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Study on Individual Investors' Intention to Use AI in Stock Price Forecasting on the Vietnamese Stock Market: A Technology Acceptance Model (TAM) Approach

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Abstract

This study aims to evaluate the factors influencing individual investors' intention to use artificial intelligence (AI) in stock price forecasting on the Vietnamese stock market, based on the Technology Acceptance Model (TAM). The research model includes the following factors: Perceived Usefulness; Perceived Ease of Use affecting Attitude; Attitude; Subjective Norms; and Trust affecting investors' intention to use AI in predicting stock prices. The study surveyed 240 individual investors, and the collected data were cleaned and processed using the PLS-SEM regression method. The results highlight the prominent role of social influence, trust in algorithms, and positive perceptions in fostering individual investors' acceptance of AI. These findings provide important practical implications for fintech companies and AI platform developers in formulating user engagement strategies, emphasizing the need to enhance ease of use, improve technological transparency, and strengthen communication through communities and social influence channels.

Keywords

Intention, use AI, stock price forecasting, individual investors, Vietnamese stock market, Technology Acceptance Model (TAM).

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1. Issue

Forecasting trends in financial markets has always been a crucial topic for both academia and professional investors. Such forecasts are typically constructed based on analyses of historical data and economic–financial indicators to support decision-making related to buying or selling financial assets (Lin & Marques, 2024). Traditionally, two common approaches are employed: fundamental analysis and technical analysis. While fundamental analysis is widely used in academic research to determine the intrinsic value of stocks, technical analysis relies on price trend patterns and is more commonly applied by professional investors (Lee, J., et al., 2021). Both methods, however, have certain limitations regarding accuracy and predictive capability, especially under highly volatile market conditions (D'Angelo & Grimaldi, 2017).

In recent years, Artificial Intelligence (AI) has emerged as a tool with the potential to revolutionize financial forecasting. Techniques such as Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP) enable the modeling of nonlinear relationships and the extraction of complex data patterns, thereby enhancing the accuracy of stock price predictions (Lin & Marques, 2024). AI is no longer merely a supporting tool; it has become a "strategic analysis hub" that helps investors make rapid, precise, and risk-aligned decisions (Belanche et al., 2019). Notably, robo-advisor systems in the Fintech sector have demonstrated their ability to replace traditional advisory services through AI-driven algorithms, offering low-cost investment solutions and 24/7 accessibility (Park & Yoon, 2025).

According to Statista (2023), the global financial services industry invested approximately USD 35 billion in AI, with the banking sector accounting for 60% of this amount. Alongside this trend is a shift from internal software systems to cloud-based platforms (SaaS), which enhances scalability and reduces operational costs. Within this context, the application of AI in financial investment has become a strategic direction in many countries, particularly in emerging markets.

In Vietnam, the stock market has been growing rapidly in both scale and the number of individual investors. However, most retail investors still lack decision-support tools based on big data analytics. Several domestic trading platforms and Fintech companies have begun integrating AI into their investment recommendation systems, yet the acceptance and use of AI among individual investors remain limited due to factors related to technological perception, trust, and social influence (Khuong, N.V., et al., 2022).

Against this backdrop, this study aims to analyze the factors influencing individual investors' intention to use AI in stock price forecasting in Vietnam, based on the Extended Technology Acceptance Model (TAM). Specifically, the study examines the roles of Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust (TR), and Subjective Norm (SN) in shaping Attitude (ATT) and Behavioral Intention (BI) to use AI in stock investment.

The research objectives include:

(1) Identifying the factors that influence individual investors' intention to use AI in forecasting stock prices;

(2) Measuring the degree of influence of each factor within the extended TAM model on behavioral intention to use AI in the context of the Vietnamese stock market.

2. Theoretical basis

2.1. Overview of Artificial Intelligence (AI) and Its Applications in Finance

Artificial Intelligence (AI) is understood as the capability of computer systems to process, learns, and make decisions that simulate human intelligence (Kaplan & Haenlein, 2019). In the financial sector, AI is driving a profound transformation, particularly through technologies such as Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP). These technologies enable systems to identify patterns, forecast trends, and make investment decisions with far greater accuracy than traditional statistical methods (Lin & Marques, 2024).

Recent studies have demonstrated the superior capability of AI in predicting stock price movements and supporting automated trading decisions. Bradley and Droisis (2024) employed a Multilayer Perceptron (MLP) neural network model to forecast stock prices and showed that the system could reduce prediction error to as low as 1.7% on real-world data. Similarly, Lin and Marques (2024) reviewed more than 379 studies on AI and stock markets, finding that models such as Long Short-Term Memory (LSTM), Artificial Neural Networks (ANN), and Support Vector Machines (SVM) are among the most effective approaches for market prediction.

In the Fintech sector, AI has been widely integrated into products such as robo-advisors, credit risk assessment systems, and automated trading platforms. According to Belanche, Casaló, and Flavián (2019), user attitude and social influence are key determinants of AI adoption in Fintech. Additionally, Park and Yoon (2025) highlight that the combination of AI and sustainable Fintech enhances transparency, efficiency, and reduces ethical risks in the financial system.

In Vietnam, AI applications in financial investment are still in their early stages. Although several Fintech companies and trading platforms have implemented AI-based analytical tools, the level of acceptance and trust among individual investors remains limited (Khuong et al., 2022). This limitation stems from psychological factors, lack of technological understanding, and concerns regarding the accuracy of AI systems. These issues highlight the necessity of studying individual investors' intention to use AI in order to promote digital transformation in Vietnam's financial sector.

2.2. Theory of Planned Behavior and Technology Acceptance Model

2.2.1. Theory of Planned Behavior (TPB)

TPB is one of the foundational behavioral theories that explains why individuals perform or do not perform a particular behavior. According to Ajzen (1991), an individual's behavior is influenced by three main factors:

(1) Attitude Toward Behavior (ATT)

Attitude reflects the degree to which an individual perceives a behavior as favorable or unfavorable. In other words, if a person believes that performing a behavior will lead to positive outcomes, they are more likely to develop a positive attitude and be willing to act.

In the context of this study, attitude toward using AI in stock price forecasting represents the extent to which individual investors feel interested, confident, or willing to incorporate AI tools into their investment activities. When investors perceive that AI helps them analyze faster, reduce errors, and enhance decision-making efficiency, a positive attitude is reinforced, thereby promoting their intention to use it (Belanche et al., 2019; Khuong et al., 2022).

(2) Subjective Norm (SN)

Subjective norm refers to the social pressure or influence from people around an individual (family, friends, colleagues, experts) that the individual perceives when considering whether to perform a behavior (Fishbein & Ajzen, 2009). This factor reflects the belief that "others expect me to do something."

In the context of stock price forecasting, SN plays a particularly important role because users often consult communities, forums, or investment experts before adopting new tools such as AI (Belanche et al., 2019). For example, if most investors in one's network trust and use AI platforms for stock prediction, that individual is likely to be positively influenced and develop a stronger intention to adopt similar technology.

(3) Perceived Behavioral Control (PBC)

PBC reflects an individual's perception of their ability to control the performance of a behavior—this includes personal capability, resource conditions (time, skills, finances), and external support (Ajzen, 1991). If investors feel they lack technological knowledge, do not understand the algorithms, or lack the necessary tools, low PBC will lead to a weaker intention to use AI (Chang et al., 2015). Conversely, when users feel confident in their data analysis skills and understand how AI operates, they are more likely to take the initiative in adopting AI.

2.2.2. Technology Acceptance Model – TAM

This study examines the intention to use AI through the Technology Acceptance Model (TAM). TAM was developed by Fred Davis (1989), based on the theoretical foundation of the Theory of Reasoned Action (TRA) by Ajzen and Fishbein (1975). The model aims to explain the factors that influence the decision to adopt and use a new technology. According to Davis (1989), TAM focuses on two core constructs:

(1) Perceived Usefulness (PU):

This refers to the degree to which users believe that using a technological system will improve their job performance, solve problems, or help them achieve desired outcomes. In this study, PU is measured through AI's ability to generate higher returns and enhance portfolion management. The usefulness of AI is reinforced by its demonstrated superior performance. Algorithmic alpha-seeking models have been shown to outperform traditional methods in improving average investment returns. PU of AI in investment is formed through three key dimensions:

- *Big Data Analytical Capability:* The ability to process large volumes of raw and unstructured data far beyond the capacity of an individual investor.
- *Accurate Prediction:* The use of deep learning and hybrid AI models enables analysis of historical data, market trends, and macroeconomic factors to forecast future stock prices.
- *Economic and Convenience Benefits:* Perceived benefits (PB), including economic benefits (EB) and convenience (CV), act as strong motivational drivers (Khuong, N.V., et al., 2022).

(2) Perceived Ease of Use (PEOU):

This factor measures the extent to which users feel that using a technological system is easy and does not require excessive effort. When a technology is designed to be intuitive and user-friendly, the likelihood of user acceptance increases significantly.

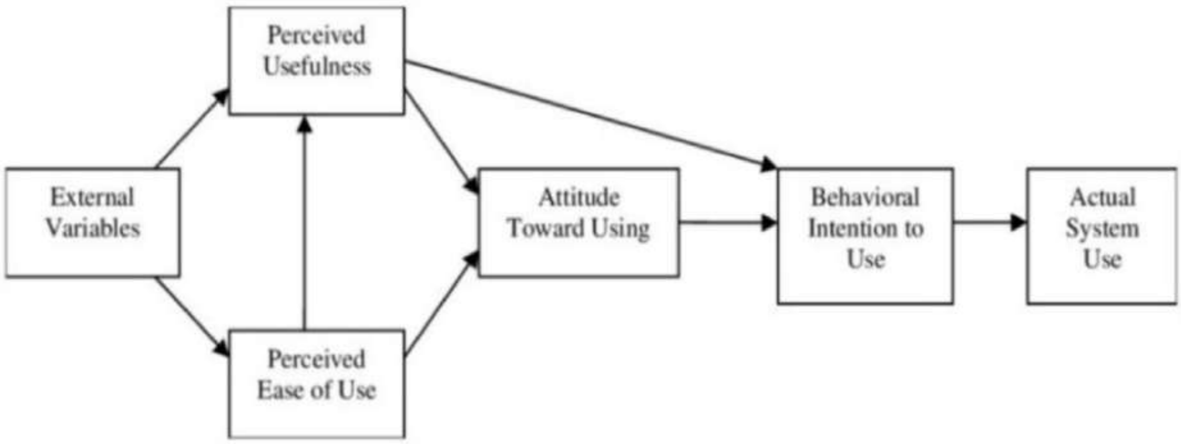

Figure 1. Technology Acceptance Model - TAM

Source: Fred Davis (1989)

According to TAM, if users believe that a technology provides value and is easy to use, they will be more inclined to adopt it. In FinTech, PEOU depends on the quality of the user experience (UX) and user interface (UI), requiring firms to prioritize investment in design and usability testing. However, for predictive AI, PEOU is not limited merely to interface simplicity (Park & Yoon, 2025).

2.3. Proposed Research Model

Investment in the stock market can only be conducted when individuals meet the necessary legal requirements and possess basic financial capacity. Therefore, the factor PBC (Perceived Behavioral Control) no longer plays a decisive role in the intention to use AI, because: (i) Behavioral conditions are already inherently ensured for individual investors; (ii) Technological capability factors are indirectly captured through the variable Perceived Ease of Use (PEOU) in the TAM model (Davis, 1989; Venkatesh & Davis, 2000).

Thus, this study excludes PBC from the extended TPB model in order to focus on cognitive, psychological, and social factors that align more closely with the behavioral characteristics of qualified individual investors.

On the other hand, given ongoing debates surrounding AI regarding accuracy, transparency, and risk, the construct of Trust is a critical determinant of user decision-making (Gefen et al., 2003). AI models employ complex algorithms that investors may find difficult to understand, making it challenging to interpret how AI generates stock price forecasts (Park & Yoon, 2025). Therefore, this study incorporates the factor **"Trust."**

Trust is a crucial mediating element in the acceptance of AI for stock price prediction. Trust in AI is often measured through dimensions such as competence, reliability, and transparency. Specialized measurement tools, such as the Trust in Automation Scale, are used to quantify users' trust in specific systems (Maier, T., et al, 2022). In investment contexts, Trust is strengthened by Performance. The improvement in investment outcomes achieved through AI-based price forecasting compared with traditional valuation methods is considered a core driver of Trust. Through demonstrated superior performance, AI systems can validate the added value they provide, thereby establishing confidence in their predictive capability. This trust becomes a critical bridge that directly influences the intention to use AI in stock price forecasting (Maier et al., 2022).

The proposed research model is as follows:

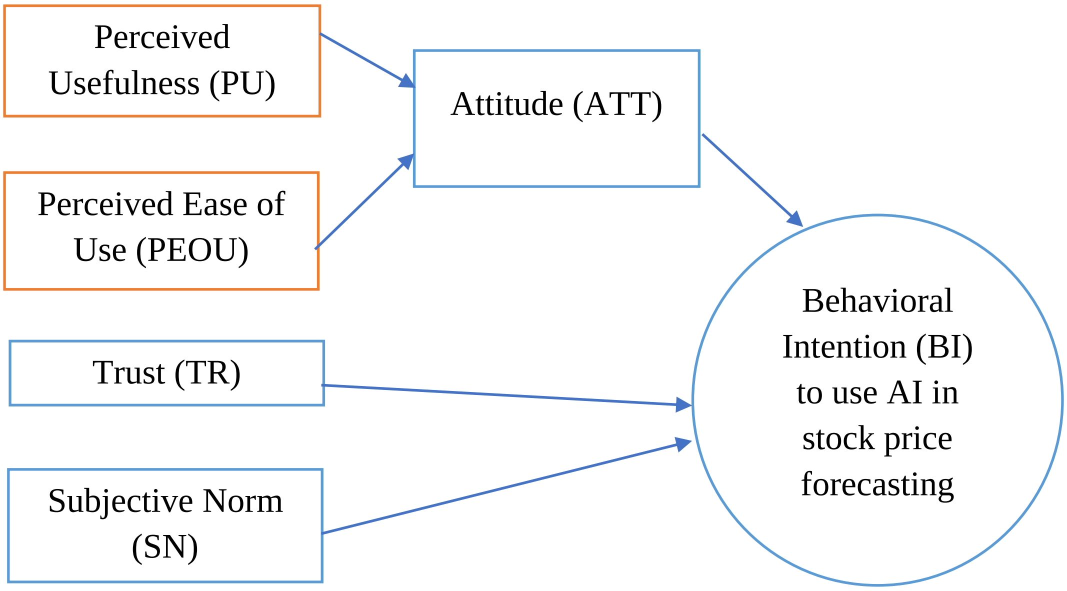

Figure 2. Proposed Research Model

Source: Proposed by the research team

The research model illustrated above is interpreted with the following research hypotheses:

Hypothesis H1: Attitude toward using AI (ATT) has a positive correlation with the intention to use AI in stock price forecasting (BI).

Hypothesis H2: Subjective Norm (SN) has a positive correlation with the intention to use AI in stock price forecasting (BI).

Hypothesis H3: Trust (TR) has a positive correlation with the intention to use AI in stock price forecasting (BI).

Hypothesis H4: Perceived Usefulness (PU) has a positive correlation with Attitude (ATT).

Hypothesis H5: Perceived Ease of Use (PEOU) has a positive correlation with Attitude (ATT).

Table 1. Proposed Measurement Scales

Variable	Measurement Scales	Source
1. Perceived Usefulness (PU): The degree to which an individual believes that using AI in stock price forecasting will provide benefits and achieve personal goals.		
PU1	AI-based stock price prediction helps me save time in market analysis	Venkatesh & Davis (2000)
PU2	Using AI in stock price forecasting enhances my decision-making in stock investment	
PU3	Using AI in stock price forecasting helps me invest more effectively	
2. Perceived Ease of Use (PEOU): The degree to which an individual believes that using a technology will not require excessive effort.		
PEOU 1	I find it easy to learn how to use AI in stock investment	Davis (1989)
PEOU 2	The AI interface and usage are easy to understand and convenient	
PEOU 3	I have sufficient skills to use AI applications for stock investment	
3. Attitude (ATT)		
ATT1	I find using AI in stock price forecasting interesting	Ajzen (1991)
ATT2	I think using AI in stock price forecasting is better than traditional forecasting methods	
ATT3	Using AI in stock price forecasting is easier than traditional forecasting methods	
4. Trust (TR): Confidence in AI's stock price prediction capabilities		
TR1	I trust the accuracy of AI tools in stock price forecasting	Gefen et al., (2003).
TR2	I trust the AI algorithms used in stock market analysis	
TR3	I believe that using AI in stock price forecasting will yield high investment performance	
TR4	I feel secure when using AI for stock investment	
5. Subjective Norms (SN)		
SN1	My family supports my use of AI in stock price forecasting	Ajzen (1991)
SN2	My friends support my use of AI in stock price forecasting	
SN3	Influential people in the stock market recommend that I use AI in stock price forecasting	
6. Behavioral Intention (BI): Intention to use AI in stock price forecasting		
BI1	I intend to use AI in stock investment in the near future	Ajzen (1991), Pavlou (2003)
BI2	I plan to use AI more frequently in stock price forecasting	
BI3	I am willing to recommend friends and family to use AI in stock price forecasting	

Source: Developed and adapted by the research team

3. Research Methodology

- Data Collection Method: The survey was designed using a 5-point Likert scale:

1. *Strongly disagree*
2. *Disagree*
3. *Neutral*
4. *Agree*
5. *Strongly agree*

After designing the questionnaire, the research team conducted a pilot survey with 10 investors, then refined the measurement scales before implementing the full-scale survey. Data collection was carried out using convenience sampling and the snowball sampling method (i.e., identifying the next respondents based on recommendations from surveyed participants) to ensure an adequate sample size.

- Data Analysis Method:

A quantitative research approach was employed to process the data collected from individual investors in the Vietnamese stock market.

The general structural regression equations are:

BI = a*ATT + b*TR+c*SN

ATT= d*PU+ e*PEOU

SMARTPLS software was used to test hypotheses and assess the impact of the factors.

Step 1: Measurement Model Assessment

The measurement model was evaluated by examining the quality of observed variables (outer loadings), reliability of the scales (Cronbach's Alpha), Convergent validity and Discriminant validity.

Step 2: Structural Model Assessment

Once the measurement model met the required criteria, the structural model was assessed through, path relationships and coefficients, overall determination coefficient (R^2), effect size (f^2).

4. Research Results

4.1. Descriptive Information of the Sample

The survey was conducted with 240 participants, all individual investors active in the Vietnamese stock market. The details of participants' age, gender, and income are as follows:

Table 2. Descriptive Statistics of the Research Sample

Age		Gender		Income	
Under 30	75,80%	Male	56,40%	Under 20 million/ month	55,40%
From 30 to under 40	13,30%	Female	42,30%	From 20 to under 50 million	33,40%
From 40 to under 50	9,20%	Prefer not to say	1,30%	50 million and above	11,20%
50 and above	1,70%				

Source: Survey results

Regarding age, the under-30 group accounted for the highest proportion (75.8%), indicating that most survey participants are young working-age individuals. This group is typically tech-savvy and more receptive to adopting new technologies. The 30–39 age group made up 13.3%, the 40–49 age group accounted for 9.2%, and the over-50 group was very small (1.7%).

In terms of gender, males accounted for 56.4%, females 42.3%, and those who chose not to disclose their gender represented 1.3%.

Regarding monthly income, more than half of the respondents (55.4%) earned under 20 million VND per month. Those earning between 20–50 million VND accounted for 33.4%, reflecting a financially stable middle-income segment. Finally, 11.2% of participants reported an income above 50 million VND per month.

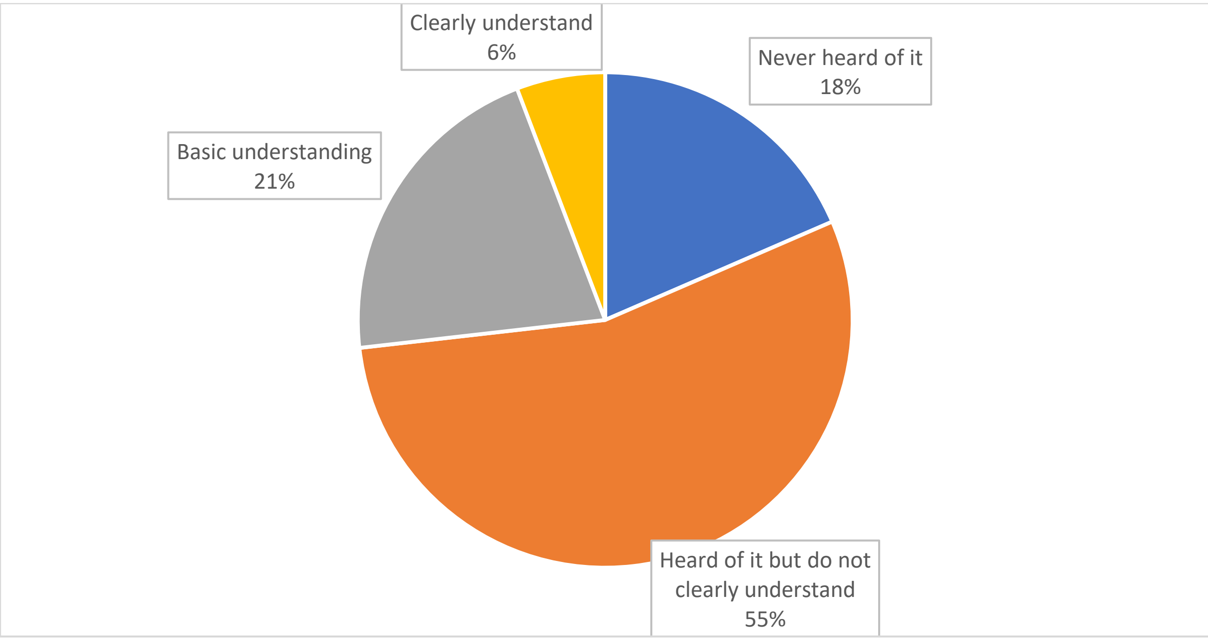

Figure 3. Awareness Level of AI Tools in Stock Price Prediction

Source: Survey results

The survey results shown in Figure 2.2 indicate that awareness of AI tools for stock price forecasting is still limited. Specifically, 18% of participants reported that they had never heard of such tools, reflecting that AI remains a relatively new concept for a segment of investors. 55% had heard of AI tools but did not understand them well, suggesting that most investors have only superficial exposure and lack hands-on experience or in-depth knowledge of AI applications in investment. Meanwhile, 21% reported that they have a basic understanding, meaning they had either researched or tried AI-based stock prediction platforms. Only 6% of respondents claimed to have a clear understanding of AI's operational principles and practical benefits. These results reveal a significant gap between awareness and practical application of AI among individual investors. They also highlight the strong potential for the growth of AI-driven investment products in Vietnam, especially if financial institutions, securities firms, and fintech companies strengthen communication, training, and investor education.

4.2. Model Testing and Hypotheses

4.2.1. Assessment of Measurement Item Quality

The quality of measurement items was evaluated using outer loadings. The impact of each observed variable is presented in Table 3.

Table 3. Outer Loadings of Factors Affecting Individual Investors' Intention to Use AI in Stock Price Forecasting

	ATT	BI	PEOU	PU	SN	TR
ATT1	**0,935**					
ATT2	**0,943**					
ATT3	**0,920**					
BI1		**0,937**				
BI2		**0,945**				
BI3		**0,922**				
PEOU1			**0,910**			
PEOU2			**0,895**			
PEOU3			**0,845**			
PU1				**0,852**		
PU2				**0,886**		
PU3				**0,882**		
SN1					**0,924**	
SN2					**0,928**	
SN3					**0,921**	
TR1						**0,809**

TR2						**0,909**
TR3						**0,912**
TR4						**0,756**

Source: Results of the research team's evaluation

The results presented in Table 3 indicate that all outer loading coefficients for the observed variables affecting individual investors' intention to use AI in stock price prediction are greater than 0.7. According to Hair et al. (2016), this demonstrates that the measurement items exhibit strong indicator reliability and are statistically meaningful.

Assessment of Scale Reliability

The reliability of the scales measuring factors influencing the intention to use AI in stock price prediction was evaluated using PLS-SEM, with two key indicators: Cronbach's Alpha and Composite Reliability (CR).

Table 4. Cronbach's Alpha and Composite Reliability of Factors Influencing Individual Investors' Intention to Use AI in Stock Price Prediction

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
ATT	0,925	0,925	0,952	0,870
BI	0,928	0,928	0,954	0,874
PEOU	0,860	0,868	0,915	0,782
PU	0,845	0,852	0,906	0,763
SN	0,915	0,915	0,946	0,854
TR	0,870	0,895	0,911	0,721

Source: Results of the research team's evaluation

According to Table 4, the analysis of scale reliability using Cronbach's Alpha shows that: Perceived Usefulness (PU) reaches 0.845, Perceived Ease of Use (PEOU) reaches 0.860, Trust (TR) reaches 0.870, Subjective Norm (SN) reaches 0.915, Attitude (ATT) reaches 0.925, and Behavioral Intention to Use AI in Stock Price Forecasting (BI) reaches 0.928. All values exceed the threshold of 0.7 (DeVellis, 2012), and none violate the criteria for item deletion. Therefore, all measurement scales are considered reliable and retained for subsequent analyses.

The Composite Reliability (CR) values of all constructs are also greater than 0.7 (Bagozzi & Yi, 1988) (Table 4), confirming that the scales possess adequate reliability and are suitable for further factor analysis.

Convergence

As shown in Table 4, the Average Variance Extracted (AVE) values for all constructs—Perceived Usefulness (PU) at 0.763, Perceived Ease of Use (PEOU) at 0.782, Trust (TR) at 0.870, Subjective Norm (SN) at 0.854, Attitude (ATT) at 0.870, and Behavioral Intention (BI) at 0.874—are all above the threshold of 0.5 (Hock & Ringle, 2010). This indicates that the model meets the requirements for convergent validity.

Discriminant Validity

Results in Table 5, based on the Fornell–Larcker criterion, show that all constructs (*PU, PEOU, TR, SN, ATT,* and *BI*) satisfy discriminant validity. Specifically, the square root of each construct's AVE (diagonal values) is greater than all cross-correlations with other constructs (off-diagonal values). Therefore, the model meets discriminant validity requirements according to both cross-loading criteria and the Fornell–Larcker criterion (Fornell & Larcker, 1981).

Table 5. Fornell–Larcker Criterion for the Research Model on Factors Influencing Individual Investors' Intention to Use AI in Stock Price Prediction

	ATT	BI	PEOU	PU	SN	TR
ATT	0,933					
BI	0,823	0,935				
PEOU	0,848	0,816	0,884			
PU	0,445	0,514	0,572	0,874		
SN	0,835	0,869	0,842	0,562	0,924	
TR	0,711	0,781	0,782	0,611	0,754	0,849

Source: Results of the research team's evaluation

Effect Size (f^2)

The $\mathbf{f^2}$ coefficient reflects the magnitude of the impact of an exogenous construct when it is removed from the model. According to Cohen (1988), $\mathbf{f^2}$ values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effect sizes, respectively. An effect size below 0.02 indicates that the construct has no meaningful influence on the endogenous variable.

Table 6. Summary of f^2 Values

	ATT	BI	PEOU	PU	SN	TR
ATT		0,099				
BI						
PEOU	**1,879**					
PU	**0,008**					
SN		**0,294**				
TR		0,126				

Source: Results of the research team's evaluation

In this model, as shown in Table 6, the factor Perceived Ease of Use (PEOU) has an $f^2 = 1.879 > 0.35$, indicating a very large effect on Attitude (ATT). The factor PU has an $f^2 = 0.008 < 0.02$, which is considered to have no meaningful effect on ATT. ATT itself has $0.02 < f^2 < 0.15$, reflecting a medium effect. Meanwhile, both TR and SN have $f^2 > 0.35$, indicating a large effect on Behavioral Intention (BI) to use AI in stock price prediction among individual investors.

4.3. Results of the Structural Model Assessment

Assessment of the Relationships

The relationships and the magnitude of the effects among the factors influencing the intention to use AI in stock price prediction among individual investors, as analyzed through SMARTPLS, are illustrated in Figure 4.

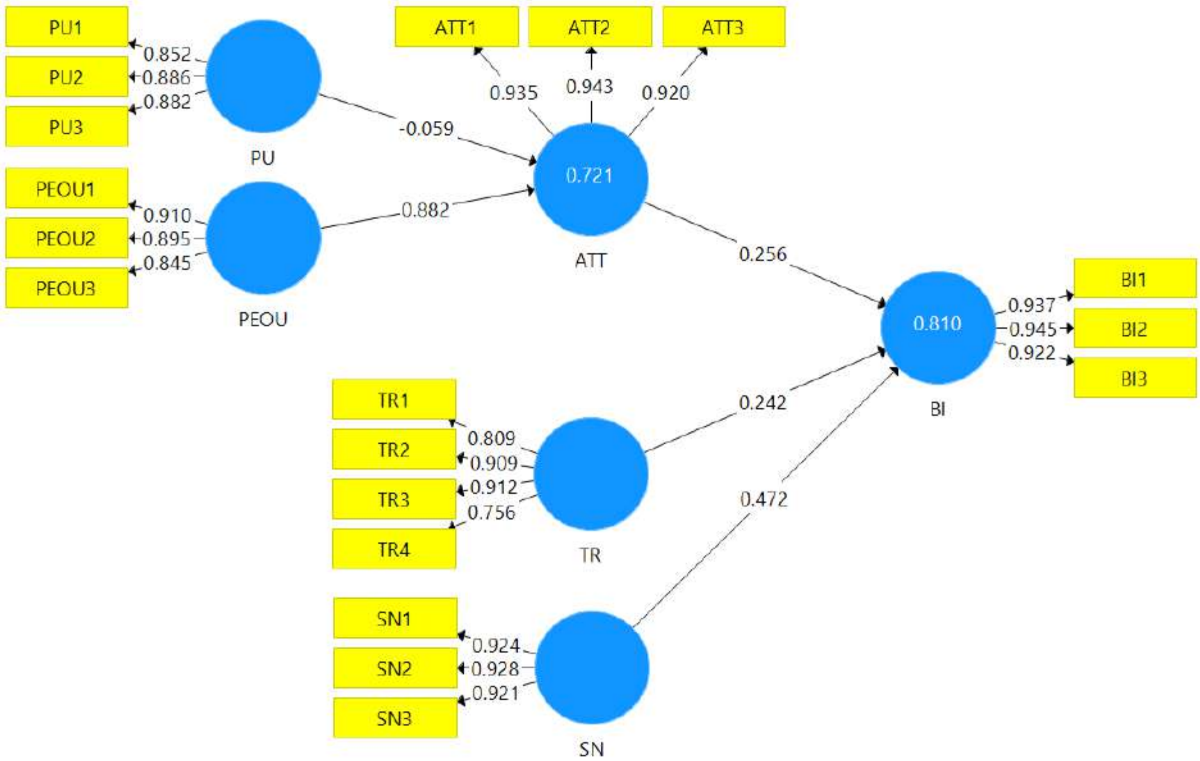

Figure 4. Factors Influencing the Intention to Use AI in Stock Price Forecasting Among Individual Investors

Source: Research team's SMARTPLS testing results

The results of the Bootstrap analysis used to evaluate the significance of the relationships are presented in Table 7. Accordingly, the variable "Perceived Ease of Use" (PEOU) was found to have an impact on "Attitude" (ATT) (Hypothesis H5 is accepted at the 5% significance level). Meanwhile, "Perceived Usefulness" (PU) has a P-value of 0.170 > 0.05, indicating that it does not affect "Attitude" (ATT) (Hypothesis H4 is not supported at the 5% significance level). The factors "Subjective Norm" (SN), "Attitude" (ATT), and

"Trust" (TR) have P-values < 0.05; therefore, they are concluded to have significant impacts on "Behavioral Intention to Use AI in Stock Price Forecasting Among Individual Investors" (BI) (Hypotheses H1, H2, and H3 are supported at the 5% significance level).

Table 7. Path Coefficients of the Structural Model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
ATT -> BI	0,256	0,265	0,095	2,686	**0,007**
PEOU -> ATT	0,882	0,878	0,052	16,940	**0,000**
PU -> ATT	-0,059	-0,059	0,043	1,373	**0,170**
SN -> BI	0,472	0,464	0,098	4,805	**0,000**
TR -> BI	0,242	0,241	0,068	3,555	**0,000**

Source: Research team's SMARTPLS testing results

The testing results in Table 7 indicate that, at the 95% confidence level, "Perceived Ease of Use" (PEOU) has an impact on "Attitude" (ATT). The regression equation is as follows:

ATT = 0.882*PEOU

The coefficient 0.882 (PEOU → ATT) is positive, consistent with Hypothesis H5, which posits a positive effect on "Attitude" (ATT).

At the 95% confidence level, "Subjective Norm" (SN), "Trust" (TR), and "Attitude" (ATT) are found to influence the "Behavioral Intention to Use AI in Stock Price Forecasting Among Individual Investors" (BI). The regression equation is presented as follows:

BI = 0.256*ATT + 0.472*SN + 0.242*TR

The coefficients 0.256 (ATT → BI), 0.472 (SN → BI), and 0.242 (TR → BI) are all positive, which is consistent with Hypotheses H1, H2, and H3, indicating positive effects on the behavioral intention to use AI in stock price forecasting (BI).

Assessment of the Overall Coefficient of Determination R^2 (R square)

The PLS analysis yields the R^2 values, which reflect the extent to which the independent variables explain the dependent variable. The R^2 index measures the coefficient of determination and indicates the model's explanatory power (i.e., the degree to which the model fits the data). According to Hair et al. (2010), the recommended R-square benchmark values are 0.75, 0.50, and 0.25.

Table 8. Coefficients of Determination (R Square) Explaining the Dependent Variables

	R Square	R Square Adjusted
ATT	0,721	0,718
BI	0,810	0,807

Source: Results of the research team's evaluation

The results from Table 7 show that the R^2 value for the factor Attitude (ATT) is 0.721, with an adjusted R^2 of 0.718. This indicates that the independent variables explain 72.1% of the variance in "Attitude" (ATT).

The R^2 value for the factor "Behavioral Intention to Use AI in Stock Price Forecasting" (BI) is 0.810, and the adjusted R^2 is 0.807, which is considered appropriate for this study. Accordingly, the independent variables explain 81% of the variance in "Behavioral Intention to Use AI in Stock Price Forecasting" (BI).

5. Discussion of Findings

(1) The Impact of Perceived Ease of Use (PEOU) on Attitude (ATT)

The PLS-SEM results show that Perceived Ease of Use (PEOU) has a strong and statistically significant effect on Attitude (ATT) toward using AI in stock price forecasting, with a path coefficient of 0.882 ($p < 0.05$). This confirms that Hypothesis H5 is accepted and aligns with previous studies by Davis (1989) and Venkatesh & Davis (2000) in the Technology Acceptance Model (TAM).

The mean values of the three observed PEOU indicators range from 3.8 to 3.918, all above the midpoint of 3 on the 5-point Likert scale, indicating that the majority of respondents have a positive perception of the convenience and accessibility of AI tools in stock investment.

Table 9. Mean Values of the PEOU Scale

Code	Mean	Interpretation
PEOU1	3,800	Users find it easy to learn how to use AI in stock investment
PEOU2	3,918	The interface and operations if AI applications are perceived as user-friendly and easy to understand.
PEOU3	3,800	Users feel confident that they possess sufficent skills to use AI for investment purposes.

Source: Research findings

The statements regarding learnability (PEOU1), interface convenience and user-friendliness (PEOU2), and users' confidence in operating the system (PEOU3) all received positive evaluations. This result is consistent with the TAM model (Davis, 1989), which posits that perceived ease of use is a key factor shaping the attitude toward technology acceptance.

In the context of an increasingly digitalized financial market, younger investors—who are familiar with technological applications—are more likely to access AI tools and tend to expect AI to help them reduce analysis time and minimize subjective errors. Therefore, the high PEOU scores indicate that AI currently meets investor expectations for convenience, which also explains why PEOU exhibits a strong impact (0.882) on the attitude toward usage (ATT) in the research model.

(2) The Influence of Factors on Behavioral Intention (BI)

The regression results show that Attitude (ATT), Subjective Norm (SN), and Trust (TR) all exert positive and statistically significant influences on the behavioral intention to use AI in stock price forecasting (BI), as expressed by the following equation:

BI = 0.256*ATT + 0.472*SN + 0.242*TR

- The Influence of SN on BI

The variable Subjective Norm (SN) has the largest coefficient, 0.472, among the three factors, indicating that it has the strongest impact on the intention to use AI (BI). In other words, when the level of support from family, friends, and influential individuals increases, investors' intention to adopt AI in stock price forecasting increases significantly. This finding aligns with the subjective norm component in TPB/TAM2, which states that the adoption of new technology is strongly influenced by the surrounding social environment.

Table 10. Mean Values of the Subjective Norm Variables

Code	Mean	Interpretation
SN1	3,747	Family members generally support the respondent's use of AI in stock price forecasting.
SN2	3,865	Friends express supportive attitudes and encourage the use of AI in stock price forecasting.
SN3	3,841	Influential market participants (expert, KOLs, well-known investors) recommend the use of AI.

Source: Research findings

The mean values of all SN observed variables exceed 3.7 (on a 5-point scale), reflecting a generally favorable social environment: investors not only receive support from family and friends but are also "pulled" by recommendations from KOLs and stock market experts. In the context where AI in investment remains relatively new and complex, this result indicates that many individual investors tend to rely on social cues when making decisions, rather than relying solely on their own technical assessments.

- The Influence of ATT on BI

In the regression model, Attitude (ATT) has a coefficient of 0.256 in predicting Behavioral Intention (BI), indicating that this is one of the key factors influencing investors' decisions to adopt AI. Prior to examining the effect, the research team analyzed respondents' level of agreement with the three ATT observed variables.

Table 11. Mean Values of ATT Variables

Code	Mean	Interpretation
ATT1	**3,971**	Users find the use of AI in stock price forecasting enjoyable.
ATT2	**3,894**	Users believe that using AI delivers better effectiveness compared to traditional forecasting methods.
ATT3	**3,918**	Users perceive AI as easier to use than traditional forecasting approaches.

Source: Research findings

The results indicate that users' attitudes toward applying AI in stock price forecasting are generally positive, with an average score of 3.928/5. ATT1 has the highest mean (3.971), reflecting that the sense of enjoyment and novelty is a prominent factor when investors first engage with AI.

ATT3 (3.918) and ATT2 (3.894) indicate that most survey participants perceive AI as easy to use and more effective than traditional analytical methods.

Overall, these results are consistent with the TAM model (Davis, 1989), where a positive attitude is a necessary condition for forming the intention to use technology. When users perceive AI as both enjoyable, effective, and user-friendly, they are more likely to trust the tool, which in turn increases their willingness to apply it in actual investment activities.

- Influence of TR on BI

The Trust (TR) factor has a path coefficient of 0.242, indicating a positive and significant influence on investors' intention to use AI. Although its effect is lower than Subjective Norm (SN) and Attitude (ATT), TR still plays an important role as trust is a core factor in decisions related to new technology.

Table 12. Mean Values of TR Variables

Code	Mean	Interpretation
TR1	3,547	Users trust the accuracy of AI tools in stock price forecasting.
TR2	3,735	Users trust the AI algothrihms used in stock analysis.
TR3	3,700	Users expect AI to deliver high investment performance.
TR4	3,312	Users' sense of security when using AI in stock investment is moderate

Source: Research findings

The results show that TR2 (3.735) and TR3 (3.700) have the highest values, indicating that users evaluate AI positively in terms of analytical capability and performance potential. TR4 (3.312) reflects a noticeably lower level of "security when using AI" compared to the other statements. This suggests that users place more trust in the technical aspects (algorithms, accuracy) than in safety and psychological comfort when applying AI. The lower sense of security reflects concerns about market risk, the transparency of AI models, or limited understanding of how the algorithms operate.

(3) Behavioral Intention to Use AI in Stock Price Forecasting (BI)

Based on the regression equation: BI = 0.256*ATT + 0.427*SN + 0.242*TR

The intention to use AI in stock price forecasting is not only driven by individual needs but is also reinforced by the social environment and the level of trust in the technology, in which:

- SN (0.427) is the strongest influencing factor, indicating that investors' behavior still depends significantly on recommendations from family, friends, the financial community, and KOLs.
- ATT (0.256) shows that a positive attitude contributes steadily to the intention to use AI.
- TR (0.242) confirms that trust in the accuracy and safety of AI also promotes the decision to adopt this technology.

The study results show that the mean values of the three BI observed variables range from 3.859 to 3.929, indicating that the behavioral intention of individual investors to use AI is relatively high. These figures reflect that most survey participants are not only interested in applying AI in the near future but also tend to continue using it and share this experience with others.

Table 13. Mean Values of BI Variables

Code	Mean	Interpretation
BI1	**3,900**	Investors intend to use AI in stock price forecasting in the near future
BI2	**3,859**	Investors plan to use AI more frequently in market analysis.
BI3	**3,929**	Investors are willing to recommend AI to family and friends for stock forecasting.

Source: Research findings

The high scores of the BI variables indicate growing user confidence in the practical benefits of AI in stock investment. Vietnamese investors are beginning to perceive AI as a reliable analytical tool that helps improve information processing speed and reduces decision-making pressure in a volatile market. Among the three observed variables, BI3 (3.929) is the highest, reflecting a tendency to share the AI experience with others. BI1 and BI2 are also above 3.8, showing that users view AI not just as a short-term interest but as a long-term tool in their investment strategy.

(4) Implications from the Research Results

From the above results, several practical implications can be drawn for AI tool providers, financial institutions, and technology platform developers to promote sustainable usage behavior among investors.

(i) Enhancing trust in technology is crucial because trust (TR) is one of the most significant factors influencing the intention to use AI. Investors are likely to maintain long-term usage only if they feel confident about the accuracy and transparency of the tools. Therefore, developers should prioritize providing clear information on how AI models process data, the sources of input data, prediction accuracy across different market conditions, and the technical limitations of the models. Publishing performance reports and illustrating results through practical examples such as backtesting or case studies can help users understand that predictions are not generated by a "black box" of unknown risk but are built on verified data and algorithms. When investors feel reassured, they are more likely to integrate AI into their investment strategy rather than treat it as a temporary experiment.

(ii) Social influence (SN) is the strongest factor in the regression model. This indicates that individual investment behavior is deeply embedded in the community context. Businesses should therefore focus on fostering network effects among users. Building online communities where users can share experiences, discuss strategies, analyze results, and provide recommendations can create psychological reinforcement among investors. Such an environment increases the feeling of being "accompanied," thereby promoting positive herd behavior toward technology adoption. At the same time, influencer-driven communication campaigns in the financial sector continue to play a critical role in shaping users' AI adoption behavior.

(iii) Enhancing user experience on AI platforms. An intuitive interface, fast processing speed, dynamic charting features, and intelligent alert mechanisms can make investors perceive AI as not only useful but also significantly more convenient than traditional methods. The high score of BI3 indicates users' willingness to recommend AI to others, showing that positive word-of-mouth is a strong motivator. This opens opportunities for businesses to implement referral programs, incentivizing users to introduce the platform to friends and colleagues. Such initiatives can not only expand the user network but also enhance trust through social confirmation from acquaintances, which is a key factor in personal finance.

6. Conclusion

This study examined the factors influencing individual investors' intention to use AI in stock price prediction in the Vietnamese stock market, based on the Technology Acceptance Model (TAM). The results indicate that Perceived Ease of Use (PEOU) has a strong effect on Attitude toward AI usage (ATT), with a regression coefficient of ATT = 0.882. The Perceived Usefulness (PU) factor was not statistically significant in the model. This suggests that investors value the convenience and ease of handling AI tools more than the expected benefits in investment performance. The regression model identifies three main factors driving the intention to use AI (BI) in stock price prediction: Attitude (ATT), Subjective Norms (SN), and Trust in technology (TR). Among them, Subjective Norms have the strongest effect (β = 0.472), followed by Attitude (β = 0.256) and Trust (β = 0.242).

The study provides empirical evidence on technology acceptance behavior in the financial sector in Vietnam and offers practical implications for AI product development and technology communication targeting individual investors. However, according to the original TAM, PEOU can affect BI both directly and indirectly. In this study, the direct relationship between PEOU and BI was excluded. Future research could extend to the UTAUT or UTAUT2 models to examine demographic moderators (e.g., investment experience, age) and post-adoption variables related to intention. Such an approach would provide deeper insights into long-term investor behavior amid the continuous evolution of AI technology.

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