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***Research paper***

# Behavioural Drivers of AI-Enabled Fintech Adoption: A Study on Digital Literacy and Investment Intentions of Equity Investors

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**Abstract**

This study investigates the role of Intention to adapt as a critical element in the adoption of Artificial Intelligence (AI) supported financial technology (FinTech) platforms among equity investors. It advances understanding of how psychological and technological factors jointly shape investor behaviour in an AI-driven equity ecosystem. Specifically, it investigates how digital literacy and perceived risk interact with Intention to invest to influence Intention to adapt and investment decision-making. The required data for the study were collected through an online survey from 233 Gen-Z equity investors. Using Structural Equation Modelling (SEM), the study tested an integrated framework combining the Unified Theory of Acceptance and Use of Technology (UTAUT2) and Behavioural Finance Theory. Reliability and validity were assessed using Confirmatory Factor Analysis (CFA), and the mediation effect was analysed to evaluate the mediating role of Intention to adapt. The study found that digital literacy, perceived risk, and financial well-being significantly impact Intention to adapt, whereas effort expectancy, performance expectancy, and social influence did not. Intention to adapt was also identified as reducing biases among different investors and strengthening the relationship between digital literacy and adoption intention. The proposed model also explained a substantial proportion of the variance in investment decision-making, highlighting the importance of intention-to-adapt-driven adoption pathways. These findings suggest that policymakers, FinTech providers, and financial educators prioritize digital literacy initiatives, strengthen data transparency, and embed ethical AI frameworks to improve investor confidence. Furthermore, the work confirms that enhancing Intention to adapt can mitigate perceived risks and raise the long-term adoption rate of AI-enabled financial services.

***Keywords***: *Artificial Intelligence; Fintech Adoption; Digital Literacy; Perceived Risk; Intention to Adapt; Equity Investment.*

## 1. Introduction

The evolution of FinTech has reshaped equity investment by offering digital platforms powered by AI. These platforms enhance the accessibility, efficiency, and speed of investment processes. However, the adoption of AI-driven FinTech services depends significantly on two critical factors: Digital Literacy and investors' long-term behavioural intention to invest. Digital literacy equips investors to navigate platforms and interpret financial data, while the investor's intention builds confidence in system security and reliability. Together, these factors influence the decision-making and reduce behavioural biases in investment contexts (Hidayat-ur-Rehman, 2024).

Behavioural Intention to invest, based on investors' mindset in AI-driven FinTech, has emerged as an essential mediator between technology adoption and investors' attitudes and preferences. As AI-based technology increasingly facilitates financial decision-making by understanding the processes underlying the development of investment intentions, it enhances portfolio management, thereby shaping investor behaviour (Ding et al., 2024). Previous research on robo-advisory adoption underscores both psychological and technological factors, highlighting the intention to adapt as a crucial predictor of acceptance of AI-driven financial instruments (Bashir et al., 2025). The swift integration of traditional techniques with AI-driven technologies has revolutionized the dissemination of investment-related information, facilitating more efficient and enhanced investor engagement. Digital literacy bolsters confidence by encouraging educated use of technologies, thereby promoting more rational and impartial decision-making. (Bhatia et al., 2021). The breakthroughs in intention to adapt remain unexamined for equity investment decisions impacted by AI-driven FinTech platforms.

The demand for transparency and data reliability in AI-driven systems is rising as investors recognize the significance of personalized financial information. The Continuous teaching of behavioural intention to adapt technology-based development is essential to enhance engagement and mitigate risk, thereby facilitating equitable and inclusive participation (Lui & Lamb, 2018). Notwithstanding the proliferation of financial accessibility via FinTech, acceptability remains variable due to barriers such as inadequate digital literacy and limited investment inclination. Financial literacy is acknowledged for reducing perceived risks; its interaction with digital literacy in influencing the acceptance of AI-based FinTech is yet insufficiently understood. This study employs the Unified Theory of Acceptance and Use of Technology (UTAUT2) to investigate the influence of digital literacy on the intention to invest in the AI-enabled FinTech platforms (Singh

et al., 2024). This study examines the influence of behavioural intention to adapt and acceptance of AI technology on investment decision-making. The research investigates the impact of digital literacy on the adoption of AI-driven FinTech by stock investors and the subsequent effects on their intention to adapt. This study also integrates UTAUT2 with the Trust Theory to explore the influence of digital literacy and behavioural intention in AI-powered FinTech payment applications and contribute to understanding the dynamics, which can be used to drive inclusive financial participation by providing FinTech solutions that can improve financial literacy and increase Trust, resulting in a broader digital finance world.

## 1.1. Research gap

Although AI has been integrated across various financial services platforms, empirical evidence is limited on how behavioural intentions to adapt influence investor behaviour and long-term investment engagement. Existing research has primarily focused on technical aspects, such as data transparency and ethical frameworks. At the same time, the psychological dimensions of behavioural intention, perceived reliability, safety, and fairness of collected data remain underexplored in real-world contexts. Furthermore, technology adoption frameworks inadequately consider user factors, such as literacy and financial status, which can influence individuals' attitudes toward technology, their level of understanding, and perceived risk. Shaping adoption has not been adequately studied. This study leaves a critical gap in understanding how human-centric AI systems can sustain investment and facilitate equitable access. Lastly, compared with earlier studies that have primarily focused on behavioural intention, there is a lack of research exploring how behavioural intention translates into investment actions in AI-powered financial environments. These gaps underscore the necessity for a holistic model that integrates technological, psychological, and economic factors to elucidate user adoption and investment behaviour within the AI-driven FinTech ecosystem.

## 1.2. Statement of the problem

Despite swift progress in AI-driven financial technologies, a lack of intent to invest and reluctance to collect information persist, preventing widespread adoption among equity investors. Despite the rapid expansion of accessibility in FinTech, acceptance remains inconsistent, with digital literacy proving a critical gap in adapting to technology. The problem lies not merely in facilitating access but also in ensuring that investors can choose platforms and possess the requisite digital literacy to engage with the investor effectively. Intention to adapt and social influence are enabling factors that interact with digital literacy to shape behavioural intentions toward adoption, underscoring their importance for building confidence, encouraging responsible use of AI-driven FinTech, and facilitating equitable engagement in equity investment.

## 1.3. Research objectives

The study sets out several objectives. First, it seeks to investigate how intention to adapt influences the implementation of AI technologies in equity investment. Second, it aims to analyse the key factors shaping the intention to adjust to AI systems, including transparency, reliability, and data integrity. Third, it examines the extent to which demographic variables, such as age, education, and occupation, affect investor beliefs on AI-based platforms. Fourth, it explores the relationship between perceived risk in AI-enabled decision-making. Finally, it examines the role of AI-based media representation in shaping investors' perceptions of their intention to adapt.

## 1.4. Research questions

a) How do demographic factors such as age, education, and digital literacy affect perceptions of AI trustworthiness in equity investment?
b) How does role intention in AI influence human–AI collaboration in shared decision-making environments?
c) To what extent does intention to adapt in AI-based FinTech platforms mediate the relationship between digital literacy and intention to adapt?
d) What is the relationship between digital literacy and performance expectancy in AI-enabled FinTech platforms?
e) Can the intention of investors through AI be effectively measured using standardised psychological or behavioural models?

Collectively, the research gap, problem statement, objectives, and research questions establish the foundation of this study. By integrating perspectives from UTAUT2 and Behavioural Finance, the study positions intention to adapt as a critical mediator in the adoption of AI-driven FinTech. This framing provides a coherent rationale for the empirical investigation and highlights its contribution to both theory and practice. The following sections present the theoretical background, a literature review, and the development of hypotheses, followed by the research methodology, data analysis, results, discussion, and conclusion.

## 1.5. Theoretical background

Recent advances in AI-enabled financial technology have altered how investors access information, assess risk, and execute equity decisions. The study recognizes that AI-powered financial systems remain limited, both theoretically and practically. Initially, findings regarding the impact of UTAUT2 factors are often ambiguous. Empirical work since 2020 emphasises four families of determinants of FinTech adoption in investor contexts: technology beliefs from UTAUT2, risk perceptions, literacy and capability factors, and behavioural finance mechanisms. Evidence is not yet convergent on how these drivers interact, especially in retail equity environments, where algorithmic opacity can heighten perceived risk and dependence on intention to adapt. Prior studies report strong roles for performance expectancy and effort expectancy, yet several 2023–2025 papers show non-significant or contingent effects. This literature review synthesises open-access findings from 2020 to 2025, identifies consistent patterns and contradictions, and motivates the mediation pathway in which digital literacy fosters the intention to adapt, thereby strengthening adoption intention. Numerous studies indicate that these factors influence how individuals evaluate AI technologies.

### 1.5.1. UTAUT2 constructs in fintech adoption

The Unified Theory of Acceptance and Use of Technology (UTAUT) identifies four primary determinants of behavioural intention and technology use—performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). The extended model, UTAUT2, incorporates hedonic motivation, price value, and habit to explain better consumer adoption behaviour (Venkatesh et al., 2012). However, empirical findings concerning UTAUT2 predictors in FinTech contexts remain inconsistent. Notably, several

studies show that traditional predictors such as effort expectancy, performance expectancy, and social influence become less influential, or even insignificant, when individuals evaluate high-risk, data-intensive, AI-mediated financial systems. In such settings, concerns related to Trust, perceived risk, and algorithmic transparency often overshadow considerations of convenience or social approval. These limitations highlight the need to integrate UTAUT2 with behavioural finance and trust-based theoretical perspectives.

#### 1.5.2. Digital literacy and capability factors

Digital literacy enhances the ability to interpret algorithmic outputs, verify platform signals, and recognise security practices, reducing ambiguity and fostering investor intent. Open-access evidence indicates that literacy and capability dimensions are increasingly used to explain heterogeneity in adoption across age cohorts and markets. The 2023 PLOS ONE study (Krupa & Buszko, 2023) documents age-dependent disparities in FinTech use that parallel literacy gaps, while open-access work in 2024–2025 shows literacy-linked pathways to adoption and inclusion (Amnas et al., 2023). The implication for equity investors is that literacy shapes both confidence in AI recommendations and resilience against bias-inducing noise.

#### 1.5.3. Financial well-being and behavioural finance cues

Behavioural finance research links perceived control and well-being with greater openness to innovative tools. Open-access studies show that individuals with stronger financial well-being are more willing to trial digital financial services. Overconfidence or loss aversion can interact with platform cues to shape adoption. Although much of this work is general to digital finance, the mechanisms align with equity contexts where volatility and learning demands are high, making decision and literacy essential moderators of affective reactions to AI support (Abdul-Rahim et al., 2022).

#### 1.5.4. Mixed and boundary findings since 2023

Recent open-access studies report that perceived risk is sometimes non-significant after accounting for intention, or that classic UTAUT paths weaken once affective or institutional variables are included in the model. This suggests boundary conditions in which intention to adapt absorbs risk effects and in which literacy substitutes for ease-of-use concerns. Such heterogeneity supports modelling intention to adapt as a mediating pathway rather than assuming uniform direct effects from all UTAUT constructs (Kurucz et al., 2025).
The 2020–2025 open-access literature indicates that adoption of AI-driven FinTech in investor settings depends on a joint configuration of technology beliefs, literacy, and risk perceptions. Intention to adapt emerges as the most consistent lever that converts literacy into intention and that resolves risk ambiguity in favour of adoption. The integrated framework, therefore, models standard UTAUT2 paths alongside literacy and well-being, and specifies a mediation from literacy to Intention, through Intention to adapt. The following section details the methodology used to operationalise these constructs, to validate the measurement model, and to test the structural relationships.

#### 1.5.5. Technology acceptance model in connection with behavioural intention

The Technology Acceptance Model (TAM) explains how stock investors choose to use AI-enhanced FinTech products. TAM provides investors with the means to formulate behavioural intentions grounded in two primary beliefs: perceived utility and perceived ease of use of the information collected. In the world of technological advancements the AI-enabled FinTech services, perceived usefulness is how much investors think that AI systems like robo-advisors, algorithmic recommendation engines, or predictive analytics can help them make better decisions, get better investment results, or make it easier to keep track of their portfolios Another important thing to think about is how easy it is to use, since AI-powered systems can seem complicated to understand or use. Investors are more inclined to adopt these technologies if they believe they are straightforward to understand, use, and navigate. This is because they are less likely to be apprehensive about technology and cognitive strain. TAM shows how digital literacy affects adoption: investors who know more about technology find AI technologies easier to use and less scary, making them more appealing.

#### 1.5.6. Theory of planned behaviour

The Theory of Planned Behaviour (TPB) enhances the study by showing the psychological mechanisms that contribute to the development of behavioral intentions. TPB says that how investors think about an action, what they consider typical, and how much control they believe they have over their conduct all affect their intention to engage in it.TPB says investors should first consider whether employing AI in FinTech aligns with how they want to invest and what they want to get out of it. When investors think that well-known peers or experts accept AI-driven decision-support systems, they are more likely to feel social pressure or motivation to use such solutions. Digital literacy is closely related to perceived behavioural control, which means thinking you can do anything. Investors who are excellent with computers and math can use AI platforms more effectively, minimize their risks, and better understand how algorithms work. This feeling of power not only makes people more likely to act on their intentions but also more likely that those intentions will lead to real investment.

## 2. Hypothesis Development and Literature Review

By incorporating Artificial Intelligence (AI) technologies into financial technology (Fintech), financial markets have been overhauled, introducing valuable systems that enable informed investment decisions, improve operational efficiency, and expand financial services. This alteration not only enriches the investor experience but also restructures how financial institutions operate and their relationships with clients. Gera et al. (2024) and Lai & Chong (2020) indicate that AI-enabled fintech solutions are enhancing access to financial services, particularly for underserved populations, thereby promoting economic growth. While the trouble and the absolute mystery of AI innovations call for a more profound understanding of these factors (such as user behaviour), it is also important to consider how trust and behavioural channels interact in the proposed calculations. As research by Hassan and Wood (2020) and Priya and Sharma (2023) shows, Trust is of paramount importance for the adoption and continued use of such systems. Given the fast pace and rising dependence on AI in Fintech, it is necessary to investigate the inherent user-based factors (namely, effort expectancy, performance expectations, social influence, digital literacy, perceived risk, and financial well-being) that influence Trust and behavioral intentions, respectively.
The theoretical frameworks that can subsequently be used to examine technology adoption behaviours need to be grounded in the frameworks mentioned above, for instance, Venkatesh et al.'s (2003) Unified Theory of Acceptance and Use of Technology (UTAUT). Four key determinants identified in UTAUT are performance expectancy, effort expectancy, social influence, and facilitating conditions, which affect

behavioral intention and usage behaviour. This model is well accepted for its ability to predict technology adoption, especially in complex, innovative platform settings. Additionally, by including trust theory into the framework, psychological and behavioural dimensions such as perceived reliability, integrity, and security are incorporated, which are particularly important in Fintech, as users are required to place their Trust in fintech intermediaries to disclose sensitive financial information to them (Gefen et al., 2003). As a result, this study adopts an integrated approach that combines UTAUT and Trust Theory to understand user adoption of AI-driven fintech platforms better.

## 2.1. Effort expectancy

The perceived ease of using a technological system is referred to as effort expectancy. In the context of AI-powered Fintech, this is an important dimension, as users encounter advanced features in unfamiliar interfaces. According to Chawla & Joshi (2020), the more user-friendly a fintech product is, the more quickly users adopt it. Furthermore, as stated by Yan et al. (2021), users prefer platforms that are mostly effortless in terms of their cognitive and technical requirements, which also leads to long-term engagement and increased user satisfaction. Therefore, as AI grows, simplifying its user interfaces and increasing its intuitiveness will become increasingly important. As ease of use can reduce anxiety and foster more positive attitudes towards technology, it is essential to address effort expectancy to improve adoption rates.
Justification: If users feel that using an AI-driven fintech platform requires little effort or technical expertise, they become more comfortable engaging with the technology. This ease of use decreases the learning curve and helps reduce resistance, especially among less tech-savvy users. Therefore, the hypothesis is justified:
H1: Effort expectancy positively influences behavioural intention to use AI-driven fintech platforms.

## 2.2. Performance expectancy

Performance expectancy measures the extent to which users believe that using AI-powered fintech platforms would lead to better financial performance. These platforms provide personalized investment advice, real-time financial insights, automate transactions, and can significantly impact economic outcomes. Following the argument by Bromberg et al. (2017), we argue that users should expect tangible benefits (i.e., higher returns on investment, better risk management, more efficient financial planning) from the systems. There are empirical studies, such as Yan et al. (2021), that reaffirm the importance of a technology's performance expectancy in predicting adoption, especially in settings where the antecedents of technology adoption are goal-oriented users. Moreover, AI systems' ability to learn users' preferences and adapt over time also makes them more attractive to customers seeking the best financial strategies.
Justification: When the advantages of fintech platforms are obvious and beneficial, users are more likely to adopt them. Favourable attitudes and intentions toward these platforms form when individuals expect them to deliver greater financial performance (through automation, analytics, or better decision support). The belief directly impacts their willingness to adopt the technology. Hence, the hypothesis is justified.
H2: Performance expectancy positively influences behavioural intention to use AI-driven fintech platforms.

## 2.3. Social influence

Social influence refers to the degree to which people believe that significant others, including friends, family members, and colleagues, think they should use a given technology. For Fintech and, more generally, for novel AI-based services, social influence is key in shaping users' perceptions and reducing uncertainty. See Kaur et al. (2020) and Oliveira et al. (2016), for example, who found that endorsements and recommendations from trusted social contacts can significantly encourage trust and adoption, particularly among users wary of adopting new technologies. In addition, social proof and peer validation are substantial in collectivist cultures and tight-knit communities. As a result, social influence affects not only the initial decision to adopt but also continued use.
Justification: Observing peers using and benefiting from an AI-driven fintech platform leads them to view these technologies as trustworthy and valuable. Social endorsement lowers users' perceived risks and fosters a sense of communal Trust, thus persuading hesitant users to follow suit. Therefore, the hypothesis is justified.
H3: Social influence positively influences behavioural intention to use AI-driven fintech platforms.

## 2.4. Digital literacy

Digital literacy refers to a user's ability to use digital technologies, understand their functionality, navigate interfaces, and keep information secure. Digital literacy is crucial in the fintech ecosystem because it directly relates to users' confidence in managing AI-driven tools. Chatterjee & Kar (2020) suggest that users with high digital literacy experience lower anxiety and greater competence in using financial applications. According to Lee & Shin (2018), digital literacy helps users to make more informed decisions by better evaluating the risks and benefits of these fintech services. This is because, in general, AI-based systems rely on complex algorithms and data analytics, and so digital literacy plays a significant role in ensuring effective user engagement.
Justification: The higher the users' digital literacy levels, the more easily and effectively they can adopt and use AI-driven fintech solutions. These users are better prepared to use the app's complex functionalities, understand AI-generated insights, and make secure financial decisions. The confidence provided in this way greatly increases their intention to work with fintech platforms. Hence, the hypothesis is justified:
H4: Digital literacy positively influences behavioural intention to use AI-driven fintech platforms.

## 2.5. Perceived risk

Users' concerns about potential adverse outcomes, such as financial loss, data breaches, or unauthorized access, are referred to as perceived risk. At the same time, mighty black boxes to which too much power has been given are seen as skeptical and feared for their transparency and reliability. Among the most significant deterrents to fintech adoption are perceived risks, as noted by Degen & Teubner (2024). In particular, users are susceptible to privacy violations, fraud, and regulatory loopholes. Mitigating these concerns requires a robust security architecture, user education, and action to declare one's data practices. Perceived risks can be mitigated through trust-building mechanisms, such as a clear privacy policy, multi-factor authentication, and visible compliance certifications.

Justification: Users confirm less Trust or adopt new technologies when perceived risks are high. On the contrary, reducing these risks through secure systems and transparent practices builds up users' confidence in the platform. Therefore, perceived risk is a key determinant of behavioural intention, depending on how it is managed. Thus, the hypothesis is justified:
H5: Perceived risk negatively influences behavioural intention to use AI-driven fintech platforms.

### 2.6. Financial well-being

Financial well-being is the overall satisfaction, stability, and security people experience in their financial situation. It influences their ability to join in with financial innovations. People who have higher financial well-being tend to have more disposable income, greater financial literacy, and be more proactive in their investments. Financial security confers greater readiness among users to explore solutions that may yield higher returns, argue Brüggen et al. (2017). Furthermore, Friedline & West (2016) note that people with a strong sense of financial control are more likely to adopt new technologies. Taking this into account, financial well-being motivates users to build confidence and be more willing to try AI-based platforms.
Justification: Those who feel financially secure and competent are more likely to explore and adopt tools considered new and novel to improve their financial status. Because of their readiness and openness to experimenting with finance, they make wonderful early adopters of fintech solutions. Hence, the hypothesis is justified:
H6: Financial well-being positively influences behavioural intention to use AI-driven fintech platforms.

### 2.7. Behavioural intention and investment decision

Behavioural Intention is a vital link between user perceptions and actual behaviour. It indicates how much an individual will use a given technology. In the practice of AI-driven Fintech, behavioural intention is not only a strong predictor of initial adoption but also a key driver of sustained engagement and real investment decisions. According to research by Gupta & Arora (2021) and Rana et al. (2017), it is mediated by behavioural intention. This relationship is essential to understand, as fintech providers can develop their services to meet user expectations better and maintain Trust.
Justification: Behavioural Intention is the immediate precursor of user action. This implies that a firm's behavioral intention is a good proxy for a high likelihood of actual use, or, in other words, a firm's behavioral intention suggests a high probability of making real investment decisions. As a result, consumer behaviour must be understood and influenced to drive fintech adoption and engagement. Hence, the hypothesis is justified:
H7: behavioural intention positively influences investment decisions on AI-driven fintech platforms.
Theoretical Integration

**Table 1:** Theoretical Integration

| Construct | Theoretical Origin |
|---|---|
| Effort Expectancy | UTAUT2 |
| Performance Expectancy | UTAUT2 |
| Social Influence | UTAUT2 |
| Digital Literacy | Cognitive Resource Theory |
| Perceived Risk | Perceived Risk Theory |
| Financial Well-being | Theory of Planned Behavior (TPB) |
| Behavioral intention | Theory of Planned Behavior (TPB) |
| Investment decision | Cognitive Resource Theory |

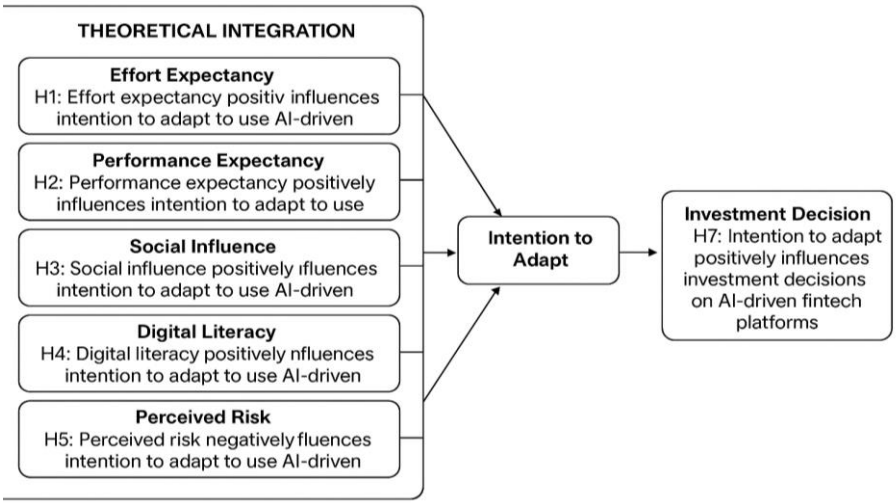


**Fig 2.1:** Theoretical Integration

## 3. Research Methodology

This study analyzes the factors influencing FinTech adoption among Gen Z equity investors in an emerging equity market using a cross-sectional quantitative survey design. The study is enhanced by integrating the constructs of behavioral intention into technology-related models, such as the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Moreover, perceived risk and digital literacy are incorporated into behavioral intention concerning attitude, psychological behavior, decision-making, and platform usability. The research design is explanatory rather than solely descriptive, as it examines direct relationships and indirect effects, including mediation, to clarify how individual perceptions affect actual usage behaviour.

The target audience consists of Gen Z investors who are currently using, or plan to use, fintech platforms for equity investment decisions and for collecting information more easily. Participants were selected through simple random sampling to ensure that each qualified individual had access to the investment preview. The final analytic sample comprised 233 valid cases, having excluded ineligible, incomplete, and patterned responses. This sample size is adequate for performing multivariate analyses, including Structural Equation Modelling (SEM).

## 3.1. Research design

The research employed a cross-sectional design, collecting data at a single point in time using a structured questionnaire. The design was chosen because it permits efficient testing of hypothesised relationships without requiring longitudinal observation. The model was tested using SEM, which is well-suited to evaluating complex relationships among multiple independent, mediating, and dependent variables simultaneously. CFA analysis was used to assess the measurement model before proceeding to the structural path testing.

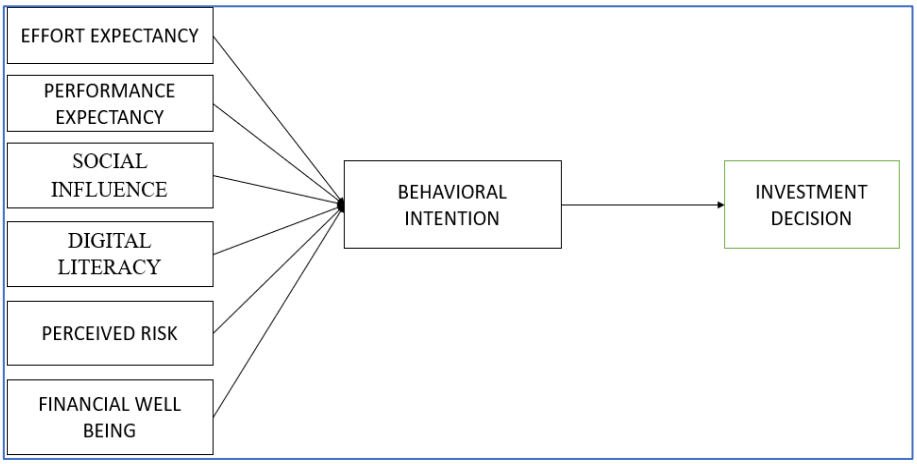


**Fig. 3.1:** Proposed Model.

## 3.2. Sampling and data collection

The population for this study consisted of Gen Z equity investors who either currently use or have the potential to use AI-enabled FinTech platforms. Since the focus was on adoption behaviour rather than on any specific region or institution, the sampling frame was broad. Data were collected through an online survey administered via digital channels, including investor forums, professional networks, and FinTech user groups. To ensure responses came from individuals with relevant exposure, the survey included a screening question that required participants to confirm either prior investment activity or current familiarity with digital financial platforms.

## 3.3. Justification for sample size

Using Cochran's formula to estimate the required sample size for data collection from Gen Z investors (n0 = Z^2 * p*(1-p) / e^2), the target sample for this study was validated. Cochran's initial sample size n0 is (1.96^2*0.25)/(0.06^2) ≈ 267 at the 95% confidence level, and the final sample size was 233 after removing incomplete responses. This sample size still provides a good level of accuracy for estimating population proportions. It allows for multivariate analyses because the 0.05 margin of error and the confidence level remain reasonable. Prior FinTech and technology-adoption research has used similar or smaller sample sizes to achieve valid CFA/SEM results Venkatesh et al., 2003; Davis, 1989.

**Table 3.4:** Demographic Characteristics of the Sample (N=233)

| S. No | Demographic Variable | Category | Frequency | Percentage (%) |
|---|---|---|---|---|
| 1 | Gender | Male | 125 | 54 |
| | | Female | 108 | 46 |
| 2 | Education | Schooling | 55 | 24 |
| | | Diploma | 43 | 18 |
| | | UG | 53 | 23 |
| | | PG | 82 | 35 |
| 3 | Age | 18-26 | 55 | 24 |
| | | 27-34 | 43 | 20 |
| | | 35-42 | 53 | 23 |
| | | 43-50 | 33 | 14 |
| | | above 50 | 39 | 19 |
| 4 | Marital status | Married | 125 | 54 |
| | | Unmarried | 108 | 46 |
| 5 | Occupation | Household | 78 | 33 |
| | | Industry | 69 | 30 |
| | | Others | 86 | 37 |
| 6 | Income | Between Rs 11,000 to Rs 20,000 | 47 | 20 |
| | | Between Rs 21,001 to Rs 30,000 | 58 | 25 |
| | | Between Rs 31,001 to Rs 40,000 | 45 | 19 |
| | | Between Rs 41,000 to Rs 50,000 | 35 | 15 |
| | | More than Rs 50,000 | 48 | 21 |
| 7 | Technology Adoption | Yes | 125 | 54 |
| | | No | 108 | 46 |

The demographic profile shows a balanced gender distribution, with 54 percent male and 46 percent female. Postgraduate education accounts for the largest share at 35 percent, followed by undergraduate degrees at 23 percent. The modal age band is 35–42 years at 23 percent, while the above-50 group accounts for 19 percent. Fifty-four percent report being married. The occupation split is more even than the older draft suggested, with 33 percent in household roles, 30 percent in industry, and 37 percent in other occupations. Income is relatively dispersed, with the largest single bracket at 25 percent between ₹21,001 and ₹30,000. A little more than half of the respondents report adopting technology, which is consistent with the focus on digital investment contexts.
Participation was voluntary and self-selected. A purposive element ensured that only equity investors were included. After excluding incomplete and ineligible cases, 233 valid responses remained. The sample included younger investors and those up to age 50, which supports variation in digital literacy.

### 3.4. Measures and instrument development

All constructs in the study were operationalised using established measurement scales adapted from prior validated studies. Items for effort expectancy, performance expectancy, and social influence were drawn from the UTAUT2. Measures of digital literacy and perceived risk were adapted from earlier FinTech adoption research, while items for financial well-being were derived from studies in behavioural finance. Intention to adapt was measured using items reflecting reliability, integrity, and benevolence, as conceptualised in the intention-to-adapt theory. Intention to adapt and investment decision were captured using standard intention-to-adapt scales adapted to the equity investment context. Each item was measured on a five-point Likert scale ranging from strongly disagree to agree strongly. The questionnaire was pretested with a small group of investors and academics to ensure clarity and content validity. Minor wording changes were made to improve comprehension before complete administration.

| Items Adapted | Source Of Variable Adapted |
|---|---|
| Effort Expectancy (EE) | (Venkatesh et al., 2003) |
| Performance Expectancy (PE) | (Venkatesh et al., 2003) |
| Social Influence (SI) | (Venkatesh et al., 2003) |
| Digital Literacy (DL) | (Featherman & Pavlou, 2003) |
| Perceived Risk (PR) | (Norman & Skinner, 2006) |
| Financial Well-being (FW) | (Netemeyer et al., 2024) |
| Behavioral Intention (BI) | (Venkatesh et al., 2003) |
| Investment Decision (ID) | (Norman & Skinner, 2006) |

### 3.5. Data analysis approach

The data were analysed in several stages. First, descriptive statistics were computed to understand the demographic profile of respondents. Second, the measurement model was assessed using Confirmatory Factor Analysis to examine reliability, convergent validity, and discriminant validity. Third, the structural model was evaluated using Structural Equation Modelling to test the hypothesised paths from effort expectancy, performance expectancy, social influence, digital literacy, perceived risk, and financial well-being to intention to adapt and ultimately to investment decision. Finally, mediation analysis was conducted to test the role of behaviour in linking digital literacy to intention to adapt. Reliability was assessed using Cronbach's alpha and composite reliability, while validity was assessed using the average variance extracted and the Fornell–Larcker criterion. Model fit indices, such as the Comparative Fit Index, Tucker–Lewis Index, Root Mean Square Error of Approximation, and Chi-square to degrees of freedom ratio, were reported to confirm the adequacy of both the measurement and structural models.

### 3.6. Ethical considerations

All respondents participated voluntarily and were informed of the study's purpose before completing the questionnaire. They were assured of the confidentiality of their responses and the anonymity of their identity. No personally identifiable information was collected, and the data were used solely for academic research.

### 3.7. Common bias method

Along with procedural fixes, statistical tests were performed to determine how much CMB remained. The study included Harman's single-factor test, a widely used method, in which all measurement items were subjected to exploratory factor analysis to determine whether a single latent factor explained the majority of the variance. The results showed that no one factor explained most of the variance. In fact, the first factor explained less than the usual 50 percent. This indicates that CMB is unlikely to present a substantial threat to the validity of the findings.

## 4. Results and Discussions

The analysis used 233 valid responses. Results are presented in two stages. The first stage reports the measurement model with evidence on reliability and validity. The second stage examines the structural model to evaluate the hypothesised relationships, including the mediating effect of intention to adapt. The sections that follow integrate the statistical findings with theoretical and practical implications.

### 4.1. Preliminary results

Before testing the measurement and structural models, descriptive statistics and one-way ANOVA checks were conducted to establish baseline characteristics and group comparability, consistent with SEM reporting norms (Hair et al., 2010). Construct means and standard deviations fell within expected ranges with no extreme outliers. Distributions were approximately normal with skewness and kurtosis within ±2.
ANOVA tests across gender, age, and investment experience categories revealed no statistically significant between-group differences in the key constructs ($p > 0.05$). For instance, male and female respondents did not differ on Digital Literacy, Perceived Risk, or Intention to

adapt; likewise, no systematic differences emerged across age or experience groups. These results support analysing the sample as a single pooled group for SEM. Summary descriptives and ANOVA checks are provided in Table 5.1.

**Table 4.1:** Descriptive Statistics and ANOVA Results Across Demographic Groups

| Construct | Mean | SD | Gender F (p) | Age F (p) | Experience F (p) |
|---|---|---|---|---|---|
| Effort Expectancy (EE) | 3.82 | 0.65 | 1.24 (0.27) | 0.98 (0.41) | 1.11 (0.33) |
| Performance Expectancy (PE) | 3.76 | 0.71 | 0.89 (0.35) | 1.04 (0.36) | 0.76 (0.46) |
| Social Influence (SI) | 3.68 | 0.66 | 1.02 (0.31) | 0.92 (0.39) | 1.15 (0.28) |
| Digital Literacy (DL) | 3.94 | 0.72 | 0.77 (0.38) | 1.09 (0.34) | 0.95 (0.41) |
| Perceived Risk (PR) | 3.55 | 0.69 | 0.83 (0.37) | 1.21 (0.29) | 1.06 (0.35) |
| Financial Well-being (FW) | 3.88 | 0.74 | 0.91 (0.34) | 1.18 (0.30) | 0.88 (0.39) |
| Behavioural Intention(BI) | 3.9 | 0.7 | 0.87 (0.36) | 0.95 (0.40) | 1.02 (0.33) |
| Investment Decision (ID) | 3.84 | 0.68 | 1.03 (0.31) | 1.12 (0.32) | 0.97 (0.38) |

## 4.2. Measurement model

The CFA was conducted to evaluate the measurement model's adequacy. Cronbach's alpha values for all constructs exceeded the recommended threshold of 0.70, confirming satisfactory internal consistency. Composite Reliability (CR) ranged from 0.807 to 0.874, and Average Variance Extracted (AVE) ranged from 0.514 to 0.582, both meeting the minimum benchmarks of 0.70 and 0.50, respectively (Fornell & Larcker, 1981; Hair et al., 2019). Reliability statistics are presented in Table 5.2.

**Table 4.2:** Reliability Statistics for the Measurement Model (N = 233)

| Constructs | No of Items | Cronbach's Alpha |
|---|---|---|
| Effort Expectancy | 5 | 0.826 |
| Performance Expectancy | 5 | 0.87 |
| Social Influence | 5 | 0.842 |
| Digital Literacy | 5 | 0.802 |
| Perceived Risk | 5 | 0.841 |
| Financial Well-being | 5 | 0.799 |
| Intention to adapt | 6 | 0.843 |
| Investment Decision | 6 | 0.849 |

Convergent validity was supported as all standardised factor loadings were significant and exceeded 0.60. Discriminant validity was assessed using the Fornell–Larcker criterion. As shown in Table 5.3, the square root of AVE (diagonal entries) was greater than the corresponding inter-construct correlations, and the maximum shared variance (MSV) did not exceed AVE. Hetero Trait Mono Trait (HTMT) ratios were also below 0.90, confirming discriminant validity.

**Table 4.2:** Discriminant Validity Based on the Fornell–Larcker Criterion

| Construct | CR | AVE | MSV | EE | PE | SI | DL | PR | FW | BI | ID |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Effort Expectancy (EE) | 0.832 | 0.558 | 0.693 | 0.747 | | | | | | | |
| Performance Expectancy (PE) | 0.874 | 0.582 | 0.709 | 0.77 | 0.763 | | | | | | |
| Social Influence (SI) | 0.849 | 0.532 | 0.709 | 0.832 | 0.842 | 0.730 | | | | | |
| Digital Literacy (DL) | 0.814 | 0.525 | 0.671 | 0.704 | 0.641 | 0.701 | 0.724 | | | | |
| Perceived Risk (PR) | 0.846 | 0.527 | 0.671 | 0.731 | 0.63 | 0.647 | 0.819 | 0.726 | | | |
| Financial well-being (FW) | 0.807 | 0.514 | 0.648 | 0.693 | 0.615 | 0.672 | 0.805 | 0.793 | 0.717 | | |
| Intention to adapt (BI) | 0.85 | 0.531 | 0.603 | 0.716 | 0.693 | 0.698 | 0.745 | 0.729 | 0.753 | 0.729 | |
| Investment Decision (ID) | 0.853 | 0.539 | 0.603 | 0.628 | 0.582 | 0.589 | 0.665 | 0.653 | 0.684 | 0.776 | 0.734 |

Model fit indices indicated a good fit: $\chi^2/df < 3$, Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI) > 0.90, and Root Mean Square Error of Approximation (RMSEA) < 0.08. These values demonstrate that the measurement model is adequate for structural testing.
Finally, Figure 4.2 presents the CFA diagram with standardised factor loadings for each observed item. All factor loadings were statistically significant and in the expected direction, providing further evidence of construct validity.

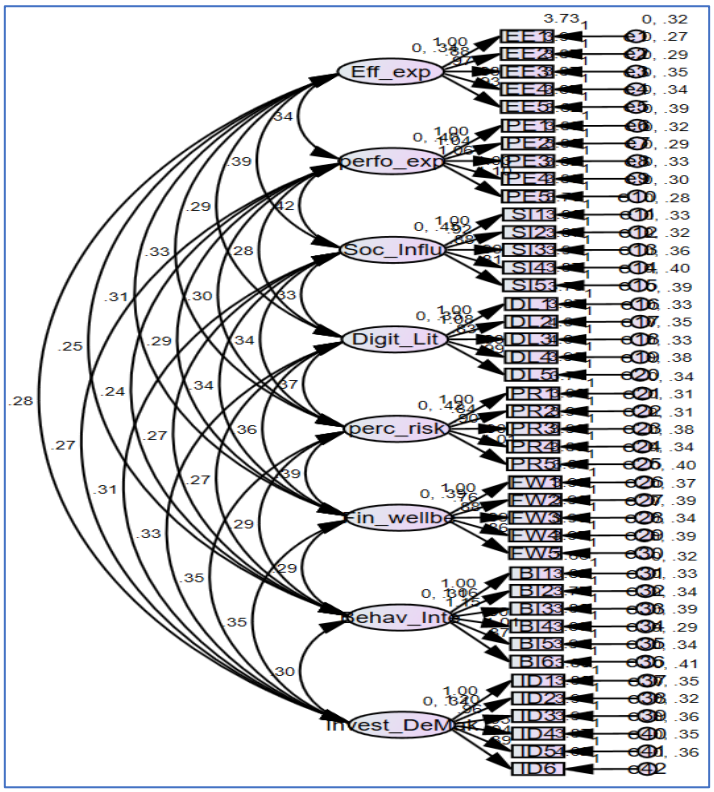


**Fig. 4.1:** Confirmatory Factor Analysis.

## 4.3. Structural model results

The structural model was estimated to test hypotheses H1–H7. Intention to adapt (BI) was regressed on Effort Expectancy (EE), Performance Expectancy (PE), Social Influence (SI), Digital Literacy (DL), Perceived Risk (PR), and Financial Well-being (FW). The model explained 59% of the variance in BI ($R^2 = 0.590$, $F = 54.278$, $p < 0.001$). Variance inflation factors (VIF < 5) confirmed the absence of multicollinearity.

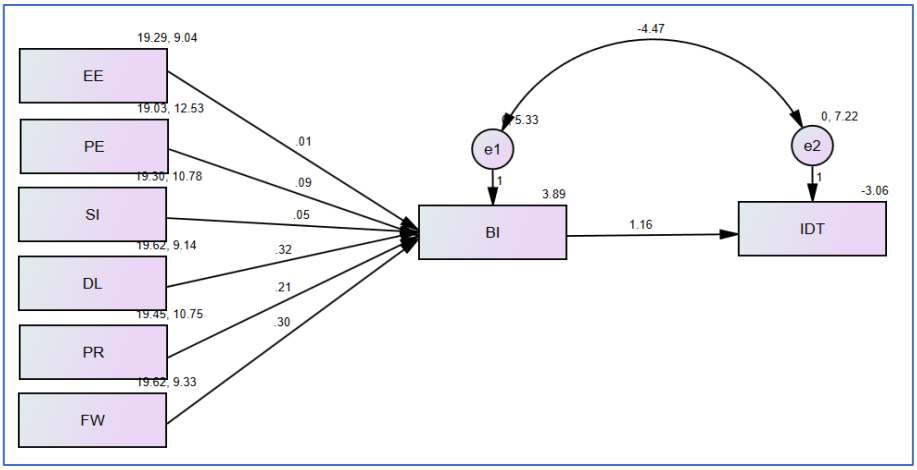


**Fig. 4.1:** Structural Equation Model with Standardised Path Coefficients.

Figure 4.1 illustrates the overall SEM model, while Table 5.4 reports the individual path estimates. EE (β = 0.063, p = 0.474), PE (β = 0.122, p = 0.136), and SI (β = 0.010, p = 0.919) were not significant predictors of BI, suggesting that ease of use, usefulness, and peer influence do not powerfully shape adoption decisions in this context. In contrast, DL (β = 0.236, p = 0.007), PR (β = 0.174, p = 0.043), and FW (β = 0.256, p = 0.002) showed significant and positive associations with BI. These findings indicate that capability (digital literacy), financial security (financial well-being), and risk perceptions are the primary drivers of intention, while traditional UTAUT2 predictors (EE, PE, SI) exert little influence.

**Table 4.3:** Paths to Intention to Adapt (BI)

| Predictor to Behavioural Intention (BI) | Standardised β | t value | p value | VIF |
|---|---|---|---|---|
| Effort Expectancy (EE) | 0.063 | 0.717 | 0.474 | 4.218 |
| Performance Expectancy (PE) | 0.122 | 1.495 | 0.136 | 3.685 |
| Social Influence (SI) | 0.01 | 0.101 | 0.919 | 5.193 |
| Digital Literacy (DL) | 0.236 | 2.726 | 0.007 | 4.121 |
| Perceived Risk (PR) | 0.174 | 2.031 | 0.043 | 4.062 |
| Financial well-being (FW) | 0.256 | 3.201 | 0.002 | 3.524 |

The path from BI to Investment Decision (ID) was then estimated. Table 5.5 shows that BI strongly and positively predicts ID ($\beta = 0.776$, $t = 18.682$, $p < 0.001$). The model explains 60% of the variance in ID ($R^2 = 0.602$), confirming BI as the proximal driver of actual behaviour in AI-enabled financial adoption, consistent with technology acceptance theory.

**Table 4.4:** Structural Path from Intention to Adapt to Investment Decision (Standardised Solution)

| Predictor to Investment Decision (ID) | Standardised β | t value | p value |
|---|---|---|---|
| Intention to adapt (BI) | 0.776 | 18.682 | 0 |

The second stage of the structural model examined the effect of Behavioral Intention (BI) on Investment Decision (ID). As shown in Table 5.5, BI exerted a large and statistically significant positive influence on ID ($\beta = 0.776$, $t = 18.682$, $p < 0.001$). The model explained 60% of the variance in ID ($R^2 = 0.602$), highlighting intention as the proximal predictor of actual investment behaviour.

This result is consistent with the Technology Acceptance Model (Davis, 1989) and UTAUT2 (Venkatesh et al., 2012), both of which position intention as the immediate antecedent of use behaviour. In the present context, this finding reinforces the critical role of investor intention in bridging perceptions of capability, risk, and financial stability with actual investment adoption in AI-enabled FinTech platforms.

**Table 4.6:** Hypothesis Testing Results

| Hypothesis | Relationship | Path Coefficient | t-value | p-value | Result |
|---|---|---|---|---|---|
| H1 | Effort Expectancy → Intention to adapt | 0.075 | 0.717 | 0.474 | Not Supported |
| H2 | Performance Expectancy → Intention to adapt | 0.124 | 1.495 | 0.136 | Not Supported |
| H3 | Social Influence → Intention to adapt | 0.011 | 0.101 | 0.919 | Not Supported |
| H4 | Digital Literacy → Intention to adapt | 0.281 | 2.726 | 0.007 | Supported |
| H5 | Perceived Risk → Intention to adapt | 0.191 | 2.031 | 0.043 | Supported |
| H6 | Financial well-being → Intention to adapt | 0.302 | 3.201 | 0.002 | Supported |
| H7 | Intention to adapt → Investment Decision | 0.814 | 18.682 | 000.0 | Supported |

The non-significant effects of EE, PE, and SI suggest that, in this AI-enabled FinTech context, interface ease, perceived usefulness, and peer cues are overshadowed by perceptions of capability and financial security. Investors' digital literacy reduces anxiety and enhances confidence when interacting with AI tools; financial well-being provides the psychological and resource buffer to engage with new technologies; and perceived risk, when operationalized such that higher scores reflect lower risk, aligns positively with adoption intention. These patterns align with emerging evidence that Behavioral intention-centered mechanisms attenuate traditional UTAUT2 paths in digitally mature user cohorts.

## 5. Integrated Discussion

The overall pattern of results indicates that traditional UTAUT2 constructs are less relevant in the present FinTech context. Unlike the early adoption scenarios, ease of use in the minds of Indian investors appears to have already been internalized through widespread use of online banking and mobile payment systems. As a result, the adoption of AI-enabled investment tools is shaped less by their availability and more by capability, risk perception, and financial resilience. Adoption is driven by digital literacy, perceived risk, and economic well-being, with intention serving as a critical mediating factor. The strong influence of digital literacy, the enforcement that capability reduces anxiety and enhances confidence in using different algorithmic systems (Venkatesh et al., 2012; Kline, 2016). Likewise, perceived risk, when operationalized as reduced uncertainty, positively shapes intention, highlighting the central role of intention-based mechanisms in technology acceptance (Gefen et al., 2003).

Financial well-being further contributes by providing the psychological safety and discretionary resources needed for experimentation, as well as consistent behavioral factors in risk-taking. The results, therefore, extend UTAUT2 by demonstrating that psychological and contextual factors may overshadow technological perceptions in shaping investor Behaviour. This finding aligns with recent calls to integrate UTAUT2 and behavioral finance, recognizing that adoption in AI-intensive domains cannot be explained solely by utilitarian constructs such as perceived usefulness. Theoretically, the study bridges these streams to explain why traditional predictors fail to hold in contexts where algorithmic opacity, security concerns, and behavioral biases interact. By serving as an intended mediating role, the model captures how competence (digital literacy), perceived safety (reduced risk), and financial stability jointly drive adoption intentions.

The findings suggest that FinTech providers and policymakers should focus on strengthening the digital literacy programs that enhance user competence and confidence, while also ensuring data transparency and explainability to mitigate investor concerns about algorithmic recommendations. Equally important is the embedding of ethical and regulatory frameworks, including fairness, accountability, and privacy protection, to enhance overall intention to adapt in AI-enabled platforms. Finally, reducing perceived risks through robust security infrastructure and visible information measures plays an important role, particularly for cautious or risk-averse investors who may otherwise hesitate to adopt such technologies. Taken together, these results indicate that successful scaling of AI-enabled investment platforms will depend less on refining usability features and more on fostering capability, security assurance, and trustworthiness.

## 6. Conclusion and Implications

This study emphasizes the significance of investing purpose in promoting the adoption and effective utilization of Artificial Intelligence (AI) technology in financial decision-making. Literacy is not merely a technical competence but a concept deeply connected to the ethical, psychological, and social dimensions of investor Behaviour. Studies demonstrate that investor confidence in AI systems is profoundly affected by transparency, data security, explainability, and the perceived dependability of AI-driven processes. Users' understanding of the operating mechanisms and recommendation processes of AI-driven FinTech platforms significantly increases their likelihood of interacting with these systems. Conversely, ongoing challenges related to privacy, data protection, and algorithmic bias still obstruct adoption. The results further demonstrate that human–AI collaboration is particularly vital for enhancing investment intention. Investors' preference towards technologies that augment rather than replace human decision-making, as these frameworks install confidence and uphold a sense of communal responsibility. Moreover, digital literacy and financial well-being play important roles in enhancing investor preparedness to utilize AI-driven solutions and in reducing perceived risk and adoption ambitions.

This work theoretically integrates UTAUT2 and behavioral finance theories by demonstrating the inadequacy of traditional predictors in contexts characterized by algorithmic opacity and increased security apprehensions. The model elucidates how competency (digital literacy), perceived safety (reduced risk), and financial stability collectively influence adoption intentions by incorporating behavioral intention as a mediating mechanism. The results suggest that FinTech providers and policymakers must prioritize digital literacy initiatives, enhance data transparency and explainability, and integrate ethical frameworks that include justice, accountability, and privacy protection. A robust security infrastructure and clear regulations are essential to make perceived risks easier to address and provide confidence for investors. This study provides valuable insights; however, future research should investigate the evolution of behavioral intention in AI using longitudinal designs that account for cross-cultural variations in investor perceptions and examine the interaction among cybersecurity policies, legal frameworks, and digital literacy in shaping adoption. Examining the importance of emotional intelligence and ethical AI design may enhance the understanding of how the desire to invest might be intentionally fostered in AI-driven finance. The findings indicate that transparency, accountability, fairness, and adaptability significantly influence investors' trust in long-term investing to ensure safety in future directions. Moreover, the roles of human-AI interaction quality, organizational ethics, and regulatory frameworks are essential in shaping investors' trust in fintech-based information. The study further highlights that building trustworthy AI systems and fintech platforms requires various approaches integrating technical robustness with human-centred design principles. Most importantly, for AI to realize its full potential in contributing to societal advancement, trust must be intentionally fostered through responsible development, deployment, and communication strategies.

## 7. Future Directions of The Study

Future research may examine the impact of digital literacy on investors' long-term behavioral outcomes and investment performance, particularly in relation to emerging FinTech innovations such as AI-driven robo-advisors (e.g., Betterment, Wealthfront), algorithmic trading platforms, AI-based credit-scoring systems, blockchain-enabled innovative contract services, and AI sentiment-analysis tools employed for market forecasting. Comparative analyses with other nations would yield substantial insights into the influence of cultural, regulatory, and technological contexts on investor trust and on the adoption of these instruments, which could play a vital role in long-term investment. It is also helpful to examine how cybersecurity rules and frameworks build investor trust and lower perceived risks in the digital world of financial assets. Subsequent research may investigate how digital literacy and behavioral traits, including overconfidence, algorithm aversion, confirmation bias, and risk perception, shape financial decision-making from the psychological and behavioral perspectives of individual investors. Longitudinal studies that examine how investor trust in AI technologies, such as robo-advisors, AI fraud-detection systems, and automated portfolio optimization tools, evolves across technologies will provide valuable insights into how trust evolves, which can help build investor confidence. It is essential to integrate cross-cultural perspectives, given significant variations in Trust and digital literacy across countries and investor demographics. Future research could examine how emotional intelligence and ethical AI design affect investor trust and perceived risk in long-term technology-driven investing, including the roles of fairness, transparency, and explainability.

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