

## Determinants of AI Adoption in Financial Decision-Making: An Empirical Study among Individual Investors in Kerala

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### ABSTRACT

This study investigates the determinants of AI adoption in financial decision-making among individual investors in Kerala using an extended Technology Acceptance Model (TAM). The model incorporates AI Awareness and AI Reliability to provide clear explanation of trust and adoption. Data from 100 respondents were analysed using SEM-PLS. The results denote that AI Awareness significantly affects Perceived Usefulness and Perceived Ease of Use, while AI Reliability strongly influences Trust. Perceived Ease of Use is found to be the key significant predictor of adoption intention, surpassing Perceived Usefulness. Despite high awareness, a trust gap remains a key challenge to adoption. The study underscores the importance of reliability, transparency, and user-friendly design in promoting AI adoption and provides practical insights for fintech developers and financial institutions.

**Keywords:** Decision-Making, Investors, Empirical Study, TAM, SEM-PLS, Financial Institutions.

### Introduction

Integrating AI in investment approaches takes place at increasing rate and providing incredible ways to polish portfolio results. Investors adopt AI technologies to improve their decision-making strategies, enhance investment decisions, and reduce risks in the market. The application of AI provides plenty of features, such as data analysis, predictive modelling, and machine learning, which further provide previously impossible insights (Mou, 2025).

It has long been believed that the major forces behind markets and investor behaviour are psychological biases such as fear, greed, and herd instinct, which leads to irrational investment decisions. Therefore, trading becomes more rational by minimizing the influence of personal biases on trading operations. This is one of the reasons for incorporating machine learning or deep learning approaches for high-quality predictions (Rahayu et al., 2024)

Robo-advisors are getting importance in wealth and asset management worldwide. As more people opened accounts for digital investment services during COVID-19, their usage was started to grow rapidly. (Padhiyar & Raval, 2026).

Nowadays, people use generative AI tools (ChatGPT, Gemini etc) for stock prediction and decision making by processing large volumes of textual and financial information more quickly and efficiently (Lopez-Lira, 2024)

Recently, deep learning has achieved a lot of success in many areas due to its strong capacity in data process. Additionally, it has been notably used in financial areas such as stock market prediction,

portfolio optimization, financial information processing and trade execution strategies. Stock market prediction is one of the most popular and valuable area in financial market. (Zhang et al., 2018).

Although, the accuracy of results obtained from AI tools are questionable and comes with a vast number of pitfalls that lead to investors achieving poor returns on their investments. To eliminate these drawbacks, upgradation of technologies, features, data, domain adaptations have been carried out. Suppose the development of trading algorithms that will not only mitigate the psychological barriers but also do ensure significant returns on investments, with these returns being evaluated by evaluating the strategies on past historical price data of different assets. The unconventional algorithmic approach to the markets tests a way of obtaining significant returns without the necessity of having low latency and human intervention or any additional resources (Blackmun et al., 2023).

There is increasing concern regarding trust in AI platforms irrespective of how it is becoming common in a variety of domains and getting popularity. Therefore, an intensive understanding of trust in the technology is required. (Choung et al., 2023)

The Credit Suisse's Advanced Execution Services introduced AT platform for Indian equities on June 22, 2009. While it took nearly a decade for algorithmic trading to account for three-fourths of all trades in the USA, India achieved this in less than five years. This rapid adoption increased concerns for regulatory authorities (such as SEBI) about the potential risk of implementing automated strategies in investment platforms (Bunkar & Ramaiah, 2024).

While growing concerns, the advancement and application of the TAM theory (Technology Acceptance Model) in AI-related applications offers a multidimensional measure of trust that can be utilized in the future study of trustworthy AI (Choung et al., 2023). Common theories for adoption behavior include not only the Technology Acceptance Model (TAM) but also the Unified Theory of Acceptance and Use of Technology (UTAUT) (Bedue et al; 2021).

The individual perception towards technological breakdown and early adoption patterns were initiated by Davis (1989) which was later named TAM. In addition, few constructs such as awareness, perceived trustworthiness, regulatory support are equally important to ensure the integration of inclusive technology in a changeable business environment (Bunkar & Ramaiah, 2024).

## **Materials and Methods**

### **Operational Definition**

The term investment includes both trading and investment activities.

An individual investor is a person other than institutional investors who buys and sells securities for their own account, typically in smaller volumes compared to institutional investors like banks, mutual funds, or insurance companies.

### **Research Objectives**

- **General Objective**

To validate an extended TAM model incorporating AI Awareness and AI Reliability in the adoption of AI for financial decision making among individual investors in Kerala.

- **Specific Objectives**

- To evaluate the impact of AI Awareness on the perceived usefulness and ease of use of AI tools among investors in Kerala.
- To examine the relationship between AI Reliability and the level of Trust investors place in automated financial systems.
- To determine how Perceived Ease of Use and Perceived Usefulness directly influence the Intention to Use AI for investment purposes.

### **Literature Review**

- **AI Awareness and Perceived Usefulness**

AI improves predictive accuracy by analyzing macroeconomic indicators, financial statements and other data sources to assess market risk dynamically. AI based portfolio optimization generates adaptive investment strategies that respond to market volatility. Moreover, AI has redefined algorithmic trading by creating high frequency trading, sentiment analysis – based strategies and automated order execution (Olanrewaju, 2025).

**H0:** AI awareness has *no significant relationship* with Perceived Usefulness

**H1:** AI awareness has *significant relationship* with Perceived Usefulness

- **AI Awareness and Perceived ease of use**

AI has transformed traditional trading practices tremendously. The speed and automation introduced by algorithms have made traditional manual trading methods less competitive and with greater ease. Traders who do not come up with algorithmic strategies may find it difficult to keep pace with the efficiency, accuracy, and speed of their algorithmic counterparts (Chesterman, 2021). This shift hurdles the role of human intuition in trading decision making and gives the importance of technological adaptation (Addy et al., 2024)

Strong AI could rise both search speed and fitness levels, significantly discovering opportunities overlooked by even the best human managers (Csaszar et al., 2024).

**H0:** AI awareness has *no significant relationship* with Perceived ease of use

**H2:** AI awareness has *significant relationship* with Perceived ease of use

- **AI Reliability and Trust**

AI's limitations may be due to the LLMs' lack of advanced reasoning capabilities and training data biases (Huang and Chang 2023). Without sufficient progress, AI may only improve search speed while inaccurate outputs and end up averaging solutions instead of the best ones (Gavetti 2012). Although, strong AI, however, could increase both search speed and accurate output and bounded rationality can lead to unprofitable positions that strong AI would avoid (Csaszar et al., 2024). Each algorithm has both strengths and weaknesses for specific financial applications, leading to combinations of algorithms in a practical system (Koshiyama et al., 2020).

**H0:** AI reliability has *no significant relationship* with Trust

**H3:** AI reliability has *significant relationship* with Trust

- **Trust and Perceived Ease of Use**

AI adoption in financial markets shows difficulties including model interpretability, algorithmic biases and so on (Olanrewaju, 2025). Technological acceptance is highly dependent on information provided by sources that people believe trustworthy. As trust leads to the effective linkage of risk-benefit information. This, in turn improves the likelihood of technology adaptation in the early stages of technology development, trust treats as a mediator of perceived benefits concerning AI. (Bedue et al; 2021)

**H0:** Trust has *no significant relationship* with Perceived ease of use

**H4:** Trust has *significant relationship* with Perceived ease of use

- **Perceived ease of use and Intention**

People tend to do actions or make decisions based on perceived benefits (Bedue et al; 2021)

The original TAM introduced perceived usefulness and perceived ease of use as the core concepts that explain individuals' adoption of technology (Davis, 1989)

**H0:** Perceived ease of use has *no significant relationship* with intention

**H5:** Perceived ease of use has *significant relationship* with intention

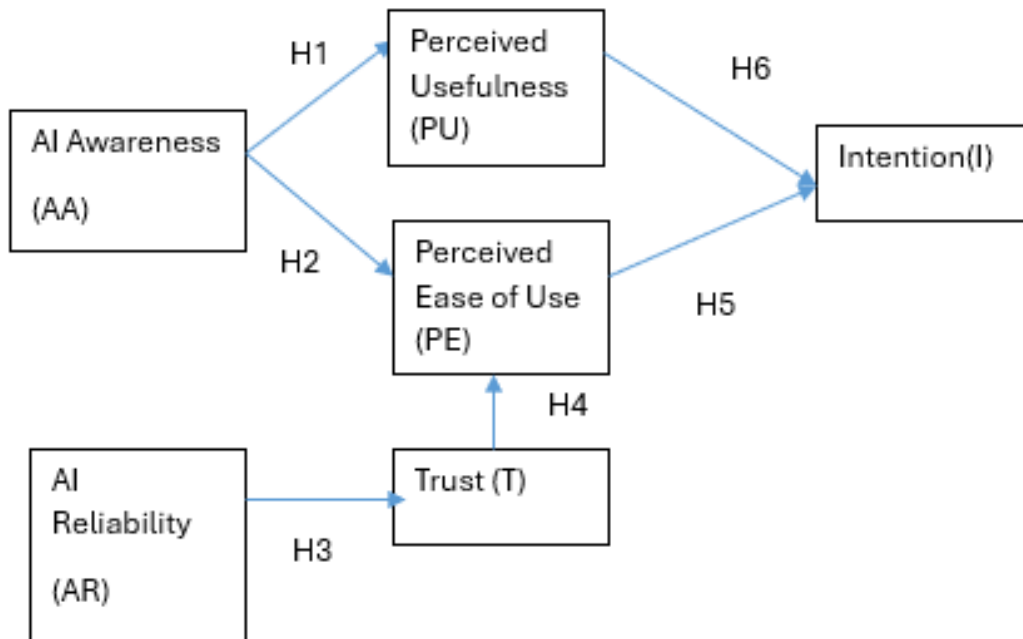
- **Perceived usefulness and Intention**

The research on individual perception towards technological disruptions and early adoption patterns was initiated by Davis (1989) which was later named TAM. Subsequently, a comprehensive deconstruction of eight IT acceptance models the TAM suited the most due to the inceptive narrative of the model states that "if person believe that a particular system can improve his/her job productivity" there is a highly likely chance of technology adoption (Venkatesh et al., 2003; Davis, 1989) by considering vital concepts such as perceived usefulness, ease of use, and subjective norms (Bunkar & Ramaiah, 2024).

**H0:** Perceived usefulness has *no significant relationship* with intention

**H6:** Perceived usefulness has *significant relationship* with intention

### Conceptual Model



**Figure 1. Research Model**

Source: The results of the research, 2026

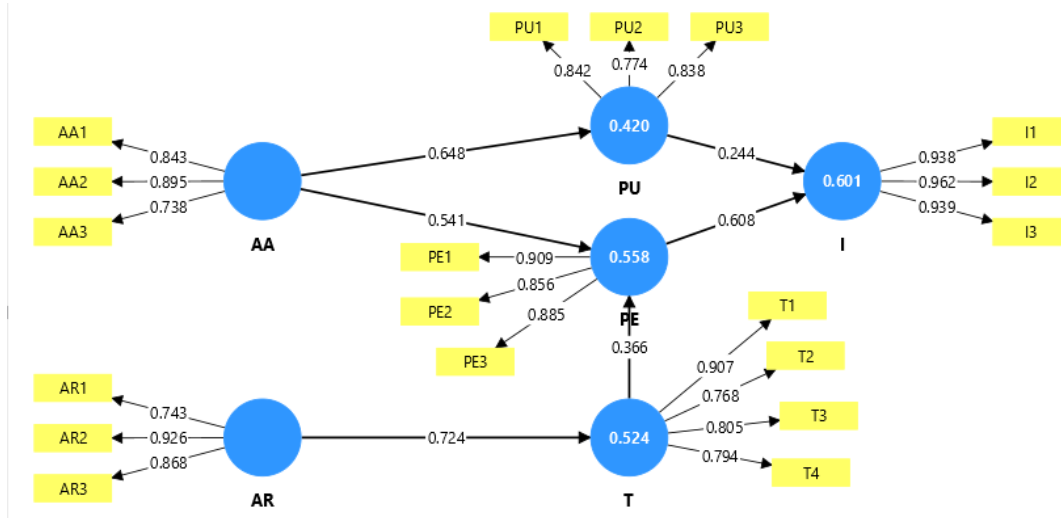
### Methodology

This study uses a quantitative method and carries out empirical research. This quantitative technique is effective as it uses statistical analyses to interpret all numerically represented information. The focus group for this study consists of individual investors who participate in the capital market and adopters of AI tools. The geography of Kerala had been divided into North, Central and South. The overall population size is not clearly defined (considered to be infinite) and purposive sampling was the technique applied. The data were gathered through a Google Forms questionnaire that employed a five-point Likert scale to measure respondents' answers.

Investor profile analysis was carried out by using SPSS software. The data assessment was performed using the Structural Equation Modelling–Partial Least Squares (SEM- PLS) method, supported by SmartPLS 4.0 software. This SEM-PLS method was used to look at two main areas: the external model (which assesses the validity and reliability of the constructs) and the internal model (which examines the relationships among variables and evaluates hypotheses). The SEM-PLS approach was chosen as it was suitable for a research framework that involved moderating variables, necessitating a study of complex relationships among constructs (Hair et al., 2022).

### Result and Discussion

This research obtained input from 100 respondents via an online questionnaire administered using Google Forms. Of these respondents, 72% were men and 28% were women, with the majority aged 20-30, representing 60% of the sample. Regarding educational background, 48% had completed post-graduation, while 36% held a college degree. Regarding annual income, the majority (64%) fall into the 100,000 – 1,000,000 annual income brackets, while 28% earn between 1,000,000 and 2,000,000. Location, primarily concentrated in Central Kerala.



**Figure 2. Smart PLS Model**

Source: The results of the research, 2026

This research, based on the results of the measurement model assessment involved 4 latent variables that were evaluated using 19 observable indicators.

**Table 1: Cross Loading Test Result**

	AA	AR	I	PE	PU	T
AA1	<b>0.843</b>	0.296	0.336	0.454	0.443	0.410
AA2	<b>0.895</b>	0.343	0.743	0.759	0.536	0.431
AA3	<b>0.738</b>	-0.133	0.382	0.367	0.629	-0.045
AR1	0.333	<b>0.743</b>	0.259	0.363	0.083	0.500
AR2	0.150	<b>0.926</b>	0.354	0.481	0.138	0.691
AR3	0.112	<b>0.868</b>	0.354	0.573	0.151	0.636
I1	0.630	0.302	<b>0.938</b>	0.725	0.567	0.325
I2	0.579	0.324	<b>0.962</b>	0.705	0.602	0.202
I3	0.550	0.467	<b>0.939</b>	0.695	0.516	0.445
PE1	0.567	0.560	0.617	<b>0.909</b>	0.391	0.591
PE2	0.624	0.439	0.576	<b>0.856</b>	0.535	0.465
PE3	0.569	0.488	0.782	<b>0.885</b>	0.596	0.396
PU1	0.515	0.134	0.570	0.503	<b>0.842</b>	0.174
PU2	0.444	0.227	0.510	0.448	<b>0.774</b>	0.130
PU3	0.629	0.011	0.377	0.460	<b>0.838</b>	0.021
T1	0.325	0.711	0.215	0.465	0.191	<b>0.907</b>
T2	0.241	0.556	0.411	0.385	0.191	<b>0.768</b>
T3	0.427	0.556	0.306	0.484	0.196	<b>0.805</b>
T4	0.085	0.537	0.207	0.456	-0.157	<b>0.794</b>

Source: The results of the research, 2026

To examine the relationships among indicators, cross-loadings were evaluated. According to Hair et al. (2022), discriminant validity through cross-loadings is considered sufficient when each indicator shows a correlation of at least 0.7 with its respective construct. Based on the analysis, all indicators satisfied this requirement, as each demonstrated a correlation value exceeding 0.7.

**Table 2: Discriminant validity: Fornell–Larcker Criterion**

	AA	AR	I	PE	PU	T
AA	<b>0.828</b>					
AR	0.218	<b>0.849</b>				
I	0.620	0.383	<b>0.946</b>			

<b>PE</b>	0.663	0.562	0.749	<b>0.884</b>		
<b>PU</b>	0.648	0.149	0.594	0.575	<b>0.819</b>	
<b>T</b>	0.333	0.724	0.341	0.546	0.133	<b>0.820</b>

Source: The results of the research, 2026

Based on the data processing results presented in Table 2, the square root of the Average Variance Extracted (AVE) is greater than its correlation coefficients with the other variables. This finding indicates that all constructs in the study satisfy the criteria for adequate discriminant validity.

**Table 3: Cronbach's Alpha, Composite Reliability, and AVE Values**

	<b>Cronbach's Alpha</b>	<b>Composite Reliability (rho_a)</b>	<b>Composite Reliability (rho_c)</b>	<b>Average Variance Extracted (AVE)</b>	<b>Conclusion</b>
<b>AA</b>	0.769	0.801	0.867	0.686	Reliable
<b>AR</b>	0.804	0.832	0.885	0.721	Reliable
<b>I</b>	0.941	0.942	0.962	0.895	Reliable
<b>PE</b>	0.859	0.862	0.914	0.781	Reliable
<b>PU</b>	0.753	0.758	0.859	0.670	Reliable
<b>T</b>	0.836	0.847	0.891	0.672	Reliable

Source: The results of the research, 2026

To assess construct reliability and convergent validity, Cronbach's Alpha and Composite Reliability were used. In addition, the AVE value of each construct needs to exceed 0.50 (Setiabudhi et al., 2024). In Table 3 shows the results of the reliability and convergent validity assessments, indicate that all constructs have Cronbach's Alpha and Composite Reliability values exceeding 0.7, and all AVE scores are above 0.50. Thus, it can be concluded that every construct in this study is both reliable and valid (Hair et al., 2022).

**Table 4: R-square and R-square Adjusted**

	<b>R-square</b>	<b>R-square adjusted</b>
<b>I</b>	0.601	0.593
<b>PE</b>	0.558	0.549
<b>PU</b>	0.420	0.414
<b>T</b>	0.524	0.519

Source: The results of the research, 2026

Data presented in Table 4 show that the model produced an R-squared values of 0.601 (60.1%), .558 (55.8%), 0.420 (42.0%) and 0.524 (52.4%). Intention (I) has an R<sup>2</sup> of 0.601 and adjusted R<sup>2</sup> of 0.593. This means that 60.1% of the variance in intention is explained by Perceived Usefulness (PU) and Perceived Ease of Use (PE). This indicates a moderate to substantial explanatory power. Perceived Ease of Use (PE) has an R<sup>2</sup> of 0.558 and adjusted R<sup>2</sup> of 0.549. This means that 55.8% of the variance in perceived ease of use is explained by AI Awareness (AA) and Trust (T). This also reflects moderate explanatory power. Perceived Usefulness (PU) has an R<sup>2</sup> of 0.420 and adjusted R<sup>2</sup> of 0.414. This indicates that 42.0% of the variance in perceived usefulness is explained by AI Awareness (AA). This is considered moderate explanatory power. Trust (T) has an R<sup>2</sup> of 0.524 and adjusted R<sup>2</sup> of 0.519. This means that 52.4% of the variance in trust is explained by AI Reliability (AR). This also shows moderate explanatory power.

**Table 5: Direct Hypothesis Test Results**

	<b>Original sample (O)</b>	<b>Sample mean (M)</b>	<b>Standard deviation (STDEV)</b>	<b>T statistics ((O/STDEV))</b>	<b>P values</b>	<b>Decisions</b>
<b>AA -&gt; PE</b>	0.541	0.541	0.079	6.886	0.000	Supported
<b>AA -&gt; PU</b>	0.648	0.649	0.053	12.155	0.000	Supported
<b>AR -&gt; T</b>	0.724	0.725	0.071	10.258	0.000	Supported
<b>PE -&gt; I</b>	0.608	0.611	0.056	10.929	0.000	Supported
<b>PU -&gt; I</b>	0.244	0.245	0.069	3.527	0.000	Supported
<b>T -&gt; PE</b>	0.366	0.365	0.074	4.925	0.000	Supported

Source: The results of the research, 2026

The structural model results indicate that all hypothesized relationships are statistically significant ( $p < 0.001$ ). AI awareness significantly influences both perceived usefulness and perceived ease of use, while AI reliability strongly predicts trust. And in turn it strongly influences the perceived ease of use. Furthermore, perceived ease of use exerts the strongest effect on behavioural intention, followed by perceived usefulness. These findings highlight that ease of use plays a more critical role than usefulness in shaping users' intention to adopt AI-driven investment tools.

### Research Gap

Even though global studies extensively exploring AI adoption, there is a geographic and contextual gap regarding the intention of retail investors in Kerala. While most existing literature studies on the technical accuracy of AI tools, this study addresses the research gap by examining the extent to which Trust and Reliability moderate the transition from 'awareness' to 'actual intent'.

### Research Limitations

- **Sample Size:** The study is confined to 100 respondents, which may not completely denote the diverse demographic of the entire state of Kerala.
- **Geographic Concentration:** A major portion of the data is from Ernakulam and Kottayam (Central Kerala).
- **Self-Reporting Bias:** Since the data is obtained via Google Forms, participants may provide socially desirable answers regarding their "Awareness" levels.
- **Cross-sectional Nature:** The concept AI evolved in mid of 20<sup>th</sup> century and not lose the importance today. The study only captures a snapshot in time.

### Conclusion

This study validates an extended Technology Acceptance Model (TAM) to elaborate AI adoption in financial decision-making among individual investors in Kerala. The findings confirm that the adoption intentions are primarily shaped by perceived ease of use and trust-related factors rather than utility alone. In other words, despite concerns about the accuracy and usefulness of AI tools, investors are willing to depend on them due to their user-friendly nature and ease of use.

A major contribution of the study is the identification of **AI reliability as the strongest determinant of trust**, which in turn profoundly influences perceived ease of use. This highlights that investors do not evaluate AI systems based on performance outcomes alone but also on their consistency, transparency, and dependability. Furthermore, **perceived ease of use emerges as the most influential predictor of intention**, surpassing perceived usefulness—indicating that simplicity and user-friendly design are critical for wider adoption.

Even though high awareness and positive perceptions of AI capabilities, a **persistent trust gap** remains a major obstacle. This suggests that technological advancement alone is inappropriate; adoption depends on how effectively these technologies communicate reliability and reduce perceived risk.

Overall, the study concludes that the shift of AI from an emerging innovation to upstream financial decision-making tool in Kerala requires a dual focus: **enhancing technical reliability and ensuring accuracy of results**. To eliminate this gap will require fintech providers to move beyond performance claims and adopt transparent, trust-building strategies that empower investors and foster long-term confidence in AI-driven systems.

### Suggestions

- **For Fintech Developers:** Prioritize "User Experience" design and focus on providing improved and sophisticated results.
- **For Financial Institutions:** Launch AI Awareness campaigns. Since awareness positively impacts both usefulness and ease of use, educate the public on how AI beneficial in making decisions and lower the barrier to entry.
- **Targeted Marketing:** Focus and expand the target groups.

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