Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

AI-DRIVEN FINANCIAL REPORTING AND INVESTMENT DECISION QUALITY: THE MEDIATING ROLE OF INVESTOR TRUST AND MODERATING ROLE OF FINANCIAL LITERACY

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DOI: https://doi.org/10.63544/jbii.v5i7.85

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Article History:
Received: 11.06.2026
Accepted: 28.06.2026
Published: 10.07.2026

Abstract

This study explores the relationship between financial reporting using AI, financial transparency and the quality of investment decisions by analysing the investor trust and the moderating effect of financial literacy. The study is based on Signalling Theory and Information Asymmetry Theory and concentrates on the focus group of individual investors in Pakistan Stock Exchange. The number of usable responses from the instruments was 428 and the data was analysed with PLS-SEM. The results reveal that AI financial reporting and financial transparency can enhance investor trust, while investor trust can improve investment decision quality. The impact of AI-driven reporting and transparency on investment decisions is also influenced by investor trust. Furthermore, elevating financial literacy enhances the bond between AI-driven reporting, transparency, and investor trust. The study highlights the importance of trustworthy digital reporting, transparent disclosures, and investor education in emerging market contexts.

Keywords: AI-Driven Financial Reporting, Financial Transparency, Investor Trust, Financial Literacy, Investment Decision Quality, PLS-SEM, Pakistan Stock Exchange.

1. Introduction

In fact, artificial intelligence (AI) is revolutionizing the accounting field by streamlining financial reporting, enhancing disclosure quality, and making financial information systems more efficient. New developments in machine learning, NLP, and generative AI have made it possible for companies to generate more timely, accurate, and comprehensive financial reports, thus mitigating information asymmetry between companies and stakeholders (Stratopoulos & Wang, 2025; Gomber et al., 2024). The credibility and transparency of financial reporting is becoming a key factor in investment decision making as investors turn increasingly to digital information environments. In emerging economies, where capital markets may be plagued by issues of transparency, information inefficiencies, and investor uncertainty, the integration of AI into financial reporting becomes even more crucial. Pakistan is an excellent case study to explore these questions due to the ongoing rapid digitalization of the financial system, and the challenges of disclosure quality and investor confidence. Retail investors' increased frequency of trading securities on the Pakistan Stock Exchange (PSX) and the rising trend of digital financial services have made it more imperative than ever to have accurate and transparent data to make informed investment choices (Demirgüç-Kunt et al., 2022; Sadiq et al., 2024).

Much has been studied about factors that influence investment decisions, such as the quality of information, transparency, and investor trust (Chen et al., 2023; Nguyen & Dang, 2024). The role of trust in investor response to financial disclosure is important because trustworthy information helps to mitigate the effects of perceived uncertainty, and it also enables rational investor decision-making. While AI has advanced into various applications across accounting and finance, there is a lack of empirical research on the process of developing investor trust and how AI-driven financial reporting impacts the quality of investment decisions, especially in emerging markets. Moreover, although financial literacy has been identified as a crucial factor in investors' processing and evaluation of financial information (Lusardi & Mitchell, 2023), its contribution to enhancing the effectiveness of AI-driven financial reporting is understudied.

The study examines the relationship between financial reporting with the help of AI, financial transparency, the investment decision quality and investor trust, based on Signalling Theory and Information Asymmetry Theory. Further, it explores how financial literacy can reinforce the bond between the AI-driven financial reporting, financial transparency, and investor trust. This study is a first study of investors in Pakistan, a developing country, and adds to the growing body of literature on AI-enabled accounting practices and extends existing knowledge of the impact of technology on financial reporting and its potential to enhance investment returns in developing countries.

2. Theoretical Underpinning and Hypotheses Development

Theoretical Underpinning

This study is based on Signalling Theory of Spence (1973) and Information Asymmetry Theory of Akerlof (1970). According to Signalling Theory, the uncertainty of market participants can be diminished by delivering credible, timely and high-quality information signals to the market. Financial markets signals are the messages that companies allow to be interpreted by investors regarding their performance, prospects and risk exposure. Signals have been recently improved by the incorporation of artificial intelligence (AI) technologies in the reporting system, which adds more accuracy, timeliness, consistency and predictiveness to these signals (Gomber et al., 2024; Cao et al., 2024). Thus, AI-powered financial reporting can help empower investors by delivering more accurate and informative insights into company performance.

The theory of information asymmetry is that this disparity in information leads to uncertainty and inefficiencies in the investment decision-making process for investors and managers. Finances reporting mechanisms are meant to reduce such asymmetries through improved transparency and disclosure. By integrating AI technologies into financial reporting processes, organizations can create more extensive and up-to-the-minute financial data, minimizing information gaps and boosting stakeholder trust (Stratopoulos & Wang, 2025). Similarly, financial transparency is a key governance tool that helps to share information and makes it accessible and comparable, enabling investors to make better decisions (Chen et al., 2024).

Investor trust is one of the main psychological mechanisms that connects financial information characteristics to investor investment. The level of trust is built when the financial information is perceived as credible, reliable and transparent. Previous research indicates that trust decreases perceived risk, uncertainty, and increases the trust in the information provided to investors when they make decisions to invest (Nguyen & Dang, 2024; Alkaraan et al., 2025). Investor trust is expected to moderate the influence of AI-based reporting and financial transparency on quality of investment decision making.

In addition, it is Financial Literacy Theory that people with greater financial literacy can more accurately process complex financial information and gain insight from sophisticated reporting technologies (Lusardi & Mitchell, 2023). Investors who are financially literate would be better able to understand the information and transparency provided by AI, enhancing the building of trust. As a result, financial literacy will be expected to further improve the ties between financial reporting by artificial intelligence, financial transparency, and investor trust.

Signalling Theory helps to describe the processes for AI-based reporting and transparency as positive informational signalling while Information Asymmetry Theory helps to explain how these processes help to eliminate uncertainty and build trust, resulting in better investment decisions.

AI-Driven Financial Reporting and Invest or Trust

AI is increasingly reshaping corporate reporting by automating data processing, enhancing the accuracy of forecasts, ensuring disclosure consistency and minimizing reporting errors by humans. By leveraging AI, companies can generate financial reports with speed and accuracy, promoting investors' trust in the information provided and thereby boosting disclosure credibility (Cao et al., 2024; Kotsantonis et al., 2025). Signalling Theory posits that good disclosures are credible signals and decrease the uncertainty of firm performance and prospects. Investors have more faith in companies using more sophisticated AI-powered reporting systems, as these systems enhance reporting objectivity and information reliability (Gomber et al., 2024). The higher the quality of information, the more likely investors are to trust information provided for investments and use it in investment analysis.

H1: *AI-driven financial reporting positively influences investor trust.*

Financial Transparency and Investor Trust

Financial transparency is the degree of openness of an organization in revealing to stakeholders relevant, accurate and understandable financial information. A transparent reporting helps to minimize information asymmetry which helps stakeholders to monitor the activities being carried out within the organization (Chen et al., 2024). Transparency disclosure mechanisms reduce uncertainty and enhance investor perceptions of organizational honesty and accountability, according to Information Asymmetry Theory. Empirical evidence has consistently shown that transparency boosts investor confidence in companies by making information more readily accessible and lessening the perception of opportunistic management behaviour (Nguyen & Dang, 2024; Alkaraan et al., 2025). Comprehensive and transparent disclosures are more likely to boost investor confidence in firms because they indicate organizational integrity and governance quality.

H2: *Financial transparency positively influences investor trust.*

Investor Trust and Investment Decision Quality

Investment decision quality is the ability and rationality of investors' investment decisions based on the information available to them. Trust is also crucial in financial decision-making because it eliminates uncertainty and perceived risk related to financial activities. Investors can adjust their investment decisions based on the information they receive and incorporate effectively when they trust the disclosures made by the company (Luo et al., 2024). Based on the literature of behavioural finance, the trust influence in investors' confidence on financial information will positively affect the investors' judgment in evaluating the investment options and make more rational investment decisions (Nguyen & Dang, 2024). Thus, investor trust is a key factor in investment decision quality in ever-digital financial markets.

H3: *Investor trust positively influences investment decision quality.*

The Mediating Role of Investor Trust

The effectiveness of information signals is said to be related to the trust in the source (and the credibility of the information) according to Signalling Theory. While AI-enabled reporting systems can enhance disclosure quality and reliability, their impact on investment decisions will be via the investor's trust in the disclosure. Likewise, clear reporting practices boost confidence in the reporting of organizational disclosures and this in turn has an effect on the quality of the decision. Trust has been shown to be a key factor in how trustworthy technology and transparency programs impact financial behaviours and investment outcomes (Alkaraan et al., 2025; Luo et al., 2024). Hence, investor trust is supposed to moderate the relationship between AI financial reporting and financial transparency on the investment decision quality.

H4: *Investor trust mediates the relationship between AI-driven financial reporting and investment decision quality.*

H5: *Investor trust mediates the relationship between financial transparency and investment decision quality.*

The Moderating Role of Financial Literacy

Financial Literacy is the capacity of an individual to comprehend, assess and apply financial information in ways that support the effective management of their finances. Financial educated investors have higher analytical skills, which helps them better read through complex financial disclosures and sophisticated reporting technologies (Lusardi & Mitchell, 2023). AI's role in financial reporting brings in complex information structures which might not be interpreted identically by all investors. Investors who are more financially literate are better able to understand the value of AI-driven reporting systems and transparency tools, further enhancing the trust-building process (OECD, 2023; Morgan et al., 2024). On the other hand, less financially informed investors might find it hard to assess the disclosures produced by AI and place trust in them.

Based on this, financial literacy will be expected to reinforce and improve the positive impacts of AI in financial reporting and in financial transparency, on investor trust.

H6: *Financial literacy positively moderates the relationship between AI-driven financial reporting and investor trust, such that the relationship is stronger when financial literacy is high.*

H7: *Financial literacy positively moderates the relationship between financial transparency and investor trust, such that the relationship is stronger when financial literacy is high.*

3. Methodology

Research Design

This study uses an explanatory research design with quantity data and a cross-sectional approach in examining how the implementation of artificial intelligence in the financial reporting process, as well as financial transparency, affects the quality of investment decisions with the intermediary variable of investor trust and the moderating variable of financial literacy. The quantitative approach is suitable for the study because it aims to test the theoretically developed hypothesis by empirical tests and quantify the relationships between the latent constructs. For collecting the primary data, a survey-based approach was used, as was done in previous studies of accounting and finance. As in the previous studies on accounting and finance, survey method was used for gathering the primary data from investors working in the Pakistan Stock Exchange (PSX). The study is based on the positivist research paradigm that views that the relationship between variables itself can be measured objectively and can be statistically analysed. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used as the main data analysis technique due to the predictive nature of the proposed framework and mediation and moderation effects. PLS-SEM can be used especially for complex models that include latent variables, theory development and prediction-oriented research objectives (Hair et al., 2024).

Population, Sample, and Sampling Technique

The study focuses on individual investors who are active on the Pakistan Stock Exchange (PSX). Individual investors were chosen because they regularly use corporate financial disclosures and financial reports in making investment decisions and valuing investment opportunities. Furthermore, Pakistan is witnessing the growing use of digital financial services and Pakistan's AI based financial information systems, making this group unique in the study of perceptions of AI financial reporting. Since there is no complete record of all the retailers in Pakistan, a non-probability purposive sampling technique was used. Purposive sampling is a common sampling technique in accounting and behavioural finance studies where the respondents need to have relevant knowledge or experience for the research objective. To assure that the responses were of quality, participants had to satisfy a set of screening criteria, such as being actively invested in the market, understanding financial statements and being involved in investment decision-making processes. Respondents were contacted via stock market discussion groups, social media geared towards investment, investor associations, brokerage firms and online investment forums.

Sample Size Determination

Recommendations for PLS-SEM analysis were used to determine the sample size. Hair et al. (2024) recommended that the minimum sample size be greater than 10 times the largest number of structural paths running to any endogenous construct in the research model. The following analysis follows the proposed structure, which has four incoming relationships: two direct and two interaction effects, implying a minimum sample size of forty observations for the analysis. But more recently, methodological studies have been advocating to increase the sample size to increase the statistical power, prediction accuracy, and parameter stability. This research employed the number of more than 400 respondents as the target sample size as suggested by Hair et al. (2024) and Kock and Hadaya (2018). Therefore, 550 questionnaires were sent to investors in the major financial centres of Pakistan. Upon screening for errors, incomplete responses and outliers were removed, leaving 77.8% of questionnaires with 428 usable questionnaires for final analysis. The final sample met the minimum criteria for PLS-SEM and had adequate statistical power to assess both mediation and moderation effects.

Data Collection Procedure

The structured questionnaire was used to gather primary data from January to March 2026. The questionnaire was created by modifying scales of existing studies in accounting, finance and information systems from previous studies. The instrument was first reviewed by three accounting scholars and two finance practitioners for its content validity and to ensure the instrument is relevant to the investment scenario in Pakistan. A pretest was done with 40 investors to test the clarity, reliability and comprehensibility of the items in the questionnaire. Slight changes of the item wording and questionnaire structure were made based on feedback received from the pilot phase. The final survey instrument was sent out both online and offline. They were conducted using Google Forms and distributed through investor communities, broker networks, and social media investment groups. Questionnaires were sent out via physical medium at brokerage offices, investor seminars and financial awareness programs. The study was conducted on a voluntary basis, and the respondents were briefed about the objective of the study. All procedures in the data collection process were conducted with confidentiality and anonymity.

Measurement Instrument

The measurement instrument was developed based on the existing scales that have been validated in accounting, finance, technology adoption and investor behaviour literature. The items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The use of scales which have been established increases the reliability, validity and comparability of study results to previous studies. The AI-Driven Financial Reporting (AIFR) construct was measured by six items adapted from the AI adoption and digital accounting literature by Dwivedi et al. (2023) and Venkatesh et al. (2022). The scale will measure investors' perceptions of the accuracy, reliability, timeliness, efficiency and predictiveness of financial reporting systems powered by AI. Sample items include "AI-based financial reporting improves the accuracy of financial reports" and "AI-generated financial reporting improves the quality of investment related information.

Financial Transparency (FT) was assessed using five items that were adapted from the disclosure and transparency literature developed by Bushman et al., (2004) and Schnackenberg and Tomlinson, (2016). These are measures of whether firms present comprehensive and clear, accurate and timely, financial information. Some examples of sample items are: Companies give adequate financial information to assess their performance and Corporate disclosures are clearly and transparently communicated. Five items adapted from the trust literature developed by McKnight et al. (2002) and Gefen et al. (2003) were used to measure investor trust (IT). The scale measures the investors' trust in the credibility, reliability and integrity of the corporate financial information. Examples are: “I trust information provided in a company's financial statements when deciding whether to invest” and “Financial statements of a company are generally reliable.”

Five items derived from the financial literacy frameworks put forward by Lusardi and Mitchell (2014, 2023) and OECD-INFE (2023) were used to evaluate FL. The scale assesses participants' knowledge of financial concepts, investment products, risk diversification and financial decision making. Examples of items are: “I have enough money knowledge to assess investment opportunities” and “I know about the risks of different investment alternatives.” Five items adapted from Pellinen et al. (2011) and Aren and Zengin (2016) were used for the Investment Decision Quality (IDQ). The scale reflects the effectiveness, rationality and confidence linked with investments. Sample items include: My investment decisions are based on a careful evaluation of information available and I am satisfied with the quality of my investment decisions.

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
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The questionnaire was composed of 26 measurement items across five constructs: AI-Driven Financial Reporting (six items), Financial Transparency (five items), Investor Trust (five items), Financial Literacy (five items) and Investment Decision Quality (five items).

Measurement and Data Analysis Techniques

The data analysis was carried out with SmartPLS 4.0 software in accordance with the two-stage PLS-SEM approach suggested by Hair et al. (2024). The first step was to examine the measurement model for reliability and validity and the second step was to examine the structural model and test the hypothesized relationships. The indicator loadings, Cronbach's alpha, composite reliability (CR), rho_A, average variance extracted (AVE), and variance inflation factor (VIF) were used for the measurement model. The cut-off values of indicator loadings, 0.70, CR values, 0.70, and AVE values, 0.50, were recognized as acceptable indicators of convergent validity. Both Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT) were used to test discriminant validity, and the values of HTMT were less than 0.85, which was considered satisfactory.

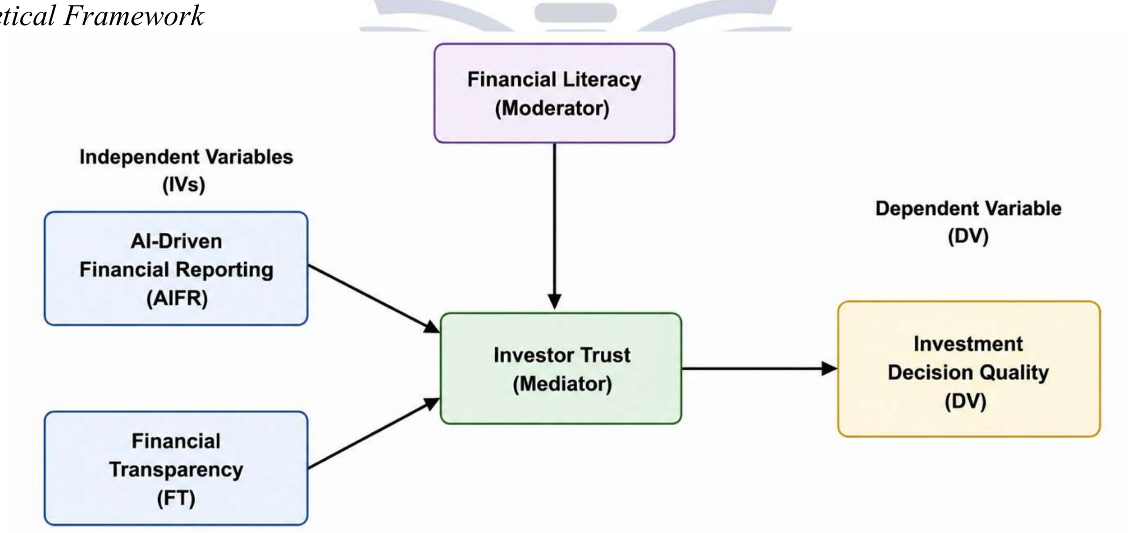
The structural model was evaluated using path coefficients (β), t statistics, p values, coefficients of determination (R2), effect size (f2) and Q2 – the predictive relevance. Hypothesized relationships were assessed by bootstrapping using 10,000 re-samples. Bootstrapped indirect effects were tested as recommended by Preacher & Hayes (2008) for mediation effects, and the product-indicator approach was used to test moderating effects in SmartPLS. Interaction terms were created between AI-Driven Financial Reporting and Financial Literacy, as well as between Financial Transparency and Financial Literacy.

Common Method Bias

Since the data were gathered from a single source, a number of procedural and statistical measures were taken to reduce common method bias. Respondent anonymity and confidentiality were ensured, and work was carried out in a manner that ensured questionnaires were well structured and that there were no right or wrong answers. Harman's single factor test and full collinearity test were carried out statistically. Common method bias was not seen as a problem because all the full-collinearity VIF values were at or below 3.30.

Figure 1

Theoretical Framework



4. Results and analysis

Measurement model

The measurement model was assessed using outer loadings, Cronbach's alpha, rho_A, composite reliability, average variance extracted, VIF, HTMT. All the indicator loadings were in the range of 0.820 to 0.889, which is higher than the minimum loading of 0.70 suggested. Thus, all measurement items were kept. The internal consistency reliability was good, with Cronbach's alpha ranging from 0.905–0.928 and composite

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

reliability between 0.930–0.943. AVE values ranged from 0.725 to 0.735, higher than the recommended value of 0.50, indicating convergent validity. In addition, none of the VIFs exceeded 3.30, suggesting that the problem of multicollinearity was not a major issue. The discriminant validity was also validated as all HTMT values are less than 0.85, which again shows the discriminant validity. The measurement model was found to be reliable, valid and convergent in general.

Table 1
Loading reliability and loading

Construct	Item	Loading	Indicator Reliability	VIF
AIFR	AIFR1	0.864	0.747	2.813
AIFR	AIFR2	0.860	0.740	2.714
AIFR	AIFR3	0.880	0.775	3.094
AIFR	AIFR4	0.851	0.724	2.585
AIFR	AIFR5	0.847	0.718	2.558
AIFR	AIFR6	0.841	0.707	2.450
FT	FT1	0.852	0.726	2.406
FT	FT2	0.871	0.759	2.697
FT	FT3	0.853	0.727	2.418
FT	FT4	0.861	0.741	2.531
FT	FT5	0.822	0.676	2.067
IT	IT1	0.889	0.791	3.055
IT	IT2	0.832	0.692	2.198
IT	IT3	0.848	0.720	2.400
IT	IT4	0.873	0.762	2.735
IT	IT5	0.820	0.672	2.104
FL	FL1	0.848	0.718	2.366
FL	FL2	0.853	0.727	2.405
FL	FL3	0.866	0.751	2.610
FL	FL4	0.844	0.713	2.302
FL	FL5	0.847	0.718	2.340
IDQ	IDQ1	0.861	0.741	2.556
IDQ	IDQ2	0.854	0.729	2.444
IDQ	IDQ3	0.866	0.749	2.622
IDQ	IDQ4	0.825	0.680	2.093
IDQ	IDQ5	0.870	0.757	2.676

Table 2
Reliability and Validity

Construct	Items	Cronbach's Alpha	rho_A	Composite Reliability	AVE	Decision
AIFR	6	0.928	0.936	0.943	0.735	Accepted
FT	5	0.905	0.918	0.930	0.726	Accepted
IT	5	0.906	0.918	0.930	0.727	Accepted
FL	5	0.905	0.917	0.930	0.725	Accepted
IDQ	5	0.908	0.920	0.931	0.731	Accepted

Table 2 presents a comprehensive summary of the measurement model's reliability and convergent validity. The internal consistency reliability of all five constructs is exceptionally high, as evidenced by Cronbach's alpha values ranging from 0.905 to 0.928 and composite reliability (CR) scores between 0.930 and 0.943. These values significantly surpass the accepted threshold of 0.70, confirming that the items for each construct consistently measure the same underlying concept. Furthermore, the rho_A values, which are

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

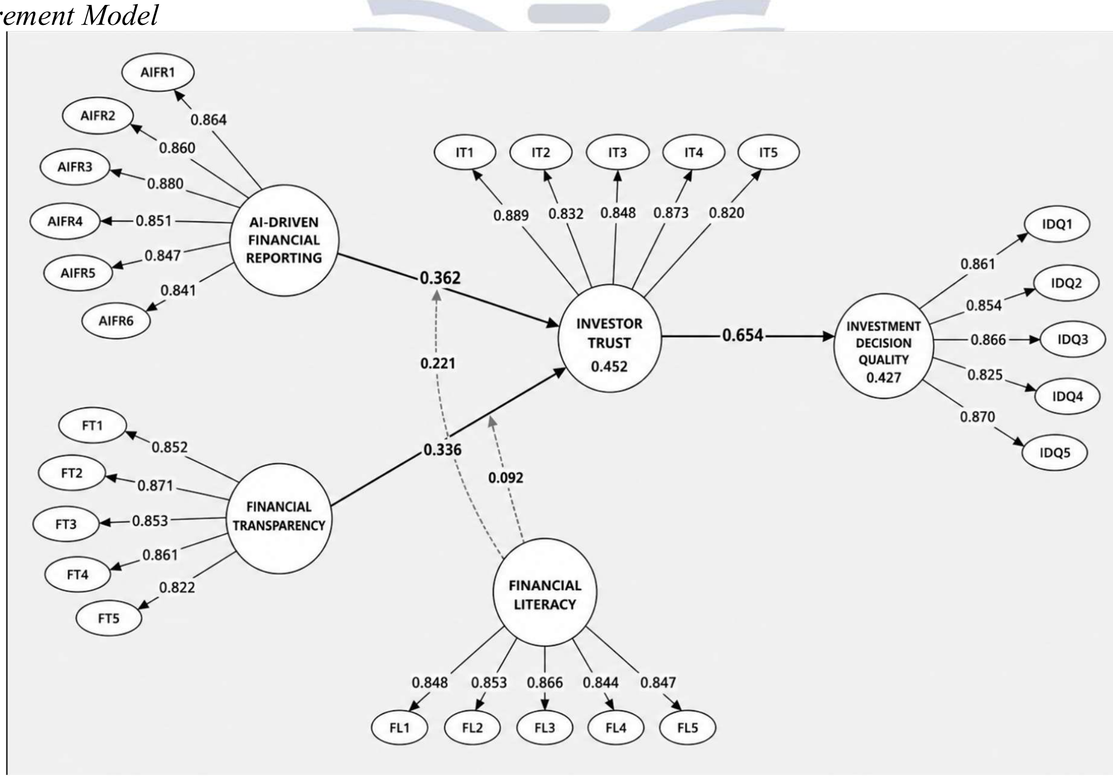
considered a more accurate measure of reliability in PLS-SEM, are also well above 0.90, reinforcing the constructs' stability. The convergent validity of the model is strongly supported by the Average Variance Extracted (AVE) for each construct, which ranges from 0.725 to 0.735. As all AVE values are considerably higher than the minimum benchmark of 0.50, it is evident that each construct explains more than half of the variance in its own indicators, thus demonstrating that the items converge well on their respective latent variables.

Table 3
Discriminant Validity

Construct	AIFR	FT	IT	FL	IDQ
AIFR	0				
FT	0.330	0			
IT	0.530	0.529	0		
FL	0.108	0.113	0.263	0	
IDQ	0.466	0.529	0.721	0.080	0

The assessment of discriminant validity, as shown in Table 3, ensures that each construct in the model is empirically distinct from the others. The analysis employs the Heterotrait-Monotrait (HTMT) ratio of correlations, a stringent criterion for establishing discriminant validity. All HTMT values are well below the conservative threshold of 0.85, with the highest value being 0.721 between IT and IDQ. This finding confirms that the constructs are conceptually and empirically distinct, as the shared variance between any two constructs is less than the variance they share with their own indicators. The lower correlations observed, such as between FL and IDQ (0.080) and FL and AIFR (0.108), further solidify this conclusion, indicating that these constructs are capturing unique facets of the theoretical framework without significant overlap. The establishment of strong discriminant validity is a critical prerequisite, as it validates the structural relationships that are tested in the subsequent analysis.

Figure 2
Measurement Model



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Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

Structural Model

Path analysis, t-statistic, p value, variance inflation factors, coefficient of determination, effect size, mediation and moderation analysis were used to assess the structural model. The results indicated that all VIF values were not exceeded the recommended value (3.30), which means that there was no multicollinearity. Investor trust had an R^2 value of 0.452, meaning that financial reporting using artificial intelligence, financial transparency, financial literacy, and the interaction terms accounted for 45.2% of the variance in investor trust. Likewise, the R^2 of the investment decision quality was 0.427, meaning that variance in investment decision quality could be attributed by investor trust with 42.7%.

The results of the direct path showed that the financial reporting using artificial intelligence had a positive and significant effect on the investor's trust ($\beta = 0.362$, $t = 10.247$, $p < 0.001$) to support H1. Financial transparency was also positively and significantly associated with investor trust ($\beta = 0.336$; $t = 9.093$; $p < 0.001$), which led to the acceptance of the hypothesis H2. In addition, the investment decision quality was positively and significantly influenced by investor trust ($\beta = 0.654$, $t = 23.343$, $p < 0.001$), which is in support of H3.

To verify H4, the mediation results showed that investor trust mediated the relationship between AI financial reporting and the investment decision quality ($\beta = 0.237$, $t = 9.084$, $p < 0.001$). As well, the relationship between financial transparency and investment decision quality was strongly mediated by investor trust ($\beta = 0.219$, $t = 7.856$, $p < 0.001$), which is consistent with H5. Results of the moderation analysis also revealed that financial literacy significantly moderated the relationship between AI financial reporting and investor trust ($\beta = 0.221$, $t = 5.901$, $p < 0.001$), thus supporting H6. The financial transparency-investor trust link was also strongly supported by financial literacy ($\beta = 0.092$, $t = 2.520$, $p < 0.05$), which supports H7.

In general, the overall data of the structural model supports the proposed theoretical framework well. The results indicate that AI financial reporting and financial transparency increase investor confidence, leading to better investment decisions. In addition, financial literacy strengthens investors' ability to develop trust from AI-enabled and transparent financial reporting practices.

Table 4

Coefficient of Determination and Predictive Relevance

Endogenous Construct	R^2	Adjusted R^2	Q^2	Interpretation
Investor Trust	0.452	0.446	0.429	Moderate explanatory power
Investment Decision Quality	0.427	0.426	0.420	Moderate explanatory power

Table 4 provides a crucial evaluation of the structural model's explanatory and predictive power through the coefficient of determination (R^2) and the Stone-Geisser Q^2 value. The R^2 value for Investor Trust is 0.452, indicating that the combined effects of AIFR, FT, FL, and their interaction terms account for 45.2% of its variance, which is considered a moderate-to-substantial level of explanatory power. Furthermore, Investor Trust explains 42.7% of the variance in Investment Decision Quality, underscoring the pivotal role of trust in the investment process. The predictive relevance of the model is confirmed by the Q^2 values, which are 0.429 for Investor Trust and 0.420 for Investment Decision Quality. As these values are significantly greater than zero, they demonstrate that the model has satisfactory predictive accuracy and can effectively forecast the endogenous constructs. This robust explanatory and predictive capacity affirm the theoretical framework's ability to not only account for but also anticipate key relationships within the studied context

Table 5

Hypotheses results

Hypothesis	Relationship	Effect Type	β	t-value	P-value	f^2 / VAF	Decision
H1	AIFR → Investor Trust	Direct effect	0.362	10.247	0.000	0.216	Supported
H2	Financial Transparency → Investor Trust	Direct effect	0.336	9.093	0.000	0.185	Supported

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

Hypothesis	Relationship	Effect Type	β	t-value	P-value	f² / VAF	Decision
H3	Investor Trust → Investment Decision Quality	Direct effect	0.654	23.343	0.000	0.746	Supported
H4	AIFR → Investor Trust → IDQ	Mediation effect	0.237	9.084	0.000	65.4%	Supported
H5	Financial Transparency → Investor Trust → IDQ	Mediation effect	0.219	7.856	0.000	51.8%	Supported
H6	AIFR × Financial Literacy → Investor Trust	Moderation effect	0.221	5.901	0.000	0.085	Supported
H7	Financial Transparency × Financial Literacy → Investor Trust	Moderation effect	0.092	2.520	0.012	0.013	Supported

Table 5 presents the results of the hypothesis testing, providing empirical support for the proposed structural relationships. The direct effects hypotheses (H1-H3) are all strongly supported, with AIFR and FT exhibiting significant positive influences on Investor Trust, and Investor Trust subsequently having a substantial positive impact on IDQ. The large f^2 effect size for the path between Investor Trust and IDQ (0.746) highlights the central importance of trust as a predictor of decision quality. The mediation hypotheses (H4-H5) are also confirmed, as the indirect effects of both AIFR and FT on IDQ through Investor Trust are highly significant, with the mediator accounting for 65.4% and 51.8% of the total effects, respectively. This underscores the critical mediating role of trust. Finally, the moderation hypotheses (H6-H7) are supported, indicating that Financial Literacy significantly strengthens the positive relationships between both AIFR and FT with Investor Trust. Although the f^2 effect sizes for these interactions are small (0.085 and 0.013), their statistical significance demonstrates that investors with higher financial literacy are better equipped to translate AI-driven and transparent reporting into greater trust.

5. Discussion

The results of this study lend robust support to the suggested framework by demonstrating that using AI financial reporting tools and financial transparency boosts investors' trust, thereby resulting in better investment decision quality. As AI-driven financial reporting is increasingly associated with trust, it is likely that investors will have greater confidence in financial information if they believe it is accurate, timely, reliable, and backed by cutting-edge technology. This result corroborates Signalling Theory that suggests that the market participants are less uncertain when they receive high-quality information signals (Spence, 1973). From a financial report perspective, AI-powered systems can enhance the accuracy, consistency, timeliness, and predictive power of reports, thereby boosting investor confidence in the information provided in the reports (Gomber et al., 2024; Cao et al., 2024; Stratopoulos & Wang, 2025).

The role of financial transparency in investor trust is also significant, further reinforcing the need for transparency, completeness and ease of understanding in minimizing information asymmetry. The finding is consistent with the theory of Information Asymmetry, which holds that clear reporting reduces the information gap, and enhances investor confidence in corporate reporting (Akerlof, 1970; Chen et al., 2024). The discovery is also consistent with previous research where transparency boosts investor confidence because it makes information more accessible, and managerial opportunism less perceived (Nguyen & Dang, 2024; Alkaraan et al., 2025).

The results also indicate that investor trust has a positive significant impact on the quality of investment decisions. This means that financial information is more likely to be trusted by investors, which allows them to make more rational investment decisions, eliminate the uncertainty they feel when evaluating investment alternatives, and reduce the reliance on other information sources. This result aligns with the previous behavioural finance studies, which suggest that trust is a pivotal factor in influencing financial judgements and investment decisions (Nguyen & Dang, 2024; Luo et al., 2024). The mediation results also indicate that investor trust is an important mechanism that can explain how AI-driven financial reporting and financial transparency affects the quality of investment decisions. So, by using advanced reporting technologies and transparent disclosure practice, the investment outcome is improved primarily by fostering investor confidence and trust.

Lastly, financial literacy plays a significant moderating role in the links between AI's financial reporting capabilities, financial transparency, and investor confidence. This means that people with high financial acumen can better comprehend financial disclosures generated by artificial intelligence and scrutinize the clear financial details. Financial Literacy Theory states that people who are more knowledgeable about finance can process complex financial information more effectively and apply it to improving their decision-making (Lusardi & Mitchell, 2023; OECD, 2023; Morgan et al., 2024). Therefore, the study concludes that the use of technology and transparency will be more effective if the investors are financially literate.

Theoretical Implications

The current study builds on Signalling Theory by demonstrating that, AI-enabled financial reporting and financial transparency act as a credible piece of information signals and promote investor trust (Spence, 1973; Gomber et al., 2024). It also adds to the Information Asymmetry Theory, which testifies that clear and tech-based disclosures lower the uncertainty in making decisions about investing (Akerlof, 1970; Chen et al., 2024). Furthermore, the study contributes to the field of trust-based financial decision literature by introducing "trust" as a mediation variable between the two variables of reporting quality and investment decision quality (Nguyen & Dang, 2024; Luo et al., 2024). In the context of reporting with AI (Lusardi & Mitchell, 2023), the moderating effect of financial literacy continues the expansion of Financial Literacy Theory.

Practical Implications

The results indicate that companies should implement AI-based financial reporting systems to enhance the quality of financial information, including its timeliness, reliability and accuracy. These systems can contribute to enhancing investor trust in corporate reporting (Cao et al., 2024; Stratopoulos & Wang, 2025). In addition, regulators should incentivize firms to enhance financial transparency, as transparent and thorough disclosures can help lower information asymmetry and boost investor confidence (Chen et al., 2024; Alkaraan et al., 2025). Further, investor education programs should be encouraged to enhance financial literacy, which will help investors better understand the AI-generated and transparent financial information (Lusardi & Mitchell 2023; OECD 2023).

Managerial Implications

Financial reporting should be a strategic, trust building tool, not just a regulatory obligation. AI-powered reporting can increase the efficiency of reporting, minimize reporting inaccuracies, and boost the trust in financial reports (Gomber et al., 2024; Cao et al., 2024). Furthermore, managers need to be transparent, understandable, and investor-friendly with financial information, as transparency fosters investor trust and confidence in the management (Nguyen & Dang, 2024; Alkaraan et al., 2025). In addition, companies can promote investor awareness initiatives, streamline the format of reports, and digitalize financial communication to enable investors to better understand financial information (Lusardi & Mitchell, 2023).

6. Limitations and Recommendations

This study has several limitations. One of the limitations of the cross-sectional design is that it does not allow for the analysis of changes in investor trust and decision quality over time. Longitudinal designs can be used in future studies to document the dynamic effects of the adoption of AI on financial reporting (Hair et al., 2024). Second, the study is limited to individual investors in Pakistan and might not be generalizable to institutional investors or other emerging markets. Comparative analyses of various economies could be carried out in the future. Third, it is possible to have self-report bias with survey-based data. In future, future studies can integrate responses to questions with actual investment behaviour or trading performance data.

7. Conclusion

The findings of this study show that the use of AI in financial reporting and financial transparency has a positive impact on the trust of investors and consequently on the quality of investment decisions. The results validate the Signalling Theory and Information Asymmetry Theory, as credible, transparent, and technology-based disclosures mitigate uncertainty and enhance investors' confidence (Spence, 1973; Akerlof, 1970; Chen et al., 2024). Investor trust is an important mediating factor, and financial literacy enhances the impact of reporting and transparency on trust through AI (Lusardi & Mitchell, 2023; OECD, 2023). The overall conclusions of the study highlight the need for reporting, transparency, and investor education in Pakistan's capital market in the era of AI.

Acknowledgments

The authors would like to thank the participants and the respective universities for their support and cooperation in conducting this study.

Contribution of Authors

All the authors participated in the ideation, development, and final approval of the manuscript, making significant contributions to the work reported.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Funding Statement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Informed Consent

Informed consent was obtained from all individual participants included in the study.

Ethical Approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of 1964 Helsinki declaration and its later amendments.

Data Availability

The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

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