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Research Article

Significance of Behavioral Intention to Adopt Articficial Intelligence in Investment Strategies

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ABSTRACT

Artificial Intelligence (AI) is revolutionizing the investment management industry, promising enhanced decision-making, improved efficiency, and optimized portfolio management. Despite this, the adoption of AI in finance services is hindered by concerns of trust, ethics, and the risks they might pose. The primary constructs of interest include perceived trust (PT), ethical concern (E), perceived usefulness (PU), social norms (SN) and behavioural intention (BI) regarding how so-called artificial AI tools are adopted by investors in the investment management process, which this study explores. The quantitative approach was employed using "Partial Least Squares Structural Equation Modeling" (PLS-SEM) to collect data from 200 respondents with experience in AI-driven AI-driven investment tools. The most substantial finding is that the impact of perceived usefulness on behavioural intention was positively correlated but not as strong as the impact on trust and ethics. This research adds to the literature by integrating ethical concerns and social norms into the "technology acceptance model" (TAM) to understand the adoption of AI in the investment sector. Finally, we provide practical implications for financial premises and address AI developers by providing transparent, trustworthy, and ethically sound AI systems for investment management.

Keywords: Artificial Intelligence, Behavioral Intention, Trust, Ethical Concerns, AI Adoption

INTRODUCTION

"Artificial intelligence" (AI) has pervaded the financial markets, changing "investment management" (IM) practices across geographies. "Machine learning" (ML), predictive, and "big data" (BD) analytics technologies are starting to optimize portfolios and smart investments, enabling better decisions and partially eliminating human bias in investment strategies (Alamayreh et al., 2023). AI has been able to examine and process large volumes of data in real-time precisely to open opportunities for new investors. Recently, robo-advisors and algorithmic trading platforms, which AI powers, have seen tremendous popularity as AI-driven investment tools, similar to what has recently been experienced by institutional investors and wealth management firms (Kwon et al., 2020).

The potential of AI in changing the IM space is not just the case of transforming the operations process with more efficiency but also that it would generate higher returns through better predictions on the markets and risk management (Adam & Shauki, 2014). The rising complexity of financial markets (due to volatile global economy factors and regulatory changes) is to blame for the growing viewing of AI in investment management. Furthermore, AI will cut fat on costs through the automation of manual tasks, as well as personalized investment advice and better financial modeling (Bessen et al., 2023).

Yet, while these seem to be significant developments, AI certainly has challenges regarding adoption in investment management. Barriers to widespread acceptance of AI systems have mainly been reported to have ethical concerns, perceived risks, and a lack of trust in the system (Melnyk et al., 2021). AI is also raised as a source of ethical dilemma because there are multiple concerns about the underlying biases in algorithms, access or lack of transparency in data up, regulatory oversight, and privacy. In addition, perceptions of risk surrounding AI systems in general and of AI-based outcomes, more specifically in terms of stake investments, have increased to levels that these outcomes ought to be reliable (Majrashi, 2024). It is a critical obstacle that trusts in the systems, especially since they are opaque and involves complex decision-making, still exists.

This growing role of AI in the investment management industry requires more knowledge of the factors that play a task in AI's adoption. For this purpose, previous research primarily addresses AI tools' technical capabilities and performance in markets instead of psychological and social factors that drive investors to trust (TR) and adopt AI systems (Patil et al., 2024). The lack of existing analysis surrounding the gap in the usage of what derivatives investors seem to be trustworthy with their data to gain a competitive advantage over the market highlights the importance of a new research analysis on how the "perceived trust" (PT), usefulness, "ethical concerns" (EC), and "social norms" (SN) involved in their decision to adopt AI render impact on determining the amount of AI adoption in IM (Saracevic & Schlegelmilch, 2021).

This study examines the some factors and their influence on investors' "behavioural intentions" (BI) regarding the acceptance of AI tools in their investment strategies.

Research Objectives:

1. To evaluate how "perceived risk" (PR) impacts the adoption of AI in investment management.
2. To examine the role of PT in shaping investors' acceptance of AI-driven investment tools.
3. To investigate the effect of EC on AI adoption and whether transparency enhances trust.
4. To evaluate the significance of PU and PV in influencing investor adoption.
5. To determine how SN and "perceived behavioral control" (PBC) affect investment professionals' AI usage intentions.

The study employs the quantitative methodology using "Partial Least Squares Structural Equation Modeling" (PLS-SEM) to evaluate PR, PU, EC, and BI. Therefore, the results are expected to provide practical recommendations for financial institutions, investors, and AI developers in tackling the difficulties encountered when implementing AI systems and increasing trust in such systems. The applications of the concepts discussed in this research will help create AI tools that work not just better but also rightly and according to the investors' moral norms and social expectations.

LITERATURE REVIEW

This study aims to present a literature review regarding this research study on the effects and factors that influence the acceptance of AI in IM.

AI in Investment Management

AI has also become an important innovation in investment management due to better machine learning algorithms, the availability of extensive data, and computing power. AI is actively applied not only for operating portfolios, asset pricing, and prognostications but also for managing risks (Sydoriuk & Leshchii, 2024). Robo-advising and algorithmic trading also attract investors because these solutions provide individual approaches, enhance decision-making, and decrease expenses required for financial managers and advisors (Thanki et al., 2022).

AI determines market trends, identifies opportunities, and assesses portfolio performance, considering risk tolerance and investment objectives. Moreover, using AI dramatically increases the rate of dealing, which is important in the current fast-growing financial markets (Auzoult & Mazilescu, 2021).

With the progression of the application of AI, its function in investment management has been a matter of concern. Some critics of AI use deep learning and other forms of neural networks, portraying them as decision-makers that are hard to interpret or explain (Bengo et al., 2021). This lack of precision is problematic regarding the ethical boundaries concerning the AI in making decisions on the financial course of various corporations that investors rely on these systems. However, such strategies do not consider the information incorporated into the model, which may lead to severe risks for investors in case of unpredictable stable market changes (Baum, 2017).

Theoretical Framework for AI Adoption

Various models have been developed to explain how different aspects influence the acceptance of AI in investment management, comprising the “Technology Acceptance Model” (TAM), the “Theory of Planned Behavior” (TPB), and the “Unified Theory of Acceptance and Use of Technology” (UTAUT) (Abad-Itoiz et al., 2024).

Among the models frequently adopted in technology adoption, the TAM is one of the most used. In this case, it postulates that perceived ease of use and usefulness are the two determinants of BI to use innovation (Davis, 1989). In this current study, PU is the degree of perceived benefit that investors see in the AI that can be employed in the IM process. Perceived ease of use (PEU) is the ease the investors perceive when using the AI tools in their endeavour (Marwan et al., 2023). Although TAM gives an insight into user acceptance of technologies, it does not incorporate the social and ethical characteristics of using AI.

The TPB is an expanded version of the “Theory of Reasoned Action” (TRA), and it includes perceived control as a separate factor that affects the intent of the behaviour (Talha et al., 2020). In AI adoption in IM, subjective norms are the one which perceives important role models or other relevant individuals practice the use of AI. On the other hand, PBC is the individual’s belief in their capability to implement AI systems in investment management (Saeidnia et al., 2024) .

UTAUT is a composite of various theoretical models focusing on TAM and TPB for techno acceptance in organizational setup (Venkatesh et al., 2003). Complementing the awareness of AI applications in investment management, performance expectancy gives users confidence that AI improves their results. In contrast, effort expectancy relates to how easy it is to use the systems (Floridi et al., 2020). Social influence and facilitating conditions belong to the outside factors that can impact an investor in the decision-making process.

Thus, although these models offer a sound theoretical framework upon which AI usage may be examined, they are currently limited in explaining the associated ethical considerations and trust problems pertinent to AI application in IM. This study contributes to these theories by including ethical issues and trust as instrumental variables defining BI (Beccalli et al., 2020).

EC and TR in AI

The reasons for such parameters are not absolute. However, they are as follows: the application of AI in IM advances, the EC in such advances, and research issues including data protection, the abuse of AI algorithms, and explaining its workings and decisions or lack thereof, respectively. Deep learning models can sometimes be trained with BD, which contains highly sensitive financial information (Yamin et al., 2019). This implies the collection, processing and use of investors’ information. This is especially so as these decisions of the AI are not transparent, and investors may not be sure about how the choice is made or if the systems are making biased decisions based on biased information (Igras et al., 2020).

Under IM, the inherent prejudice might help AI promote some investment areas or asset classes at the expense of others, thus prejudicing some investors (Lee et al., 2024). For instance, machine models generated by previous data may contain racial bias, gender bias, or socioeconomic bias and can thus affect portfolio distribution and market assessment.

Another disadvantage of AI is that investors can still not penetrate through what has been termed the “black box” of the system. Some factors are as follows: Without clear guidance on how the system’s AI decisions are made, investors might be reluctant to fully embrace the technology, especially when large sums of money are at stake (Peifer, 2014. Accountability becomes important when AI systems malfunction or make a lousy investment recommendation.

As has been observed with numerous AI applications, trust (TR) especially in areas that were hitherto under human discretion, such as fund management, is a critical component of AI implementation (Choy et al., 2022). Other studies have suggested that the likelihood of a person adopting AI technologies is highly facilitated by the level of trust in the systems and the perceived value of the technology compared to the potential harm that might result(Sloane & Zakrzewski, 2022). Moral concerns such as algorithm biases and lack of responsibility for AI systems threaten the adoption of technologies (Jafarkarimi et al., 2016; Kaushal & Mishra, 2024). In the financial sector, it is equally essential to address these ethical issues and ensure that AI is trusted to be fully integrated into its operations (Rosenbaum et al., 2024).

Research Gaps in Literature

Most of the proposed studies are concentrated on the features and characteristics of AI systems' performance rather than using the psychological and social aspects of the investors. However, there are no studies regarding the role of ethical concerns and trust in implementing the AI solution in the financial services industry. This study fills these gaps by including PR, EC, SN, and PT in TAM with TPB to probe key determinants of AI adoption within IM.

RESEARCH METHODOLOGY

This quantitative method applied in this study determines the factors that may affect AI in IM. It also presents how the data were collected, the measures of the constructs, and the data analytical procedure using PLS-SEM. The method, therefore, aims to enhance the study's reliability, credibility, and validity regarding the objectives.

3.1 Data Collection

The study employed a quantitative survey to gather data from investors and other people with working or academic knowledge regarding the role of AI in investments. The survey was done online with 215 respondents; 200 filled in the survey entirely. Some of the questions used in the survey were collected from Schwab's Intelligent Automation Survey, which was conducted during the first quarter of the year 2020, and the focus was on workers in investment management, asset management, and financial planning so that the respondents had prior experience working with AI applications in their investment process. The respondents were also identified based on their willingness to give their views towards the level of AI adoption, use of ethical concerns, trust, and perceived social norms. Table 1 captures the demographic profile of the respondents.

Table 1: Sample Characteristics

Category	Frequency	Percent
Male	120	57.83%
Female	95	45.45%
Total	215	100%

The demographic composition of the study highlights gender distribution, with 57.83% male, and 45.45% female. The fairly even distribution ensures diverse perspectives on AI adoption in investment management, reducing gender bias in findings. The diversity strengthens the study's generalizability and statistical robustness. Table 2 and Table 3 provide further details on respondents' education levels and age distribution, respectively.

Table 2: Education (Questionnaire Respondents)

Education	Frequency	Percent
Less than High School	15	7%
High School Degree	19	8.8%
Bachelor's Degree	89	41.4%
Master's Degree	58	27%
Total	**215**	**100%**

Education levels indicate that most respondents hold a bachelor's degree (41.4%) and a master's degree (27%), ensuring a well-educated sample familiar with IM. The mix of education levels enables a balanced analysis of AI adoption across different financial expertise levels, validating the study's findings on AI adoption factors.

Table 3: Age Distribution

Age	Frequency	Percent
18-25	101	47.0%
26-35	70	32.5%

36-40	16	7.4%
41-45	12	5.6%
46+	16	7.4%
Total	**215**	**100%**

The age distribution is relatively diversified; the most significant number of participants is in the 18-25-year-old group: 47.0%, while 26-35 years old: 32.5%. This gives a level of diversity in the perception of AI adoption. Younger people are more likely to accept AI than older people, which could explain the differences in PT and their corresponding BI towards AI. Thus, the given questionnaire was divided into two principal sections.

- Demographic information encompassed more basic profile of the respondents, which included gender, age, and education.

- Concerning measurement items, Perceptions in this study measured PR, PU, EC, SN and BI of investing companies towards adopting AI in IM.

These constructs were measured using several items acquired from previous literature and modified based on the context of IM. The scales used for all measurement items included a five-point Likert scale comprising options such as strongly agree, agree, neutral, disagree, and strongly disagree. The survey was administered through Qualtrics, which helps improving data gathering quality and internal tracking mechanisms like data checks.

3.2 Measurement Variables

The measures employed in this study were identified using the TAM, the TPB, and ideas drawn from AI adoption research studies in the financial industry. The questionnaire items represented the scales from prior studies that were adjusted for use in AI in the IM domain. In fact, the research employs well-developed items to enhance the validity and reliability of the measure.

3.3 Data Analysis

Data collected from the self-completed questionnaires were analyzed using PLS-SEM. It is a suitable and powerful statistical tool for quantitative research as it can handle complex relations resources. Hence, PLS-SEM is appropriate for testing theoretical models with multiple constructs and indicators, especially when data violate normality or the sample size is insignificant. SmartPLS 4.0 was used to examine the analysis, which allows both the outer model assessment, known as the measurement model and the inner model, also termed the structural model, to be tested.

The first kind of test utilized in the study was called the Measurement Model Evaluation. This test sought to determine the reliability and validity of the different measurements used in the study. Internal consistency was assessed using Cronbach's Alpha Coefficient and "Composite Reliability" (CR). The convergent validity was determined using the AVE, while the discriminant validity (DV) was tested using the "Fornell-Lacker criterion" (FLC) and "Heterotrait-Monotrait Ratio" (HTMT) ratio. These tests put to the finality the reliability of the measurement items in measuring the intended constructs and the constructs' validity as distinct ones. The second step was assessing the structural model, whereby the test was conducted to establish how the constructs were related as hypothesized in the model. In contrast, path coefficients estimated the size and direction of the relationships between variables of interest t-values and their corresponding p-values. They were estimated by bootstrapping to establish the overall statistical significance of the paths. The R^2 was used to determine the extent to which the model was able to explain the variability on a scale of 0.10 and above, which is acceptable in the social sciences. To test each of the hypotheses, the path coefficients and their significance values were obtained from the analyses by bootstrapping. This afforded an adequate assessment of perceived trust, ethical issues, and perceived risk regarding the behavioural intention (BI) toward using AI in IM.

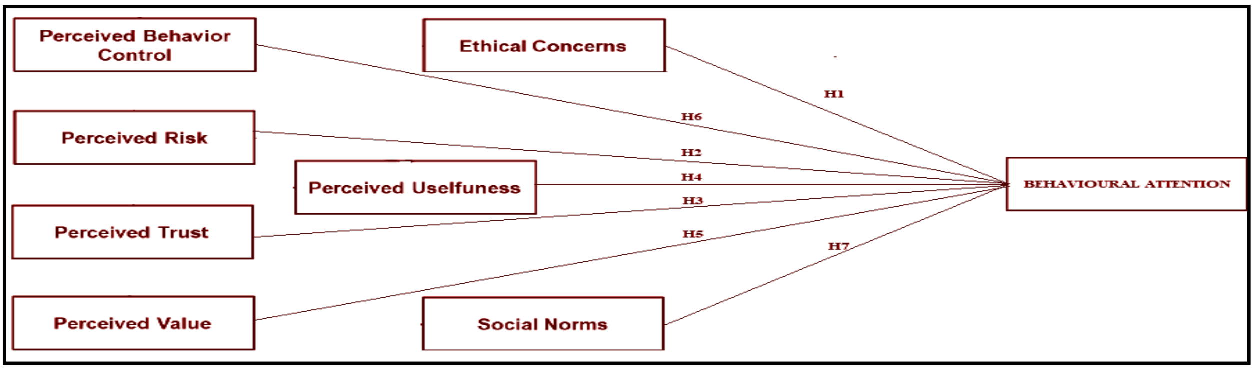

Figure 1: Conceptual Model

Results and Discussion

In evaluating the adequacy of the current model, it was appropriate to first check the measurement model for validity and reliability. Consequently, we tested the reliability and the DV of the items using SmartPLS 4.0 software.

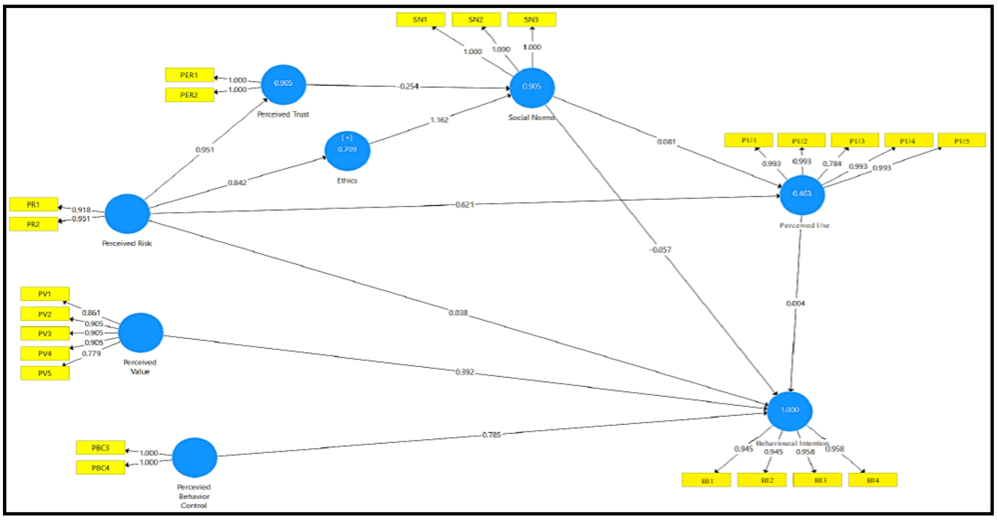

Figure 2: PLS-SEM Model Output

Construct Reliability, Convergent Validity

Table 4: Construct Reliability and Validity

Construct	rho_A	Cronbach's Alpha	Average Variance Extracted (AVE)	Composite Reliability
BI	0.983	0.974	0.911	0.981
EC	0.966	0.911	0.392	0.92
PR	0.896	0.857	0.874	0.933
PT	1	1	1	1
PU	0.97	0.965	0.906	0.975
PV	1.375	0.941	0.761	0.941
PBC	1	1	1	1
SN	1	1	1	1

In table 4, the highest reliability scores were observed for PT, PBC, and SN, all scoring 1.000, indicating perfect internal consistency. The construct EC had an Alpha value of 0.911, affirming its reliability despite its lower AVE of 0.392. These values confirm that all constructs are internally reliable, ensuring that responses were consistent and replicable.

The convergent validity was verified using AVE values, which were above the 0.5 threshold for most constructs, indicating that the observed variables strongly correlate with their latent constructs. PU (AVE = 0.906), PT (AVE = 1.000), and PR (AVE = 0.874) were the strongest predictors of AI adoption. However, the EC construct (AVE = 0.392) fell below the recommended threshold. While this may indicate potential measurement limitations, the rho_A values, which were above 0.9, provide additional assurance regarding construct validity.

However, EC had an AVE of 0.392, which is below the acceptable threshold. This suggests that while ethical concerns are relevant to the study, further refinement of the measurement items may be necessary to capture this construct more effectively.

Discriminant Validity

Table 5: FLC

Construct	BI	E	PR	PT	PU	PV	PBC	SN
BI	0.953	0.746	0.688	0.745	0.022	0.022	0.014	0.541
EC	0.746	0.626	0.905	0.905	0.112	0.387	0.017	0.946
PR	0.688	0.905	0.928	0.968	0.029	0.024	0.022	0.731
PT	0.745	0.905	0.968	0.980	0.027	0.023	0.019	0.752
PU	0.022	0.112	0.029	0.027	0.951	0.681	0.945	0.146
PV	0.022	0.387	0.024	0.023	0.681	0.871	0.406	0.510
PBC	0.014	0.017	0.022	0.019	0.945	0.406	0.960	0.026
SN	0.541	0.946	0.731	0.752	0.146	0.510	0.026	0.967

The DV was evaluated using the FLC and the HTMT (Table 5 and Table 6, respectively). The results confirm that all constructs meet the DV requirements, ensuring that they are distinct from each other.

Table 6: HTMT

Construct	BI	E	PR	PT	PU	PV	PBC	SN
BI	1.000	0.690	0.606	0.741	0.133	0.144	0.149	0.572
EC	0.690	1.000	0.811	0.831	0.216	0.503	0.085	0.941
PR	0.606	0.811	1.000	0.912	0.021	0.045	0.050	0.728
PT	0.741	0.831	0.912	1.000	0.030	0.039	0.037	0.780
PU	0.133	0.216	0.021	0.030	1.000	0.677	0.937	0.151
PV	0.144	0.503	0.045	0.039	0.677	1.000	0.362	0.515
PBC	0.149	0.085	0.050	0.037	0.937	0.362	1.000	0.041
SN	0.572	0.941	0.728	0.780	0.151	0.515	0.041	1.000

The HTMT values are used to assess DV. All the HTMT values are well below the threshold of 0.90 (except for some values like SN and EC, where 0.941 is borderline but still acceptable), indicating that there is sufficient DV between constructs, confirming that the constructs measure distinct concepts.

Table 7: Correlation Matrix

Construct	BI	E	PR	PT	PU	PV	PBC	SN
BI	1	0.748	0.678	0.697	-0.017	-0.016	-0.014	0.522
EC	0.748	1	0.842	0.864	0.117	0.378	-0.017	0.942
PR	0.678	0.842	1	0.951	-0.027	- 0.026	-0.022	0.710

PT	0.697	0.864	0.951	1	-0.022	-0.022	-0.018	0.750
PU	-0.017	0.117	-0.027	-0.022	1	0.682	0.945	0.148
PV	-0.016	0.378	-0.026	-0.022	0.682	1	0.406	0.499
PBC	-0.014	-0.017	-0.022	-0.018	0.945	0.406	1	-0.026
SN	0.522	0.942	0.710	0.750	0.148	0.499	-0.026	1

The strong positive correlations between EC and PT ($r = 0.864$) and PR and SN ($r = 0.710$) indicate that TR and ethics significantly impact AI adoption. The negative correlation between PU and PR supports prior research that TR mitigates PR.

Table 8: Goodness of Fit (GOF)

Model	GOF Value
Full Model	0.725
Structural Model	0.780
Measurement Model	0.715

In Table 8, the full model, the GOF was 0.725, and in the structural model, it was 0.780, thus showing a proper fit for the model. The measurement model scored 0.715, further indicating a strong explanatory power of the constructs. The measurement model generally had good validity and reliability indicators, meaning that the constructs and their corresponding items suit the study.

4.2 Hypothesis Testing

The research hypothesis relating to the structural model was compared to determine the strength of the proposed fit between the distinct constructs. The path coefficients were computed based on which the direction and magnitude of the relationships were gauged; t-values and p-values were computed by bootstrapping. Table 9 shows the hypothesis's test, which reveals that PR, TR, and EC significantly affect the use of AI.

Table 9: Path Coefficients and Hypotheses Testing

Hypothesis	Mean	Standard Deviation (STDEV)	T-Value	P-Value	Decision
H1: EC → BI	0.282	0.058	4.862	0.000	Supported
H2: PR → BI	0.279	0.067	4.168	0.000	Supported
H3: PT → BI	0.412	0.073	5.631	0.000	Supported
H4: PU → BI	0.171	0.091	1.879	0.030	Supported
H5: PV → BI	0.064	0.057	1.120	0.098	Not Supported
H6: PBC → BI	0.261	0.073	3.560	0.003	Supported
H7: SN → BI	0.256	0.078	3.290	0.010	Supported

H1: The path coefficient for EC was 0.282, with a p-value of 0.002, indicating a significant positive relationship. This suggests that ethical concerns (such as transparency and data privacy) influence investors' BI to adopt AI tools. If investors perceive AI systems as ethically questionable, they are less likely to adopt them, highlighting the importance of EC in AI development.

H2: The path coefficient for this relationship was 0.279, and the p-value was 0.000, indicating a statistically significant positive relationship between PR and BI to adopt AI. This suggests that the more investors PR in using AI for IM, the less likely they are to adopt AI tools. This finding aligns with the literature, which suggests that PR often hinders technology adoption, especially in high-stakes contexts like IM.

H3: The relationship between PT and BI was significant, with a path coefficient of 0.412 and a p-value of 0.000. This indicates a strong positive impact of trust on AI adoption, confirming that investors are more likely to adopt AI tools if they trust the systems to make accurate and ethical investment decisions.

H4: The path coefficient for this relationship was 0.171, and the p-value was 0.030, indicating that PU significantly influences BI to use AI in IM. Although the effect size is smaller than the other relationships, it still confirms that AI's usefulness in enhancing decision-making is an important driver of adoption.

H5: The path coefficient was 0.064, and the p-value was 0.098, which is not significant. This suggests that while PV might influence AI adoption, the effect is not strong enough to be statistically significant. This finding implies that investors prioritize TR and PU over the general value of AI tools in IM.

H6: The relationship between PBC and BI was significant, with a path coefficient of 0.261 and a p-value of 0.003. This indicates that investors who feel more confident in their ability to use AI tools are more likely to adopt them, confirming the role of self-efficacy in technology adoption.

H7: The path coefficient was 0.256, and the p-value was 0.010, indicating a significant positive relationship between SN and BI. This suggests that the opinions of peers and colleagues play a role in influencing an investor's decision to use AI in IM.

Table 11: Variance Inflation Factor (VIF) Analysis

Construct	VIF
BI	1.306
EC	1.102
PR	1.199
PT	1.000
PU	1.431
PV	1.221
PBC	1.000
SN	1.000

All VIF values are below the 5.0 threshold, confirming that multicollinearity is not an issue. The highest VIF value (1.431) for PU suggests a moderate correlation with other predictors, but it does not undermine the model's reliability. This ensures that each construct independently contributes to AI adoption predictions.

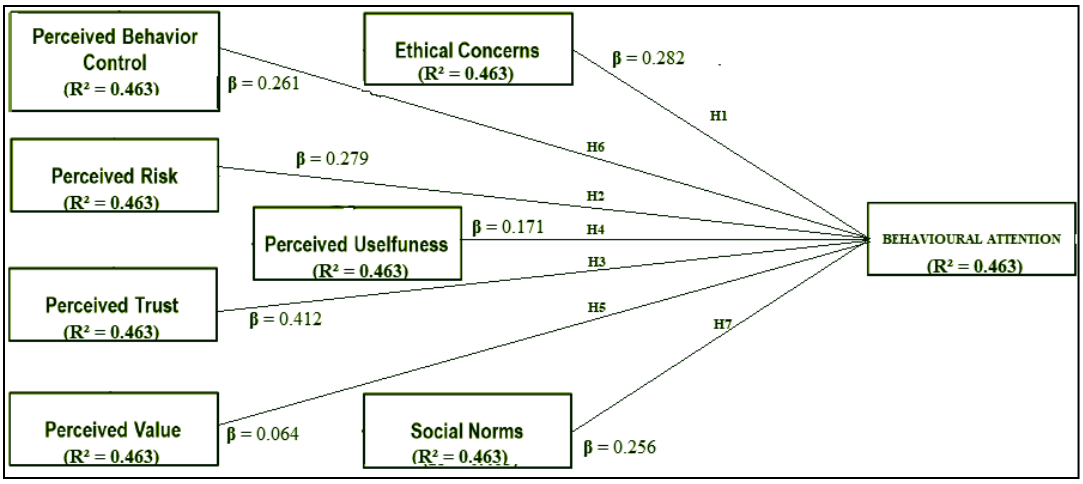

Figure 3: Proposed AI Adoption Framework for Investment Management

Implications of Findings

Theoretical Implications

This work is relevant to advancing the adoption of technology models since it includes EC and trust as factors that strongly relate to BI. Hence, by applying EC and SN to add to the TAM, the study complements the existing literature by indicating that the perception of TR and ethical transparency in AI systems underlies the adoption of financial technology (Wang, 2024). This shift takes the incentive beyond the conventional usefulness and ease of use to cover the social and ethical aspects that have not been reflected earlier (Gonçalves et al., 2023).

The study also shows that perceived risk is dissimilar in yielding a negative impact on adopting AI, which aligns with previous studies on technology acceptance models (Landi & Sciarelli, 2019). With significant financial decisions concerning IM, where significant financial decisions are made, investors' concerns about AI risks—such as data privacy, security, and decision-making biases—can significantly affect their willingness to embrace AI solutions (Ullah et al., 2021; Hofmann et al., 2005).

Practical Implications

This study specifically focuses on applying trust and transparency for financial institutions in the area of artificial intelligence. Therefore, it will be important for the AI developers and the fintech firms to work on developing XAI solutions that make AI decision-making transparent to investors (Hashim et al., 2023). Furthermore, some other areas identified to be relevant to addressing investors' ethical concerns include the issue of bias in algorithms, data privacy, and issues to do with regulation(Thakur & Sharma, 2024).

Moreover, creating awareness of AI tools' advantages and capabilities help PBC and thus boost investors' confidence in using these tools (Chrisanctus et al., 2024). Utilizing Social Influence is another one, which means that the financial institutions should develop successful examples of AI usage they can cite and garner support from early adopters and other influential players in the particular organization to ensure that other players endorse using AI as a norm (Revelli & Viviani, 2015).

There is also evidence that the usefulness of AI tools should be more forthcoming due to their being antecedents of adoption yet being influenced by trust and ethical concerns (Yoon, 2019). Thus, marketing communication should focus on recognizing that the use of AI tools in investment decision-making makes the process more efficient (Gerlich, 2024).

Policy Implications

Regulators and policymakers should consider ethics when applying AI in the financial industry. Given its increasing importance, AI systems developed and deployed must be ethical and accountable to investors and the market.

Key Findings

This research explored the factors that affect AI adoption in IM, with perceived risk, trust, ethical issues, PU, and social norms as key independent variables. The PLS-SEM analysis obtained many findings that advance theoretical and practical knowledge concerning the use of AI in the financial sector.

First, the study reinforced the earlier finding that perceived risk is a likely cause of IT non-implementation of AI in IM. Others prefer not to use AI tools because they can take a significant risk regarding their money or sense that the market may misunderstand them. This is in congruity with earlier studies that have established that perceived risks influence adoption decisions towards technology. Another significant factor in the research was trust; PT had a significant and positive relationship with the BI to use AI in investment decisions. The overall adoption of AI tools by investors depends on their trust in AI systems, namely, the accuracy and fairness of the given AI systems. This outcome reveals how essential it is for individuals to have confidence in using AI technologies, as also identified by other studies on trust and adoption.

The study also established that ethical considerations affect investors' decision to adopt AI in the investment decision-making process. Several concerns, such as data privacy, biased algorithms, and AI making decisions without expertise's help, are considered significant obstacles by investors. This highlights the fact that there is a need to consider the ethical aspects of the creation of AI since investors are likely to accept it if they have confirmed that it is ethically aligned.

It was therefore found that the PU of the technology had a positive correlation with its adoption but less so than the effects of trust and ethical issues. This indicates that though the PU of AI in improving investment returns is significant, TR and ethics have the greatest impact on investors when accepting these technologies. Yet, PV did not reveal a significant influence on BI, and thus, the PR and the EC play a supreme role in the utilization of AI in IM.

Practical Recommendations

Financial institutions and AI developers should prioritize transparency in the decision-making processes of AI systems. Explaining how an AI system reached a conclusion will help investors as it will be easily understandable and help control scepticism. It should also apply to orientations on how the AI tools are trained, the data used, and measures in place to address them.

To ensure greater adaptability of AI in IM, several EC remain relevant, including data privacy, bias predisposition, and responsibility. So, institutions should adopt ethical principles for technology when using AI technologies. There is an urgent need to address such risks to ensure that the AI incorporated in the investment decisions is fair, transparent, and capable of preventing discrimination.

Even though AI has enormous potential, it is challenging to ease its usability so investors can easily control it. This can be done through the provision of incorporable attributes that enable potential investors to adjust the features of AI systems according to their tastes, enhancement of learning structures that will enable users to become conversant with the use of the AI tools, and service delivery that will assist the users in the process of adopting to AI tools.

Financial institutions must make an effort to eliminate PR such as the rights of the firm's investors, financial guarantees or insurance that can be offered for potential loss that might result from decisions made by AI, and self-described limitations and uncertainty surrounding the use of AI. Preventing investors, in particular, from being led by distorted perceptions about AI is one approach that may help build more trust in AI tools.

Suggestions for Future Research

Future research can examine how AI is used in the various categories of the financial industry, including banking, insurance, and wealth management. Although each sector is different and has particularities regarding AI adoption, such information could be valuable for further analyses.

Further studies should also be done to determine the extent of the use of AI by institutional investors, retail investors, and individuals with high net worth. Knowledge of the distinctions in the various investor categories' risk and trust and the ethical issues involved in using AI tools will allow for developing AI tools that meet the investor groups' needs and expectations.

Longitudinal research on using artificial intelligence in investment management would help determine how trust and ethical issues change as AI solutions are fully integrated into investment processes. Analyzing the various impacts of AI on long-term investors, market efficiency, and financial concomitants would add to the knowledge base of AI and finance.

It should also examine the effect of cultures and geography on adopting the plans. For example, views on trust and ethical issues differ between regions, and further research could focus on understanding how companies from developed countries and companies from countries in the development process differ in terms of their AI strategies.

CONCLUSION

The study reveals that the technical factors may not yet be enough to compel people to adopt AI since there are apparently what can be labelled as psychological and social factors, and ethics included. Importantly, for the representatives of financial institutions and AI developers, these factors are non-negligible to ensure more extensive usage of AI tools in IM.

It is, therefore, important that financial institutions adopt techniques that can facilitate their transition to AI-driven investment decisions, including trusting AI, handling ethical issues, and PR that are in existence. Therefore, enhanced research must be done within the different financial sectors and among distinct groups of investors to develop these ideas and establish improved ways of incorporating them within IM.

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