GCCR
Global Conference on Contemporary Research

GLOBAL CONFERENCE ON CONTEMPORARY RESEARCH



CONFERENCE THEME:

SUSTAINABLE FUTURES:
INNOVATION, DIGITAL TRANSFORMATION AND GLOBAL COLLABORATION THROUGH CONTEMPORARY RESEARCH

INNOVATION | DIGITAL TRANSFORMATION | GLOBAL COLLABORATION | SUSTAINABLE FUTURES

JOURNAL

PEER-REVIEWED PROCEEDINGS

NOVEMBER 2026

TORONTO, CANADA

gccr.academy

IMPACT OF ARTIFICIAL INTELLIGENCE AND THE HUMAN ROLE IN THE FUTURE STOCK MARKET
THEORETICAL AND IDEOLOGICAL EXPECTATIONS FOR UZBEKISTAN

Graduate of Tashkent State University of Economics

Alisher Shavkidinov

https://doi.org/10.5281/zenodo.24361590

Abstract. Artificial intelligence (AI) can change stock markets by reducing information-processing costs, supporting investment analysis and strengthening surveillance. These gains depend on institutions that can verify data, challenge models and assign responsibility. This article develops a conceptual framework for Uzbekistan through a focused narrative synthesis of financial theory, empirical machine-learning research and official policy documents. It connects informational efficiency, behavioural finance and task-based technological change with questions of investor autonomy, inclusion and public accountability. The analysis suggests that disclosure processing and supervised decision support are more defensible initial applications than unrestricted autonomous trading. A division of responsibility is proposed in which AI produces bounded analytical outputs while people define objectives, assess suitability and retain authority over exceptions. Three testable propositions and a phased evaluation design translate the framework into a research agenda. The contribution is a context-specific explanation of how technological capability and human governance interact; it does not estimate trading returns or demonstrate causal effects in Uzbekistan.

Keywords: artificial intelligence; stock market; human oversight; Uzbekistan; behavioural finance; investor protection; financial inclusion.

1 Introduction

The future stock market is often imagined as a competition between human judgement and machine prediction. A more useful research problem concerns how analytical tasks and decision rights should be distributed. The IMF identifies potential gains in market monitoring,

liquidity and risk management, alongside faster transmission of shocks and operational vulnerabilities [6]. For Uzbekistan, the central issue is therefore whether AI can make capital allocation more informed and accountable, rather than whether it can promise superior returns. This article asks how AI may alter information processing, which human functions remain essential, and what ideological expectations should guide adoption. Here, ideological expectations mean normative views about market efficiency, fairness, professional agency and national development. The proposed contribution is a framework linking these values to verifiable responsibilities and measurable outcomes in Uzbekistan's equity-market setting.

2 Research approach

The study uses a purposive narrative review of 15 foundational studies and primary institutional publications, selected for relevance to information efficiency, prediction, human work, governance or Uzbekistan's policy context. Sources were checked through publisher, author, regulator and official government websites on 5 November 2026. The synthesis compares mechanisms, boundary conditions and local implications; it is neither a systematic review nor a meta-analysis. Exchange observations retain their original reference dates. No investor survey, transaction-level dataset, backtest or causal estimation is reported. The figures and tables present analytical synthesis and proposals, not observed treatment effects.

3 Theoretical foundations and analytical expectations

Informational efficiency provides the first mechanism. In Fama's framework, market efficiency concerns how prices reflect available information [1]. AI could accelerate the extraction of relevant information from company reports and news. However, faster processing is not equivalent to perfect pricing. Grossman and Stiglitz show why costly information acquisition is incompatible with prices that reveal all information perfectly [2]. Applied to AI, this implies that data access, computing costs and incentives to produce reliable research remain important even when prediction becomes cheaper.

Empirical work by Gu, Kelly and Xiu finds that nonlinear machine-learning methods improve return prediction in their studied setting [4]. That finding supports methodological exploration,

not automatic transfer to Uzbekistan. Differences in disclosure frequency, trading activity and the available history can change performance. Financial machine learning also requires careful evaluation of noisy data and model complexity [15]. A model selected because it fits historical prices well may fail when its signals cannot be executed at realistic costs.

Behavioural finance supplies a second mechanism. Shiller's analysis challenges an exclusively rational interpretation of market movements and highlights behavioural explanations [3]. AI may help investors compare alternatives consistently, but persuasive generated explanations can also encourage excessive confidence. This article infers that the interface through which a forecast is presented matters alongside forecast accuracy. Showing uncertainty and allowing users to question recommendations are therefore part of the proposed design, rather than optional additions.

Table 1. Theoretical mechanisms and their conditional relevance to Uzbekistan

Perspective	Expected AI contribution	Main limiting condition	Local research implication
Information efficiency [1, 2]	Faster reading of public disclosures	Unequal access and costly verification	Measure disclosure-to-analysis time and correction rates
Machine learning [4, 15]	Nonlinear prediction and risk signals	Overfitting and changes in the data-generating process	Compare against simple models on unseen periods
Behavioural finance [3]	Consistent screening and decision prompts	Automation bias and persuasive misinformation	Test comprehension and willingness to challenge AI
Task-based change [5]	Automation of routine analytical tasks	Displacement without creation of skilled tasks	Track task quality, retraining and review capacity

Source: conceptual synthesis of [1–5, 15]. Expected contributions are conditional, not measured outcomes.

The task-based account of Acemoglu and Restrepo distinguishes labour displacement from the creation of new tasks [5]. In securities services, extracting figures may become cheaper while validating models, investigating anomalies and explaining decisions become more important. This does not guarantee a net employment gain. The proposed implication is to evaluate changes in tasks and skills before predicting the disappearance of brokers or analysts. Human expertise remains valuable when objectives are ambiguous or historical patterns no longer describe the decision environment.

Together, these perspectives suggest a conditional result: AI can improve the supply and use of information, but benefits depend on data quality, competitive access and the capacity to reject misleading outputs. Technology alone cannot determine whether those gains are widely shared.

4 Uzbekistan as an institutional setting

Uzbekistan's Presidential Resolution PQ-358 of 14 October 2024 approved an AI development strategy extending to 2030 [10]. Its targets include raising the value of AI-based software products and services to USD 1.5 billion. This is an economy-wide policy target, not an observed outcome or a forecast of stock-market income. The strategy's attention to infrastructure, data and skills supplies a policy context for financial applications; it does not establish that autonomous equity trading is already effective or authorised.

A dated exchange announcement provides evidence of improving information access. On 25 November 2024, the Republican Stock Exchange "Toshkent" reported the availability of its market data on the Bloomberg Terminal. It reported 103 listed companies at the end of September 2024 and 43% year-on-year growth in the number of trades during the first nine months of 2024 [11]. These historical indicators describe market participation and connectivity. They do not measure AI adoption, tradable free float, execution quality or the profitability of algorithmic strategies.

The practical inference is to start with the quality of market information. Before training a forecasting system, an institution should assess publication timestamps, corporate-action adjustments, missing observations, security identifiers and the distinction between no trading and no data. Models using Uzbek, Russian and English disclosures also need language-specific checks. A fluent translation can still reverse the meaning of a qualification in an audit opinion or omit a material exception.

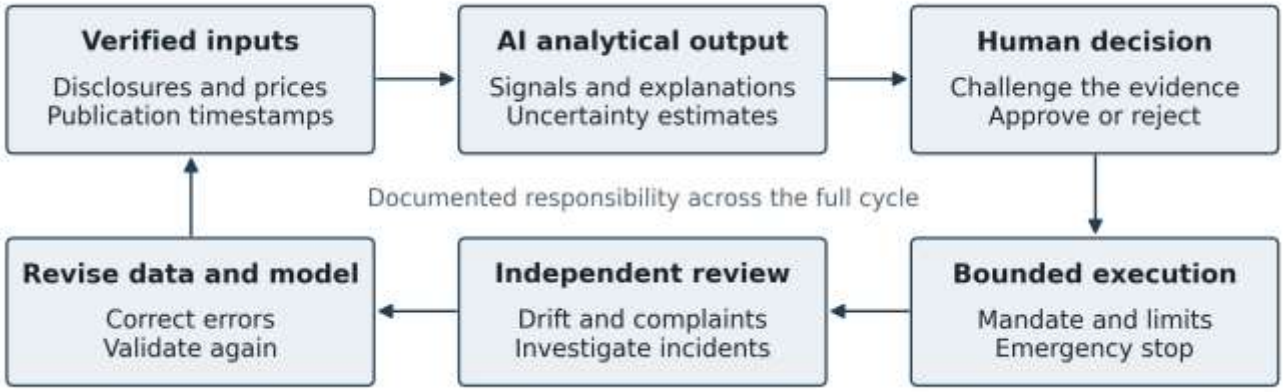


Figure 1. Proposed division of AI tasks and human authority. Original conceptual diagram informed by [8, 12]; arrows represent workflow and feedback, not measured causal effects.

Figure 1 treats approval as an informed decision. Reviewers require access to source evidence, uncertainty and the ability to stop a process. A signature without time, competence or authority to challenge the model would not constitute effective oversight. Conversely, people should not be assumed to outperform a validated system in every repetitive task; delegation should depend on the task's consequences and evidence of reliability.

A suitable initial pilot is an assistant that extracts selected figures from published issuer reports, links each output to its source and sends uncertain cases to an analyst. Another is a surveillance tool that prioritises unusual trading patterns for investigation. Neither application should treat an alert as proof of wrongdoing. BIS analysis describes opportunities for AI-supported supervisory and financial tasks [14]; local deployment would still require separate validation, access controls and an accountable institution.

5 Ideological expectations and the human role

Three normative expectations shape the proposed framework. The first is economic modernisation: AI should improve the usefulness of market information and support productive financing. This expectation should be judged through service quality and allocation outcomes, not simply the number of AI products deployed. The second is inclusion: affordable analysis should help less-experienced investors understand risks. Lower fees are valuable only if explanations are understandable and investors can obtain human assistance. The third is accountable national capability: domestic expertise and language resources should grow alongside international cooperation.

These expectations involve trade-offs. Stronger verification can slow product launches; inexpensive outsourced models can create dependence on a small number of suppliers. The FSB identifies provider concentration, market correlations, cyber risk and model/data governance as potential financial-stability vulnerabilities [7]. For Uzbekistan, this article proposes portable data arrangements, documented service dependencies and operational fallback procedures. The aim is institutional resilience, without assuming that local ownership alone guarantees model quality.

UNESCO's ethics recommendation grounds AI governance in human dignity, transparency and responsibility [9]. In a stock-market setting, the proposed interpretation is that investors should know when AI materially informs a recommendation and should be able to challenge consequential errors. "Human-centred" consequently describes decision rights and remedies, not merely the presence of a person in the process. International guidance is used here as an analytical benchmark, not presented as automatically binding domestic law.

Table 2. Proposed allocation of tasks, responsibility and evaluation measures

Function	AI-supported task	Human responsibility	Evaluation measure
Issuer analysis	Extract figures and compare reports	Verify sources and interpret qualifications	Material extraction errors per reviewed report

Function	AI-supported task	Human responsibility	Evaluation measure
Investor service	Explain scenarios and summarise risks	Assess suitability and resolve complaints	Comprehension and harmful-advice incidence
Trading support	Generate signals within approved limits	Approve mandate and stop exceptions	Net execution cost and limit breaches
Market surveillance	Rank unusual patterns for review	Investigate evidence and determine action	Precision of alerts and investigation time
Model governance	Detect drift and log outputs	Approve changes and assess vendors	Incident recovery time and overdue reviews

Source: original implementation proposal informed by [7–9, 12, 13]. Measures are proposed indicators; no baseline or target values are asserted.

IOSCO's guidance emphasises accountable management, testing, monitoring and adequate expertise [8]. The proposed local application is a documented approval process proportionate to consequences: a report-summary tool and an order-execution system should not face identical controls. NIST's voluntary AI Risk Management Framework provides a general structure for identifying and managing risks [12]. OECD evidence across 49 jurisdictions further indicates that regulatory approaches differ [13]; importing a foreign framework therefore requires attention to domestic mandates and supervisory capacity.

6 Testable propositions and an evaluation pathway

P1 concerns information quality: source-linked AI assistance should reduce analysts' processing time without increasing material errors relative to manual analysis. A future study could randomly allocate comparable issuer reports to manual and assisted workflows, use independent adjudication of errors, and record both time and correction burden. Report complexity and reviewer experience should be balanced across groups. Rejection of the proposition would be informative if apparent speed gains merely shift work into later verification.

P2 concerns investor agency: explanations that display uncertainty and offer human escalation

should improve risk comprehension relative to unqualified AI answers. A controlled study could compare responses to the same investment scenarios, measuring comprehension, calibration and inappropriate reliance. P3 concerns market resilience: dependence on similar models or providers may increase correlated reactions during stress. This should initially be tested through simulated market conditions and dependency mapping, without interpreting simulated outcomes as evidence of actual losses in Uzbekistan [6, 7].



Figure 2. Conditional scenarios for AI adoption. Original analytical matrix; positions are qualitative and are not forecasts, estimated probabilities or a ranking of existing Uzbek institutions.

Implementation should proceed through evidence-based gates. First, audit data and establish manual and simple statistical baselines. Second, run models in a shadow environment with no live orders. Third, permit bounded pilots only after independent validation and a tested stop procedure. Any return-prediction study should use chronological training, validation and test periods, preserve publication lags, and include fees, spreads and feasible execution assumptions. Report performance across liquid and infrequently traded securities, rather than relying only on an aggregate result. Costs and data access constraints may make a simple method preferable.

The framework's limits are substantive. International findings may not transfer to local market conditions, and the cited exchange announcement is a historical snapshot. The study cannot quantify employment effects, forecast returns or establish whether existing oversight is adequate. Its research contribution is a set of explicit mechanisms and falsifiable propositions

that can guide subsequent data collection.

7 Conclusion

AI's strongest prospective contribution to Uzbekistan's stock market is the improvement of verifiable information and supervised decisions. Human roles should concentrate on objectives, contextual judgement, suitability, validation and responsibility for consequences. Theoretical gains in efficiency remain conditional on data quality and governance, while ideological expectations require inclusion and investor agency to be assessed alongside productivity. A staged programme beginning with disclosure analysis and surveillance offers a defensible path for testing these expectations before expanding autonomous execution.

References

[1] Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), 383–417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

[2] Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. American Economic Review, 70(3), 393–408. https://www.jstor.org/stable/1805228

[3] Shiller, R. J. (2003). From efficient markets theory to behavioral finance. Journal of Economic Perspectives, 17(1), 83–104. https://doi.org/10.1257/089533003321164967

[4] Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. The Review of Financial Studies, 33(5), 2223–2273. https://doi.org/10.1093/rfs/hhaa009

[5] Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3

[6] International Monetary Fund. (2024). Advances in artificial intelligence: Implications for capital market activities. In Global Financial Stability Report, October 2024 (Chapter 3). https://www.imf.org/en/Publications/GFSR/Issues/2024/10/22/global-financial-stability-report-october-2024

[7] Financial Stability Board. (2024, November 14). The financial stability implications of

artificial intelligence. https://www.fsb.org/uploads/P14112024.pdf

[8] International Organization of Securities Commissions. (2021). The use of artificial intelligence and machine learning by market intermediaries and asset managers (FR06/2021). https://www.iosco.org/library/pubdocs/pdf/IOSCOPD684.pdf

[9] UNESCO. (2021). Recommendation on the ethics of artificial intelligence. Adopted 23 November 2021. https://www.unesco.org/en/legal-affairs/recommendation-ethics-artificial-intelligence

[10] President of the Republic of Uzbekistan. (2024, October 14). Resolution PQ-358 on approving the strategy for the development of artificial intelligence technologies until 2030 [in Uzbek; consolidated text consulted 5 November 2026]. https://lex.uz/docs/-7158604

[11] Republican Stock Exchange "Toshkent". (2024, November 25). Republican Stock Exchange "Toshkent" market data now available on the Bloomberg Terminal. https://www.uzse.uz/boards/3905?locale=en

[12] Tabassi, E. (2023). Artificial intelligence risk management framework (AI RMF 1.0). National Institute of Standards and Technology, NIST AI 100-1. https://doi.org/10.6028/NIST.AI.100-1

[13] OECD. (2024). Regulatory approaches to artificial intelligence in finance. OECD Artificial Intelligence Papers, No. 24. OECD Publishing. https://doi.org/10.1787/f1498c02-en

[14] Bank for International Settlements. (2024). Artificial intelligence and the economy: Implications for central banks. In Annual Economic Report 2024 (Chapter III). https://www.bis.org/publ/arpdf/ar2024e3.htm

[15] Kelly, B., & Xiu, D. (2023). Financial machine learning. NBER Working Paper No. 31502. National Bureau of Economic Research. https://doi.org/10.3386/w31502