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DECODING INVESTOR INTEREST IN AI-ASSISTED INVESTING: KEY DETERMINANTS AND IMPLICATIONS

SUPPANUNTA ROMPRASERT*
Faculty of Economics
Srinakharinwirot University (Thailand)

I-HSIEN TING
National University of Kaohsiung (Taiwan).

THANAPAT ROMPRASERT
Kyoto University of Advanced Science (Japan)

JIRAYUT MONJAGAPATE
Lecturer, Department of Business Administration
Institute of Entrepreneurial Science of Ayothaya (IESA) (Thailand)

Abstract

This paper examines the drivers that determine the adoption of artificial intelligence (AI) by investors as a decision support tool in financial investments. With quantitative research design, 400 respondents who either use AI now to make investment or will in future were used to collect data. The data has been collected using an online questionnaire. The characteristics of the participants were summarized using descriptive statistics, including frequency, percentage, mean, and standard deviation. The SPSS was used to perform inferential analyses consisting of an Independent-Sample t-test and structural equation modeling (SEM) at a 0.05 significance level. These findings indicate that individual factors such as demographic characteristics and investment experience have a strong influence on the adoption of AI. The similarities and differences between the groups are however found in some variables and other variables do not show any significant differences. The technological aspects, which include perceived usefulness, ease of use, and trust, have a significantly positive correlation with the AI adoption intentions, indicating the significance of technology preparedness and reliability of the system to investor acceptance.

Keywords: Artificial intelligence, investment decision-making, investor behavior, technology adoption, structural equation modeling

*Corresponding author Email: suppanunta@g.swu.ac.th

Introduction

Artificial Intelligence (AI) refers to computer systems designed to perform tasks that typically require human intelligence, including learning, reasoning, and decision-making (Kureshi, 2022). By simulating human thought processes through advanced algorithms and computational models, AI enables machines to analyze information and make decisions autonomously. The concept of AI originated in the mid-20th century, with its formal recognition as a scientific discipline during the Dartmouth Conference in 1956, where the term "Artificial Intelligence" was first introduced (McCarthy, Minsky, Rochester & Shannon, 1955). Since then, AI has evolved into a transformative technology across industries, driven by rapid advances in hardware, software, and data analytics. In today's digital economy, the financial sector generates massive volumes of data requiring timely and precise analysis. Traditional analytical methods often prove inadequate for handling such complex datasets. AI offers a powerful alternative, providing faster, more accurate insights that enhance investment decision-making and portfolio management. In Thailand, the economic context underscores the importance of effective investment strategies. In 2023, the country's GDP grew by 1.9%, down from 2.5% in 2022, while inflation rose by 1.23%, largely due to higher food and energy costs (National Economic and Social Development Council, 2024; Office of Trade Policy and Strategy, 2024). Rising living expenses and market volatility have prompted younger generations to seek investment opportunities to grow savings and secure financial stability (Chakrapipat, 2024). However, successful investing demands specialized knowledge and continuous monitoring, which can be challenging for individuals with limited expertise or time. AI-driven investment platforms, such as automated trading systems and robo-advisors, offer accessible solutions by streamlining data analysis and minimizing human error (Poonsathianthap, 2023). Despite these advantages, AI systems remain dependent on data quality and algorithmic design, making transparency and reliability critical. Comprehensive research is therefore essential to understand how investors perceive these technologies and what factors drive their adoption.

This study investigates the critical factors that influence investors—especially members of younger generations—in adopting artificial intelligence (AI) as a tool to support investment decision-making in Thailand. Rapid technological development and increasing market complexity have created new opportunities and challenges for individual investors. AI-based investment advisors, including automated trading platforms and robo-advisors, promise faster analysis, improved accuracy, and the ability to process large datasets beyond human capability. However, the decision to embrace these systems depends on a range of personal and technological considerations that remain underexplored in the Thai context. The research framework identifies two major groups of independent variables. The first group, Personal Factors, includes demographic characteristics such as gender, age, occupation, educational level, and monthly income. These elements capture differences in risk tolerance, financial literacy, and attitudes toward technological change. The second group, Technological Factors, focuses on attributes of the AI systems themselves, including the accuracy of AI-generated investment recommendations, the convenience of system

use, the ease with which users can understand the interface, and the security and privacy protections offered.

In addition to its technological and financial significance, the rise of AI-assisted investing must also be viewed within the broader context of socio-economic development. As digital technologies reshape global financial systems, AI-driven investment tools have the potential to promote financial inclusion, particularly in emerging economies like Thailand. Automated platforms lower traditional barriers to entry by reducing minimum investment requirements, simplifying complex financial products, and offering real-time guidance that was once accessible only through professional advisors. This democratization of investment opportunities is especially relevant for younger generations, who increasingly rely on digital platforms for banking, payments, and wealth management. However, these advancements also highlight persistent concerns related to digital inequality. Access to AI-based investment systems requires stable internet connectivity, adequate digital literacy, and confidence in technology—conditions that may not be evenly distributed across socio-economic groups. As a result, technological adoption patterns among younger Thai investors not only reflect a preference for convenience and automation but also mirror broader transitions in the country's economic structure, labor market, and consumption behaviors. Understanding these dynamics can help ensure that the expansion of AI-assisted investing contributes not only to improved financial decision-making but also to more equitable and sustainable economic participation.

Regarding to the above information, these independent variables are hypothesized to shape the dependent variable, defined as the *decision to use AI-based investment advisors*. By examining how personal characteristics interact with perceptions of technology, this study seeks to reveal which factors most strongly motivate or discourage adoption. The findings will provide valuable insights for financial institutions, technology developers, and policymakers aiming to design AI investment tools that align with investor needs, foster trust, and encourage broader participation in data-driven investment practices.

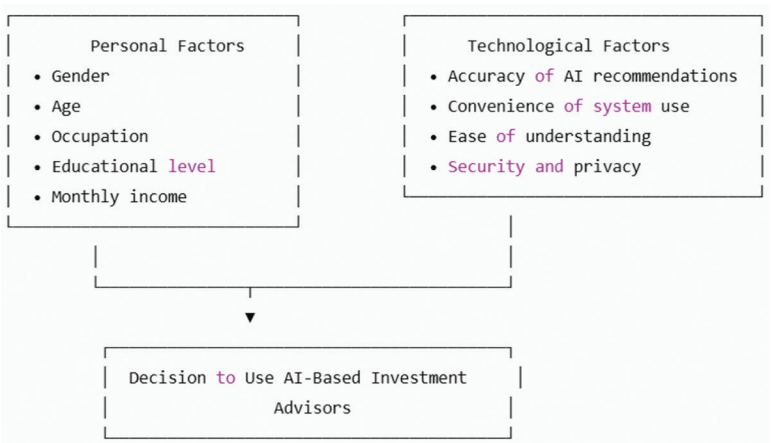

Figure 1. Factors Influencing the Decision to Use AI-Based Investment Advisors.

Research Hypotheses

Hypothesis Group 1: Personal Factors

Gender

H_{01}: Gender has no significant influence on the decision to adopt artificial intelligence (AI) for investment purposes.

H_{11}: Gender has a significant influence on the decision to adopt AI for investment purposes.

Age

H_{02}: Age has no significant influence on the decision to adopt AI for investment purposes.

H_{12}: Age has a significant influence on the decision to adopt AI for investment purposes.

Occupation

H_{03}: Occupation has no significant influence on the decision to adopt AI for investment purposes.

H_{13}: Occupation has a significant influence on the decision to adopt AI for investment purposes.

Education Level

H_{04}: Education level has no significant influence on the decision to adopt AI for investment purposes.

H_{14}: Education level has a significant influence on the decision to adopt AI for investment purposes.

Monthly Income

H_{05}: Monthly income has no significant influence on the decision to adopt AI for investment purposes.

H_{15}: Monthly income has a significant influence on the decision to adopt AI for investment purposes.

Hypothesis Group 2: Technological Factors

Accuracy of AI Recommendations

H_{06}: The perceived accuracy of AI investment recommendations has no significant influence on the decision to adopt AI for investment purposes.

H_{16}: The perceived accuracy of AI investment recommendations has a significant influence on the decision to adopt AI for investment purposes.

Service Fee

H_{07}: The service fee of AI-based investment systems has no significant influence on the decision to adopt AI for investment purposes.

H_{17}: The service fee of AI-based investment systems has a significant influence on the decision to adopt AI for investment purposes.

Ease of Use

H_{08}: Perceived ease of use of AI systems has no significant influence on the decision to adopt AI for investment purposes.

H_{18}: Perceived ease of use of AI systems has a significant influence on the decision to adopt AI for investment purposes.

Security and Privacy

H_{09}: Perceived security and privacy of AI systems have no significant influence on the decision to adopt AI for investment purposes.

H_{19}: Perceived security and privacy of AI systems have a significant influence on the decision to adopt AI for investment purposes.

Literature Review

A thorough review of existing literature is essential to clarify the factors that influence investors to adopt artificial intelligence (AI) in their investment decisions. This chapter provides the conceptual and empirical foundation for the study and is organized into two principal sections: (1) Theoretical Review and (2) Empirical Literature Review. These sections synthesize key concepts, models, and prior studies directly related to AI adoption in financial investment contexts.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis (1986), serves as a fundamental framework for understanding how individuals accept and utilize new technologies. TAM posits that users' attitudes toward adopting a technology are primarily shaped by two core perceptions: Perceived Ease of Use and Perceived Usefulness.

Perceived Ease of Use reflects the degree to which an individual believes that employing a particular system will require minimal effort.

Perceived Usefulness represents the extent to which a person believes that using the technology will enhance performance, productivity, or goal achievement, thereby increasing the likelihood of adoption.

The model further identifies a set of interrelated variables.

1. External Variables – Individual or environmental characteristics that influence perceptions of usefulness and ease of use.
2. Attitude Toward Using – The user's positive or negative feelings about employing the technology, shaped by perceived ease of use and usefulness.
3. Behavioral Intention – The intention or willingness to adopt and continue using the system.
4. Actual System Use – The observable implementation or utilization of the technology in practice.

TAM has been widely applied to examine technology adoption across diverse domains, making it particularly relevant for exploring how investors evaluate AI-based investment tools and the factors that drive or impede their adoption as shown in the Figure below:

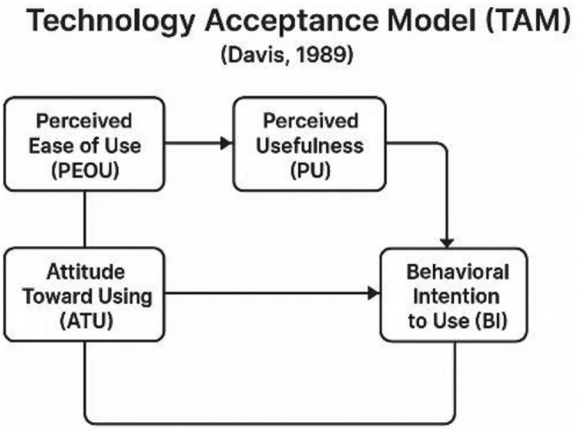

Figure 2. Illustrates the Technology Acceptance Model
Source: Davis (1989).

Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) posits that an individual's actual use of technology is primarily influenced by their behavioral intention and their perception of the opportunities to utilize the technology. This perception is shaped by four central constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. Furthermore, the impact of these constructs is moderated by demographic and behavioral factors, namely age, gender, experience, and voluntariness of use (Venkatesh et al., 2003). The primary constructs can be described as follows:

1. Performance Expectancy – The degree to which an individual believes that using the technology will enhance job performance and contribute to achieving work-related goals.
2. Effort Expectancy – The perceived ease associated with using the technology.
3. Social Influence – The extent to which an individual perceives those important peers or authorities expect them to use the technology.

Additionally, Facilitating Conditions represent the extent to which an individual believes that organizational, environmental, or technological resources are available to support system use. This factor can significantly affect both technology acceptance and actual usage behavior. UTAUT also emphasizes the moderating role of specific variables on the relationship between the primary constructs and behavioral intention. These moderators include gender, age, experience, voluntariness of use.

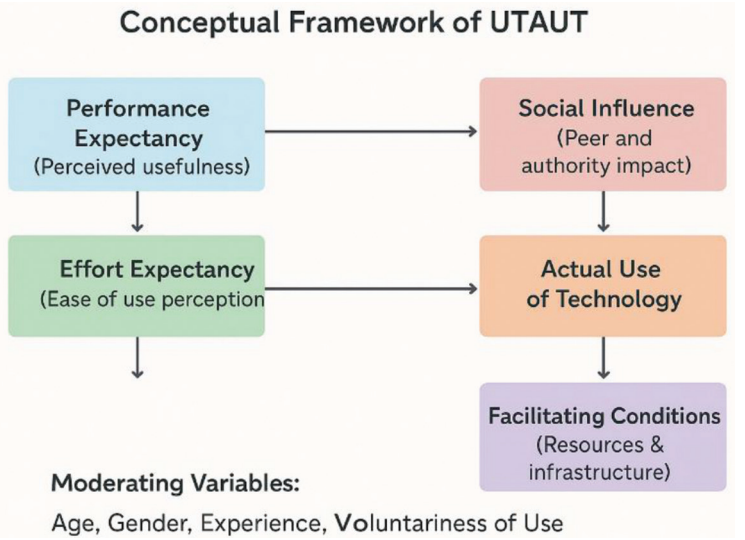

Figure 3. Illustrates the conceptual framework of the Unified Theory of Acceptance and Use of Technology (UTAUT).
Source: "User Acceptance of Information Technology: Toward a Unified View," by V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003, MIS Quarterly, 27(3), p. 447.

Based on the review of relevant literature, the researcher adopted the Technology Acceptance Model (TAM) as the theoretical framework to explain the factors influencing the adoption of artificial intelligence (AI) in investment decisions among the younger generation. TAM is internationally recognized as a credible and robust theory, emphasizing critical determinants such as perceived ease of use and perceived usefulness of technology. Compared to alternative models, TAM provides a more comprehensive and systematic understanding of the factors that affect technology acceptance. The literature on AI in investment can be categorized into four primary dimensions: (1) ease of use, (2) accuracy of AI, (3) security and privacy, and (4) service cost. These dimensions collectively shed light on the factors that influence the perception and usage of AI by the new generation in investment contexts. A review of recent studies shows both similarities and differences across research designs and variables. Abulail, Badran, Shkoukani & Omeish (2025), Akinnagbe (2024), Berger, Dowling, Feinberg & Hammond (2023) examined different factors affecting AI adoption. For instance, Zhang, Wu, Xie & Xie (2023) focused on accuracy and examined system efficiency, including processing speed and result accuracy. Despite the different variables, all studies aimed to improve the overall efficiency of AI systems. Methodologically, data collection approaches varied, with some studies using experiments exclusively and others combining experiments with broader data collection. The theoretical models employed also differed: Zhang, Wu, Xie & Xie (2023) applied the Human-AI Interaction Framework utilized the Collaboration Framework.

Lu, Sun, Zhang & Li (2022), LeCun (2022), Hinton (2022), Bengio (2022), Brynjolfsson (2022), Blei (2014), Berners-Lee (2022), Schmidhuber (2022), and Etzioni (2022) investigated diverse variables. For example, Blei (2014) analyzed demographic variables such as gender, age, income, and occupation, whereas Brynjolfsson (2022) examined

economic growth indicators, including GDP and productivity. Despite differences in variables, the overarching objective remained the same: to explore the economic and societal impacts of AI and related digital technologies. Most studies employed experimental or testing methods and applied deep learning and statistical models to assess AI implementation, safety, and accuracy. Acemoglu (2021), Veloso (2021), Bender, Gebru, McMillan-Major & Mitchell (2021), Ghahramani (2021), Jain, Chan, Brown & Dragan (2021), Calo (2021), Crawford (2021), Selbst, Venkatasubramanian & Kumar (2023) focused on the societal and economic implications of AI, particularly regarding its accuracy and safety. These studies consistently aimed to evaluate AI's impact across multiple domains using deep learning, data analysis models, and data management technologies. Nissenbaum (2020) examined AI learning capabilities, particularly the effects of restricting input data on AI performance. Both studies sought to enhance data processing technologies while addressing AI safety and usability concerns, using models focused on learning limitations and personal data security. Finally, Zuboff (2019) investigated customer data and behavior, focusing on data security, ease of use, and service costs.

In addition to the positive factors driving AI adoption, recent literature highlights a parallel set of conflict dimensions that shape investor perceptions and create potential barriers to the use of AI-based investment tools. These tensions often rooted in socio-technical, institutional, and governance issues reveal the complex environment in which investors evaluate digital investment platforms. One of the most widely discussed concerns is algorithmic bias, which arises when AI systems generate outputs that inadvertently favor or disadvantage certain groups due to skewed training data or flawed model design. Scholars such as Bender, Gebru, McMillan-Major and Mitchell (2021) and Selbst, Venkatasubramanian and Kumar (2023) argue that seemingly neutral algorithms can reproduce historical inequalities, leading to distorted predictions or unfair investment recommendations. In financial contexts, such biases may amplify investor vulnerability, particularly among novice investors who rely heavily on automated guidance without fully understanding its limitations. Another critical dimension involves data privacy and surveillance concerns. As AI-driven investment tools depend on large quantities of personal and behavioral data, users must trust that platforms will handle sensitive information responsibly. Zuboff (2019) and Nissenbaum (2020) emphasize that extensive data collection practices can create "asymmetric visibility," where system operators gain increasing power over users, while users possess limited knowledge of how their data are analyzed or monetized. For younger investors, this raises concerns about digital footprints, cybersecurity risks, and the potential misuse of personal financial data, all of which may reduce willingness to adopt AI-driven systems despite their functional advantages. A further layer of complexity arises from regulatory asymmetry, were governance frameworks lag rapid technological developments. Calo (2021), Acemoglu (2021), and Crawford (2021) note that existing financial regulations were designed for traditional advisory services, not algorithmic decision-making. As a result, there are gaps in accountability: when AI-driven investment advice results in financial loss, liability is often unclear. The absence of standardized rules on algorithmic transparency, explain ability, and data protection creates uncertainty for both investors and financial institutions. This regulatory inconsistency can

undermine institutional trust and weaken confidence in the long-term reliability of AI-driven investment platforms.

Finally, these tensions contribute to broader trust gaps between investors and AI systems. Trust remains a core determinant of technology adoption, as highlighted in both TAM and UTAUT literature. However, as Ghahramani (2021) and Jain, Chan, Brown and Dragan (2021) point out, trust in AI is shaped not only by perceptions of usefulness or accuracy but also by concerns about autonomy, fairness, and governance. Younger investors may be technologically confident yet still skeptical of opaque algorithms that appear to make decisions without human oversight. The lack of transparency surrounding AI decision-making processes often described as a "black box" creates additional psychological barriers to adoption. Collectively, these conflict dimensions underscore that AI adoption in investment contexts cannot be understood solely through technological characteristics or user perceptions of efficiency. Instead, adoption is intertwined with social expectations, institutional structures, governance practices, and ethical considerations. Recognizing these tensions enriches the theoretical foundation of the study and highlights the need for a comprehensive framework such as TAM enriched by insights from socio-technical literature to capture both the drivers and inhibitors of AI adoption among younger investors in Thailand.

Therefore, the primary objective across these studies was to align AI systems with customer needs, employing methodologies such as deep learning, economic control models, and statistical analysis. Collectively, these studies provide a comprehensive understanding of the factors influencing AI adoption in investment, supporting the selection of TAM as the guiding theoretical framework for this research.

Research Methodology

The present study employs a quantitative research design using a survey-based approach. Data were collected via structured questionnaires and analyzed using statistical software. The research methodology comprised the following components.

Population and Sample

The population for this study included individuals residing in Bangkok who either currently use or are interested in using artificial intelligence (AI) for investment purposes. According to the Department of Health (2023), Bangkok's population is 5,494,932. The sample size was determined using Yamane's formula (1973) for a known population, with a 95% confidence level and a 5% margin of error, resulting in a final sample of 400 respondents.

$$n = N / 1 + N * (e)^2 \quad (1)$$

Where:

n = sample size

N = population size

e = margin of error (0.05)

$$n = 5{,}494{,}932 / 1 + 5{,}494{,}932 * (0.05)^2 \approx 400 \quad (2)$$

Sampling Method

A probability sampling technique, specifically simple random sampling, was used to ensure that everyone in the population had an equal chance of selection. Participants were drawn from individuals who voluntarily agreed to participate and were either current or potential AI users for investment purposes in Bangkok. The final sample comprised 400 respondents.

Research Instruments

Data were collected using a structured questionnaire, developed in three parts.

Part 1 Personal information, including gender, age, marital status, education level, occupation, and monthly income (5 closed-ended questions, single choice).

Part 2 Technological factors related to AI, including accuracy, service fees, ease of use, and security/privacy (20 closed-ended questions, single choice).

Part 3 Attitudes toward AI usage in investment, including perceived usefulness and confidence in AI versus traditional methods (2 closed-ended questions, single choice).

Data Collection Methods

Primary data collected directly from Bangkok residents using AI for investment via Google Forms, with the survey link distributed through social media platforms such as Facebook, LINE, and Instagram. A total of 400 completed responses were obtained.

Secondary data collected from relevant academic research, theses, journals, printed publications, and credible online sources to support the theoretical framework of the study.

Data Analysis

Data were systematically processed and analyzed as follows.

Questionnaires were reviewed for completeness and accuracy. Reliability and content validity were assessed, followed by a pilot test with 30 participants. Data were then coded and entered statistical software for analysis.

Descriptive Statistics are Frequencies, percentages, means, and standard deviations were computed to summarize data.

Inferential Statistics: Independent Sample T-Test: Used to test Hypothesis 1 at a 0.05 significance level.

One-Way ANOVA employed to test mean differences, with post-hoc pairwise comparisons conducted using the LSD (Least Significant Difference) method.

Pearson's Correlation Coefficient applied to test relationships between variables for Hypothesis 2.

This methodology ensured a rigorous and systematic approach to examining the factors influencing AI adoption for investment among the new generation in Bangkok.

Results

The present study investigates the factors influencing individuals' interest in adopting artificial intelligence (AI) for investment decision-making. Specifically, the study aims to examine the factors that affect investors' interest in using AI to support investment

activities. Data were collected through a structured questionnaire administered to a sample of 400 participants. The results of the data analysis are summarized below.

Symbols Used in Data Analysis

For clarity and consistency in reporting the statistical results, the following symbols are used:

$\bar{x}$	Mean
S.D.	Standard Deviation
F	F-distribution
t	t-distribution
r	Pearson's Correlation Coefficient
df	Degrees of Freedom
SS	Sum of Squares
MS	Mean Square
Sig.	Statistical Significance
*	Statistically significant at the 0.05 level
**	Statistically significant at the 0.01 level

These conventions facilitate the interpretation of the descriptive and inferential statistical analyses conducted in this study.

Section 1 General Information Analysis of the Respondents

To examine the personal characteristics of the respondents, demographic data were analyzed using frequency and percentage distributions. The results of this analysis are presented in Table 1.

Table 1. Number and Percentage of Respondents Classified by Gender

Gender	Number	Percentage
Male	211	52.75
Female	171	42.75
LGBTQIA+	18	4.50
Total	**400**	**100.00**

Analysis of gender distribution among the 400 respondents, as shown in Table 1, indicates that the majority were male (n = 211; 52.75%), followed by female (n = 171; 42.75%). A smaller proportion of respondents, 18 individuals (4.50%), identified as LGBTQIA+.

Table 2. Shows the number and percentage of respondents classified by age group.

Gender	Number	Percentage
20–23 years	112	28.00
23–30 years	221	55.25
31–40 years	55	13.75
Over 40 years	12	3.00
Total	**400**	**100.00**

Analysis of age distribution among the 400 respondents, as presented in Table 2, reveals that the majority were aged 23–30 years (n = 221; 55.25%), followed by those aged 20–23 years (n = 112; 28.00%). Respondents aged 31–40 years accounted for 55 individuals (13.75%), while the smallest group comprised those over 40 years old (n = 12; 3.00%).

Table 3. Number and Percentage of Respondents Classified by Education Level

Education Level	Number	Percentage
Secondary School	15	3.75
Bachelor's Degree	333	83.25
Master's Degree	41	10.25
Doctoral Degree	11	2.75
Total	**400**	**100.00**

Analysis of education levels among the 400 respondents, as shown in Table 3, indicates that the majority held a bachelor's degree (n = 333; 83.25%), followed by those with a master's degree (n = 41; 10.25%). Respondents with a secondary school education accounted for 15 individuals (3.75%), while the smallest group held a doctoral degree (n = 11; 2.75%).

Table 4. Number and Percentage of Respondents Classified by Occupation

Occupation	Number	Percentage
Student/Intern	75	18.75
Private Company Employee	185	46.25
Government Officer	65	16.25
Business Owner/Self-employed	47	11.75
General Worker	28	7.00
Total	**400**	**100.00**

Analysis of occupational distribution among the 400 respondents, as presented in Table 4, shows that the majority were employees of private companies (n = 185; 46.25%), followed by students or interns (n = 75; 18.75%), and government officers (n = 65; 16.25%). Respondents who were business owners or self-employed comprised 47 individuals (11.75%), while those in other occupations accounted for 28 respondents (7.00%).

Table 5. Number and Percentage of Respondents Classified by Monthly Income

Monthly Income Range	Number	Percentage
Less than 20,000 THB	74	18.50
20,001 – 40,000 THB	212	53.00
40,001 – 60,000 THB	77	19.25
60,001 – 100,000 THB	22	5.50
More than 100,000 THB	15	3.75
Total	**400**	**100.00**

Analysis of monthly income among the 400 respondents, as shown in Table 5, indicates that the majority earned 20,001–40,000 THB per month (n = 212; 53.00%). This was followed by respondents earning 40,001–60,000 THB (n = 77; 19.25%), and those earning less than 20,000 THB (n = 74; 18.50%). Smaller proportions of respondents reported incomes of 60,001–100,000 THB (n = 22; 5.50%) and over 100,000 THB (n = 15; 3.75%).

Section 2: Analysis of Respondents' Opinions on Technology-Related Factors

Table 6. Mean and Standard Deviation of Opinions on Technology Factors (Overall)

1. Success in the operation	$\bar{x}$	**S.D.**	**Interpretation**	**Rank**
Accuracy on AI investment	3.98	0.848	High	3
Fees on using AI	3.99	0.883	High	2
Understanding on operation	4.05	0.865	High	1
Security and Privacy	3.94	0.909	High	4
Total	**3.98**	**0.836**	**High**	

Analysis of respondents' perceptions of technology-related factors, as shown in Table 6, indicates that the overall evaluation was high (mean = 3.98, S.D. = 0.836). Among the specific factors, ease of use received the highest mean score (mean = 4.05, S.D. = 0.865), followed by AI service cost (mean = 3.99, S.D. = 0.883), and accuracy of AI in investment decisions (mean = 3.98, S.D. = 0.848). Although data privacy and security received the lowest mean score, it was still rated at a high level (mean = 3.94, S.D. = 0.909).

Table 7. Mean and Standard Deviation of Opinions on Technology Factors: Accuracy of Artificial Intelligence in Investment

Statement	$\bar{x}$	**S.D.**	**Interpretation**	**Rank**
Do you believe the accuracy of AI contributes to your investment decision-making?	4.18	0.936	High	1
Do you feel that the accuracy of AI is not useful for investment data analysis?	3.81	0.985	High	5
Do you think the accuracy of AI helps reduce investment risks?	3.91	1.049	High	4
Do you trust the accuracy of AI-generated data in relation to investment?	4.00	1.069	High	3
Do you believe the accuracy of AI affects the choice of investment platforms using AI?	4.00	1.039	High	2
Total	**3.98**	**0.848**	**High**	

Analysis of respondents' perceptions regarding the accuracy of artificial intelligence (AI) in investment decision-making, as presented in Table 7, indicates a high overall level of agreement (mean = 3.98, S.D. = 0.848), suggesting that accuracy is a significant factor influencing AI adoption. Among the individual items, the highest-rated statement was: *"Do you believe that the accuracy of AI affects your investment decision-making?"* (mean = 4.18, S.D. = 0.936), followed by: *"Do you think the accuracy of AI affects your choice to use AI-based investment platforms?"* (mean = 4.00, S.D. = 1.039) and *"Do you trust the*

information provided by AI in investment?" (mean = 4.00, S.D. = 1.069). The item *"Do you think the accuracy of AI can help reduce investment risk?"* also received a high level of agreement (mean = 3.91, S.D. = 1.049). The lowest-rated item, *"Do you feel that the accuracy of AI is insufficient for analyzing investment data?"*, while relatively lower, was still evaluated at a high level (mean = 3.81, S.D. = 0.985).

Table 8. Mean and Standard Deviation of Opinions on Technology Factors: AI Service Usage for Investment Decision-Making

AI Service Usage for Investment Decision-Making	$\bar{x}$	**S.D.**	**Interpretation**	**Rank**
Do you think AI services affect your investment decision-making?	3.99	1.027	High	2
Do you think AI services for investment are of high quality?	4.04	1.042	High	1
Do you think AI services offer reliable investment recommendations?	3.99	1.083	High	3
Do you think the cost of using AI services is worth the investment return?	3.97	1.094	High	4
Do you think AI services influence your choice of investment platforms that use AI?	3.95	1.111	High	5
Total	**3.99**	**0.883**	**High**	

Analysis of respondents' perceptions regarding AI service usage for investment decision-making, as presented in Table 8, indicates a high overall level of agreement (mean = 3.99, S.D. = 0.883), suggesting that AI service quality significantly influences investment behavior. The highest-rated item was: *"Do you think AI services for investment are of high quality?"* (mean = 4.04, S.D. = 1.042), followed by: *"Do you think AI services affect your investment decision-making?"* (mean = 3.99, S.D. = 1.027) and *"Do you think AI services offer reliable investment recommendations?"* (mean = 3.99, S.D. = 1.083). The item *"Do you think the cost of using AI services is worth the investment return?"* received a slightly lower but still high score (mean = 3.97, S.D. = 1.094). The lowest-rated item, *"Do you think AI services influence your choice of investment platforms that use AI?"*, was also rated at a high level (mean = 3.95, S.D. = 1.111).

Table 9. Mean and Standard Deviation of Opinions on Technology Factors: Ease of Understanding in Using Artificial Intelligence

Ease of Understanding in AI Usage	$\bar{x}$	**S.D.**	**Interpretation**	**Rank**
Do you think the ease of use of AI affects your investment decisions?	4.02	1.025	High	5
Do you feel that you can easily learn to use artificial intelligence?	4.03	1.065	High	4
Do you think the complexity of artificial intelligence systems affects investment choices?	4.10	0.987	High	1

Ease of Understanding in AI Usage	$\bar{x}$	**S.D.**	**Interpretation**	**Rank**
Do you find the instructions for using AI clear and easy to understand?	4.06	1.023	High	2
Do you think the ease of understanding of artificial intelligence affects your investment confidence?	4.04	1.062	High	3
Total	**4.05**	**0.865**	**High**	

Analysis of respondents' perceptions regarding ease of understanding in AI usage, as presented in Table 9, indicates a high overall level of agreement (mean = 4.05, S.D. = 0.865), suggesting that system clarity and simplicity play an important role in AI adoption for investment. The highest-rated item was: *"Do you think the complexity of AI systems affects your investment usage?"* (mean = 4.10, S.D. = 0.987), followed by: *"Do you feel confident in using AI with clear instructions and understanding?"* (mean = 4.06, S.D. = 1.023) and *"Do you think the simplicity of AI systems affects your confidence in investment decisions?"* (mean = 4.04, S.D. = 1.062). The item *"Do you think you can easily learn and understand how to use AI?"* also received a high rating (mean = 4.03, S.D. = 1.065). The lowest-rated item, *"Do you think the clarity of AI systems affects your investment decision-making?"*, was slightly lower but still indicated a high level of agreement (mean = 4.02, S.D. = 1.025).

Table 10. Mean and Standard Deviation of Opinions on Technology Factors: Security and Privacy

Security and Privacy	$\bar{x}$	**S.D.**	**Interpretation**	**Rank**
Do you feel confident in the security standards of systems using AI?	3.91	1.091	High	5
Do you think data privacy is protected when AI is used to assist investment decisions?	3.96	1.037	High	1
Do you think the privacy of personal data affects your choice to use AI for investment?	3.95	1.085	High	3
Do you believe companies provide sufficient data protection when offering AI investment services?	3.96	1.048	High	2
Do you think there are privacy risks from apps or platforms using AI when installing or using them?	3.94	1.103	High	4
Total	**3.94**	**0.909**	**High**	

Analysis of respondents' perceptions regarding security and privacy in AI usage, as presented in Table 10, indicates a high overall level of agreement (mean = 3.94, S.D. = 0.909), highlighting the importance of data protection in AI adoption for investment. The highest-rated items were: *"Do you think the security of data when using artificial intelligence affects your investment decisions?"* (mean = 3.96, S.D. = 1.037) and *"Do you believe your data will be securely stored when using artificial intelligence for investment?"* (mean = 3.96, S.D. = 1.048), followed closely by *"Do you think personal data privacy influences your decision to use artificial intelligence in investing?"* (mean = 3.95, S.D. = 1.085). The item with the lowest score, *"Do you think the current privacy measures on AI*

platforms are sufficient?", was still rated at a high level (mean = 3.94, S.D. = 1.103).

Section 3 Analysis of opinion data on the choice of using artificial intelligence in investment

Table 11. Mean and Standard Deviation of Opinions on Choosing to Use Artificial Intelligence in Investment

Choosing to Use AI in Investment	$\bar{x}$	S.D.	Interpretation	Rank
Do you think AI is beneficial for analyzing investment information?	4.01	0.767	High	1
Do you feel more confident in making investment decisions using AI compared to traditional methods?	4.00	0.746	High	2
	4.00	**0.670**	**High**	

Analysis of respondents' perceptions regarding the security and privacy of AI usage, as shown in Table 11, indicates a high overall level of agreement (mean = 3.94, S.D. = 0.909). The highest-rated item was: *"Do you think the security of data when using artificial intelligence affects your investment decision-making?"* (mean = 3.96, S.D. = 1.037), highlighting the critical role of data protection in influencing AI adoption for investment purposes.

Section 4 Analysis of Variance for Hypothesis Testing

Hypothesis 1.1 – Personal Factors: Gender Differences

H0: Gender does not affect the decision to choose artificial intelligence (AI) for investment.

H1: Gender affects the decision to choose artificial intelligence (AI) for investment.

Table 12. ANOVA Results Comparing Mean Differences in the Decision to Choose AI for Investment by Gender

Source of Variation	Sum of Squares	Df	Mean Square	F	.Sig
Between Groups	1.003	2	0.502	0.600	0.550
Within Groups	332.231	397	0.837		
Total	333.234	399			

* Significant at the 0.05 level 0.05

As presented in Table 12, the significance value (Sig.) is 0.550, exceeding the 0.05 threshold. Consequently, the null hypothesis (H_0) cannot be rejected, indicating that there is no statistically significant difference in the adoption of artificial intelligence for investment decisions across gender groups.

Hypothesis 1.2 Personal Factors: Age Groups

H0: Age does not affect the decision to choose artificial intelligence (AI) for investment.
H1: Age affects the decision to choose artificial intelligence (AI) for investment.

Table 13. The statistical values used to compare differences in the decision to adopt artificial intelligence for investment, categorized by age

Source of Variation	Sum of Squares	Df	Mean Square	F	.Sig
Between Groups	5.112	3	1.704	2.056	0.105
Within Groups	328.123	396	0.829		
Total	333.234	399			

* Significant at the 0.05 level

As shown in Table 13, the significance value (Sig.) is 0.105, exceeding the 0.05 threshold. Therefore, the null hypothesis (H_0) is not rejected, indicating no statistically significant difference in the adoption of artificial intelligence for investment decisions across different age groups.

Hypothesis 1.3 Personal Factors: Occupation

H0: Occupation does not affect the decision to choose artificial intelligence (AI) for investment.

H1: Occupation affects the decision to choose artificial intelligence (AI) for investment.

Table 14. The statistical values used to compare differences in the decision to adopt artificial intelligence for investment, categorized by occupation

Source of Variation	Sum of Squares	Df	Mean Square	F	.Sig
Between Groups	10.795	3	3.598	4.419	0.005*
Within Groups	322.440	396	0.814		
Total	333.234	399			

* Significant at the 0.05 level

As presented in Table 14, the significance value (Sig.) is 0.005, which is below the 0.05 threshold. Thus, the null hypothesis (H_0) is rejected, indicating a statistically significant difference in the adoption of artificial intelligence for investment decisions across respondents' occupations. A subsequent analysis using the Least Significant Difference (LSD) method, shown in Table 15, was conducted to determine which occupational groups differ significantly.

Table 15. Pairwise Comparison Using LSD Method of the Decision to Use National Identification Number in Investment, by Occupation

Occupation	$\bar{x}$	Student / Intern	Private Company Employee	Government Officer	Business Owner/Self-Employed	General Worker
Student/Intern	3.51	-	-0.342*	-0.163	-0.142	0.025
Private Company Employee	3.85		-	0.179	0.200	.366*
Government Officer	3.67			-	0.020	0.187

Occupation	$\bar{x}$	Student / Intern	Private Company Employee	Government Officer	Business Owner/Self-Employed	General Worker
Business Owner/Self-Employed	3.65				-	0.167
General Worker	3.48					-

*Significant at the .05 level

Table 15 presents the pairwise comparisons using the LSD method, indicating that occupation significantly influences the decision to use the national identification number in investment. Specifically, two occupational pairs show statistically significant differences: (1) Students/Interns versus Private Company Employees, and (2) Private Company Employees versus General Workers. These results suggest that individuals in these occupations differ in their decisions regarding the use of the national ID number for investment purposes. No significant differences were observed among the other occupational groups.

Hypothesis 1.4: Personal Factors – Education Level

H0: Education level does not affect the decision to use the national identification number in investment.

H1: Education level affects the decision to use the national identification number in investment.

Table 16. Statistical Values Used to Compare the Differences in the Decision to Use National Identification Number in Investment, by Educational Level

Source of Variation	Sum of Squares	Df	Mean Square	F	.Sig
Between Groups	8.389	4	2.097	2.550	0.039*
Within Groups	324.846	395	0.822		
Total	333.234	399			

*Statistically significant at the .05 level

Table 16 presents the comparison of mean differences in the decision to use a national ID number for investment by educational level, revealing variation among individuals in the Bangkok area who currently use or intend to use a national ID for investment. Although differences in mean scores are observed, these variations are statistically significant at the 0.05 level. Consequently, a pairwise comparison using the LSD method was conducted, as shown in Table 17.

Table 17. LSD Pairwise Comparison Results of the Decision to Use National Identification Number in Investment, by Educational Level

Educational Level	$\bar{x}$	Secondary	Bachelor's degree	Master's degree	Doctoral degree
Secondary	4.50	-	.844*	.683*	.773*
Bachelor's degree	3.66		-	-0.161	-0.071
Master's degree	3.82			-	0.090
Doctoral degree	3.73				-

*Statistically significant at the .05 level

Table 17 presents the pairwise comparisons using the LSD method, showing that educational level significantly affects the decision to use artificial intelligence in investment. Specifically, three pairs exhibit statistically significant differences: (1) high school versus bachelor's degree, (2) high school versus master's degree, and (3) high school versus doctoral degree. No significant differences were observed among the other educational level pairs.

Hypothesis 1.5 Personal factors classified by monthly income

H0: Monthly income does not affect the choice to use artificial intelligence for investment.

H1: Monthly income affects the choice to use artificial intelligence for investment.

Table 18. Statistical values used to compare the difference in opinions regarding the choice to apply the sufficiency economy philosophy in investment based on monthly income level

Source of Variation	Sum of Squares	Df	Mean Square	F	.Sig
Between Groups	3.881	4	0.970	1.164	0.326
Within Groups	329.353	395	0.834		
Total	333.234	399			

* Significant at the 0.05 level

Table 18 presents a comparison of opinions on the application of the sufficiency economy philosophy in investment across different monthly income levels. The results indicate that individuals in Bangkok, regardless of their income level, do not differ in their choices regarding the application of the sufficiency economy philosophy in investment.

Hypothesis 2.1 Technological Factors Classified by the Accuracy of Artificial Intelligence

H0: The accuracy of artificial intelligence does not affect the decision to adopt artificial intelligence for investment purposes.

H1: The accuracy of artificial intelligence affects the decision to adopt artificial intelligence for investment purposes.

Table 19. Shows the relationship between technological factors, the accuracy of artificial intelligence, and the decision to adopt artificial intelligence for investment purposes.

Technological factors related to the decision to adopt artificial intelligence for investment purposes	The decision to adopt artificial intelligence for investment purposes		
	r	Level of relationship	p-value
1. Accuracy of artificial intelligence	0.393*	Low	0.000

*Statistically significant at the 0.01 level

Table 19 presents the relationship between technological factors—specifically the accuracy of artificial intelligence—and the decision to adopt AI for investment. The results indicate a positive correlation between AI accuracy and the overall decision to adopt AI for investment, with a low correlation coefficient ($r = 0.393$).

Hypothesis 2.2 Technological Factors Classified by Usage Fees

H0: Usage fees do not affect the decision to adopt artificial intelligence for investment purposes.

H1: Usage fees affect the decision to adopt artificial intelligence for investment purposes.

Table 20. Shows the relationship between technological factors—specifically usage fees—and the decision to adopt artificial intelligence for investment purposes.

Technological factors related to the decision to adopt artificial intelligence for investment purposes	The decision to adopt artificial intelligence for investment purposes		
	r	Level of relationship	p-value
2. Usage fees	0.348*	Low	0.000

*Statistically significant at the 0.01 level

Table 20 presents the relationship between technological factors—specifically usage fees—and the decision to adopt artificial intelligence for investment. The results show a positive, albeit low, correlation between usage fees and the overall decision to adopt AI for investment ($r = 0.348$).

Hypothesis 2.3 Technological Factors Classified by Ease of Use

H0: Ease of use does not affect the decision to adopt artificial intelligence for investment purposes.

H1: Ease of use affects the decision to adopt artificial intelligence for investment purposes.

Table 21. Shows the relationship between technological factors—specifically ease of use—and the decision to adopt artificial intelligence for investment purposes.

Technological factors related to the decision to adopt artificial intelligence for investment purposes	The decision to adopt artificial intelligence for investment purposes		
	r	Level of relationship	p-value
3. Ease of use	0.372*	Low	0.000

*Statistically significant at the 0.01 level

Table 21 presents the relationship between technological factors—specifically ease of use—and the decision to adopt artificial intelligence for investment. The findings indicate a positive, though low, correlation between ease of use and the overall decision to adopt AI for investment ($r = 0.372$).

Hypothesis 2.4 Technological Factors Classified by Perceived Security and Privacy

H0: Perceived security and privacy do not affect the decision to adopt artificial intelligence for investment purposes.

H1: Perceived security and privacy affect the decision to adopt artificial intelligence for investment purposes.

Table 22. Shows the correlation analysis results between technological factors—specifically perceived security and privacy—and the decision to adopt artificial intelligence for investment purposes.

Technological factors related to the decision to adopt artificial intelligence for investment purposes	The decision to adopt artificial intelligence for investment purposes		
	r	Level of relationship	p-value
4. Perceived security and privacy	0.305*	Low	0.000

*Statistically significant at the 0.01 level

Table 22 presents the relationship between technological factors—specifically perceived security and privacy—and the decision to adopt artificial intelligence for investment. The results show a positive, albeit low, correlation between perceived security and privacy and the overall decision to adopt AI for investment ($r = 0.305$).

Table 23. Hypothesis Testing Results

Research Hypotheses	Research Result	Conclusion
H0: Gender does not affect the decision to adopt artificial intelligence for investment purposes. H1: Gender affects the decision to adopt artificial intelligence for investment purposes.	Accept H0 and reject H1	Gender does not affect the decision to adopt artificial intelligence for investment purposes.
H0: Age does not affect the decision to adopt artificial intelligence for investment purposes. H1: Age affects the decision to adopt artificial intelligence for investment purposes.	Accept H0 and reject H1	Age does not affect the decision to adopt artificial intelligence for investment purposes.
H0: Occupation does not affect the choice to use AI in investment. H1: Occupation affects the choice to use AI in investment.	Reject H0 and accept H1	Occupation affects the decision to adopt artificial intelligence for investment purposes.
H0: Educational level does not affect the decision to adopt artificial intelligence for investment purposes H1: Educational level affects the decision to adopt artificial intelligence for investment purposes	Reject H0 and accept H1	Educational level affects the decision to adopt artificial intelligence for investment purposes
H0: Monthly income does not affect the decision to adopt artificial intelligence for investment purposes. H1: Monthly income affects the decision to adopt artificial intelligence for investment purposes.	Reject H0 and accept H1	Monthly income affects the decision to adopt artificial intelligence for investment purposes.

Research Hypotheses	Research Result	Conclusion
H0: The accuracy of artificial intelligence does not affect the decision to adopt artificial intelligence for investment purposes. H1: The accuracy of artificial intelligence affects the decision to adopt artificial intelligence for investment purposes.	Reject H0 and accept H1	The accuracy of artificial intelligence affects the decision to adopt artificial intelligence for investment purposes.
H0: Usage fees do not affect the decision to adopt artificial intelligence for investment purposes. H1: Usage fees affect the decision to adopt artificial intelligence for investment purposes.	Reject H0 and accept H1	Usage fees affect the decision to adopt artificial intelligence for investment purposes.
H0: Ease of use does not affect the decision to adopt artificial intelligence for investment purposes. H1: Ease of use affects the decision to adopt artificial intelligence for investment purposes.	Reject H0 and accept H1	Ease of use affects the decision to adopt artificial intelligence for investment purposes.
H0: Perceived security and privacy do not affect the decision to adopt artificial intelligence for investment purposes. H1: Perceived security and privacy affect the decision to adopt artificial intelligence for investment purposes.	Reject H0 and accept H1	Perceived security and privacy affect the decision to adopt artificial intelligence for investment purposes.

Findings have concluded that the understanding on the socio-economic environment of respondents is essential for interpreting AI adoption behaviors, particularly in an academic setting where access to technology, financial literacy, and investment exposure vary widely. The sample was drawn from the Faculty of Economics at a private university, a context that reflects relatively high digital exposure but uneven levels of investment experience and socio-economic resources. Most respondents possessed at least a bachelor's degree (83.25%), indicating a population with strong educational backgrounds and foundational knowledge of economic principles. This likely enhanced their ability to understand AI-driven investment tools conceptually, even if their practical investment experience differed. The presence of postgraduate respondents (13%) further suggests a segment with potentially greater analytical skills and familiarity with digital technologies, which may partially explain why education level significantly influenced AI adoption.

Income distribution shows that more than half of the participants earn between 20,001–40,000 THB monthly, consistent with early-career professionals living in urbanized areas. These income levels may shape perceptions of AI investment tools: while they are not prohibitively expensive, respondents may still be sensitive to usage fees and risk-related concerns. This aligns with the finding that usage fees positively correlate with AI adoption suggesting respondents equate cost with perceived quality or reliability rather than financial burden.

The occupational distribution further contextualizes adoption decisions. Nearly 46% of respondents work in private companies, where exposure to digital tools and productivity technologies is common. This group may be more open to AI adoption due to workplace digitalization and familiarity with data-driven systems. Conversely, government officers and general laborers who typically operate in more standardized or manual environments may have fewer opportunities to interact with advanced AI tools, contributing to the significant differences found across occupations. Additionally, the socio-economic setting of a private university in an urban area provides access to digital infrastructure, high-speed internet, and technology-based learning platforms. These conditions may elevate overall comfort with AI technologies compared to populations in rural or public-sector institutions. However, this also introduces a limitation: the findings may reflect a relatively privileged technological context, where barriers such as digital literacy gaps or limited financial access are less pronounced. As a result, the positive correlations between technological factors and AI adoption may not generalize to populations with lower digital exposure or financial constraints.

Taken together, the socio-economic characteristics of the sample suggest that education, occupational environment, and access to digital infrastructure play meaningful roles in shaping perceptions of AI-assisted investment tools. This context helps explain why occupation and education emerged as significant predictors, while age, gender, and income did not highlighting that socio-economic experiences, rather than demographic categories alone, influence openness to adopting AI for financial decision-making.

Conclusion

This study aimed to examine the factors affecting individuals' interest in using artificial intelligence (AI) for investment decisions. Data were collected via a structured questionnaire comprising 30 items, which demonstrated high internal consistency (Cronbach's Alpha ≥ 0.7). The survey was administered to 400 respondents from the Faculty of Economics at a private university (pseudonym used), and data were analyzed using descriptive and inferential statistics in SPSS. Questionnaire Design provides to Section 1: Personal demographics, including gender, age, status, income, education, and occupation (5 items, close-ended, single response). Section 2: Technological factors, including AI accuracy, usage fees, ease of use, and perceived security and privacy (4 items, 20 sub-items total, close-ended, single response). Section 3: Decision to adopt AI in investment, including perceptions of AI's usefulness in data analysis and confidence in AI-assisted decisions (2 close-ended items).

Respondent Profile explains on Gender: 211 males (52.75%), 171 females (42.75%), 18 LGBTQIA+ (4.50%), Age: 23–30 years, 221 (55.25%); 20–23 years, 112 (28.00%); 31–40 years, 55 (13.75%); over 40 years, 12 (3.00%), Education: Bachelor's degree, 333 (83.25%); Master's, 41 (10.25%); High school, 15 (3.75%); Doctoral, 11 (2.75%), Occupation: Private company employees, 185 (46.25%); students, 75 (18.75%); government

officers, 65 (16.25%); business owners/self-employed, 47 (11.75%); general laborers, 28 (7.00%), Monthly Income: 20,001–40,000 THB, 212 (53.00%); 40,001–60,000 THB, 77 (19.25%); <20,000 THB, 74 (18.50%); 60,001–100,000 THB, 22 (5.50%); >100,000 THB, 15 (3.75%)

Hypothesis Testing

1. Personal Factors show that Gender has No significant difference in AI adoption ($p = 0.550$). Age has No significant difference in AI adoption ($p = 0.105$). Occupation has Significant difference in AI adoption ($p < 0.05$). Education Level has Significant difference in AI adoption ($p < 0.05$). Monthly Income has No significant difference in AI adoption ($p = 0.326$).
2. Technological Factors express that Accuracy of AI has Positively correlated with AI adoption ($r = 0.393$, $p = 0.000$). Usage Fee has Positively correlated with AI adoption (r = 0.348, $p = 0.000$). Ease of Use has Positively correlated with AI adoption ($r = 0.372$, $p = 0.000$). Security and Privacy: Positively correlated with AI adoption ($r = 0.305$, $p = 0.000$).

The findings indicate that among personal factors, occupation and education level significantly influence the decision to adopt AI for investment, while gender, age, and income do not. All examined technological factors—accuracy, usage fees, ease of use, and perceived security and privacy—positively affect AI adoption, though the correlations are low to moderate. These results suggest that both personal characteristics and technological perceptions play a role in shaping interest in AI-assisted investment, with particular emphasis on occupation, education, and perceived AI performance.

Recommendation

The findings of this study offer several implications that extend beyond individual adoption behavior and touch on broader issues relevant to financial governance, institutional planning, and national development. Although the study was conducted in an academic setting, the patterns observed reflect emerging trends in digital financial behavior that policymakers and financial regulators should consider when designing frameworks for safe and equitable AI adoption in investment. The significant influence of education and occupation on AI investment adoption suggests that financial regulators must address disparities in digital financial literacy. Occupations with lower exposure to digital tools may face greater risks of misunderstanding AI-generated financial advice, potentially leading to suboptimal investment decisions. Financial governance institutions such as the Securities and Exchange Commission (SEC Thailand) could develop guidelines ensuring transparency in AI-generated investment recommendations, mandate clearer disclosure of algorithmic limitations, risks, and data sources, and promote investor education programs tailored to different occupational groups. Since technological factors (accuracy, security, ease of use) positively correlate with adoption, governance bodies should also consider certification or auditing mechanisms for AI investment platforms to ensure model reliability

and cybersecurity standards. Moreover, the results indicate increasing public interest in AI-driven financial tools, reinforcing the need for policies that promote responsible digital financial transformation. Public policy strategies may include digital inclusion policies to ensure equitable access to AI-based financial tools for individuals with lower income or digital literacy, data protection regulations to strengthen public trust in AI systems, particularly given the strong correlation between security/privacy perceptions and AI adoption, and consumer protection laws that clearly define liability when automated systems generate erroneous or biased investment recommendations. Public policy can also encourage the integration of AI education into higher education curricula to reduce disparities stemming from educational background.

AI-assisted investment is part of a broader transition toward digital financial ecosystems. The moderate correlations observed in this study suggest that adoption is influenced not only by the technology itself but also by social structures and economic opportunities. For development planning, this means the National financial development strategies must incorporate digital investment tools as part of long-term inclusivity and financial empowerment plans. Workforce development programs can be aligned to prepare individuals especially those in manual or public-sector roles for increasing AI integration in financial services. AI-based financial tools may support economic participation among young adults, who constitute a large portion of the respondent sample and are likely early adopters. In the long run, understanding population-level adoption patterns helps government agencies anticipate how digital finance will evolve and what forms of support or regulation the public will require. In addition, Institutions such as the universities, financial institutions, and regulatory bodies—play a central role in shaping perceptions of AI. Since perceived accuracy, trust, and ease of use strongly influence adoption, institutional frameworks must prioritize by establishing ethical AI standards, ensuring transparency in data usage and algorithmic decision-making, providing channels for dispute resolution when AI-generated investment advice results in financial loss. The clear institutional guidelines help reduce conflicts between consumers and service providers, particularly in cases where algorithmic decisions may appear opaque or biased. Strengthening these frameworks promotes fairness and reduces mistrust, which can destabilize financial participation and public confidence.

This study is particularly relevant in an era where artificial intelligence (AI) is increasingly developed and applied across various sectors, notably in finance and investment. AI's ability to process large volumes of data and generate highly accurate predictions has contributed to its growing adoption in investment decision-making. However, it is crucial to understand the factors influencing investors' decisions to adopt AI, which may include technological aspects, ease of use, trust in the system and its outcomes, individual investment behavior, and broader economic conditions. In this research, the sample included both investors who have used AI and those who have not, without distinguishing between prior and current users. Consequently, the findings may not fully capture the specific perspectives of investors actively interested in AI-assisted investment, as users and non-users may hold differing viewpoints. Future studies are therefore recommended to focus on more targeted data collection, distinguishing between different user groups, to enable more precise and actionable insights.

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