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Research paper

Examining The Mediating Effect of Technology Attitude on Retail Investors' Adoption of Artificial Intelligence in Investment Decisions

Sarjas. MK [1] *, Dr G. Velmurugan [2]

[1] *Research scholar, School of Social Sciences and Languages, Vellore Institute of Technology, Vellore, Tamil Nadu, India*
[2] *Professor, School of Social Sciences and Languages, Vellore Institute of Technology, Vellore, Tamil Nadu, India*
**Corresponding author E-mail: gvelmurugan@vit.ac.in*

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Abstract

The purpose of this study is to investigate the variables influencing the adoption of artificial intelligence among retail investors in South India, with a specific focus on the mediating role of belief in AI in the usage experience. The 'Technology Acceptance Model' (TAM) is the background of this research. Four hundred samples were gathered using a structured questionnaire in a selected state in South India. Of these 97, unsatisfactory samples were eliminated, leaving 303 genuine samples for analysis. 'Partial Least Squares Structural Equation Modelling' (PLSEM) was used to examine the planned idea. The findings reveal that Perceived Functional Usefulness, Personalized Usefulness, and ease of use significantly affect the behavioural intention to adopt AI. Moreover, attitude towards AI acted as a mediating variable between these factors and intention to use AI. The intention to use something was primarily determined by people's perceived usefulness and level of ease of use. Personalized usefulness had a positive influence, although not as intense. Data from people's own reports is a limitation of the study. Self-report is often influenced by social desirability bias, which means people may exaggerate positive feelings or intentionally think to match socially acceptable responses. Factors like geographical context and AI security issues are the future scope of this study. The results are very useful for banks, investment firms, and policymakers planning to use AI in India and other places. In contributing to the extant literature, the study developed a country-specific framework and underlined the mediating influence of attitude on AI adoption.

Keywords: *Artificial Intelligence; Attitude; Behavioural intention; PLS- SEM; TAM; Technology Adoption.*

1. Introduction

Artificial intelligence is continually improving in its ability to learn, think, correct its own mistakes, and replicate human decision-making processes, often by drawing inspiration from the way humans think. (Russell et al., 2016; Watson, 2019). Furthermore, AI systems can work in different ways, so people don't always have to watch over or control them. Humanoid features and natural language processing capabilities are inspired by various AI-enabled equipment, which makes them act more like social beings (Watson,2019). Technology has made it possible for computer programs to take care of everyday decisions. In the financial world, it's now common for software to suggest stock market investments without much help from people (Park et al, 2016). Concerns regarding the ethics and regulating principles of AI have been growing in use and impact.

In the world, various industries are using AI, including finance, telecommunications, and health care, which are Prominent .AI that helps the finance and investment sector detect fraud, score credit, and trade algorithms, which improve risk management. Many asset management firms, including 'Merrill Lynch,' 'Goldman Sachs,' and 'Charles Schwab,' have switched to Artificial intelligence-based investment advising through AI and robot advisers in response to the evolving environment and technology (Phoon, 2017). In 2015, robo-advisors managed approximately $30 million worldwide. By 2020, that amount was expected to grow to $ 500 million. (Manrai & Gupta, 2022). AI offers an immense opportunity to advance wealth management and the financial services sector by increasing the company's profits and offering customers more value (Park et al., 2016).

The phrases "robo" and "advisor" are combined to form the word "robo advisor". This means providing online investment suggestions based on the investors' risk assessment and algorithms. Fintech programs that are easy to use, inexpensive, and effective in their operation are robo–advisors, which are expanding quickly (Manrai & Gupta, 2022). Robo-advisors' investment recommendations are based on mean-variance optimisation with algorithms and logical reasoning; they do not include emotionally influenced choices (Terlit et al., 2018). It assesses its customers' risk tolerance and maintains their risk profile. A robo-advisor helps people choose the right mix of investments and how much to put into stocks, based on their personal details. The main idea behind robo-advisors is to build new smart financial tools, not

just act like online banking or basic digital services. (Belance, 2019). Robo-advisors guide people in making investment choices in risky investment choices. These digital advisors can offer good advice or even better than a human financial expert because robo-advisors use computer programs and math formulas for investment decisions. Robo-advisors' decisions are not affected by emotions. They work based on factual information and rational analysis, which allows them to make more accurate and efficient selections than human choices (Au et al.,2021). Every investor's portfolio is managed and regulated by robo–advisors with the help of an algorithm. Moreover, the single system can operate for many investors at the same time. Operations like improving a portfolio and selecting investments can be done without human effort. This will help avoid mistakes by human judgment and control money very cheaply (D'Acunto & Rossi, 2021; Graveish & Kolm,2021). Robo-advisors give effective direction at a lower price, and a huge volume of services to investors is the main advantage.
Investors in South India are beginning to use new technology in their everyday investment tasks, which is the basic objective of the study. It analyses how their opinion of AI influences the relations between the main constructs, such as Functional Usefulness, Personalised Usefulness, and Ease to Use, and their readiness to accept AI- based investment advice. For designing the role of AI, this research analyses the elements like industry trend, age, gender, and job position. For AI developers, policymakers, and the government, the findings offer practical and psychological barriers to integrating AI recommendations.

1.1. Artificial intelligence adoption

By automating tasks and analysing data, artificial intelligence enables businesses to enhance efficiency, improve decision-making, and optimise operations (Badghis & Soomro, 2024). Effectively, AI implementation enhances customer satisfaction, quality, and efficiency for businesses, ultimately leading to improved operational performance (Duan et al, 2019). Organisations can predict market trends and pro-actively address customer needs by utilising AI-driven real-time insights and predictive analytics (Badghis &Soomro, 2024). Using smart technology helps services get faster and better (Phongsatha, 2024) and reduces operating costs and shortens the cycle durations (Lada et al., 2023). Investment firms need to use modern technology to stay ahead of the current digital economy (Verma et al., 2024). Without human intervention, AI starts to handle banking transactions in great numbers (Atwal and Bryson,2021). According to a McKinsey Global Institute assessment, the banking industry may use AI and machine learning to enhance risk management, personalised services, and make better judgments (Bable et al., 2019).

1.2. Investors' perceptions

Investors' perception means that a common view, attitude, or emotion that investors hold about a business, the market, or a particular investment. It is influenced by their interpretation of the available information, their emotions, and the market dynamics. Many people think that Investors make choices mainly based on how risky they believe a stock is and how much profit they expect it to bring (Mclnish and Srivastava 1984, Antonides and Van der Sar, 1990). Investors' perception may be impacted by how they view a company's ESG performance (Zhu and Huang, 2023). Attitudes are shaped by perceptions and then impact intention and action (Ajzen and Fishbein, 1977).

2. Literature Review

Pavlou (2002a) identifies a number of behavioural decision theories and behavioural intention models in the scientific literature, most of which focus on individuals' responses to innovation. The framework developed by Fishbein and Ajzen (1980) is commonly used, which explains the inter-relationship among beliefs, attitude (ATTI), intention (INT), and behaviour. This theory identifies two major determinants of intention: attitude toward the behaviour, and subjective norm (SN). Ajzen (1991) expanded this framework by including three categories of beliefs that influence perceptual constructs. These include behavioural beliefs that influence ATTI, normative beliefs that influence SN, and control beliefs that influence perceived behavioural control.
Technology acceptance is widely regarded as being explained predominantly by the Technology Acceptance Model (TAM; Davis, 1989) and characterizes behavioural intention or the willingness to employ technology through its underlying attitudes (Kelly et al., 2023). This model identifies two major predictors: perceived usefulness, which it defines as the belief that technology use enhances performance, and perceived ease of use, defined as the belief that its use requires little effort (Davis, 1989). These predictors jointly affect attitude toward use, which in turn affects the behavioural intention to use. The model extended by Venkatesh and Davis (2000) further included additional cognitive constructs, such as subjective norm, to denote the influence of peer or supervisory pressure and identification with technology acceptance. As organisations increasingly seek to improve employee productivity by using AI (Østerlund et al., 2021) and are adopting this technology, subjective norms have emerged as a critical predictor in examining AI technology acceptance.
This study explores the reasons behind how people in South India decide where to invest when they use technology to help them. The study is grounded in the 'Technology Acceptance Model' (TAM). Davis introduced this model in 1982. This study investigates these ideas by examining what drives retail investors in South India who adopt AI tools. The paper examines how affective responses to AI moderate the relationship between investors' perceptions about AI's usefulness for performing meaningful tasks, its compatibility with individual needs, and ease of use, on one hand, and attitude to comply with AI-generated guidance.

2.1. Theoretical background and hypothesis development

According to the Technology Continuation Theory, people choose to continue using a technology or decide not to use it. This theory was developed by Liao and his colleagues (2009). This theory explains how people continue to use new technologies over a period by interrelating three concepts: how they perceive the technology (cognitive model), their expectations of technology satisfaction (Expectation Confirmation Theory), and reasons for acceptance or rejection of technology (Technology Acceptance Model) (Liao et al, 2009). The ECT model provides an early indication of how customers behave once they have purchased something (Oliver, 1980). In the field of information technology, Bhattacharjee (2001) used the expectation confirmation model to provide the reasons for the continued use of IT systems over a period. The 'theory of Planned Behaviour' and the 'Technology Acceptance Model' have been popularly used by researchers in the study of factors that make people accept new technologies at the initial stage. Human beings need to find ways to utilize technology that is safe for the environment. (Bergmann et al, 2023) In this section, we present a summary of major theories on the adoption and use of artificial intelligence in making investment recommendations. Such a summary provides a starting point for our study. We focus on how people respond to new technologies and what factors influence their decisions to use them. A tool or system will only be effective if people can choose to use it and believe it is really useful (Bhattacharjee & Lin, 2015).

The research should better distinguish between developed and emerging market contexts in its study of the adoption of Artificial Intelligence by retail investors. Greater digital maturity, more robust regulatory environments, and increased exposure to AI-enabled financial instruments generally lead to more favourable and stable technology attitudes in developed economies. In contrast, emerging markets face myriad issues such as constrained technological infrastructure, relatively inadequate levels of financial and digital literacy, and increased data security and trust concerns. Such contextual differences may well alter significantly how technology attitude mediates AI adoption decisions. A focus on these differences will increase the theoretical contribution of the study and improve the generalizability of TAM-based results to different market contexts.

2.2. Technology acceptance model. (TAM)

The Theory of Reasoned Action was absorbed into the 'Technology Acceptance Model' by Davis (1989) to explain various processes involved in information system adoption. This theoretical framework describes not only the drivers of technology uptake but also has a cost-efficient theoretical basis. The TAM can be applied to different computer systems and populations to predict user behaviour (Davis, 1989). Two key factors that influence attitudes toward the use of a technology are 'perceived ease of use' and 'perceived usefulness'. According to available evidence, attitudes are mainly based on beliefs about the potential usefulness (Davis, 1989; Taylor & Todd, 1995; Venkatesh & Davis, 2000). Davis (1989) defined the TAM as a way to forecast and explain individuals' choices on how they will use information technology; it elucidates the motives and mechanisms of technology adoption. The main proposition along which the theory is constructed is that the perceptions of a system's usefulness and the degree of ease with which it can be used enhance the intention to use, which eventually results in actual system acceptance.

2.3. Modification of the TAM model

Davis developed the 'Technology Acceptance Model' in 1989. It has often been regarded as a significant development in Ajzen's 'Theory of Reasoned Action' (Zhang et al., 2023). The idea behind the model was to understand how a person feels about the use of technology. Within TAM, people decide to use new technology basically on two factors: how useful they perceive (PU) the technology to be and how easy it is to use (PEU). In this study, usefulness will be divided into two parts: Functional Usefulness (PFU) is how well the technology does the task, while Personalised Usefulness (PPU) is how well it fits an individual's needs. Perceived usefulness is the 'degree to which a person thinks using a system will improve their job performance" (Davis, 1989. It involves two concepts: Perceived functional usefulness: how much a person believes a tool or system will help them in doing their work better, or finish tasks more easily. Perceived personalised usefulness: a person's belief that a customised service or product is helpful and valuable for reaching their goals or improving their experience. Perceived ease of use refers to the "degree to which a person believes that using a particular system will be effortless" (Davis, 1989).

2.4. Perceived usefulness

The TAM suggests that perceived usefulness determines an individual's decision to adopt a technology. According to Khalif et al. (2023), perceived usefulness occurs when one feels the technology will enable them to perform a job more effectively. The TAM, therefore, claims that perceived usefulness leads to favourable attitudes and approaches towards technology use. Consumers evaluate technology positively because of the perceived advantages of artificial intelligence in terms of enabling smooth and easy transactions (Rahman et al., 2023). Empirical evidence shows that consumers' decisions and actions concerning financial technology depend on perceived usefulness (Singh, Sahni, and Kovid, 2020; Singh and Sinha, 2020). Thus, realisation of the technology's benefits creates positive attitudes and use behaviours. Those who gain from technology are willing to use it for their financial transaction, showing a steady intention to keep relying on it in banking and other financial services. (Aprilia and Amalia, 2023; Ashfaq et al., 2020; Inam et al., 2023; Nagadeepa et al., 2021). Technology helps make financial transactions smoother for customers, as explained by this study. As it is easier to use, people continue using it and gain good habits and positive feelings. Two different descriptions of "usefulness" were mentioned in the study: functional usefulness and personalised usefulness.

2.4.1. Perceived functional usefulness

Perceived functional usefulness originates from Davis's concept of perceived usefulness (1989). Functional usefulness is about how useful people believe a tool, product, or service will be when they use it. It's someone who judges whether it can meet their needs, improve their work, or give them real benefits. It's about trusting that the system will make things simpler and help you finish tasks more effectively. This belief plays an important role in whether people decide to use new technology and accept it, which leads to the following idea or hypothesis.

H_1. If people think the system is genuinely helpful, they'll be more willing to use its suggestions

2.4.2. Perceived personalized usefulness

The concept of personalised usefulness refers to how it supports people's emotions towards a technology when it is customised to their own desires. It expands on the earlier idea of Perceived usefulness (PU) introduced by Davis in 1989. PU explained that people are highly influenced to accept and use a system if they believe it is helpful. PPU takes this further by focusing on how useful a system feels when it is tailored to the individual user. Someone feels that system, technology, or services, or situation, and increasingly its overall usefulness to them, is called personalised usefulness. Personalised usefulness means to people's belief that a personalised service or product is beneficial and valuable in achieving their goals or improving their experience. Personalised usefulness highlights how well a technology adapts its features, suggestions, or outputs to each particular user. The perceived usefulness, as pointed out by the 'Technology Acceptance Model', mainly refers to the "degree to which a system supports humans in doing their tasks well". Additionally, this variable also has a great influence on whether or not humans select the use of new technology. Based on this, the given assumption may be made.

H_2 When people feel that AI recommendations are personally useful, they are more likely to want to use them

2.5. Perceived ease of use

Perceived ease of use is basically how simple they think it is to learn, handle, and apply something new. (Masoud and Abu Taqa, 2017). As a result, how customers react to technology may influence how they decide to use it or not. Furthermore, people want to take some risk to understand technology if they are unsure about it or worried about using it. Negative attitude regarding technology can result from worries about the difficulty of accepting it. On the other hand, investors who utilise technology readily produce beneficial and positive views that result in behavioural intention to adopt it. (Malaquias and Hwang,2019). In this study, "ease of use" means that investors think the technology is simple to grasp and helps them with their investment decisions. Research shows that when people think AI tools are simple to use, they also believe these tools are more useful for task checking financial records (Damerji and Salimi, 2021) and designing business systems (Jnr and Petersen,2023). Internet banking (Rahi et al, 2021), and education (Roy et al., 2022; Wang, Liu, and Tu, 2021). Technology usability has the power to influence consumers' perceptions and sustainability. Studies have found that when people feel a system is easy to use, they are more likely to have a stronger attitude toward it. For example, researchers in education using AI showed this effect, and similar findings were reported in internet banking, where ease of use shaped how clients felt about the service. (Kashive et al., 2021; Roy et al., 2022; Wang, Liu, Tu, 2021 et Rahi et al., 2021). The same results are also applicable when considering mobile banking (Asnakew, 2020). Customers are more likely to use fintech services when they feel the technology is easy to handle (Singh, Sahni, and Kovid, 2020). How long chatbots last depends a lot on whether people find them easy to use, as shown in a study on customer service (Ashfaq et al., 2020). This study assumes that an investment sector investing in easily understood AI-based technology will have a favourable impact on investment efficiency and attract retail investors, depending on the findings of an earlier study. Thus, the given assumption is put forth in this study.
H_3. When people find a system easy to use, they are more likely to want to follow its suggestions

2.6. Mediating effect of attitude toward technology in AI usage

This study looks at how people's opinions affect whether they follow advice from AI. It focuses on how helpful they think the system is, how personal it feels to them, and how easy it is to use. Attitude means how someone usually responds or feels about an idea (Morosan, 2014). The way someone feels or thinks (their attitude) acts like a bridge between what they do and how easily they trust it to use something. In a well-known adoption theory, such as the 'Theory of Planned Behaviour' (Ajzen,1991), the 'Theory of Reasoned Action' (Fishbein & Ajzen, 1975), and the 'Technology Acceptance Model' (TAM), a person's attitude often acts as a middle factor that helps predict their intention to carry out a certain behaviour. In the 'Technology Acceptance Model' (TAM), A Person's behaviour is seen as positive if they feel they must carry out that behaviour (Davis et al., 1989). People tend to use a new technology more easily when they feel it is simple and convenient. This makes them more willing to accept it. In this study, we look at how people's attitudes play a role in deciding whether to follow artificial intelligence. Suggestion for making investment choices. Based on this idea, we have set out the following assumptions.
H4a. Attitude will mediate the association between functional usefulness and behavioural intention to accept AI Recommendations.
H4b. Attitude mediates the association between personalised usefulness and behavioural intention to adopt AI recommendations.
H4c. Attitude will mediate the association between ease of use and behavioural intention to accept AI recommendations.

2.7. Attitude toward technology

Attitude plays a significant role in framing people's intentions to act, because it reflects both how they think about a technology and how ready they feel emotionally and in context to use it. An individual's attitude reveals how they feel about a particular behaviour, whether positively or negatively (Premkumar et al., 2008). According to the UTATU, attitudes affect and predict user intentions, particularly when new technologies challenge accepted norms (Venkatesh, 2021). In accordance with TAM, customers' attitudes toward using a system are defined by their actual use of it. These attitudes might be acceptance or rejection, depending on their experience with technology at work (Bidar, 2018). Studies show that when professionals think positively about a technology, they are more likely to want to buy and use it. Other researchers claimed that one factor influencing a person's conduct is their attitude. Various traits comprise the attitude, including behavioural, affective, and cognitive elements. (Known and Vogt,2009). According to the above discussion, we can make the given assumption.
H5. Attitude will strongly influence the behavioural intention to use Artificial AI recommendations.

2.8. Behavioural intention to use AI recommendation

People's ability to act on their intentions depends on their personality traits, according to Bagozzi et al (1992). People's use of technology is strongly influenced by their intention to use it (Venkatesh and Zhang, 2010). The stronger their intention, the easier it becomes for them to adopt new tools. In his well-known 'Technology Acceptance Model' (TAM), Davis (1989) explained that a person's decision to embrace new technology depends on three key factors: how easy they think it is to use, how useful they believe it will be, and their overall attitude toward it. Belanche et al. (2019) explained that a customer's behavioural intention refers to their ability to complete what they set out to do. Ajzen (1991) explains in the 'Technology Acceptance Model' (TAM) that a person's intention to use a technology mostly depends on their attitude toward it, that is, whether they see the technology as good or bad, useful or not. Perceived usefulness is the degree to which a person believes that using a system will help them perform their tasks better. According to Davis's "perceived ease of use means how much someone feels that using a technology will be straightforward and not difficult". A behavioural intention to use is the willingness or plan to keep using a specific technology. One way to gauge proficiency is by observing how proficient the person is in using technology and how intensively they interact with it, as reflected in their behaviour and awareness of it. In this study, the main focus will be on whether people are willing to follow suggestions made by artificial intelligence.

3. Research Framework

The framework in Figure 1 is built around three main factors: how useful the technology seems for a practical task, how well it feels tailored to the user, and how simple it is to use. These elements influence people's willingness to follow AI recommendations. Moreover, Attitude toward technology acts as a mediating role in this study.

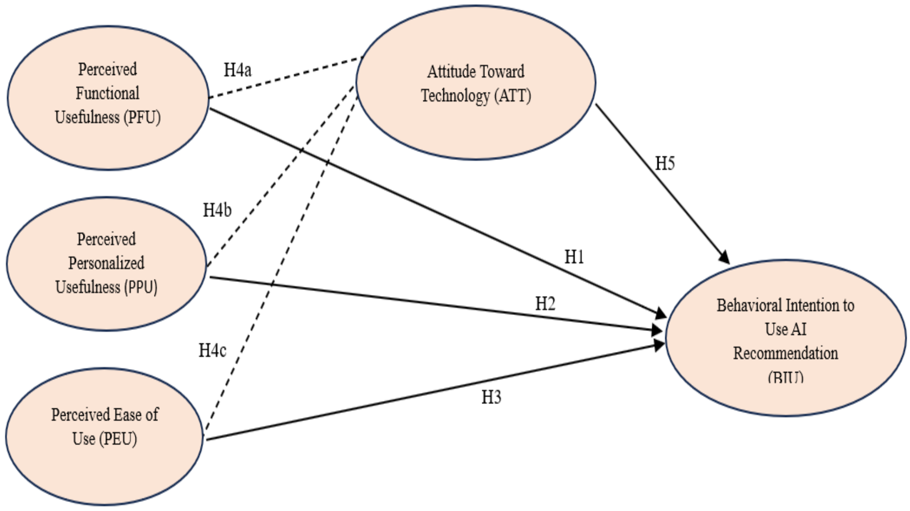

Fig. 1: Theoretical Framework.

4. Methodology

4.1. Research design

This research explores how AI features influence investors' perceptions of retail enterprises in South India. The region has been selected because it possesses relatively higher levels of digital literacy compared to other parts of the country. This research stresses the testing of relationships among theoretical constructs rather than the estimation of population parameters. Convenience and snowball sampling may constrain generalizability, but these methods are appropriate in this exploratory study because of difficulties in identifying retail investors employing AI tools. Snowball sampling helped in accessing experienced respondents who are knowledgeable about technology.

Data were gathered by surveying a 23-item instrument developed from previously validated instruments, each rated on a five-point Likert scale anchored from “Strongly Disagree” to “Strongly Agree.” The sample size included regular South Indian investors who used AI-driven guidance to make decisions on stock market investment. A two-stage sampling framework was employed. First, stratified sampling by block was used for the selection of participants from Karnataka, Tamil Nadu, and Kerala. In the second stage, Convenience and snowball techniques of sampling were employed in tandem. Overall, 400 participants were included during the period May-September 2025. To obtain a representative sample from all regions, South India was divided into zones based on geographical and administrative boundaries, and stratified random sampling was used. A small number of investors were identified in each zone with the help of local contacts, investor networks, business chambers, or SEBI-approved stockbrokers. Snowball sampling was then used, whereby initial respondents referred other investors in their network who met the inclusion criteria of the study based on their prior investment experience. This resulted in a snowball effect that continued until the desired population size was reached in targeted numbers. Data were collected by a structured questionnaire. To determine the validity and reliability of the measurement tool, it underwent expert evaluation. All measurements proved to be reliable, since ‘Cronbach’s alpha coefficients’ for all items exceeded 0.70. Data analysis was carried out using a measurement model and SEM to evaluate both direct and indirect effects of factors. The results show that investors’ cognitions and affect have an important influence on investors’ responses to the advice given by AI.

4.2. Data collection and sampling method

The study looks at everyday investors who already have some experience in investing. It focuses on those who have made investment decisions using advice or suggestions from AI tools. The selected groups are chosen so that participants have enough understanding and experience with how technology is used and how it affects their investment decisions. Hair et al. (2010) suggest that for Structural Equation Modelling (SEM), a sample size of at least 200 is generally sufficient if the model is not too complicated. Following the guidelines, the study included 400 investors so that the findings would reflect the larger group.

The research first approached accessible participants and then relied on their suggestions to reach more people. The contribution of this paper is in adopting a two-stage sampling design to attain representativeness, with a focused exploration into investors from Karnataka, Tamil Nadu, and Kerala. South India was divided into zones based on geographical or administrative grounds so that each main zone fell into one category. These sub-sets of investors were selected through local networking, business associations, chambers of commerce, or SEBI-registered brokers in each partition. Finally, snowball sampling was used, wherein the initial participants named the subsequent investors within their networks who fit into the various criteria set out for the study, such as asset class preference and past investment experience. This process continues until each group has the needed number of participants. From May to September 2025, 400 people joined the survey through convenience and snowball sampling. However, 97 of the responses were not fully completed, so they were left out. The remaining 303 valid responses were used for this research. The information will be gathered through a well-defined questionnaire. Samples were collected from May to September in 2025 for around five months. This duration gave sufficient time to reach respondents, share the survey on different platforms, and collect all the answers. The professionals thoroughly verified the tool to ensure the questions were practical and realistic. A small group of experts made for these purposes; they are as follows

1) A professional focused on understanding systems and how they work in everyday situations.
2) Banking and finance expert with sufficient knowledge of AI technologies.
3) Financial and Investment Advisors are using an AI tool for analytics and prediction.

The scale's accuracy was confirmed through expert review and trial testing, showing that it measured the right factors (Ahmad et al., 2019). The questionnaire was then shared with retail investors through their network and online platforms for data collection. The data were analysed using ‘Smart PLS,’ a statistical software particularly framed for ‘structural equation modelling’ (SEM) (Hair et al., 2018; Hair et al., 2017). This method was selected because it can support a complex structure with a high number of components and interrelations. It allows testing the direct and indirect influences of different elements on the use of artificial intelligence technology, following Hair et al. (2018). Smart PLS allowed analyzing the research objectives and model by testing the relationships proposed and the attitude as a mediating variable. There was a proper, well-defined process to check the validity and reliability of the scales of the questionnaire.

5. Results

5.1. Reliability measurement

Table 1 demonstrates the reliability estimates (Cronbach's alpha) for the study variable. The measurement ranged from 0.751 to 0.866, pointing to acceptable to high internal consistency. To enhance the veracity of the results, the study used Smart PLS for data analysis and instrument design/validation. Both methodological decisions enhance the rigour and significance of the results (Hair et al., 2018; Hair et al., 2017

Table 1: Reliability Measurement

Construct	Items	Cronbach's alpha
'Perceived Functional Usefulness'	7	0 .866
'Perceived Personalised Usefulness'	5	0 .751
'Perceived Ease of Use'	4	0 .805
'Attitude Toward Technology'	3	0 .793
'Behavioural Intention to Use'	5	0 .844

5.2. Demographics details

Table 2 shows the background details of the 303 samples that were included in this study. Among them, 206 (68%) are men and 97 (32%) are women. Looking at the age category, the biggest group is the range of 25 to 40 years old, numbering 143 people (47.2%). Another 76 participants (25.1%) are under 25, while 74 (24.4%) are between 41 and 60 years old. Only 10 represents (3.3%) are above 60. In terms of education, most participants are well qualified. Around 38.6% have a postgraduate degree, and 43.6% hold an undergraduate degree. A smaller portion, 9.2%, completed higher secondary education, while 8.6% were included in other education categories.

Table 2: Demographics Details

Sample attributes		Frequency	%
Gender	Male	206	68
	Female	97	32
	Below 25	76	25.1
Age	25 - 40	143	47.2
	41 - 60	74	24.4
	Above 60	10	3.3
	HSE	28	9.2
Education Qualification	UG	132	43.6
	PG	117	38.6
	Others	26	8.6
	Privet employees	135	44.5
Organisation Type	Government Employee	30	9.9
	Business	66	21.8
	Others	72	23.8
	Below ₹5,00,000	154	50.8
	₹5,00,001 – ₹10,00,000	117	38.6
Annual Income	₹10,00,001 - ₹15,00,000	19	6.3
	Above ₹15,00,000	13	4.3
	Below 50,000	120	39.6
Annual Average	₹50,000- ₹1,00,000	135	44.5
Investment Amount	₹1,00,001- ₹1,50,000	16	5.3
	Above ₹1,50,001	32	10.6
Total		303	100.00

According to the organisation type, 44.5% of the sample are employed by private companies. A significant percentage is occupied by others and business owners, with 23.8% and 21.8%, respectively. At 9.9%, government employees represent the smallest group. The data on annual income shows that over half of the participants (50.8%) earn below ₹ 5,00,000. About 38.6 of people earn between ₹ 5,00,001 and ₹ 10,00,000. A smaller share, 6.3%, earn between ₹ 10,00,001 and ₹ 15,00,000, while only 4.3 % make more than 15,00,000. This shows that the highest income groups (above ₹ 10,00,000) are from only a small portion of the population. When it comes to investments, most people put in less than ₹ 1,00,000 a year. In fact, 39.6% invest under ₹ 50,000, and 44.5% (135 participants) invest between ₹ 50,000and 1,00,000. Higher investment levels are much less common, with 10.6% (32 participants) investing more than ₹ 1,50,001 and 5.3% (16 participants) investing between ₹ 1,00,001 and ₹ 1,50,000.

5.3. Measurement model

In the present Study, it has been established that the measurement model is reliable and valid. The factor loadings of each construct are presented in Table 3 above, with 'composite reliability' and 'average variance extracted'. The findings indicate a good level of accuracy in assessing all five constructs. The items in the research instrument largely represent the constructs, ensuring a good level of convergence with factor loadings varying from 0.701 to 0.856. As all factor loadings are above the cut-off level of 0.70, they established a standard level of reliability.

Each of the items within the surveys effectively captures what it was designed to measure. Overall, it focuses on five key domains. First, it looks at the perceptions regarding the functional usefulness of technology, which is measured using seven items. Second, it examines perceived personalised usefulness as gauged with four items. Third, it examines ease of use, also measured with four questions. Fourth, it examines people's attitudes toward technology through three questions. Finally, it explores their intention to use the technology, assessed with five questions. With these strong loadings, the participants seemed to understand the questions quite well and reacted according to the studied theories.

The AVE values represent the extent to which each variable tells the variation in its respective indicators and, hence, provide evidence of the quality of measurement. The AVE values in this research range from 0.554 for Perceived Functional Usefulness to 0.707 for Attitude Toward Technology. All five value items are therefore regarded as reliable since they are above the recommended threshold of 0.50. Overall, this substantiates that values are measured efficiently and consistently. To be precise, each concept explains between 55% and 71 % variation in the survey responses. But this is reflected in their AVE scores: Attitude Toward Technology 0.707, Ease of Use 0.631, and Behavioural Intention to Use 0.616. From these figures, it could then be assumed that the questions for those variables captured what they were supposed to capture pretty well. Two constructs, namely Functional Usefulness and Personal Usefulness, have lower AVE values of 0.554 and 0.572, respectively. These are, however, within a reasonable limit and thus acceptable for reliability.

Table 3: Measurement Model

Construct	Number of Items	Factor Loading	AVE	CR (rho-c)
Perceived Functional Usefulness (PFU)	PFU_1	0.715	0.554	0.897
	PFU_2	0.746		
	PFU_3	0.768		
	PFU_4	0.766		
	PFU_5	0.726		
	PFU_6	0.777		
	PFU_7	0.710		
Perceived Personalised Usefulness (PPU)	PPU_1	0.776	0.572	0.842
	PPU_2	0.790		
	PPU_3	0.701		
	PPU_4	0.757		
Perceived Ease of Use	PEU_1	0.758	0.631	0.872
	PEU_2	0.800		
	PEU_3	0.805		
	PEU_4	0.814		
Attitude Toward Technology (ATT)	ATT_1	0.851	0.707	0.879
	ATT_2	0.856		
	ATT_3	0.814		
Behavioural Intention to Use (BIU)	BIU_1	0.788	0. 616	0. 889
	BIU_2	0.779		
	BIU_3	0.756		
	BIU_4	0.814		
	BIU_5	0.784		

All the constructs are highly reliable, as evidenced by the CR scores, which range from 0.842 to 0.897. The fact that these are way above the threshold value of acceptability of 0.70 means that items constituting a specific construct are consistent in measuring a concept. The Behavioural Intention to Use scale is particularly highly reliable, with a Composite Reliability score of 0.889. The measures are very highly reliable. The Perceived Functional Usefulness score is almost perfectly at 0.897, indicating strong dependence. Even the lowest score, Perceived Personalised Usefulness at 0.842, is still an indication of solid and consistent results across items. The importance of the results from this study is that your assessment model works well and can be trusted. It sets a good ground for taking a closer look at how different parts of your structural model might fit together and for understanding how people come to adopt technology.

5.4. Discriminant validity

The discriminant validity of the measurement model constructs was measured by using the 'Fornell-Larcker criterion,' as shown in Table 4. This criterion suggests that for discriminant validity to be established for each construct, the square root of its AVE, represented on the diagonal, must be greater than the respective off-diagonal correlations of the construct with other constructs. That is, a given construct must share a higher correlation with its indicators rather than sharing correlations with indicators of other constructs (Fornell & Larcker; Hair et al., 2019). This research investigates five major drivers that have an influence on the acceptance and use of technology. The diagonal entries represent the square roots of the AVE for each factor. AVE indicates the degree to which a question is representative of the concept that it is supposed to measure. Ranging between 0.741 and 0.841, the outcomes provide evidence of reliability, indicating that measures will adequately capture intended constructs and reflect a strong internal consistency.

Table 4: Fornell Lacker Criterion

Constructs	ATT	BIU	PEU	PFU	PPU
ATT	0 .841				
BIU	0.628	0.758			
PEU	0.606	0.644	0.794		
PFU	0.599	0.653	0.707	0.744	
PPU	0.580	0.618	0.705	0.696	0.757

Data suggest that different factors relate to one another in differing ways. The closest association is between attitudes and the desire to use, at 0.628. This refers to the fact that the affective or cognitive judgments about something significantly affect an individual's readiness to begin using it. Perceived ease of use influences perceived usefulness: the rating for practical usefulness stands at 0.707, and for perceived usefulness to the user stands at 0.705. What this basically means is that the more ease there is with handling a system, the more value is placed on it, both in terms of functional utility and satisfaction to the user.

Discriminant validity is exhibited in the fact that the diagonal factors in each row and column are bigger than the respective inter-item correlations. That is, the construct demonstrates relative independence and represents a unique facet rather than converging with other constructs. At the same time, attitude, intention to use, perceived usefulness, and ease of use are themselves highly intercorrelated, underlining the closeness of the relationships among these constructs. In their totality, these factors represent the cognitive processes that accompany the evaluation and adoption of a new technology.

5.5. Checking of hypothesis results

Table 5: Hypothesis Results

Hypothesis	Relationships		T Statistics	P values	Decisions
H_1	PFU	BIU of AI	2. 892	0. 004	Supported
H_2	PPU	BIU of AI	2. 244	0. 025	Supported
H_3	PEU	BIU of AI	2. 699	0. 007	Supported
H_{4a}	PFU	ATT BIU of AI	3. 768	0. 000	Supported
H_{4b}	PPU	ATT BIU of AI	2. 681	0. 007	Supported
H_{4c}	PEU	ATT BIU of AI	3. 627	0. 000	Supported
H_5	ATT	BIU of AI	4. 864	0. 000	Supported

The findings in Table 5 highlight key factors that shape retail investors' intention to use AI in South India. The assumptions were examined using the SEM method, where the links between different variables were measured through T-values and P-values. The result found that people are more likely to want to use AI when three things are true: they see it as helpful for everyday tasks (PFU), they feel it matches their personal needs (PPU), and they think it's easy to use (PEU). The finding reveals that people are willing to use AI if they feel it is useful, easy to understand, and suited to their wants.

These results also show that behavioural intentions are significantly influenced by the attitude toward AI (ATT). As illustrated by the adoption of hypotheses H4a, H4b, and H4c with the strongest t-statistics (3.768, 2.681, and 3.627) and very significant P-values, all three utility perception – 'Perceived Functional Usefulness,' 'Perceived Personalised Usefulness,' and 'Perceived Ease of Use' mainly affect behavioural intention through attitude. This suggests that these perceived benefits have an indirect effect on influencing people's overall impression of AI, while also having a direct impact on their usage intention. With a t-value of 4.864 and a P-value of 0.00, the study shows that people's attitude toward AI is the strongest factor influencing their intention to use it. When people feel good about AI, they will want to use more. Having a positive attitude helps people move from just thinking AI is useful to actually choosing to use it.

5.6. R2- and adjusted R -square

Table 6 highlights the value of R^2 and adjusted R^2, indicating how effectively the model accounts for the Results. According to the study, three factors – 'Perceived functional usefulness,' 'Perceived personalised usefulness,' and 'Perceived ease of use' together explain about 44.3% of the differences in how people view AI technology ($R^2 = 0.443$). People's view on how useful it is, whether they personally like it, and how easy it feels to use, explains about half of why they feel the way they do about the technology. The other half comes from different influences that aren't covered in this explanation.

Table 6: R^2 and Adjusted R-squared

Variables	R - Square	Adjusted R- Square
'Attitude toward Technology'	0. 443	0. 437
'Behavioural Intention to Use'	0. 552	0. 546

The model fits fairly well with an R^2 of 0.552. Put differently, it explains a little more than half of the reasons people feel more or less comfortable using AI. About 55% of those variations are associated with how useful they believe AI can be in various ways, as well as their overall attitude towards the technology. The research demonstrates a decent ability to explain why people adopt the model, and it does a good job of identifying the primary drivers. The findings appear to be trustworthy and can most likely be generalised to other groups of people. The adjusted R-squared values-0.437 and 0.546-are almost equal compared to the original R-squared value. This implies the reliability and precision of the model.

Fig. 2 presents the 'Structural Equation Model,' which maps out how the different components are connected using the 'PLS-SEM' approach. The model investigates the direct and indirect impacts of PFU, PPU, and PEU on the attitude of people toward technology, and their Behavioural intentions to use AI. The key insight into the strength of these relationships: about 44% of how people feel about technology is explained by three things. First, does the technology feel personally useful? Second, does the technology help them with daily tasks, or is it easy to use? In simple terms, if the technology fits the needs of people, helps them achieve something, and doesn't feel complicated, then people have more positive attitudes toward technology. This model now does a good job of explaining why people opt to use the technology. It accounts for around 55% of the difference in behaviour, which means the included factors are reliable signs of what drives adoption.

The way things are connected shows that people's goals can be influenced both directly and indirectly. Since the link to their intention is fairly strong (0.275), it means that having a strong attitude toward technology plays a significant role. In other words, when people feel good about technology, they are much more likely to want to use it. Furthermore, people's intention to use something is framed by three main perceptions. How easy it feels to use (0.202) has a strong influence on how useful it seems (0.201), for practical tasks, also almost equally, and how much it feels personally useful (0.146) has a smaller effect. Since all the measurement values are between 0.70 and 0.86, the model used to measure these factors is reliable and accurately reflects each idea. People's attitude toward a new technology is framed by how beneficial it feels to them. Ease of use often matters more than anything else when people choose whether to adopt a tool. Making technology simple and accessible is the real key to encouraging adoption.

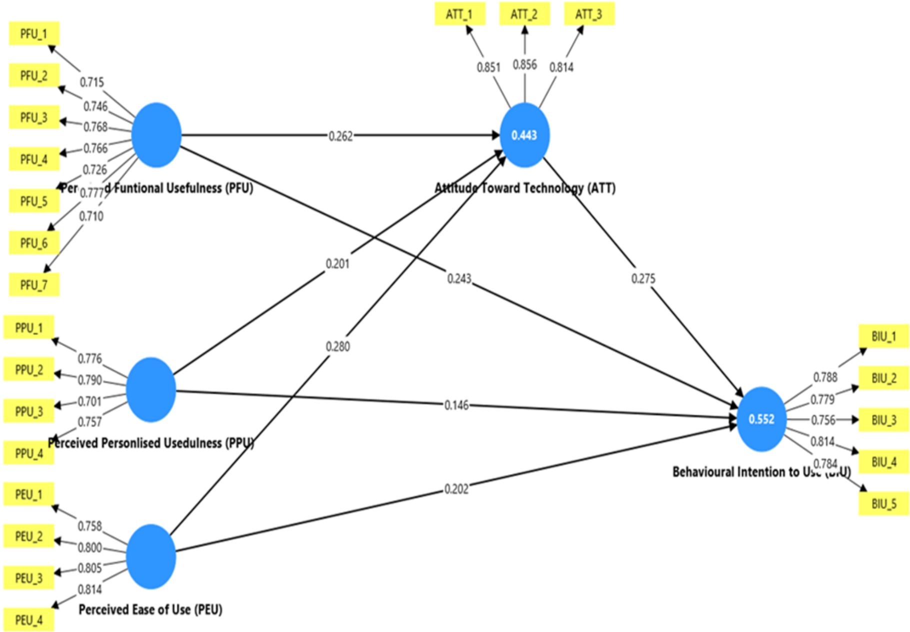

Fig 2: Path Coefficient and Structural Equation Modelling.

6. Discussion and Implications

This study aims to understand the factors that influence retail investors in South India to adopt AI tools, with a specific focus on how their attitude toward AI influences this decision and whether mentality serves as a means of connecting these factors to AI adoption. This study is grounded in the ‘Technology Acceptance Model’ to examine the determinants of an individual's adoption of a new technology. The interrelationships among the main constructs- ‘Perceived Usefulness’ (PU), ‘Perceived Personal Usefulness’ (PPU), and ‘Perceived Ease of Use’ (PEOU)-and their consequent influence on behavioural intention (BI) to use AI are assessed by means of ‘structural equation modelling’ (SEM) with a sample size of 303 across different states in South India. In general, the results add to the growing literature on AI applications, specifically within the context of an emerging economy like India, where there is a significant rise in technology adoption within the investment sector.

This thus represents a significant theoretical and empirical contribution. The results provide information relevant to policymakers, financial institutions, and technology developers who expect further AI integration in India. On a practical note, the findings indicate imported factors of the adoption of AI and emphasise a mediating function of attitudes toward AI, which is crucial in the process of its use. The analysis reveals that an individual’s intention to use the system is well determined by ‘Perceived Usefulness,’ ‘Perceived Ease of Use,’ and system performance, with a small positive effect. In sum, these findings collectively enhance the understanding of AI usage trends and support prior literature, which has captured diverse cultural and economic contexts (Emon et al., 2023; Venkatesh, 2021; Dwivedi et al., 2023).

The analysis should further distinguish between managerial implications and policy and regulatory implications to enhance practical clarity. From a managerial perspective, fintech firms and investment service providers need to focus on enhancing the perceived usefulness, ease of use, and reliability of AI-based recommendation systems, as these factors mould favourable technology attitudes and adoption intentions. On the other hand, policy and regulatory implications relate to strong data protection laws, ethical guidelines on the use of AI, and full disclosure requirements that will help engender investor trust in AI-driven financial services. The findings also have overarching implications for financial literacy and investor education in developing economies, where poor awareness and knowledge of AI could be an inhibitor to adopting these technologies. Targeted investor education programs, digital literacy initiatives, and awareness campaigns will help retail investors make more effective judgments about AI tools, decrease perceived risks, and develop informed attitudes toward making investment decisions with the use of AI.

The present study investigates the use of artificial intelligence by everyday investors in South India. Depends on the ‘Technology Acceptance Model,’ this paper attempts to explain the process through which technology adoption actually takes place. As the findings have shown, the basic tenet of TAM holds good in this study; however, the way its factors manifest themselves can greatly differ according to the pertinent cultural, economic, and technological conditions. Investigating technology adoption, attention should be paid to how people perceive the technology and use it, at the same time, treating attitude as an intrinsic factor shaping the process of adoption. This implication is that there are wider influences involved when it comes to an in-depth understanding of the multifaceted drivers of technology adoption across disparate contexts, including workplace culture and cultural values (Heinze & Heinze, 2018; Chatterjee et al., 2020). In addition, SEM is applied in this study to investigate the relationships among various variables that determine technology adoption, thus ensuring more robust findings in the scholarly research on technology acceptance. The results mention that in order for the process of adoption behaviour to be comprehended, both direct and indirect effects of factors need to be taken into consideration. This enables a far finer-grained insight into the way investors in disparate milieus respond to changes brought about by technology, and the theoretical framework must allow for flexibility on issues about cultural and economic heterogeneity milestone that yields promise for further research on technology adoption.

The literature has established that PFU, PPU, and PEU are drivers of one's behavioural intentions. The findings reported in this study affirm other studies published on technology adoption. The important implication here is that attitude works as a mediator since it connects investors' cognitive frames to the perception and acceptance of AI. Stated differently, positive affect toward a technology is associated with perceived usefulness and ease of use, which, in turn, intensifies the willingness to use AI. That is an argument supported by Bessadok and Hersi (2023). In addition, establishing steps for implementing the technology should be accompanied by narratives of success, and such systems should be able to demonstrate their operational efficiency to attain the belief of consumers in their use. The findings will be of practical importance to banks, investment companies, and government agencies in their desire to increase the confidence of the general public, as well as the ease with which AI can be used in making investment decisions. The open discussions of ethical considerations and safety of investments, together with clear communication of tangible benefits, discourage reluctance and enable consumers to begin trusting. When the framing of discourse resonates with the social and economic particularities of South India, such adoption may become more inclusive and reach out to greater, grassroots sections.

7. Conclusion

This study makes a theoretical contribution by extending TAM into the domain of artificial intelligence adoption among retail investors, a context that has received only limited empirical attention. It extends TAM by conceptualising technology attitude as a mediating mechanism through which core TAM constructs, such as perceived usefulness and perceived ease of use, influence investors' adoption of AI-based investment tools. Empirically demonstrating the mediating role of technology attitude serves to refine TAM's explanatory power, underlining the importance of affective-cognitive evaluations in high-stakes, uncertainty-driven financial decision-making environments. This contribution enhances theoretical understanding of how traditional technology acceptance constructs operate within emerging AI-enabled financial services and therefore offers a more nuanced application of TAM beyond organisational and utilitarian technology contexts.

The present study is an attempt to explain the factors governing the adoption of artificial intelligence by retail investors in South India, with a specific focus on the mediating role of attitude toward AI use. It aims to develop an integrated framework based on the 'Technology Acceptance Model' (TAM) in explaining investors' intention to use artificial intelligence. The results point to the prominence of Perceived Financial Utility (PFU), Perceived Personal Utility (PPU), and Perceived Ease of Use (PEU) in the determination of investors' AI adoption decisions. Results indicated that these factors have a strong impact on the investors' use of AI, just as anticipated by the 'Technology Acceptance' (TAM). As was expected, this study established the fact that people's attitude towards AI works in bridging these factors and their willingness to use them. This, therefore, means that personal opinion, adapting to new technology, and cultural mindset will go a long way in influencing AI adoption. Indeed, the findings show that the adoption of AI into several spheres works when personalised strategies with the right components are put in place.

This study has a few limitations that are worth mentioning. Since this study is cross-sectional, it is impossible to say that any causation may exist between TAM variables and technology attitude and the adoptability of AI technology. The participants of this study are limited to retail investors in South India, and it may be very hard to generalise this study across different areas and cultures. The assumption made in this study could be prone to self-reporting, which could be biased and may not accurately reflect the actual utilisation of AI investment technology by users.

Future studies can extend the present research by adopting longitudinal designs in order to examine how attitudes towards technology and intentions to adopt AI evolve among retail investors as experience with AI tools accumulates and technologies mature. This would allow for much stronger causal inferences and the ability to assess whether technology attitude is a stable mediator over time. Secondly, cross-regional or cross-country comparative studies are needed to test the influence of cultural values, regulatory frameworks, financial literacy, and technological infrastructure on AI adoption, including the mediating effect of technology attitude, thereby assessing the generalizability of TAM across different contexts. Finally, the inclusion of constructs related to trust, perceived risk, and ethics of AI, including issues of transparency, data privacy, and ethical use, would provide a more complete extension of TAM by capturing the unique uncertainties and ethical considerations driving retail investor attitudes and the adoption of artificial intelligence.

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