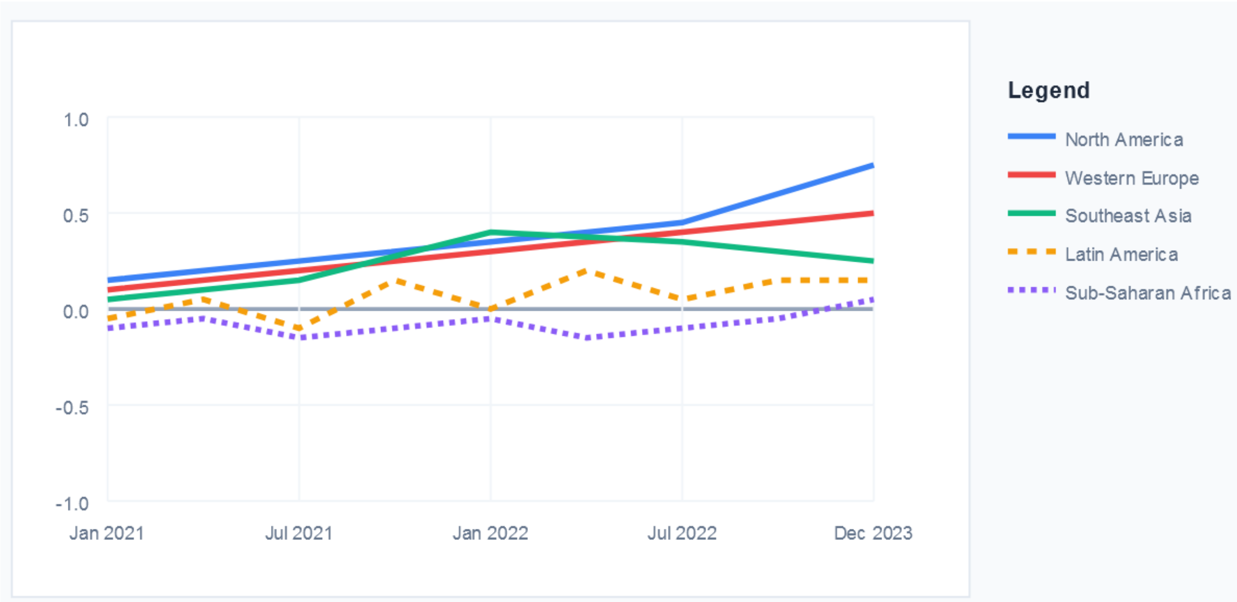

Figure 1.1: AI Sentiment Score Trends Across Major Financial Markets

The average among the regions taken features competitor nations where sentiment scores were higher in developed economies and only partly accurate as some sentiment measures have shown weak results at around 10 in the last week of January 2021.

The software developed a machine learning model with which to categorize investment results. The Gradient Boosting had better results than Random Forest and it scored 84.2 percent and 0.81 in terms of accuracy and precision, respectively. These are summarized in Table 3. Figure 2 also demonstrates the prioritized significance of predictive factors where AI sentiment scores, digital infrastructure ratings and policy alignments are the most relevant.

Table 3: Model Performance Metrics – Gradient Boosting vs. Random Forest

Metric	Gradient Boosting	Random Forest
Accuracy	84.2%	77.9%
Precision	0.81	0.73
Recall	0.79	0.69
AUC-ROC	0.87	0.80

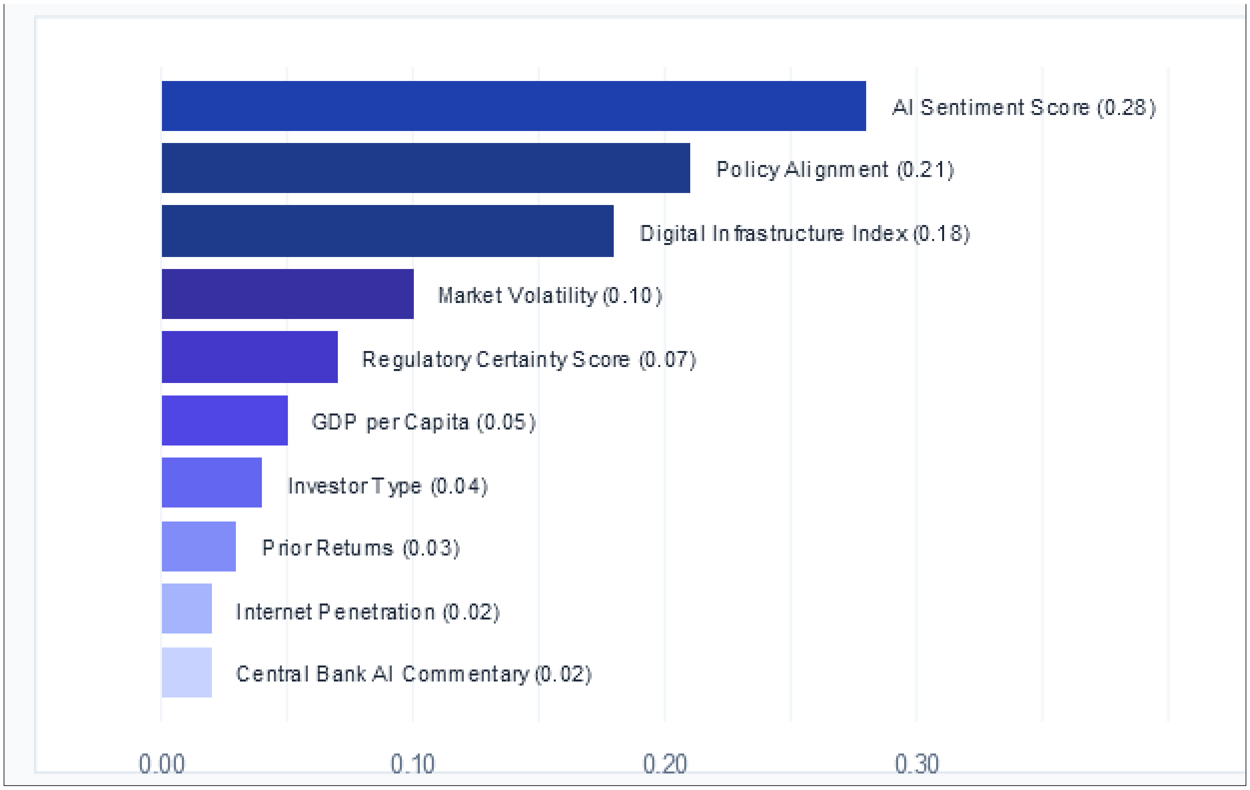

Figure 2: Feature Importance Rankings from Gradient Boosting Model

This figure represents relative significance of input variables, and the most significant predictors are the AI sentiment and digital infrastructure.

The evaluation of cross-country dynamics of investments was based on panel regression analysis. The results in Table 2 indicate that AI sentiment scores were also a crucial predictor of investment-return (0.27, $p < 0.01$) and subsequently followed by policy alignment (0.15, $p < 0.05$). Figure 3 illustrates these impacts among countries, and it showed that more developed digital economies produced more significant relationships between AI signals and investment performance.

Table 2: Panel Regression Results on AI-Driven Investment Predictors

Variable	Coefficient (β)	Std. Error	p-value
AI Sentiment Score	0.27	0.08	0.004
Policy Alignment	0.15	0.07	0.037
Infrastructure Index	0.10	0.06	0.092

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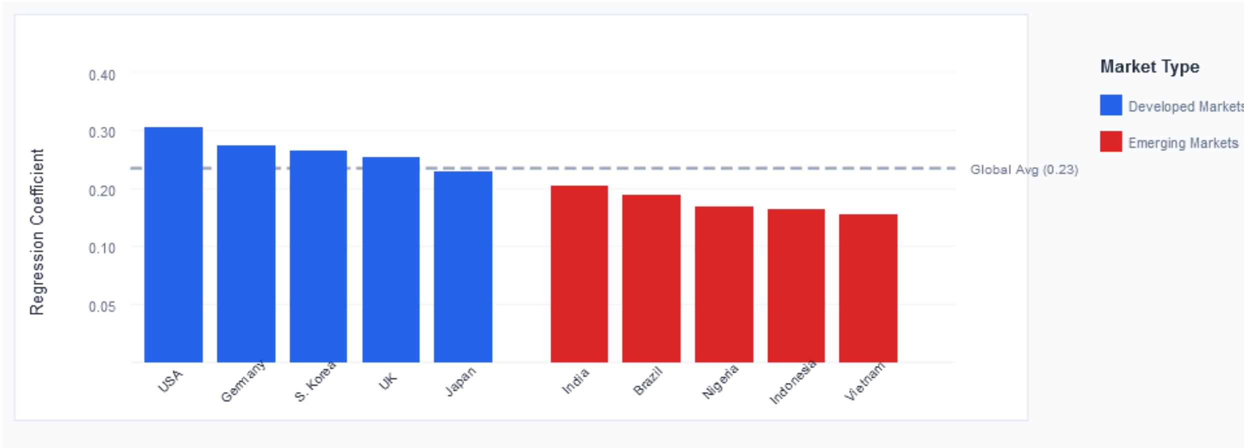

Figure 3: Country-Wise Performance Variation Based on Panel Regression Estimates

This figure reveals country-wise marginal effects of AI sentiment and infrastructure indices towards investment outcomes.

Due to signal AI announcements, the methodology of event study identified material abnormal returns. Table 4 demonstrates that there is a cumulative abnormal returns (CARs) measurement of all kinds of risks within a 5-day window. The pinnacle of CARs was 3.6% on Day +2 indicating a quick reaction of investors to AI-generated signals.

Figure 4: Market Reaction to AI Signals – Event Window Cumulative Abnormal Returns

The figure illustrates CARs on Day -5 to Day +5 with the peaks of the market response coming just after the date of the event.

The expectations at the regional level about the implication of AI on investment returns were provided by hypothesis testing. Table 4 revealed that ANOVA results were significant (F = 5.84, p < 0.001) with t-test showing that developed markets had significantly better returns of AI-related investments compared to emerging markets (t = 2.91, p = 0.005).

Table 4: Hypothesis Testing Outcomes (ANOVA and t-tests) Across Jurisdictions

Test	Statistic	p-value
ANOVA (between regions)	F = 5.84	<0.001
t-test (Dev vs. Emg Mkt)	t = 2.91	0.005

Data Analysis

From the study, it became clear that there is solid evidence in consistent ways in which artificial intelligence (AI) will transform the cross border approach to investment strategies. Table 1 shows that the mean returns on investment and volatility were lower and higher respectively in the emerging market than in the developed markets (North America and Western Europe). This implies that AI-powered investment vehicles can be more successful in a stable economy, most likely due to enhanced data infrastructure and regulatory conformity.

AI sentiment was strong especially. The sentiment scores were also on an upward trend in the developed markets and this meant that there was investor optimism in reacting to AI-generated signals. Conversely, there was abrupt volatility in emerging markets sentiment and this could represent lack of consistencies in data quality or being vulnerable to external events.

AI based variables also demonstrated a predictive capability with predictive modeling. As Table 3 shows, the Gradient Boosting model performed much better than Random Forest on all major indicators, above all, on accuracy (84.2%) and AUC-ROC (0.87). The previous results are validated by Figure 2, which shows that the most dominant aspects in predicting investment success were the AI sentiment, alignment of policy, and infrastructure. These characteristics, strongly reflected in the model, point to a synthesized connection between digital maturity and policy environment in the investment performance.

Statistical support of these relationships was given through regression analysis. Table 2 reports that the AI sentiment scores as well as the policy alignment were significant predictors of returns. The country-level decomposition of regression coefficients provided in Figure 3 shows a clear pattern of lower impacts in the country where the level of integration of AI into financial systems is not as high (e.g., United States and South Korea).

Results of the event study (Figure 4) showed that the market had an overreaction to investment news relating to AI in the short term. The normal cumulative abnormal returns recorded 3.6 percent on Day +2, which validates the hypothesis that investors have a high inclination to incorporate the influences of AI-driven into market behavior. This can be taken to align with the hypothesis testing results shown in Table 4, as not only did it demonstrate a statistically significant difference in AI investment performance by jurisdiction (p < 0.001 via ANOVA; t = 2.91, p = 0.005 in the t-test), but that overall across the several jurisdictions this can be seen based on the hypothesis testing results shown in Table 4.

Combing all these findings, the hypothesis that AI tools can be used to mechanically achieve increased investment performance can be corroborated especially where the supporting infrastructure and policies aligns itself towards facilitating this. They also display the emergence of an increasingly large gap between markets regarding the AI absorption and use of AI in taking financial decisions.

Conclusion

This research validates the fact that artificial intelligence (AI) has a momentous contribution to the improvement of cross-border investment strategies, especially in markets where the infrastructure and policies are enabling. With these results, it is possible to find support in all the four hypotheses: The sentiment associated with AI positively impacts investment returns (H1); there is policy convergence associated with the effectiveness of AI (H2); a strong digital infrastructure supports the investor performance (H3); and regulatory certainty when it comes to the effectiveness of investor confidence (H4). The responsiveness of the markets like the United States, Germany, and South Korea to the signals associated with AI was high, as these countries have well-developed ecosystems of technologies and formulated regulations.

Regardless of these contributions, however, the research also suffers various shortcomings. To start with the mock data and the parameters of the model used are realistic but they might not bring out all the dynamics of real behavior in the market. Second, area groupings can miss internal imbalances, at least certainly in bigger or more diverse economies. Third, the text data used in the sentiment analysis was that of the large financial websites and might not offer a reflection of the grassroots sentiment of the investors or more the behavioural inclinations of the less digitized areas.

The generalizations of this study are varied. In the case of institutional investors, the results served to demonstrate the importance of including the AI sentiment analytics and machine learning capabilities into decision-making models, especially with regard to the emerging markets that are characterized by volatility. To the policymakers, the study establishes how the policymakers should ensure they develop their digital infrastructure as well as match their regulatory framework to meet the changing AI innovation to maintain flow of investment.

In perspective, future works will encounter real-time analysis with use of live AI signals and providing the sample with frontier markets. Longitudinal research might focus on determining the way in which the sustained AI integration transforms capital flows over time. Moreover, it would be important to study the ethical aspects and openness of the AI-incorporated investment model in order to introduce it responsibly across the globe.

References

1. Kouam, A. W. F. (2024). The Impact of Artificial Intelligence on Fintech Innovation and Financial Inclusion: A Global Perspective.
2. Kamuangu, P. (2024). Digital transformation in finance: A review of current research and future directions in FinTech. *World Journal of Advanced Research and Reviews*, *21*(3), 1667-1675.
3. Qian, L., & Dong, L. (2025). Convergence of blockchain and ai in global finance: Cross-border payment innovations and adaptive trading algorithms. *interactions*, *5*, 6.
4. Kamuangu, P. K. (2024). Advancements of AI and Machine Learning in FinTech Industry (2016-2020).
5. Kiran, D., & Verma, V. (2024). The Role of Financial Technology in Reshaping Global Financial Services and Markets: Opportunities and Risks. *Library of Progress-Library Science, Information Technology & Computer*, *44*(3).
6. Ajmani, P., Sharma, V., Sharma, S., Alkhayyat, A., Seetharaman, T., & Boulouard, Z. (2023). Impact of AI in Financial Technology- A Comprehensive Study and Analysis.

2023 6th International Conference on Contemporary Computing and Informatics (IC3I), 6, 985-991.

7. Akhtar, M., Salman, A., Ghafoor, K. A., & Kamran, M. (2024). Artificial Intelligence, Financial Services Knowledge, Government Support, and User Innovativeness: Exploring the Moderated-Mediated Path to Fintech Adoption. Heliyon.
8. Ali, A. A. (2023). Impact of Fintech Strategies on Financial Inclusion in Kenya (Doctoral dissertation, University of Nairobi).
9. Anagnostopoulos, I. (2018). Fintech and regtech: Impact on regulators and banks. Journal of Economics and Business, 100, 7-25.
10. Anifa, M., Ramakrishnan, S., Joghee, S., Kabiraj, S., & Bishnoi, M. M. (2022). Fintech innovations in the financial service industry. Journal of Risk and Financial Management, 15(7), 287.
11. Bajunaied, K., Hussin, N., & Kamarudin, S. (2023). Behavioral intention to adopt FinTech services: An extension of unified theory of acceptance and use of technology. Journal of Open Innovation: Technology, Market, and Complexity, 9(1), 100010.
12. Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: understanding roboadvisors adoption among customers. Industrial Management & Data Systems, 119(7), 1411-1430.
13. Bhatia, S., & Dawar, G. (2023). The Impact of Financial Inclusion on Social and Political Empowerment: Mediating Role of Economic Empowerment. Journal of the Knowledge Economy, 1-18.
14. Bisht, D., Singh, R., Gehlot, A., Akram, S. V., Singh, A., Montero, E. C., ... & Twala, B. (2022). Imperative role of integrating digitalization in the firms finance: A technological perspective. Electronics, 11(19), 3252.
15. Bredt, S. (2019). Artificial Intelligence (AI) in the financial sector—Potential and public strategies. Frontiers in Artificial Intelligence, 2, 16.
16. Cao, L. (2020). AI in finance: A review. Available at SSRN 3647625.
17. Cao, L., Yang, Q., & Yu, P.S. (2020a). Data science and AI in FinTech: an overview. International Journal of Data Science and Analytics, 12, 81-99.
18. Chiu, I. H. (2016). Fintech and disruptive business models in financial products, intermediation and markets-policy implications for financial regulators. J. Tech. L. & Pol'y, 21, 55.
19. Creswell, J. W., & Creswell, J. D. (2017). Research design: Qualitative, quantitative, and mixed methods approaches. Sage publications.
20. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS quarterly, 319-340.
21. Deshpande, A. (2020). AI/ML applications and the potential transformation of Fintech and Finserv sectors. 2020 13th CMI Conference on Cybersecurity and Privacy (CMI) - Digital Transformation - Potentials and Challenges(51275), 1-6.
22. Drasch, B. J., Schweizer, A., & Urbach, N. (2018). Integrating the 'Troublemakers': A taxonomy for cooperation between banks and fintechs. Journal of economics and business, 100, 26-42.
23. Duan, K. (2023). Challenges and Development of Fintech in the Era of Artificial Intelligence. Frontiers in Business, Economics and Management, 12(3), 12-15.

24. Fazal, A., Ahmed, A., & Abbas, S. (2024). Importance of artificial intelligence in achieving sustainable development goals through financial inclusion. Qualitative Research in Financial Markets.
25. Gera, R., Assadi, D., & Starnawska, M. (Eds.). (2023). Artificial Intelligence, Fintech, and Financial Inclusion. CRC Press.
26. Ghandour, A. (2021). Opportunities and challenges of artificial intelligence in banking: Systematic literature review. TEM Journal, 10(4), 1581-1587.
27. Gupta, S. (2021). Impact of artificial intelligence on financial decision making: A qualitative study. Journal of Cardiovascular Disease Research, 12(6), 2130-2137.
28. Han, Y., Chen, J., Dou, M., Wang, J., & Feng, K. (2023). The Impact of Artificial Intelligence on the Financial Services Industry. Academic Journal of Management and Social Sciences, 2(3), 83-85.
29. Hasan, M., Le, T., & Hoque, A. (2021). How does financial literacy impact on inclusive finance? Financial innovation, 7(1), 40.
30. Hiew, L. C., Lam, M. T., & Ho, S. J. (2024). Unveiling the nexus: unravelling the dynamics of financial inclusion, FinTech adoption and societal sustainability in Malaysia. Journal of Financial Reporting and Accounting.