An Empirical Assessment of Artificial Intelligence in Financial Decision-Making

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Abstract:

Artificial intelligence (AI) is increasingly embedded in financial decision-making, spanning investment advisory, credit appraisal, fraud detection, and portfolio management. While the technological capability of AI-based decision-support systems has advanced rapidly, the behavioural and statistical determinants of their adoption and effectiveness in real-world financial decision contexts remain insufficiently understood, particularly in emerging-market settings. This paper reviews the extant literature on AI in finance and proposes an integrated statistical framework linking AI trust, perceived usefulness, financial risk perception, and adoption intention to decision-making efficiency. The framework is demonstrated using an illustrative dataset (n = 250) constructed to mirror a Likert-scale survey instrument, analysed through reliability testing, descriptive statistics, correlation, multiple regression, and analysis of variance. The illustrative results indicate that AI trust, perceived usefulness, and adoption intention are significant positive predictors of decision-making efficiency, while financial risk perception exerts a significant negative influence, together explaining approximately seventy-five per cent of the variance in the outcome construct. The paper concludes with theoretical and managerial implications, limitations, and directions for primary empirical validation.

1. Introduction:

Financial decision-making has traditionally relied on human judgement supported by quantitative models such as discounted cash flow analysis, mean-variance optimisation, and credit scoring heuristics. Over the last decade, the diffusion of artificial intelligence (AI) — encompassing machine learning, deep learning, and natural language processing — has begun to reshape how individuals, financial institutions, and regulators arrive at decisions under uncertainty. AI-enabled systems are now used for algorithmic trading, robo-advisory, credit underwriting, fraud detection, and personalised financial planning, offering the promise of faster, more consistent, and potentially less biased decisions than purely human processes.

At the same time, the adoption and effectiveness of AI in financial decision-making is not purely a technical matter; it is contingent on behavioural and organisational factors such as user trust in algorithmic outputs, perceived usefulness relative to traditional methods, risk perception, and regulatory or governance maturity. Recent systematic reviews of the finance literature confirm that algorithmic capability alone does not guarantee superior decision outcomes unless it is embedded within transparent and auditable governance structures, and unless users hold sufficient trust in the system to act on its recommendations.

Given this context, the present paper adopts a statistical lens to examine how AI-related perceptual constructs relate to financial decision-making efficiency. The paper (a) synthesises

recent literature on AI in finance, (b) proposes a testable conceptual model linking AI trust, perceived usefulness, risk perception, and adoption intention to decision-making efficiency, and (c) demonstrates the associated statistical analysis — reliability testing, correlation, multiple regression, and group-comparison tests — that a researcher can replicate once primary survey data are collected.

2. Review of Literature

A growing body of research has examined AI's role in financial forecasting and market prediction. Systematic reviews covering equities, cryptocurrencies, commodities, and foreign exchange markets report that models such as LSTM, GRU, and XGBoost, along with hybrid deep-learning architectures, dominate the forecasting literature, typically evaluated using error metrics such as RMSE and MAPE.

Beyond forecasting, scholars have studied AI's optimisation role in constrained financial decision problems, including portfolio optimisation, asset–liability management, and risk-based decision-making, identifying two broad research streams: predictive AI/ML applications and optimisation-based decision support.

A separate stream of research foregrounds behavioural finance, arguing that AI can reduce psychological biases such as herd behaviour and improve the accuracy of financial decisions by uncovering hidden patterns in large datasets. Related bibliometric work traces a thematic shift in AI-and-finance scholarship from technical applications toward behavioural and governance-oriented themes, including trust, ethics, and adoption determinants.

Governance and ethics have emerged as recurring concerns. A large-scale systematic review spanning over a thousand peer-reviewed studies found that data-governance maturity mediates the relationship between AI integration and financial outcomes, implying that the benefits of AI are conditional on transparent and accountable implementation rather than algorithmic sophistication alone. Complementary work has examined the ethical implications of AI adoption in financial decision-making and the perception and adoption barriers facing AI-based investment tools, underscoring those trust and perceived usefulness are proximate behavioural determinants of adoption, in line with established technology-acceptance theorising.

Collectively, the literature suggests three broad conclusions relevant to this paper: first, AI demonstrably improves predictive and optimisation capability in financial contexts; second, its practical benefit is conditional on governance, transparency, and user trust; and third, empirical work quantifying the statistical relationship between these behavioural constructs and decision-

making outcomes — especially in emerging-market academic settings — remains comparatively limited, motivating the present study.

3. Research Gap

While technical performance of AI models in forecasting and optimisation is well documented, comparatively fewer studies statistically model how end-user perceptions — trust, perceived usefulness, and risk perception — jointly influence the efficiency of financial decisions actually taken with AI assistance, particularly using validated multivariate techniques such as multiple regression or structural equation modelling within emerging-market, non-institutional-investor samples. This paper addresses that gap by proposing and statistically demonstrating such a model.

4. Objectives of the Study

- To review the current literature on the application of artificial intelligence in financial decision-making.
- To develop a conceptual and statistically testable model linking AI trust, perceived usefulness, and financial risk perception to AI adoption intention and decision-making efficiency.
- To demonstrate the statistical analysis techniques — reliability analysis, correlation, multiple regression, and hypothesis testing — appropriate for empirically validating the proposed model.
- To derive theoretical and managerial implications for financial institutions and individual decision-makers adopting AI-based tools.

5. Hypotheses of the Study

- H1: AI Trust (AIT) has a significant positive effect on Decision-Making Efficiency (DME).
- H2: Perceived Usefulness (PU) has a significant positive effect on Decision-Making Efficiency (DME).
- H3: Financial Risk Perception (FRP) has a significant negative effect on Decision-Making Efficiency (DME).
- H4: AI Adoption Intention (AAI) has a significant positive effect on Decision-Making Efficiency (DME).
- H5: Decision-Making Efficiency (DME) does not differ significantly across respondents' levels of financial experience.
- H6: AI Adoption Intention (AAI) does not differ significantly by gender.

6. Research Methodology

6.1 Research Design

The study adopts a descriptive-cum-analytical research design combining a structured literature review with a quantitative statistical framework suited to survey-based empirical validation.

6.2 Population and Sample

The target population comprises individual investors, financial advisors, and finance/accounting professionals who use or are exposed to AI-based financial decision-support tools. A sample of 250 respondents, selected through stratified random or purposive-convenience sampling, is recommended as adequate for the multivariate techniques specified below (a minimum of 10 observations per estimated parameter, per common regression sample-size heuristics).

6.3 Research Instrument

A structured questionnaire employing a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) is proposed, comprising five constructs — AI Trust (AIT), Perceived Usefulness (PU), Financial Risk Perception (FRP), AI Adoption Intention (AAI), and Decision-Making Efficiency (DME) — each measured through four items adapted from established technology-acceptance and behavioural-finance scales, together with a demographic section (gender, financial experience, and AI usage frequency).

6.4 Statistical Tools

Cronbach's alpha for construct reliability; descriptive statistics (mean, standard deviation); Pearson correlation; multiple linear regression (Ordinary Least Squares) to test H1–H4; one-way ANOVA to test H5; and an independent-samples t-test to test H6. Analysis is illustrated using Python (NumPy, pandas, SciPy, statsmodels).

6.5 Note on the Dataset Used for Illustration

No primary field survey has been conducted for this version of the paper. To demonstrate the statistical procedures in a methodologically transparent manner, a simulated illustrative dataset (n = 250) was generated with realistic inter-item and inter-construct correlations consistent with the hypothesised model. All statistics reported in Section 7 are genuine computed outputs from this simulated dataset, not fabricated figures — but the substantive findings are illustrative of the method only and require replication with actual primary survey data before being reported as empirical evidence in a journal submission or thesis chapter.

7. Data Analysis and Interpretation

7.1 Reliability Analysis

Cronbach's alpha values for four of the five constructs exceed the conventional threshold of 0.70, indicating acceptable internal consistency; the Financial Risk Perception (FRP) scale falls marginally below this threshold and would benefit from item refinement in an actual field study.

Construct	No. of Items	Cronbach's Alpha
AI Trust (AIT)	4	0.759
Perceived Usefulness (PU)	4	0.762
Financial Risk Perception (FRP)	4	0.582
AI Adoption Intention (AAI)	4	0.794
Decision-Making Efficiency (DME)	4	0.770

Table 1: Reliability Statistics (Illustrative Data, n = 250)

7.2 Descriptive Statistics

Construct	Mean	Std. Deviation
AI Trust (AIT)	2.78	0.55
Perceived Usefulness (PU)	2.95	0.58
Financial Risk Perception (FRP)	2.86	0.52
AI Adoption Intention (AAI)	2.95	0.61
Decision-Making Efficiency (DME)	2.84	0.58

Table 2: Descriptive Statistics of Study Constructs

7.3 Correlation Analysis

	AIT	PU	FRP	AAI	DME
AIT	1.000	0.767	-0.685	0.745	0.778
PU	0.767	1.000	-0.682	0.742	0.794
FRP	-0.685	-0.682	1.000	-0.676	-0.725

	AIT	PU	FRP	AAI	DME
AAI	0.745	0.742	-0.676	1.000	0.780
DME	0.778	0.794	-0.725	0.780	1.000

Table 3: Pearson Correlation Matrix (all correlations significant at $p < 0.01$)

All predictor constructs correlate strongly with Decision-Making Efficiency in the hypothesised direction, and Financial Risk Perception is negatively associated with the other four constructs, consistent with theoretical expectations and supporting the appropriateness of proceeding to multiple regression.

7.4 Multiple Regression Analysis

Decision-Making Efficiency (DME) was regressed on AI Trust, Perceived Usefulness, Financial Risk Perception, and AI Adoption Intention.

Predictor	B (Coefficient)	Std. Error	t-value	p-value
(Constant)	1.196	0.284	4.216	0.000
AI Trust (AIT)	0.232	0.059	3.958	0.000
Perceived Usefulness (PU)	0.297	0.055	5.375	0.000
Financial Risk Perception (FRP)	-0.216	0.053	-4.053	0.000
AI Adoption Intention (AAI)	0.252	0.051	4.956	0.000

Table 4: Regression Coefficients (Dependent Variable: DME)

Model fit: $R^2 = 0.754$, Adjusted $R^2 = 0.750$, $F(4, 245) = 187.7$, $p < 0.001$. The model explains approximately 75.4 per cent of the variance in Decision-Making Efficiency. All four predictors are statistically significant at the 1 per cent level and in the hypothesised direction — AI Trust, Perceived Usefulness, and AI Adoption Intention exert significant positive effects, while Financial Risk Perception exerts a significant negative effect. Accordingly, H1, H2, H3, and H4 are supported.

7.5 Group Comparison Tests

Test	Statistic	p-value	Result
One-way ANOVA: DME across financial experience groups	$F = 0.070$	0.932	Not significant

Test	Statistic	p-value	Result
			— H5 supported
Independent t-test: AAI by gender	$t = -0.762$	0.447	Not significant — H6 supported

Table 5: Hypothesis Testing — Group Differences

Decision-making efficiency does not differ significantly across levels of financial experience, and adoption intention does not differ significantly by gender, suggesting that in this illustrative sample, AI-related perceptions are relatively uniform across these demographic segments rather than being confined to any one sub-group.

8. Findings of the Study

- AI Trust, Perceived Usefulness, and AI Adoption Intention are significant positive predictors of Decision-Making Efficiency, while Financial Risk Perception is a significant negative predictor.
- The four predictors jointly explain roughly three-quarters of the variance in Decision-Making Efficiency, indicating strong explanatory power for the proposed model.
- Perceived Usefulness emerges as the strongest single predictor (highest standardised contribution), followed by AI Adoption Intention and AI Trust.
- Financial experience and gender do not significantly moderate AI-related decision-making perceptions in the illustrative sample.
- Reliability analysis indicates that four of the five constructs meet conventional internal-consistency thresholds; the risk-perception scale warrants refinement.

9. Discussion

The illustrative results are consistent with the broader literature reviewed in Section 2: trust and perceived usefulness are recurring proximate determinants of technology adoption and, by extension, of the efficiency with which AI-assisted decisions are made. The negative and significant coefficient for financial risk perception aligns with prior findings that users who perceive greater algorithmic or financial risk are less likely to act efficiently on AI-generated recommendations, reinforcing the argument that transparency and explainability in AI systems are prerequisites for realising their decision-making benefits, rather than optional design features. That decision-making efficiency does not vary by experience level or adoption

intention by gender suggests that, once trust and usefulness perceptions are accounted for, AI's influence on financial decisions may be broadly distributed across user segments rather than concentrated among more experienced or male respondents — though this proposition, like all findings in Section 7, requires confirmation with primary data before being generalised.

10.Theoretical and Managerial Implications

10.1 Theoretical Implications

The study extends technology-acceptance and behavioural-finance frameworks by integrating financial risk perception as a distinct negative predictor alongside the conventional trust–usefulness–adoption chain, offering a parsimonious model for future empirical work on AI-assisted financial decision-making.

10.2 Managerial and Policy Implications

- Financial institutions deploying AI-based advisory or credit-decision tools should prioritise explainability and transparent communication of model logic to strengthen user trust.
- Training and demonstration programmes that visibly improve perceived usefulness are likely to yield disproportionate gains in decision-making efficiency, given the coefficient magnitudes observed.
- Risk-communication strategies — clearly framing the boundaries and limitations of AI recommendations — may mitigate the negative influence of risk perception on efficient AI-assisted decision-making.
- Regulators and IQAC/institutional bodies incorporating AI-literacy content into finance and commerce curricula can draw on this framework to structure competency modules around trust, usefulness, and risk literacy.

11.Limitations of the Study

- The empirical results reported in Section 7 are derived from a simulated illustrative dataset constructed to demonstrate the statistical methodology; they do not represent validated primary field data and must not be cited as empirical evidence.
- The proposed model excludes potentially relevant moderators such as digital literacy, institutional AI-governance maturity, and prior investment losses.
- Cross-sectional design (as proposed) cannot establish causality between AI perceptions and decision-making efficiency.

12.Scope for Future Research

Future research should (a) administer the proposed instrument to an actual sample of investors or finance professionals, ideally across multiple institutions or regions to enable comparative analysis; (b) apply confirmatory factor analysis and structural equation modelling to validate the measurement and structural model more rigorously than OLS regression alone; (c) incorporate longitudinal data to assess whether AI trust and usefulness perceptions evolve with sustained usage; and (d) extend the model to sector-specific contexts such as cooperative banking, insurance, or retail investment platforms.

13.Conclusion

This paper has reviewed the growing literature on artificial intelligence in financial decision-making and proposed an integrated statistical framework linking AI trust, perceived usefulness, financial risk perception, and adoption intention to decision-making efficiency. The illustrative statistical demonstration — spanning reliability analysis, correlation, multiple regression, and group-comparison testing — indicates strong explanatory potential for the proposed model, with trust, usefulness, and adoption intention positively, and risk perception negatively, predicting decision-making efficiency. While the specific figures reported here are illustrative rather than empirically validated, the framework and statistical procedure provide a ready template for researchers seeking to empirically examine AI's role in financial decision-making using primary survey data.

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