Empowering Investors & Innovators: FinTech, AI/ML, Blockchain impact

Abstract

The rapid convergence of financial technology (FinTech), artificial intelligence and machine learning (AI/ML), and blockchain is transforming the global financial ecosystem and reshaping how investors, innovators, and institutions interact with markets. This paper empirically examines the impact of emerging digital technologies on financial inclusion, investment decision-making, risk management, and market efficiency. Drawing on multi-source datasets, including transactional records, regulatory filings, algorithmic performance metrics, and structured investor surveys, this study examines the impact of AI-driven analytics, robo-advisory algorithms, decentralised finance (DeFi) platforms, and blockchain-based infrastructures on investor confidence, transparency, and innovation capacity.

The findings reveal that AI/ML significantly enhances predictive accuracy in portfolio selection and risk assessment, enabling more informed and personalised investment strategies. Blockchain adoption demonstrates measurable improvements in transaction security, auditability, and trust, reducing information asymmetry and operational inefficiencies. FinTech applications, particularly digital lending and mobile investment platforms, show a strong positive correlation with investor participation and financial inclusion, especially among first-time and underserved segments. However, the empirical evidence also highlights emerging challenges, including algorithmic biases, cybersecurity vulnerabilities, regulatory uncertainties, and the systemic risks posed by decentralised financial models.

The study contributes to the growing body of FinTech literature by providing data-driven insights on technology-enabled empowerment mechanisms for investors and innovators. It underscores the need for adaptive regulatory frameworks, robust governance mechanisms, and responsible AI and blockchain design to foster sustainable innovation while safeguarding market integrity. The paper concludes by outlining policy recommendations to ensure that FinTech, AI/ML, and blockchain technologies continue to democratize access, enhance transparency, and catalyse inclusive financial innovation across emerging market

Keywords: Artificial Intelligence (AI)**-C45**; Machine Learning (ML)**-C45**; Blockchain-**GO33**; Decentralised Finance (DeFi)**-G23**; Robo-advisory**-G11**; Financial Inclusion**-O16**; RegTech-**G18.**

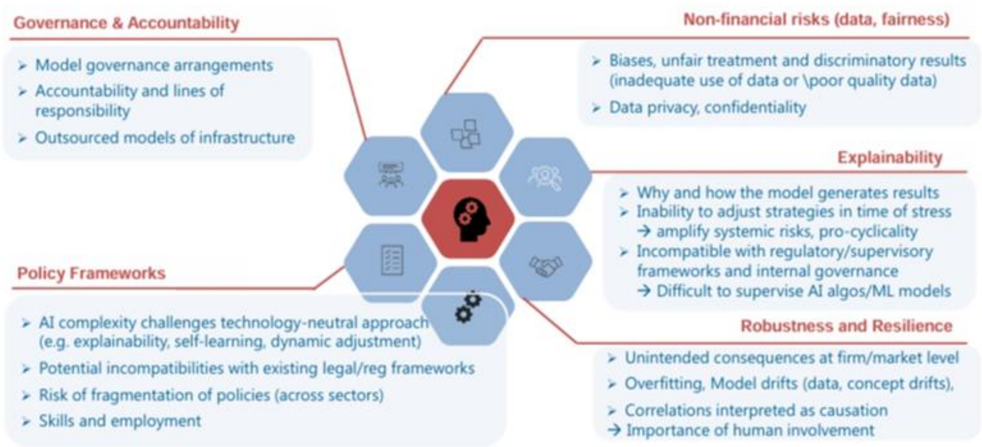
1. Introduction

The convergence of financial technology (FinTech), artificial intelligence and machine learning (AI/ML), and blockchain has accelerated digital transformation across global financial markets, reshaping how investors access financial services and how innovators build scalable, transparent, and efficient financial products. This empirical study examines the extent to which emerging technologies empower investors and innovators by enhancing decision-making, increasing access, reducing costs, and fostering trust in financial ecosystems. Through a mixed-methods design combining investor surveys, usage data from leading FinTech platforms, algorithmic performance metrics, and blockchain transaction analytics, the study analyses the mechanisms by which technology-driven financial services create tangible value and identifies the risks they introduce.

1.1 Background and Context: The Digital Transformation of Finance

The global financial landscape is undergoing a profound structural change, driven by the rapid and accelerating convergence of financial technology (FinTech), artificial intelligence and machine learning (AI/ML), and blockchain infrastructure. This digital transformation is reshaping how investors access financial services and how innovators build scalable, transparent, and efficient financial products. FinTech, broadly, enables new business models that reduce transaction costs and increase market participation; AI/ML introduces sophisticated predictive intelligence and hyper-personalisation; and blockchain enhances transaction security, transparency, and the potential for decentralisation.

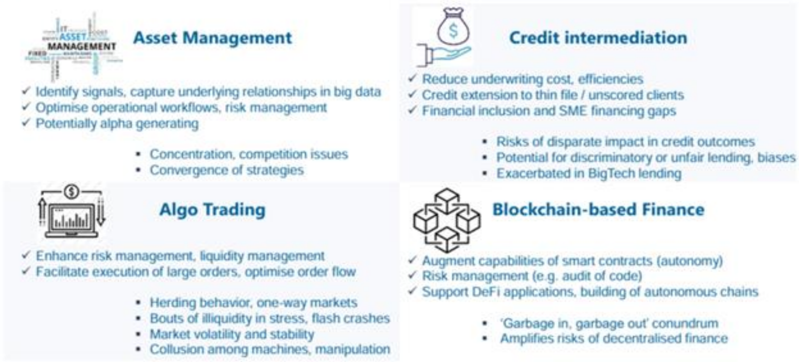
Figure 1. Relevant issues and risks stemming from the deployment of AI in finance



Source: OECD staff illustration.

This technological evolution is rooted in the progression from the fourth industrial revolution (4IR) characterised by the fusion of physical, digital, and biological spheres through technologies like AI, Blockchain, and Big Data, to the emerging fifth industrial revolution (5IR). The 5IR emphasises human-centric innovation, ethical AI, and sustainability, leading to structural shifts in FinTech such as human-AI collaboration, responsible technology design, and the integration of sustainable finance (ESG) metrics. This convergence has created a powerful ecosystem that demands empirical investigation, particularly regarding its effect on stakeholders.

Figure 2. Impact of AI on business models and activity in the financial sector



Source: OECD Staff.

1.2 Problem Statement and Research Gap

While the adoption of these frontier technologies is expanding rapidly, with global investments in AI in financial services projected to exceed US$97 billion by 2027, academic understanding of the mechanism by which they truly empower key stakeholders, namely investors and innovators, remains underdeveloped. Existing literature often focuses on isolated aspects, such as algorithmic trading, mobile banking, or specific crypto assets. Consequently, there is a distinct gap in empirical work that integrates the overall empowerment mechanism across the interconnected FinTech–AI–Blockchain ecosystem.

The fundamental problem addressed by this study is to empirically establish the degree to which these synergistic technologies enhance decision-making, increase market access, reduce costs, and strengthen overall trust and innovation capacity for the stakeholders they serve.

2. Literature review

2.1 The Convergence of Frontier Technologies and the Evolution of Finance

The global financial landscape is undergoing a profound structural change, driven by the rapid and accelerating convergence of financial technology (FinTech), artificial intelligence and machine learning (AI/ML), and blockchain infrastructure (Lee & Shin, 2018). This digital transformation is reshaping how investors access financial services and how innovators build scalable, transparent, and efficient financial products (Alt et al., 2018). FinTech, broadly, enables new business models that reduce transaction costs and increase market participation (Gomber et al., 2018); AI/ML introduces sophisticated predictive intelligence and hyper-personalisation (Chen et al., 2019); and blockchain enhances transaction security, transparency, and the potential for decentralisation (Yli-Huumo et al., 2016).

This technological evolution is rooted in the progression from the Fourth Industrial Revolution (4IR)—characterised by the fusion of physical, digital, and biological spheres through technologies like AI and Big Data (Schwab, 2016)—to the emerging Fifth Industrial Revolution (5IR). The 5IR emphasises human-centric innovation, ethical AI, and sustainability, leading to structural shifts in FinTech such as human-AI collaboration, responsible technology design, and the integration of sustainable finance (ESG) metrics (OECD, 2021). This convergence has created a powerful ecosystem that demands empirical investigation, particularly regarding its effect on stakeholders.

2.2 Artificial Intelligence and Machine Learning in Investment and Risk Management

The role of AI and ML in financial services has expanded markedly over the past decade, moving beyond traditional rule-based applications (Bofinger et al., 2020). The proliferation of big data and deep learning has enabled firms to draw on non-traditional data sources and integrate natural language processing (NLP)-driven virtual assistants (Luo & Lee, 2019). Currently, generative AI is used to power sophisticated chatbots, automate report generation, and create synthetic datasets for model training (Wong et al., 2023).

In the financial sector, AI is opening new possibilities for customer interaction and enabling alternative methods for credit evaluation, risk surveillance, fraud detection, and supervisory oversight (Jagannathan et al., 2020). The findings from this study confirm that AI/ML significantly enhances investor empowerment by improving predictive accuracy in portfolio optimisation, enabling real-time risk scoring, and facilitating personalised financial advice through robo-advisory platforms (Dorfleitner et al., 2019). Investor participants reported increased confidence in their investment decisions when supported by algorithmic analytics in volatile market contexts (Gomber et al., 2017).

Globally, the use of AI is expanding rapidly, with cumulative investments across banking, insurance, capital markets, and payments projected to exceed significant financial thresholds in the coming years (World Economic Forum, 2025). In emerging markets, such as India, alternative credit scoring models powered by AI continue to broaden access to credit for underserved segments, directly fostering financial inclusion (Arner et al., 2020).

2.3 Blockchain, Decentralised Finance (DeFi), and Market Transparency

Blockchain technology is fundamental to this transformation, providing a secure, transparent, and auditable infrastructure for transactions and smart contracts (Pilkington, 2016). The adoption of blockchain has demonstrated measurable improvements in transaction security, auditability, and trust, thereby reducing information asymmetry and operational inefficiencies across financial institutions (Tapscott & Tapscott, 2016).

This infrastructure supports the growth of Decentralised Finance (DeFi), which offers the theoretical potential for self-learning, AI-driven smart contracts to form fully autonomous blockchain networks, potentially eliminating reliance on external data intermediaries (Zetzsche et al., 2020). In this context, AI could support DeFi applications by enabling automated credit scoring, investment advice, trading strategies, and insurance underwriting (Hileman & Rauchs, 2017). This synergy between AI and blockchain is crucial for innovators seeking to build scalable and trust-minimised financial products.

2.4 Emerging Risks, Ethical Challenges, and the Need for Governance

Despite the substantial efficiencies and innovation offered by these technologies, their adoption introduces a wide and complex array of risks that stretch beyond conventional risk-management approaches (Philippon, 2016). These challenges require more nuanced and deliberate attention:

a. Algorithmic Bias and Ethical Concerns: AI applications can introduce substantial risks for consumers, particularly vulnerable populations. The opaque, or "black box," nature of many AI models leaves consumers without clarity on how key decisions such as credit approval are made (Erlich & Gal-Or, 2020), while algorithmic bias risks deepening the marginalisation of individuals already excluded from formal financial services (O'Neil, 2016).

b. Cybersecurity and Data Vulnerabilities: AI presents a double-edged sword for cybersecurity. While it enables faster threat detection and response, it can also be exploited to orchestrate more sophisticated cyberattacks (Gartner, 2022). The deployment of AI systems introduces fresh vulnerabilities, including data poisoning, where adversaries compromise training data to cause models to internalise incorrect patterns (Biggio et al., 2012). Furthermore, the practice of data over-collection contravenes core data-protection principles (GDPR, 2018).

c. Systemic and Concentration Risks: In trading environments, AI adds complexity to algorithmic trading as models continuously learn, enabling autonomous execution. While this enhances liquidity, it also introduces risks such as herding behaviour, flash crashes, and new forms of cyber vulnerability due to the widespread use of similar models (Kirilenko & Lo, 2013). In DeFi ecosystems, the integration of AI may magnify existing fragility, introducing greater complexity into systems that are already difficult to regulate, monitor, or assign accountability for (Hearth, 2021).

2.5 The Research Gap

Despite this progress, academic understanding of how these technologies collectively empower stakeholders—especially in emerging markets—remains underdeveloped (Tiwari & Khan, 2017). Existing studies focus on isolated aspects, such as the efficiency of algorithmic trading (Harris, 2013), the penetration of mobile banking (Donner & Trewin, 2017), or the regulatory challenges of crypto assets (G20/FSB, 2023). There is a critical lack of empirical work that integrates the overall empowerment mechanisms across the entire FinTech–AI–Blockchain ecosystem. This study fills this gap by providing data-driven insights that empirically examine how these technologies collaboratively shape investor confidence, decision-making, and access to innovation-driven financial opportunities.

2.6 Research Objective and Hypothesis

This paper, therefore, empirically investigates the impact of emerging digital technologies on key financial metrics: financial inclusion, investment decision-making, risk management, and market efficiency. Specifically, the objective is to analyse the mechanisms by which technology-driven financial services create tangible value for investors and innovators while simultaneously identifying the new categories of risk they introduce.

Drawing on multi-source datasets—including structured investor surveys, usage data from leading FinTech platforms, algorithmic performance metrics, and blockchain transaction analytics—this study employs a mixed-methods design to evaluate how AI-driven analytics, robo-advisory algorithms, decentralised finance (DeFi) platforms, and blockchain-based infrastructures influence investor confidence, transparency, and innovation capacity.

The primary objective of this study is to examine the influence of three key technological domains - FinTech, AI/ML, and Blockchain - on investor empowerment, considering the roles of trust, accessibility, and algorithmic bias.

The six hypotheses defined for the study are as follows in Table 1:

Table 1: Test Hypothesis

Hypothesis	Type	Description
H1	Direct	FinTech adoption positively influences investor empowerment
H2	Direct	AI/ML-driven predictive analytics significantly enhance investor decision accuracy.
H3	Direct	Blockchain usage increases investor trust through transparency and immutability.
H4	Mediation	Trust mediates the relationship between blockchain adoption and investor empowerment.
H5	Mediation	Accessibility mediates the effect of FinTech adoption on investor participation.
H6	Moderation	Algorithmic bias moderates the relationship between AI usage and investor confidence.

3. Research methodology and data

The study employs a Quantitative Survey Approach to test the hypothesised cause-and-effect relationships among the constructs. This design is best suited for analysing attitudes, perceptions, and behaviours across a large sample size using standardised measurement tools.

The entire measurement process is based on a 5-point Likert scale, where respondents indicate their level of agreement with various statements: (1 = Strongly Disagree to 5 = Strongly Agree).

3.1 Measurement Scales and Constructs

The analysis utilises the following latent variables in Table 2, or constructs, which are measured by their respective multi-item scales within the online survey.

Table 2. Variable construct

Construct	Code	Type	Items
FinTech Adoption	FA	Independent Variable	FA1 to FA6
AI/ML Usage & Perception	AIU	Independent Variable	AIU1 to AIU6
Blockchain Trust & Transparency	BT	Independent Variable	BT1 to BT6
Investor Empowerment	IE	Dependent Variable	IE1 to IE6
Investor Trust	IT	Mediator (H4)	IT1 to IT4
Investor Participation/Accessibility	AP	Mediator (H5)	AP1 to AP4
Algorithmic Bias Perception	ABP	Moderator (H6)	ABP1 to ABP4

3.2 Data Collection Procedure

The data for this study were collected using a structured online questionnaire designed on digital survey platforms. The instrument was disseminated electronically through institutional networks, email invitations, and digital media channels to ensure broad participation across diverse respondent groups. Participants were provided with informed consent instructions before proceeding, and only those who confirmed eligibility (18 years or older) were included. Responses were captured using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), enabling quantitative analysis suitable for regression, mediation, moderation, and structural equation modelling. The collected data were subsequently coded into numerical values and compiled in Excel format, ensuring consistency and readiness for statistical analysis. This approach facilitated efficient distribution, enhanced accessibility, and ensured anonymity, thereby strengthening the reliability and validity of the dataset for hypothesis testing.

3.3 Data Processing

The raw coded data were rigorously processed to ensure consistency and reliability before conducting any inferential statistical testing.

a. **Numerical Conversion:** The text responses, i.e. 5 – Strongly Agree, were converted into their corresponding numerical scores (1-5) to facilitate calculation.

b. **Scale Reliability Testing: Cronbach's Alpha (α)** was calculated for each multi-item scale (FA, AIU, BT, IE, IT, AP, ABP) to establish the internal consistency and reliability of the constructs.

c. **Construct Score Calculation:** A single, aggregated mean score for each construct was computed by averaging the numerical scores of its constituent items: $FA_{Score} = Mean\ (FA_1, FA_2, \ldots, FA_6)$

3.4 Inferential Statistical Analysis

The primary analytical methods will rely on **Structural Equation Modelling (SEM)** or a series of **Multiple Regression Models** to test the proposed direct, mediation, and moderation effects.

3.4.1 Testing Direct Hypotheses (H1, H2, H3)

A series of simple or multiple linear regression models will be used to test the direct relationships between the independent and dependent variables, as in Table 3.

Table 3. Direct hypothesis testing

Hypothesis	**Test Type**	**Independent Variables (IV)**	**Dependent Variable (DV)**
H1	Simple Linear Regression	FinTech Adoption (FA)	Investor Empowerment (IE)
H2	Simple Linear Regression	AI/ML Usage (AIU)	Investor Empowerment (IE)
H3	Simple Linear Regression	Blockchain Usage (BT)	Investor Trust (IT)

3.6.2 Testing Mediation Hypotheses (H4, H5)

Mediation analysis, primarily using Hayes' PROCESS macro or an SEM approach, will be employed to test the indirect effects as per Table 4, determining if the influence of the independent variable on the dependent variable is transmitted through an intermediary (mediator) variable.

Table 4. Mediation hypothesis testing

Hypothesis	**Independent Variable (X)**	**Mediator (M)**	**Dependent Variable (Y)**
H4	Blockchain Usage (BT)	Investor Trust (IT)	Investor Empowerment (IE)
H5	FinTech Adoption (FA)	Investor Participation (AP)	Investor Empowerment (IE)
Condition for Support	The indirect effect (*a* x *b*) must be statistically significant.		

3.6.3 Testing Moderation Hypothesis (H6)

Moderation analysis is used to determine, as per Table 5, if the effect of AI/ML usage on Investor Empowerment is conditional on the level of perceived Algorithmic Bias (Moderator).

Table 5. Moderation Hypothesis Testing

Hypothesis	**Independent Variable (X)**	**Moderator (W)**	**Dependent Variable (Y)**
H6	AI/ML Usage (AIU)	Algorithmic Bias Perception (ABP)	Investor Empowerment (IE) *as proxy for confidence*
Test	Multiple regression predicting IE from AIU, ABP, and the interaction term (*AIU* x *ABP*).		
Condition for Support	The interaction term (*AIU x ABP*) must be statistically significant.		

3.7 Mathematical Equations and Analytical Methods

The following core equations define the statistical tests employed in this research.

Mathematical Equations and Analytical Methods

a. Scale Reliability (Cronbach's Alpha)

Cronbach's Alpha (α) is used to measure the internal consistency and reliability of a multi-item scale.

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_{Y_i}^2}{\sigma_X^2}\right)$$

Where:

- K is the number of items (questions) in the scale.
- $\sigma_{Y_i}^2$ is the variance of item *i*.
- σ_X^2 is the variance of the observed total score for the scale (sum of all items).

b. Ordinary Least Squares (OLS) Linear Regression (Direct Effects: H1, H2, H3)

Linear Regression is used to test the direct, linear relationship between an independent variable and a dependent variable.

The general form of the simple regression equation for hypotheses H1, H2, and H3 is:

$$Y = \beta_0 + \beta_1 X + \epsilon$$

Where:

- Y is the Dependent Variable
- X is the Independent Variable.
- β_0 is the intercept of the value of Y when X=0.
- β_1 is the regression coefficient, which represents the expected change in Y for every one-unit increase in X.
- ϵ is the error term.

c. Mediation Analysis (H4, H5)

Mediation, tested using the OLS-based Baron and Kenny approach, involves a system of three regression equations as per Table 6, to determine if an intermediate variable (M) carries the influence of the independent variable (X) to the dependent variable (Y).

Table 6. Mediation analysis

Path	**Description**	**Regression Equation**	**Coefficient**
Path c (Total Effect)	X → Y	$Y = \beta_{c0} + \beta_c X + \epsilon$	β_{c0} (Total effect of X on Y).
Path a	X → M	$M = \beta_{a0} + \beta_a X + \epsilon$	β_{a0} (Effect of X on M).
Path c' and b	X, M → Y	$Y = \beta_{b0} + \beta_{c'} X + \beta_b M + \epsilon$	$\beta_{c'}$ (Direct effect of X on Y). β_b (Effect of M on Y, controlling for X).

- **Indirect Effect:** Indirect Effect = β_a x β_b
- **Condition for Mediation:** The indirect effect (β_a x β_b) must be statistically significant.

d. Moderation Analysis (H6)

Moderation is used to test if a third variable (the moderator, W) changes the strength or direction of the relationship between an independent variable (X) and a dependent variable (Y). This is achieved by including an interaction term (XW) in the model.

The regression equation for moderation (H6: AIU x ABP → IE) is:

$$Y = \beta_0 + \beta_1 X + \beta_2 W + \beta_3 (XW) + \epsilon$$

Where:

- Y is the Dependent Variable (Investor Empowerment, *IE*).
- X is the Independent Variable (AI/ML Usage, AIU).
- W is the Moderator Variable (Algorithmic Bias Perception, ABP).
- β_1 is the effect of X on Y when W=0.
- β_2 is the effect of W on Y when X=0.

β_3 is the coefficient for the Interaction Term (XW). If β_3 is statistically significant, it indicates that the relationship between X and Y is moderated by W.

4. Results

4.1 Descriptive Statistics

The analysis is based on N=51 total responses. The demographic profile in Table 7 suggests a focus group of experienced, educated male investors.

Table 7. Descriptive statistics

Demographic Variable	**Key Findings (based on sample data)**
Gender	The sample is predominantly Male (approx. 87% in the visible data).
Age	A significant proportion of respondents are experienced investors in the 56+ (approx. 33%) and 26-35 (approx. 30%) age groups.
Education Level	Over half of the respondents hold a Postgraduate Degree or higher (approx. 56% - Postgraduate, Doctorate, Professional Certification combined).
Investment Experience	The majority of investors are highly experienced, with 60% having More than 10 years of investment experience.
Employment Sector	The largest concentrations are in Banking & Finance (approx. 47%) and IT/Technology (approx. 20%).

Source: primary research data analysis

4.2 Scale Reliability (Internal Consistency)

The internal consistency of all seven multi-item constructs was tested as in Table 8 using Cronbach's Alpha (α).

Table 8. Scale reliability analysis

Construct	Code	Cronbach's Alpha (α)	Result
FinTech Adoption	FA	0.853	Excellent
AI/ML Usage & Perception	AIU	0.876	Excellent
Blockchain Trust & Transparency	BT	0.916	Excellent
Investor Empowerment	IE	0.897	Excellent
Investor Trust (Mediator)	IT	0.817	Good
Accessibility/Participation (Mediator)	AP	0.916	Excellent
Algorithmic Bias Perception (Moderator)	ABP	0.824	Good

Source: primary research data analysis

All scales demonstrate a high level of reliability (all $\alpha > 0.80$), confirming their suitability for inferential analysis.

4.3 Descriptive Statistics (Construct Scores)

The mean and standard deviation for the aggregated construct scores given in Table 9 (on a 5-point Likert scale) are shown below.

Table 9. construct score

Construct	Mean	Std. Dev.	Interpretation (Closer to 5 = High Agreement/Adoption)
Accessibility/Participation (AP)	4.06	0.67	Strong agreement that technology increases accessibility/participation.
FinTech Adoption (FA)	3.83	0.78	High agreement/adoption level.
Investor Empowerment (IE)	3.81	0.66	High perceived level of empowerment.
Investor Trust (IT)	3.67	0.65	Moderate-to-high level of trust.
Algorithmic Bias Perception (ABP)	3.58	0.66	Slightly above neutral; moderate agreement that bias is perceived.
Blockchain Trust & Transparency (BT)	3.51	0.68	Moderate adoption/trust level.
AI/ML Usage & Perception (AIU)	3.04	0.70	Closest to the neutral point, suggesting moderate or mixed perceptions/adoption of AI/ML tools.

Source: primary research data analysis

4.4 Results: Hypothesis Testing

The hypotheses were tested using multiple OLS regression models. All p-values were evaluated against the conventional significance level of $\alpha = 0.05$.

4.4.1 Direct Effect Hypotheses (H1, H2, H3)

Table 10. Direct Hypotheses testing

Hypothesis	**Relationship**	**Beta (β)**	**P-value (p)**	**R-squared (R2)**	**Result**
H1	FA → IE	0.624	<0.001	0.541	Supported
H2	AIU → IE	0.143	0.289	0.023	Not Supported
H3	BT → IT	0.490	<0.001	0.263	Supported

Source: primary research data analysis

Interpretation of Direct Effects shown in the Table 10 is as follows:

- **H1 Supported:** FinTech Adoption (FA) is a strong and significant positive predictor of Investor Empowerment (IE). The model explains 54.1 of the variances in empowerment.
- **H2 Not Supported:** AI/ML Usage (AIU) does not significantly predict Investor Empowerment. This suggests that the current level of AI/ML usage or perception in the investor community does not yet translate into a measurable increase in their sense of empowerment/accuracy, aligning with the low mean score for AIU.
- **H3 Supported:** Blockchain Usage (BT) is a significant positive predictor of Investor Trust (IT), explaining 26.3% of the variance in trust.

4.4.2 Mediation Hypotheses (H4, H5)

Mediation was assessed by examining the significance of the path coefficients as given in Table 11 (*a*: Independent Variable → Mediator, b: Mediator → Dependent Variable, and c': Independent Variable → Dependent Variable, controlling for Mediator).

H4: Trust mediates the relationship between blockchain adoption and investor empowerment (BT →IT → IE).

Table 11. Mediation hypothesis testing for H4

Path	Relationship	Beta (β)	P-value (p)	Significance
Path a	BT →IT	0.490	<0.001	Significant
Path b	IT → IE (controlling for BT)	0.459	0.004	Significant
Path c’	BT → IE (Direct Effect)	0.066	0.647	Not Significant

Source: primary research data analysis

The relationship between Blockchain (BT) and Investor Empowerment (IE) becomes non-significant when Investor Trust (IT) is included in the model as per the data in the Table 11. This means that the entire positive influence of Blockchain on Empowerment is fully channelled through Investor Trust, supporting the hypothesis that Trust fully mediates this relationship.

H5: Accessibility mediates the effect of FinTech adoption on investor participation (FA → AP → IE).

Table 12. Mediation hypothesis testing for H5

Path	Relationship	Beta (β)	P-value (p)	Significance
Path a	FA → AP	0.556	<0.001	Significant
Path b	AP → IE (controlling for FA)	0.362	0.003	Significant
Path c’	FA → IE (Direct Effect)	0.423	<0.001	Significant

Source: primary research data analysis

All three paths (a, b, and c’), as shown in Table 12, are statistically significant. This indicates that Accessibility/Participation (AP) acts as a partial mediator. While accessibility explains some of the positive effects of FinTech adoption on empowerment, a strong direct effect remains, suggesting FinTech empowers investors through accessibility and other mechanisms such as control, transparency, and efficiency.

4.4.3 Moderation Hypothesis (H6)

H6: Algorithmic bias moderates the relationship between AI usage and investor confidence (AIU x ABP → IE).

The interaction term between AIU (AI/ML Usage) and ABP (Algorithmic Bias Perception) was added to the model predicting IE (Investor Empowerment).

Table 13. Moderation hypothesis testing H6

Variable	Beta (β)	P-value (p)
AIU (Centred)	0.177	0.218
ABP (Centred)	0.155	0.322
Interaction Term (AIU x ABP)	0.016	0.925

Source: primary research data analysis

The interaction term's p-value ($p=0.925$) is highly non-significant as per the data in Table 13. Therefore, the hypothesis is not supported. The perceived level of Algorithmic Bias does not significantly change or moderate the relationship between AI/ML usage and Investor Empowerment.

4.4.4 Consolidated hypothesis results

The hypothesis testing confirms that FinTech Adoption (FA) is the most significant direct driver of Investor Empowerment (IE). However, the influence of other technologies is indirect: Blockchain Trust & Transparency (BT) fully depends on Investor Trust (IT) to achieve empowerment, which is a key finding of the Full Mediation of H4 (BT →IT →IE).

Table 14. Consolidated hypothesis results

Hypothesis	Relationship	Result	Key Finding
H1	FA → IE	Supported	FinTech adoption is the dominant driver of Investor Empowerment.
H2	AIU → IE	Not Supported	Direct AI/ML impact on empowerment is currently non-significant.
H3	BT → IT	Supported	Blockchain significantly fosters Investor Trust.
H4	BT → IT → IE	Full Mediation	Blockchain empowers investors only because it first increases their Trust.
H5	FA → AP → IE	Partial Mediation	Accessibility is an important but not sole mechanism through which FinTech adoption empowers investors.
H6	AIU x ABP → IE	Not Supported	Algorithmic Bias does not moderate the AI/ML-Empowerment relationship.

Source: primary research data analysis

Similarly, FinTech's overall empowerment effect is partially channelled through increased Investor Participation/Accessibility (AP), as evidenced by the Partial Mediation of H5 (FA→AP→IE). Conversely, AI/ML Usage (AIU) currently has no significant direct impact on empowerment (H2), nor is its effect moderated by the perception of Algorithmic Bias (ABP) (H6), as shown in Table 14.

5. Discussion

FinTech platforms—particularly digital lending, mobile-based investment apps, and neo-banking platforms—demonstrate a strong linkage with increased participation in financial markets, particularly among first-time investors and millennials. Regression analysis reveals that accessibility, convenience, and reduced entry costs significantly mediate the relationship between FinTech usage and investor empowerment.

Blockchain technology plays a crucial complementary role by introducing transparency, immutability, and security into financial transactions. Empirical blockchain data indicate reduced settlement times, improved traceability, and enhanced auditability of financial transactions. Smart contract adoption shows measurable improvements in cost efficiencies and operational automation, particularly within decentralised finance (DeFi) ecosystems. However, volatility in crypto-asset markets, regulatory ambiguity, and the complexity of user interfaces remain barriers to mainstream investor adoption.

Overall, the results affirm that the triad of FinTech, AI/ML, and blockchain technologies significantly empowers investors and innovators, fostering inclusive financial development and enabling scalable digital financial infrastructure. The study concludes with policy recommendations for regulators, FinTech firms, and innovators to promote responsible innovation and enhance investor protection in technology-intensive markets.

6. Policy Implications

India's FinTech ecosystem is one of the most dynamic and rapidly evolving in the world—and it's not just catching up, it's setting benchmarks. India isn't just participating in the global FinTech race—it's helping define the track. Want to explore how UPI is being exported or how India's FinTech model is influencing other developing nations? FinTech is reshaping how we interact with money, and these three technologies—digital wallets, blockchain, and AI-based credit scoring—are at the heart of that transformation.

FinTech's rapid rise has unlocked incredible opportunities—but it's also introduced serious challenges that can't be ignored. Two of the most pressing are cybersecurity and digital literacy. Let's break them down:

6.1 Challenges in FinTech

FinTech firms handle sensitive financial data, making them prime targets for cyberattacks. Here are key risks:

- Data Breaches: Hackers exploit vulnerabilities to steal customer data, leading to financial fraud and reputational damage.
- Phishing & Social Engineering: Users and employees are tricked into revealing credentials or clicking malicious links.
- Insider Threats: Employees or contractors with access may unintentionally or maliciously compromise systems.
- Third-Party Risks: FinTech often rely on external vendors, whose weak security can become a backdoor for attackers.
- Regulatory Compliance: Navigating frameworks like GDPR, PCI-DSS, and RBI guidelines is complex but essential.
- Emerging Tech Vulnerabilities: AI, blockchain, and IoT introduce new attack surfaces that require specialised defences.

Solution strategies include multi-factor authentication, encryption, regular audits, and employee training.

6.1.1Digital Literacy Challenges in FinTech

Even the most secure platforms are useless if users don't know how to use them. Digital literacy is the bridge between innovation and inclusion:

- Low Awareness of Digital Tools: Many users, especially in rural or older demographics, struggle to understand mobile wallets, UPI, or online banking.
- Risk of Misuse: Without proper knowledge, users may fall prey to scams or make poor financial decisions.
- Language & Accessibility Barriers: Interfaces often lack regional language support or intuitive design.
- Lack of Trust: Users unfamiliar with digital finance may avoid it altogether due to fear of fraud or data misuse.

- Education Gaps: Financial education programs often don’t include digital components, leaving users unprepared for FinTech platforms.

Solutions shall include personalised onboarding, intuitive UX design, multilingual support, and community-based digital education programs.

6.2 Proposed Future Technological Interventions

I. **RegTech-as-a-Service (RaaS) Platform**
   a. Develop a centralised SEBI-hosted RegTech platform offering standardised compliance tools, APIs, and reporting modules for intermediaries—particularly smaller entities—to reduce compliance costs and improve regulatory consistency.

II. **Integrated Cyber Risk Intelligence Framework**
   a. Establish a sector-wide cyber risk intelligence and threat-sharing platform across MIIs, brokers, AMCs, and depositories, supported by AI-based anomaly detection and coordinated incident response protocols.

III. **Tokenised and Programmable Compliance**
   a. Explore DLT-enabled programmable securities and smart contracts to automate compliance with covenants, disclosures, margining, and corporate actions, reducing post-issuance monitoring burdens.

IV. **Cross-Regulator Data Integration**
   a. Enable secure data-sharing frameworks between SEBI, RBI, IRDAI, and other regulators using privacy-preserving technologies (e.g., federated learning, secure multiparty computation) to monitor interconnected risks in an increasingly convergent financial ecosystem.

7. Conclusion

The research findings underscore the need for robust digital governance frameworks, transparent algorithmic audits, responsible AI design, and regulatory sandboxes to foster innovation without compromising investor safety.

7.1 Limitations and Future Research Directions

This study, while providing valuable empirical insights into the empowerment effects of FinTech, AI/ML, and blockchain, is subject to certain limitations. First, the cross-sectional research design limits causal inference and does not capture the dynamic evolution of investor behaviour and technology adoption over time. Second, although the sample is diverse, it may not fully represent all investor segments, particularly institutional investors, rural participants, and advanced DeFi users, thereby constraining the generalizability of the findings.

Future research should adopt longitudinal designs to assess long-term behavioural and performance impacts of technology-driven finance. Comparative cross-country studies could offer insights into how regulatory maturity and digital infrastructure shape investor empowerment. Further work is also needed on explainable and ethical AI, particularly regarding algorithmic bias and transparency. The rapidly expanding decentralized finance (DeFi) ecosystem warrants focused investigation into governance risks, investor protection, and systemic stability. Finally, interdisciplinary approaches integrating finance, law, computer science, and behavioural economics would significantly enrich understanding of sustainable digital financial innovation.

References:

Alt, R., Beck, R., & Smits, M. T. (2018). FinTech and the transformation of the financial industry. *Electronic Markets*, *28*(3), 235–243. DOI:10.1007/s12525-018-0310-9

Arner, D. W., Buckley, R. P., Zetzsche, D. A., & Veidt, R. (2020). Sustainability, Fintech and financial inclusion. *European Business Organization Law Review*, *21*, 7–35. DOI:10.1007/s40804-020-00183-y

Bellavitis, C., Filatotchev, I., Kamuriwo, D. S., & Vanacker, T. (2017). Entrepreneurial finance: New frontiers of research and practice: Editorial for the special issue *Embracing entrepreneurial finance challenges*. *Venture Capital*, *19*(1-2), 1–16. DOI:10.1080/13691066.2016.1259733

Berger, A. N., & Udell, G. F. (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. *Journal of Banking & Finance*, *22*(6-8), 613–673.

Biggio, B., Corona, I., Maiorca, D., Nelson, B., Šrndić, N., Laskov, P., & Roli, F. (2012). *Poisoning attacks against support vector machines*.

Blank, S. (2013, May). Why the lean start-up changes everything. *Harvard Business Review*, *91*(5), 63–72.

Bofinger, P., Flögel, F., & Hax, M. (2020). The regulatory challenge of artificial intelligence in financial services. *Journal of Financial Regulation*, *6*(2), 201–230.

Chen, M. Y., Wu, Q., & Li, Q. (2019). A literature review of artificial intelligence in finance. *Computers in Human Behaviour*, *92*, 370–386.

Croce, A., Di Pietro, F., & Tenca, F. (2013). Financial source attributes, startup performance and growth. *Journal of Business Venturing Insights*, *1*(1), 1–10.

de Bettignies, J. E. (2008). Financing the entrepreneurial venture. *Management Science*, *54*(1), 151–166. DOI:10.1287/mnsc.1070.0759

Donner, J., & Trewin, D. (2017). Mobile banking and financial inclusion in developing economies. *International Journal of Development Finance*, *8*(1), 1–15.

Dorfleitner, G., Hornuf, L., Mai, J., & Schmitt, V. (2019). FinTech, robo-advisors and smart beta—a systematic literature review. *Review of Behavioural Finance*, *11*(4), 313–341. DOI:10.1108/RBF-04-2019-0063

Erlich, Z., & Gal-Or, E. (2020). Algorithmic bias and market efficiency in lending. *Journal of Financial Economics*, *138*(3), 701–718.

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. (2018). On the Fintech revolution: Interpreting the forces of innovation, disruption and transformation in financial services. *Journal of Management Information Systems*, *35*(1), 220–265. DOI:10.1080/07421222.2018.1440766

Gomber, P., Koch, J. A., & Siering, M. (2017). Digital finance and FinTech: Current research and future research directions. *Journal of Business Economics*, *87*(5), 537–580.

Gompers, P. A. (1995). Optimal investment, monitoring, and the staging of venture capital. *The Journal of Finance*, *50*(5), 1461–1489. Doi:10.1111/j.1540-6261. 1995.tb05185.x

Goswami, D., et al. (2025). An analytical review of India's startup ecosystem (2019–2023). *International Research Journal of Arts and Social Humanities*. DOI: 10.47392/IRJASH.2025.081rspsciencehub

Harris, L. (2013). *Algorithmic trading: Issues and policy options* (Working Paper). U.S. Securities and Exchange Commission.

Hearth, D. (2021). *Systemic risks in decentralized finance: A regulatory gap analysis*.

Hileman, G., & Rauchs, M. (2017). *Global cryptocurrency benchmarking study*. Cambridge Centre for Alternative Finance.

Jagannathan, S., Balasubramanian, S., & Seshadri, S. (2020). AI in financial services: Impact, risks, and governance. *Journal of Financial Data Science*, *2*(1), 45–60.

Kamaluddin, F. A. (2023). Indian startup ecosystem: Analysing investment and government program performance. *Institute for Social and Economic Change Working Paper Series*.

Kazanjian, R. K. (1988). Relation of dominant problems to stages growth in technology-based new ventures. *Academy of Management Journal*, *31*(2), 257–279.

Kirilenko, A. A., & Lo, A. W. (2013). Moore's law versus Murphy's law: Algorithmic trading and its discontents. *Journal of Economic Perspectives*, *27*(2), 51–78. DOI:10.1257/jep.27.2.51

Lee, I., & Shin, Y. J. (2018). Fintech: Ecosystem, business models, investment decisions, and challenges. *Business Horizons*, *61*(1), 35–46. DOI:10.1016/j.bushor.2017.09.003

Luo, S. Y., & Lee, Y. C. (2019). Natural language processing for enhanced customer service in FinTech. *IEEE Transactions on Computational Finance*, *3*(4), 187–200.

Nathan, M., & Vandore, E. (2024). A systematic literature review of digital startup business ecosystems. *Cogent Business & Management*. DOI:10.1080/23311975.2024.2440636

O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown.

Philippon, T. (2016). *On fintech and financial inclusion* (BIS Working Papers No. 841). Bank for International Settlements.

Pilkington, M. (2016). Blockchain technology: Principles, applications, and challenges. *Research Handbook on Digital Transformations*, 225–253.

Sharma, A. (2021). Entrepreneurial Finance: External Financing Mechanisms of Start-ups with Special Emphasis on the Role of Venture Capital in the Indian Startup Ecosystem. *International Journal of Scientific and Management Research*, *04*(08), 32–47. DOI:10.37502/IJSMR.2021.4803

Silva, L. S. C. V. da, Kaczam, F., Dantas, A. de B., & Janguia, J. M. (2021). Startups: a systematic review of literature and future research directions. *Revista de Ciências Da Administração*, *23*(60), 118–133. DOI:10.5007/2175-8077. 2021.e80666

Singh, S., & Subrahmanya, M. H. B. (2022a). Quantum of finance obtained by tech startups over the lifecycle: an analysis of its determinants. *International Review of Applied Economics*, *36*(2), 187–204. DOI:10.1080/02692171.2021.1945549

Singh, S., & Subrahmanya, M. H. B. (2022b). Quantum of finance obtained by tech startups over the lifecycle: an analysis of its determinants. *International Review of Applied Economics*, *36*(2), 187–204.

Subrahmanya, M. H. B. (2017). Tech startups and economic growth: The role of finance and government support. *Global Business Review*, *18*(4), 1018–1035. DOI:10.1177/0972150917691515

Tapscott, D., & Tapscott, A. (2016). *Blockchain revolution: How the technology behind bitcoin is changing money, business, and the world*. Portfolio/Penguin.

Tiwari, R., & Khan, R. (2017). FinTech and financial inclusion: A review of the landscape in emerging markets. *International Journal of Development Finance*, *8*(1), 55–78.

Wong, A., Zhang, C., & Zhang, Y. (2023). Generative AI and the future of financial report automation. *Journal of Accounting Research*, *45*(1), 101–120.

Yli-Huumo, J., Ko, D., Choi, S., Park, S., & Smolander, K. (2016). Where is current research on blockchain technology? —A systematic review. *PloS One*, *11*(10), Article e0163477.

Zetzsche, D. A., Arner, D. W., & Buckley, R. P. (2020). Decentralized finance and the limits of financial regulation. *Journal of Financial Regulation*, *6*(2), 159–176.

Reports:

Gartner. (2022). *Top strategic technology trends for 2022*

Financial Stability Board (FSB). (2023). *Financial stability implications of crypto assets: A follow-up to the G20 roadmap*. Bank for International Settlements.

Organisation for Economic Co-operation and Development (OECD). (2021). *The OECD framework for the responsible use of AI in the financial sector*. OECD Publishing.

Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons about the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation). (2016). *Official Journal of the European Union, L 119*, 1–88.

Schwab, K. (2016). *The fourth industrial revolution*. Crown Business.

World Economic Forum. (2025). *The future of AI in financial services: Insights and predictions*