Advance Journal of Econometrics and Finance
Vol-4, Issue-2, 2026

Advance Journal of Econometrics and Finance

Online ISSN
2959-8990
Print ISSN
2959-8982
https://ajeaf.com/index.php/Journal/About s://ajeaf.

Name of Publisher: SCHOLAR CRAFT EDUCATION & RESEARCH HUB
Review Type: Double Blind Peer Review
Jurnal Frequency: Quarterly Research Journal

Enhancing AI-Based Investment Decision Quality: The Roles of Perceived AI Transparency, Algorithmic Fairness, Trust, and Financial Literacy

Alsaf Bibi*[1], Suresh Kumar[2], Syed Muhammad Shoaib Wasim[3], Zulfiqar Ali Rajper[4]

	Abstract
Alsaf Bibi* Senior Auditor, Auditor General of Pakistan alsafalishah@gmail.com **Suresh Kumar** Sukkur IBA University sureshkumar@iba-suk.edu.pk ORCID: 0000-0002-1655-5452 **Syed Muhammad Shoaib Wasim** Senior Assistant professor Business studies department Bahria business school Karachi (BBSK) smshoaib.bukc@bahria.edu.pk **Zulfiqar Ali Rajper** Associate Professor The Shaikh Ayaz University Shikarpur Email: zulfiqar.rajper@saus.edu.pk	Artificial intelligence (AI) is becoming a game-changer in shaping investment decision-making processes, with automated financial advice services and intelligent recommendation systems leading the way. Nevertheless, transparency, fairness, and trust issues remain within the sphere of investor acceptance for AI-driven financial services. In this study, AI transparency and algorithmic fairness are shown to influence the quality of investment decisions made using AI, with the effects being mediated by the trust placed in AI-based financial services and moderated by financial literacy. The sample size consisted of 487 investors from Pakistan that were analyzed by the Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that trust through perceived transparency of AI and fairness of algorithms is a key factor in improving the quality of investment decisions based on AI. Additionally, financial literacy enhances the positive association between trust and investment decision quality. The study also builds on existing theories such as Trust Theory, Signaling Theory, and Information Processing Theory, and offers valuable implications for fintech companies, financial institutions, and policymakers aiming to foster trustworthy and efficient AI-powered financial services in developing nations.
Keywords:	Artificial Intelligence, AI Transparency, Algorithmic Fairness, Trust in AI-Based Financial Services, Financial Literacy, Investment Decision Quality.

Introduction

AI is being brought to bear by revolutionizing the way investment information is processed, analyzed and delivered to investors, fundamentally changing the way the global financial services industry operates. AI-driven financial technologies aim to improve the speed, accuracy, and efficiency of investment decision-making processes (Dwivedi et al., 2023; Huang & Rust, 2024). The demand and the use of AI for financial institutions to use AI in their advisory and investment practices has made the factors that affect investor acceptance and the use of AI financial systems an important research agenda. However, investors question the transparency of AI models, the possibility of bias in automated processes, and the trustworthiness of AI-driven investment advice, which hinder the adoption and trust in AI tools (Glikson & Woolley, 2020; Rai, 2023).

These concerns are even more pronounced in developing nations like Pakistan, where digital financial transformation has been quickening in the recent years. The digital banking, fintech services, mobile payment system and technology enhanced financial services platforms have seen tremendous growth in Pakistan through the efforts of State Bank of Pakistan (SBP), National Financial Inclusion Strategy (NFIS), and the recently issued National AI Policy (State Bank of Pakistan, 2024) (Ministry of Information Technology and Telecommunication, 2025). The proliferation of smart devices and internet services has ushered a new era for Pakistani investors to explore digital investment platforms and AI-powered financial services. Despite this, several problems have prevented adoption such as trust in the technology, information inequality, cybersecurity risks, and weak investor trust in automated decision-making processes (Ahmed et al., 2024; Khan et al., 2025). This has made it urgent to understand how investors can build trust in AI-based financial services, an area vital for the long-term development of the digital financial market in Pakistan.

One of the factors affecting investor confidence is how transparent they feel AI is. AI transparency is the ability of the users to comprehend how recommendations and decisions are being made by the AI systems (Shin, 2021). Transparent AI systems help minimize uncertainty, make AI systems more explainable, and boost users' perceptions of competence and accountability, thereby building user trust in services that integrate AI systems (Bussone et al., 2015; Rai, 2023). Likewise, algorithmic fairness has been becoming more prominent as an important feature of Responsible AI. When AI systems are seen as decision-making processes that are unbiased, equitable and non-discriminatory, investors are more likely to trust them (Lee, 2024; Shin & Park, 2024). Particularly, in high-stakes scenarios like making financial investment decisions, where the perceived risks are significant, transparency and fairness are cited as two of the pillars of trustworthy AI (Dwivedi et al., 2023; European Commission, 2024).

Trust in AI-based financial services is thus hypothesized to be a central mediating variable between the characteristics of the AI systems and investment outcomes. The trust others have in AI systems is the confidence they have in the ability of AI to deliver useful financial advice that is reliable, trustworthy, and honest (Glikson & Woolley, 2020). Previous studies have shown the strong effect of trust on technology adoption, people's use of financial services, and behavioral intention for AI applications (Choung et al., 2023; Huang & Rust, 2024). The empirical evidence testing the link between algorithmic fairness, the transparency of AI and investment decision quality, however, is limited, especially in developing countries like Pakistan.

In addition, investors have varying skills at interpreting financial data and understanding AI-driven suggestions. Financial literacy – the knowledge and ability to grasp financial concepts and make sound financial choices – might reinforce the impact of trust on investments (Lusardi & Messy, 2023). People with higher financial literacy are more likely to be able to evaluate the advice generated by AI, comprehend the risks involved, and make good use of algorithmic recommendations. Thus, financial literacy can be recognized as a pertinent boundary condition for the financial services trust-AI-based investment decision quality link.

In this context, the present study proposes a moderated mediation approach that explores the impact of perceived AI transparency and algorithmic fairness on the quality of AI-based investment decisions via increasing the trust in AI-based financial services, and also examines financial literacy as a moderating influence in the context of Pakistan. This study offers practical implications for policymakers, financial institutions, and fintech companies aiming to build trustworthy AI-driven investment ecosystems and bridges the gap in the literature regarding rapidly digitalizing emerging economy and investor behavior alongside AI enabled finance and responsible AI literature.

Theoretical Underpinning

This study primarily adopts the perspectives of Trust Theory, and combines those of Signaling Theory and Information Processing Theory to understand how perceived AI transparency and algorithmic fairness affect the quality of investment decisions made using AI-based financial services through trust in such services. The growing role of artificial intelligence in the financial sector, particularly in providing advisory and decision support services, has created significant investor uncertainty over the reliability, objectivity and accountability of AI-driven recommendations and reports. Trust Theory argues that people are more inclined to trust technological systems when they believe that the systems are competent, reliable and benevolent (Mayer et al., 1995; Glikson & Woolley, 2020). When it comes to AI-powered financial services, trust is a key element that mitigates uncertainty and helps investors embrace and trust AI-driven recommendations.

The signaling theory goes on to describe how the characteristics of an AI system act as information signals which influence investor perceptions and trust in an AI system. Perceived AI transparency offers clues about the explainability, accountability and transparency of algorithmic processes, which diminishes information gaps between investors and the AI system (Connelly et al., 2011; Rai, 2020). Similarly, algorithmic fairness indicates that investment advice is made in an objective and nondiscriminatory manner, boosting the trust of users in the honesty of AI-driven financial services (Shin, 2021). These signals enhance trust by assuring investors that AI systems operate in a transparent and equitable manner.

The study has also followed Information Processing Theory which posits that people vary with respect to their information interpretation, evaluation, and utilization skills in making decisions (Galbraith, 1974). Financial literacy is the ability of an investor to comprehend financial information and the implications of the AI-generated recommendations. Therefore, investors who have a higher level of financial literacy can make better investment decisions than those with a lower level of financial literacy, due to their ability to place trust in AI-based financial services based on their financial literacy.Thus, those with a higher financial literacy can place their trust in AI-based financial services tools and make better investment decisions compared to those with lower financial literacy. Hence, financial literacy acts as a key moderating variable that further reinforces the positive effect of trust on the quality of investment decision making using AI.

This study is an integration of Trust Theory, Signaling Theory, Information Processing Theory, and explains the role of transparency and fairness in building trust towards AI-based financial services and consequently overall quality of investment decision making in the evolving digital financial ecosystem in Pakistan.

Hypotheses Development

Perceived AI Transparency and Trust in AI-Based Financial Services

AI has revolutionized the financial services industry with advanced analytical tools and automated investment suggestions for investors. But the success of AI in the finance industry will largely rely on how much consumers will trust AI systems. Perceived AI transparency is the degree to which users are aware of how AI algorithms make recommendations and make decisions (Shin, 2021). Transparency in AI systems helps minimize uncertainty, as they explain their decision-making processes, making them more reliable and accountable (Rai, 2020). The Signaling Theory suggests that transparency is a positive signal, diminishing information asymmetry between the user and AI systems, thereby increasing AI system confidence (Connelly et al., 2011). There have been previous studies that have consistently shown that users' trust in AI systems is positively affected by explainability and transparency (Glikson & Woolley, 2020; Shin, 2021). When it comes to financial scenarios with high risk to invest, clear AI systems are likely to build trust in AI recommendations.

H1: *Perceived AI transparency positively influences trust in AI-based financial services.*

Algorithmic Fairness and Trust in AI-Based Financial Services

Algorithmic fairness is the extent to which AI systems make decisions objectively, consistently and without discrimination (Lee, 2018). Fairness is an integral part of trustworthy AI as no one wants to rely on an AI that produces biased results, especially when it comes to investing (Shin & Park, 2024). According to Trust Theory, perceptions of fairness improve an individual's trust in a system's integrity and benevolence (Mayer et al., 1995). In the financial sector, financial biases could turn off investors from accepting financial advice based on AI. On the other hand, if investors trust AI systems to be fair and unbiased, their confidence in the technology grows. The findings from recent studies show that in different digital environments, the algorithmic fairness has a positive correlation with the trust in algorithms and in AI applications (Shin & Park, 2024; Choung et al., 2023).

H2: *Algorithmic fairness positively influences trust in AI-based financial services.*

Trust in AI-Based Financial Services and AI-Based Investment Decision Quality

When considering how to reduce uncertainty and help individuals when they are making an important decision, trust comes into play (Glikson & Woolley, 2020). Investors' confidence in AI financial services is driven by their belief in the competence and reliability of AI systems to offer precise and advantageous financial advice. The Trust Theory states that a trusted system would be accepted and used efficiently and successfully, thereby resulting in better decision outcomes (Mayer et al., 1995). Investors who have faith in the AI generated recommendations are more likely to take them into their investment strategies, making more informed and rational decisions. Trust has been previously shown to positively impact on the use of technology and decision effectiveness in digital financial settings (Belanche et al., 2019; Choung et al., 2023).

H3: *Trust in AI-based financial services positively influences AI-based investment decision quality.*

Mediating Role of Trust in AI-Based Financial Services

Trust Theory hypothesizes that trust is a way in which the characteristics of a system can affect the user's behavior and decisions (Mayer et al., 1995). The transparency and fairness of AI and algorithms are anticipated to boost investor confidence, thereby improving investment decisions. While transparency and fairness are essential for investors to consider, they cannot directly influence the quality of their investment decisions; instead, they foster trust, making it easier for investors to act on the AI-generated recommendations. Thus, it is hypothesized that trust will be an intervening variable between AI attributes and investment results.

H4: *Trust in AI-based financial services mediates the relationship between perceived AI transparency and AI-based investment decision quality.*

H5: *Trust in AI-based financial services mediates the relationship between algorithmic fairness and AI-based investment decision quality.*

Moderating Role of Financial Literacy

Financial Literacy is a person's financial knowledge and their ability to use financial data to make investment decisions (Lusardi & Messy, 2023). According to Information Processing Theory, people who have more knowledge about money are able to better evaluate, understand and use the information they have when making financial decisions (Galbraith, 1974). Despite high trust in AI-based financial services, investors who lack financial expertise might not be able to comprehend and apply AI-generated recommendations effectively. However, a financially informed investor can use AI tools in conjunction with their own knowledge of finance to make better investment choices. Thus, we can assume that financial literacy will enhance the positive relationship of trust with investment decision quality.

H6: *Financial literacy positively moderates the relationship between trust in AI-based financial services and AI-based investment decision quality, such that the relationship is stronger at higher levels of financial literacy.*

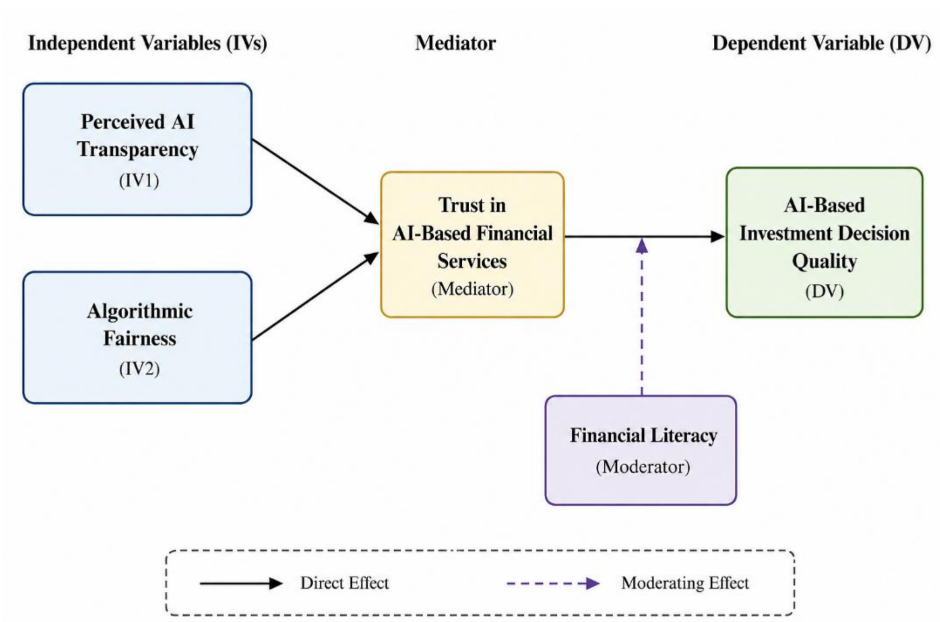

Figure 01: Framework

3. Methodology

3.1 Research Design

The study used a quantitative, cross-sectional survey design to assess the impact of perceived transparency of AI and algorithmic fairness on AI-investment decision quality by examining the construct of trust in AI-based financial services and financial literacy serving as a moderator. A quantitative approach was deemed to be suitable because the proposed framework explored causal relationships between the various latent constructs, and aimed to test the hypotheses, which were postulated on a theoretical basis, with empirical data. The study is based on Trust Theory, Signaling Theory and Information Processing Theory on individual investors using AI for financial services in Pakistan.

3.2 Research Context

Pakistan is an appropriate context to explore the issue of AI-driven financial services because of the growing trend of fintech usage, digital banking, mobile financial services, and technology-based investment platforms. The State Bank of Pakistan (SBP), Securities and Exchange Commission of Pakistan (SECP) and the Government of Pakistan have rolled out a series of initiatives that have helped to propel digital financial transformation and spur the uptake of new financial technologies. With the emergence of more AI-driven investment tools for Pakistani investors, it becomes even more crucial to understand the factors that impact trust and investment decision quality.

3.3 Population and Sampling

The target population comprised Pakistani investors who are actively using digital financial platforms and have experience in the use of AI financial services like robo advisors, AI-driven investment recommendation systems, algorithmic trading applications, and digital wealth management platforms.

No comprehensive sampling frame was available for the users of AI based financial services in Pakistan and purposive sampling technique was used. To maximize the respondent relevance, three criteria were used for screening the participants: Must be at least 18 years old. Have experience using digital financial or investment platforms. Experienced financial advisory services or investment recommendations using AI within the last year. This study has surveyed the investors who are residing in the major metropolitan areas of Pakistan (Karachi, Lahore, Islamabad, Rawalpindi, Faisalabad, Hyderabad, Multan and Peshawar) where digital financial adoption is comparatively high.

550 questionnaires were given out. Incomplete questionnaires, duplicate responses and cases with non-completion of attention checks were excluded in order to obtain 487 valid responses for final analysis (88.5% effective response rate). Hair et al. (2022) stated that the sample size in this study is far from the minimum sample size needed for PLS-SEM and has enough power to test the relationships in which there are multiple moderators influencing the relationship between the variables.

3.4 Data Collection Procedure

The data were gathered from January to March 2026 using a structured online questionnaire using Google Forms. The survey link was sent out via investor groups, stock market groups, fintech user groups, digital banking groups, LinkedIn professional networks, and social media investment groups.

A pilot study with 35 respondents was carried out before the main survey to test the clarity of the items, the readability of the questionnaire and the content validity. Some minor wording changes were made based on the feedback received from the participants. The pilot responses were not included in the data set. There was no mention of any obligation for respondents to participate, and the academic goal of the study was explained to the participants. Confidentiality and anonymity were assured and informed consent was obtained prior to respondents completing the questionnaire.

3.5 Measurement of Constructs

All constructs were assessed by previously validated scales, adapted from existing studies. The responses were taken on a 5-point Likert scale ranging from very much disagree (1) to very much agree (5).

Perceived AI Transparency: Perceived transparency of AI was assessed with five items adapted from Shin (2021) and Rai (2020). The scale measures the degree of understanding that investors have about the AI systems that provide financial recommendations and investment advice. **Algorithmic Fairness:** Algorithmic fairness was evaluated by five items consisting of those from Lee (2018) and Shin and Park (2024). The scale measures investors' awareness of the non-biased, objective, and fair nature of AI-based financial recommendations. **Trust in AI Based Financial Services.:** The trust in AI-based financial services was assessed with six items modified from Glikson and Woolley (2020). The scale reflects investors' trust in the competence, reliability, and integrity of financial services using AI.

Financial Literacy: Measure of financial literacy was based on six items adapted from Lusardi and Mitchell (2014). The scale measures the knowledge on basic financial terms, investment principles, diversification of risks, inflation and financial planning. **Investment Decision Quality based on AI.:** The quality of the investment decisions made using AI was assessed through six items adapted from Pellinen et al., (2011) and Aren and Zengin, (2016). The scale assesses how effective and rational the recommendations are, and how much they enhance the overall quality of investment decisions, when made by AI.

3.6 Assessment of Common Method Bias

To reduce the common method bias (CMBI) (Podsakoff et al., 2003), several procedural remedies were made. Firstly, the respondent anonymity and confidentiality were ensured. Second, the items on the questionnaires were randomly ordered to minimize response pattern bias. Third, there were brief directions given to minimize EAE. Full collinearity variance inflation factor (VIF) were statistically performed. As in Kock (2020), the VIF values below 3.3 suggest that common method bias is unlikely to cause serious issues regarding the validity of the results.

3.7 Data Analysis Technique

The proposed model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 software. PLS-SEM was selected because it is particularly suitable for prediction-oriented research, complex models involving mediation and moderation effects, and studies containing multiple latent variables measured through reflective indicators (Hair et al., 2022).

4.0 Finding and Analysis

4.1 Measurement Model

The findings shown in Table 1 indicate good reliability and convergent validity of the measurement model. The outer loadings of the indicators are all between 0.780 and 0.866, which is higher than the 0.70 recommended level, and thus allows for high indicator reliability. The Cronbach's alpha scores are in the range of 0.886-0.921 and the composite reliability (CR) scores are 0.913-0.938, indicating excellent internal consistency for the constructs. Also, the average variance extracted (AVE) is from 0.636 to 0.716, which exceeds the threshold of 0.50, thereby demonstrating convergent validity. The VIF values are between 1.000 and 1.112 and are far below the limit of 3.3, which meant that there was no issue with multicollinearity. The overall measurement model has good psychometric properties and can be used for further evaluation of the structural model.

Table 01: Reliability, Validity, and Collinearity assessment

Construct	Item	Outer Loading	Alpha	CR	AVE	VIF
AF	AF1	0.833	0.894	0.922	0.703	1.112
	AF2	0.847				
	AF3	0.828				
	AF4	0.836				

Construct	Item	Outer Loading	Alpha	CR	AVE	VIF
	AF5	0.848				
AIDQ	AIDQ1	0.805	0.886	0.913	0.636	1.000
	AIDQ2	0.796				
	AIDQ3	0.803				
	AIDQ4	0.780				
	AIDQ5	0.820				
	AIDQ6	0.782				
AIT	AIT1	0.866	0.898	0.925	0.711	1.112
	AIT2	0.844				
	AIT3	0.823				
	AIT4	0.835				
	AIT5	0.848				
FL	FL1	0.817	0.921	0.938	0.716	1.007
	FL2	0.855				
	FL3	0.852				
	FL4	0.861				
	FL5	0.848				
	FL6	0.841				
TAI	TAI1	0.825	0.904	0.926	0.676	—
	TAI2	0.818				
	TAI3	0.835				
	TAI4	0.831				
	TAI5	0.824				
	TAI6	0.800				

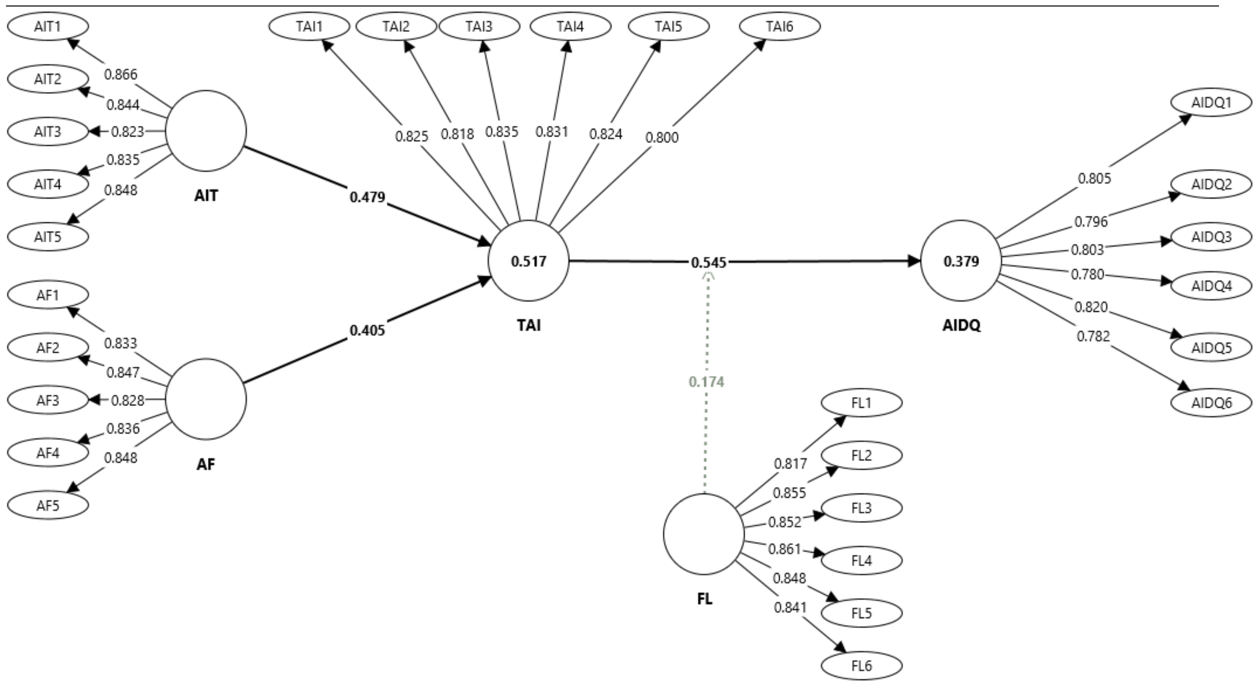

Figure 02: Measurement Model

4.1.1 Discriminant Validity

Discriminant validities of the study constructs were confirmed using the HTMT results shown in Table 2. Henseler et al. (2015) suggest that values of HTMT < 0.85 suggest that the constructs are empirically different from each other. The values of the HTMT parameter in the model range from 0.026 to 0.674, which are significantly lower than the recommended value. Perceived AI Transparency (AIT) and Trust in AI Based Financial Services (TAI) exhibit the highest (0.674) value for the correlation of the HTMT indicating a moderate correlation but a sufficient level of distinctiveness. These results show that the constructs are measuring theoretical concepts distinct from each other, which indicates good discriminant validity of the measurement model.

Table 02: HTMT Criteria

Constructs	AF	AIDQ	AIT	FL	TAI
AF	0				
AIDQ	0.346	0			
AIT	0.354	0.382	0		
FL	0.038	0.248	0.043	0	
TAI	0.618	0.611	0.674	0.032	0

4.1.2 Variance and effect size

The results shown in Table 3 indicate that the structural model has acceptable level of explanation and prediction. The model has 51.7% of the variance in Trust in AI Based Financial Services (TAI) explained and 37.9% of the variance in AI Based Investment Decision Quality (AIDQ), which is moderately to substantially explained (Hair et al., 2022). In terms of effect size, the Perceived AI Transparency (AIT) has a large effect on the Algorithmic Transparency Index ($f^2 = 0.427$), and Algorithmic Fairness (AF) has a medium effect ($f^2 = 0.304$). In addition, TAI has a significant influence on AIDQ ($f^2 = 0.479$), indicating its important role for boosting the quality of investment decisions. Financial Literacy (FL), on the other hand, shows a relatively small but significant effect ($f^2 = 0.085$). In general the results support the validity of the proposed model, its use, and its predictive value.

Table 03: Coefficient of Determination (R^2) and Effect Size (f^2)

constructs	R^2	Adjusted R^2	f^2	effect
(AIDQ)	0.379	0.376	—	Moderate
(TAI)	0.517	0.515	—	Substantial
AF → TAI	—	—	0.304	Medium effect
AIT → TAI	—	—	0.427	Large effect
FL → AIDQ	—	—	0.085	Small effect
TAI → AIDQ	—	—	0.479	Large effect

4.2 Structural Model

The outcome of the present study in the above mentioned framework is presented in Table 4 and this is in support of the proposed framework. Algorithmic Fairness ($\beta = 0.405$, $t = 13.406$, $p < 0.001$) and Perceived AI Transparency ($\beta = 0.479$, $t = 16.668$, $p < 0.001$) both significantly enhance Trust in AI-Based Financial Services, supporting H1 and H2. This effect of trust on the AI-Based Investment Decision Quality ($\beta = 0.545$, $t = 17.382$, $p < 0.001$) is also significant, thus supporting H3. The moderation effect of Financial Literacy is significant ($\beta = 0.174$, $t = 5.149$, $p < 0.001$) and hence, H4 was accepted. Furthermore, Trust partially buffers the relationship between Algorithmic Fairness and investment decision quality (H5) and between AI Transparency and the investment decision quality (H6). Overall, all hypothesized relationships were significant and supported.

Table 04: path co-efficient

Hypothesis	Path	β	STDEV	t-value	p-value	Decision
H1	AF → TAI	0.405	0.030	13.406	0.000	Supported
H2	AIT → TAI	0.479	0.029	16.668	0.000	Supported
H3	TAI → AIDQ	0.545	0.031	17.382	0.000	Supported
H4	FL × TAI → AIDQ	0.174	0.034	5.149	0.000	Supported
H5	AF → TAI → AIDQ	0.221	0.020	10.866	0.000	Supported
H6	AIT → TAI → AIDQ	0.261	0.024	11.026	0.000	Supported

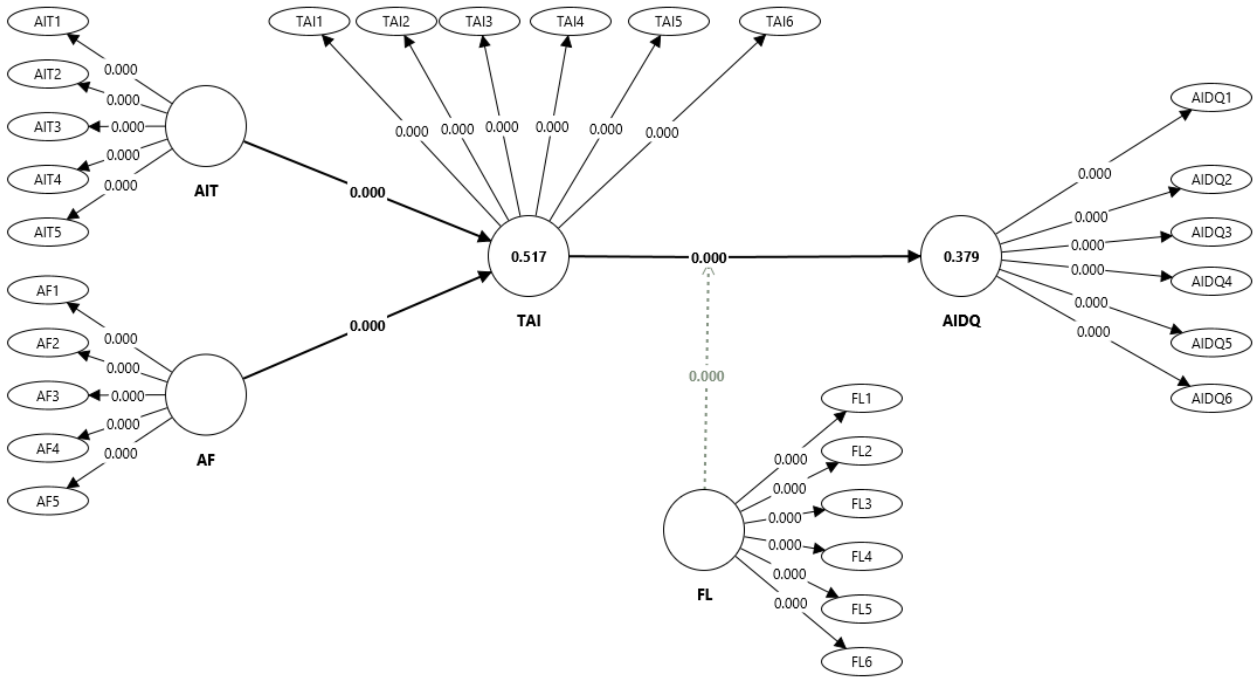

Figure 03: Structural Model

4.2.1 Predictive relevance (Q^2)

As can be seen from the results presented in the blindfolding Table 5, the proposed model has a satisfactory predictive relevance. AI for Trust in AI-Based Financial Services ($Q^2 = 0.344$) shows good predictive relevance and AI for AI-Based Investment Decision Quality ($Q^2 = 0.238$) has a moderate predictive relevance. Hair et al. (2022) state that Q^2 values higher than zero indicate the model's predictive power for endogenous constructs. The relatively high Q^2 values indicate that the independent variables explain the dependent variables in a meaningful way and that the variables are trust and investment decision quality. Based on this, the model has a satisfactory predictive ability outside the sample and can validate the predictability of the proposed model.

Table 5: Blindfolding

Construct	SSO	SSE	Q^2 (= 1 − SSE/SSO)	Interpretation
AIDQ	2922.000	2226.171	0.238	Medium predictive relevance
TAI	2922.000	1916.050	0.344	Large predictive relevance

4.2.2 Predictive Power Assessment

As shown in Table 6, the results of the CVPAT indicate the high predictive power of the proposed PLS-SEM model. In comparison with the benchmark IA model, both endogenous constructs (Trust in AI-Based Financial Services (TAI) and AI-Based Investment Decision Quality (AIDQ) have lower prediction loss values in the PLS model. The negative average loss differences (-0.090 and -0.252) suggest that the predictive ability of the PLS model is better. In addition the values between 5.745 and 9.979 and the p values < 0.001 are statistically significant. The overall average loss difference of -0.171 indicates that the model has good predictive ability in the future, and it can be used to make predictions with high accuracy and reliability, which validates the practical application value of the model and the reliability of the predictions it can make.

Table 6: CVPAT analysis

Construct	PLS Loss	IA Loss	Average Loss Difference	t-value	p-value	Predictive Performance
AIDQ	0.555	0.646	-0.090	5.745	0.000	PLS performs significantly better
TAI	0.478	0.730	-0.252	9.826	0.000	PLS performs significantly better
Overall	0.517	0.688	-0.171	9.979	0.000	Strong predictive performance

5.0 Discussion

This study explored the moderating effect of financial literacy on the relationship between perceived AI transparency and algorithmic fairness on the one hand and the investment decision quality on the other hand, and investigated the influence of trust in AI-based financial services on this relationship. The results are substantial evidence for the theoretical framework proposed. First, perceived transparency of AI was found to have a significant impact on trust in AI-based financial services. The discovery implies that investors will be more inclined to trust AI systems when they can comprehend how the recommendations are generated and when decision-making processes are transparent and explainable. This finding aligns with Signaling Theory that posits that communication that is transparent decreases information asymmetry and uncertainty, which increases users' trust in technological systems (Connelly et al., 2011; Rai, 2020). The discovery also aligns with prior research that has indicated that explainable AI can encourage users' trust and acceptance (Shin, 2021; Glikson & Woolley, 2020).

Second, algorithmic fairness greatly boosted the trust in algorithmic financial services. The results suggest that investors gain trust in AI systems when they view the investment suggestions as objective, unbiased, and fair. It is consistent with the Trust Theory, which is based on the idea that the initial and crucial factors that lead to the establishment of trust are the perceptions of integrity and fairness (Mayer et al., 1995). It also aligns with recent research highlighting the need for fairness to establish trust in AI use and decision-support systems (Shin & Park, 2024; Choung et al., 2023).

Third, the effects of trust were highly positive on the investment decision quality based on ART. This discovery aligns with the fact that trust is a key factor in driving investors to trust AI-based recommendations for investments. When investors trust AI systems as capable and trustworthy, they are more inclined to effectively leverage algorithmic advice for enhanced investment choices. Previous studies have identified trust as an important factor affecting technology use, decision effectiveness and AI adoption (Glikson & Woolley, 2020; Belanche et al., 2019).

In addition, the mediation analysis uncovered that the transparency of AI tools and the fairness of algorithms act as two important mediators between trust and investment decision quality.Moreover, the mediation analysis found that transparency of AI tools and algorithmic fairness are two major mediators between trust and investment decision quality. The results indicated that transparency and fairness enhance investment results primarily by boosting investor trust in AI systems. This finding corroborates earlier research which found that trust is one of the key factors that connects the attributes of artificial intelligence with behavioral outcomes (Shin, 2021; Choung et al., 2023). Last but not least, financial literacy greatly moderated the relationship between trust and the quality of investment decisions. This result is consistent with the Information Processing Theory which suggests that people with higher financial knowledge are more likely to assess, process and use information in making financial decisions (Galbraith, 1974). As in past studies, financially knowledgeable investors were able to implement trust in AI investment suggestions and achieve better investment results (Lusardi & Mitchell, 2014; Lusardi & Messy, 2023).

5.1 Theoretical Implications

This research has made significant and important contribution to the literature in several ways. First, it builds on Trust Theory by showing how trust can act as a key intermediary variable between AI transparency and algorithmic fairness and investment decision quality (Mayer et al., 1995; Glikson & Woolley, 2020). Second, the results contribute to Signaling Theory by demonstrating that transparency and fairness are positive signs that helps to unravel uncertainty and instill confidence in AI-powered financial services (Connelly et al., 2011; Rai, 2020). Thirdly, the research adds to the Information Processing Theory as it defines financial literacy as a boundary condition that enhances the effectiveness of trust in improving the decision outcomes (Galbraith, 1974). Last, the study adds to the growing field of AI finance by offering evidence from Pakistan, which is relatively unexplored in the realm of AI adoption and fintech studies.

5.2 Practical Implications

The results have implications for policy makers and financial institutions. Financial service providers should focus on creating explainable and transparent AI systems that can easily and accurately explain their investment advice. This transparency can help to alleviate investor uncertainty and increase trust (Shin, 2021). Moreover, it is essential to have algorithmic auditing and fairness assessment mechanisms to reduce bias and enhance the perception of fairness (Shin & Park, 2024). Policymakers can also create regulations to promote transparency, accountability, and responsible use of AI in finance. Furthermore, public program on financial education should also include education on AI to assist investors in assessing and applying AI-created suggestions (Lusardi & Mitchell, 2014).

5.3 Managerial Implications

Trust is a valuable asset that managers of fintech companies, digital investment platforms, and financial institutions need to leverage for successful AI implementation. The investment in explainable AI technologies, user-friendly interfaces, and communication transparency could help build trust and engagement with customers (Rai, 2020). To mitigate potential concerns about algorithmic bias and ensure fairness, managers should implement monitoring systems that keep an eye on the recommendations made by the algorithms.Managers should also set up monitoring systems to track the recommendations generated by the algorithms and ensure that they are fair. Moreover, companies should offer educational materials, tutorials, and financial literacy initiatives to boost the financial literacy and comprehension of investors regarding AI-generated advice. Such efforts can boost confidence among customers, improve platform adoption, and ultimately help to improve investment decisions.

6.0 Limitations and Future Research Directions

This study does have a couple of drawbacks. First, the cross-sectional design does not allow for the ability to make causal inference over time. Longitudinal study designs could be used to investigate the changes in trust and the adoption of AI at various phases of technology use (Hair et al., 2022). Second, the study has been conducted on Pakistani investors only thus results may not be generalized to other countries or financial markets. Comparative studies of developed and emerging economies should be carried out in the future. Thirdly, the model analyzed only transparency, fairness, trust and financial literacy. Other factors like perceived risk, privacy concerns, AI anxiety, technological readiness and regulatory trust can give another insight into the investment behavior using AI (Dwivedi et al., 2023; Choung et al., 2023).

7.0 Conclusion

This research study explored the impact of perceived transparency and algorithmic fairness of the Artificial Intelligence on the quality of investment decisions of the Pakistani investors with the role of trust in AI-based financial services to moderate the effect and also the impact of perceived transparency on the quality of investment decisions of the Pakistani investors. The results indicate that transparency and fairness have a significant positive impact on investor trust which in turn leads to better investment decisions. In addition, financial literacy boosts the positive impact of trust on investment returns. The findings underscore the need for trustworthy, transparent, and equitable AI systems and highlight the need for increased investor financial literacy. With AI's ongoing impact on the financial services sector worldwide, trust and responsible use of AI will be crucial to unlocking the potential of AI in investment decision-making in emerging digital economies like Pakistan.

References:

Aren, S., & Zengin, A. N. (2016). Influence of financial literacy and risk perception on investment choices.

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology, 52*(1), 1–26. https://doi.org/10.1146/annurev.psych.52.1.1

Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2019). Service robot implementation: A theoretical framework and research agenda. *Service Industries Journal, 40*(3–4), 203–225.

Bussone, A., Stumpf, S., & O'Sullivan, D. (2015). The role of explanations on trust and reliance in clinical decision support systems. In *2015 International Conference on Healthcare Informatics* (pp. 160–169). IEEE. https://doi.org/10.1109/ICHI.2015.26

Choung, H., David, P., & Ross, A. (2023). Trust in AI and its role in the adoption of artificial intelligence technologies: A systematic review. *Computers in Human Behavior Reports, 9*, 100274. https://doi.org/10.1016/j.chbr.2022.100274

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of Management, 37*(1), 39–67.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., ... Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, 102642.

European Commission. (2019). *Ethics guidelines for trustworthy AI*. High-Level Expert Group on Artificial Intelligence. https://digital-strategy.ec.europa.eu

Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces, 4*(3), 28–36.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage Publications.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50.

Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society, 5*(1), 1–16.

Lee, M. K. (2018). Understanding perception of algorithmic decisions. *Big Data & Society, 5*(1), 1–16.

Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society, 5*(1).

Lusardi, A. (2019). Financial literacy and the need for financial education: Evidence and implications. *Swiss Journal of Economics and Statistics, 155*(1), 1–8.

Lusardi, A., & Messy, F. A. (2023). The importance of financial literacy and its impact on financial behaviour. *OECD Working Papers on Finance, Insurance and Private Pensions*. OECD Publishing.

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy. *Journal of Economic Literature, 52*(1), 5–44.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review, 20*(3), 709–734.

Ministry of Information Technology and Telecommunication. (2025). *National Artificial Intelligence Policy of Pakistan*. Government of Pakistan.

Pellinen, A., Törmäkangas, K., Uusitalo, O., & Raijas, A. (2011). Measuring the financial capability of investors.

Rai, A. (2020). Explainable AI: From black box to glass box. *Journal of the Academy of Marketing Science, 48*(1), 137–141.

Shin, D. (2021). The effects of explainability and causability on perception, trust and acceptance: Implications for explainable AI. *International Journal of Human–Computer Studies, 146*, 102551.

Shin, D., & Park, Y. J. (2024). Algorithmic fairness, transparency, and accountability in AI systems. *Telematics and Informatics, 89*, 102104.

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. *Journal of Business Research, 69*(10), 4552–4564. https://doi.org/10.1016/j.jbusres.2016.03.049

State Bank of Pakistan. (2024). *Payment systems review and digital financial services report 2023–2024*. State Bank of Pakistan.