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Algorithmic Transparency and Trust in AI-Enabled FinTech: An Integrated Model of Investment Decision-Making

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Abstract
The swift expansion of financial technology (FinTech) has transformed investment methods. Ordinary investors can now utilise digital investing platforms powered by artificial intelligence (AI). Despite this, there is a lack of study regarding the impact of algorithmic openness and trust in AI on investment decisions. This study examined the effects of 'Digital Financial Literacy (DFL)', 'Government Support (GS)', 'Perceived Risk (PR)', and 'Perceived Algorithmic Transparency (PAT)' on 'FinTech Trust (FT)', and subsequently the effects of FT on 'Attitude (ATT)' and Investment Decision-making (IDM). The study examined the moderating effect of AI advisory trust (AIT) on the connection among attitude and investment decision-making. The research employed a quantitative design, collecting data from 425 retail investors utilising FinTech investment platforms in India. The suggested model was analysed utilising SmartPLS 4 through Partial Least Squares Structural Equation Modelling (PLS-SEM). Findings demonstrate that digital financial literacy, governmental support, and perceived algorithmic transparency positively influence FinTech confidence, whereas perceived risk has a significant negative effect. Perceived algorithmic transparency was the most powerful indicator of FinTech trust. Moreover, FinTech trust significantly and positively affects the attitude of investors. AI advising serves as a mediator and reinforces the advantageous correlation between mindset and financial decision-making. This research enhances the Theory of Planned Behaviour by incorporating trust and explainable artificial intelligence. The research has practical ramifications for the development of transparent, reliable, and investor-focused FinTech systems.

Keywords: AI Advisory Trust, Digital financial literacy, FinTech, Government Support, Perceived algorithmic transparency, Retail investors.

1. Introduction

The swift advancement of financial technology (FinTech) has transformed the investment environment by providing individual investors access to financial markets via digital platforms that deliver efficient, cost-effective, and user-friendly investment services. The democratization of investing has been driven by the incorporation of 'artificial intelligence (AI), big data analytics, and mobile technologies' into investment processes by platforms such as Groww, Zerodha, Upstox, INDmoney, and others that have made retail investors' access to capital markets easier than ever before (Lee & Shin, 2018; Gomber et al., 2018; Challa, 2025). The proliferation of smartphones, inexpensive internet access, and government initiatives such as 'Digital India and Unified Payments Interface (UPI)' in India have expedited the adoption of digital investment platforms, especially among first-time and young investors (Gandhi & Kak, 2025).

However, the investment decision-making process in FinTech contexts is still complex and influenced by cognitive, technological, institutional and psychological aspects, despite the great developments in technology. Digital Financial Literacy (DFL) is a crucial competency for investors to comprehend digital financial products, assess investment prospects, and effectively use FinTech applications (Lusardi & Mitchell, 2014; Morgan et al., 2019; Mishra et al., 2024). Similarly, the laws and regulatory frameworks that enable secure digital financial ecosystems enhance investor confidence. In contrast, supplementary obstacles for investors utilising FinTech platforms may include perceived risks concerning money loss, cybersecurity, and privacy concerns.

Alongside these primary factors, additional difficulties of transparency and trust develop with the advent of AI-driven recommendation systems along with algorithmic investment tools. Investors frequently receive tailored investment recommendations, fund rankings, and portfolio alternatives, often lacking understanding of the methodology behind these proposals. This highlights the significance of Perceived Algorithmic Transparency (PAT) – the degree to which investors recognise a FinTech platform's clarity in disclosing the reasoning, criteria, and processes underlying its algorithmic recommendations (Shin, 2021). The transparency of algorithms minimizes uncertainty and boosts consumer confidence, improving trust in digital financial platforms (Rai, 2020). Therefore, FinTech Trust is an important channel via which technology and institutional factors impact investor behaviour.

Investor attitude is a significant driver of behavioural outcomes, according on the Theory of Planned Behaviour (Ajzen, 1991). But in AI-enabled financial contexts, a positive sentiment may not translate into actual investment decisions. AI Advisory Trust thus becomes a key contextual issue as investors increasingly rely on AI-assisted suggestions. Individuals who trust AI-based investment recommendations are more likely to convert positive views into actual investment decisions than those who continue to be suspicious of AI-based recommendations (Glikson & Woolley, 2020; Belanche et al., 2022). Therefore, AI Advisory Trust can enhance the connection between attitude and investment decision-making.

Previous research have examined the influence of financial literacy, perceived risk, and trust on FinTech adoption; nevertheless, significant gaps remain in the literature. One, Despite the rising use of AI-powered decision-support systems, Perceived Algorithmic Transparency has not been much studied empirically in the FinTech investment research. Second, whereas earlier studies have mostly studied trust as a direct predictor, less work has explored trust as a process linking cognitive, institutional and technological aspects to investing behaviour. Third, the moderator role of AI Advisory Trust in the investor attitude and investment decision-making relationship remains underexplored. Finally, most of the previous research are based on developed economies with minimal evidence from emerging economies such as India where digital financial inclusion and AI-enabled investment platforms are growing at a rapid pace.

Accordingly, this study addresses the following research questions:

(RQ1) How do Digital financial literacy, Government support, Perceived risk, and Perceived algorithmic transparency influence FinTech trust?

(RQ2) Does FinTech trust positively influence investors' attitudes toward FinTech platforms? (RQ3) How does attitude influence investment decision-making?

(RQ4) Does AI Advisory Trust strengthen the relationship between attitude and investment decision-making?

Thus, this study intends to accomplish four objectives in order to address these questions: (1) to investigate the impact of 'Digital Financial Literacy, Government Support, Perceived Risk, and Perceived Algorithmic Transparency on FinTech Trust'; (2) to determine how FinTech Trust affects investors' attitudes; (3) to find out how attitude affects investment decision-making; and (4) to find out how AI Advisory Trust moderates the relationship among attitude and decision-making regarding investments

Three significant contributions to the literature are made by the study. To begin with, it adds elements to the Theory of Planned Behaviour that pertain to the investment decision-making process, such as Perceived Algorithmic Transparency and FinTech Trust. To further understand how investors' faith in AI-powered financial advice influences their actions, it incorporates AI Advisory Trust as a moderator. The study concludes with actual evidence from a developing nation by focusing on the dynamic Indian FinTech industry, where retail investors are being more influenced by AI-powered investing platforms. Researchers expect the results to add to the existing body of knowledge in the field while also providing policymakers and FinTech companies with actionable advice on how to increase transparency, foster confidence among investors, and promote ethical use of artificial intelligence.

2. Literature review and hypothesis development

The proliferation and development of FinTech, integrating digital platforms and artificial intelligence (AI) and algorithm-based decision support tools into financial services, have transformed the retail investing scene. Although the causes of FinTech adoption have been researched as financial literacy, perceived risk and trust, there are few studies on the impact of explainable AI and algorithmic transparency on investor trust and investment behaviour. This work builds on the Theory of Planned Behaviour (TPB) (Ajzen, 1991), Trust Theory and the expanding literature on Explainable Artificial Intelligence (XAI) to propose FinTech Trust as a mediating mechanism and AI Advisory Trust as a contextual moderator.

2.1. Digital Financial Literacy and FinTech Trust

'Digital Financial Literacy (DFL)' is the ability of an individual to comprehend and utilise digital financial products and services efficiently. Investors with high digital literacy are more likely to check financial data on the Internet, identify investment opportunities and detect fraud and so reduce the uncertainty of using FinTech platforms (Lusardi & Mitchell, 2014; Morgan et al., 2019). Enhanced digital financial literacy cultivates trust in digital financial environments and engenders faith in technology-driven investing platforms. Recent data indicates that digital financial literacy is crucial for boosting confidence in FinTech platforms by reducing uncertainty and improving consumers' capacity to assess digital financial products (Gomber et al., 2018; Morgan et al., 2019; Banna et al., 2024; Nguyen et al., 2023). Hence the hypothesis is as follows

H1: Digital financial literacy (DFL) positively influences FinTech trust (FT).

2.2. Government Support and FinTech Trust

Government policies are important for facilitating digital financial inclusion by increasing regulatory frameworks, consumer protection, cybersecurity and digital infrastructure. Supportive policies decrease ambiguity and strengthen the legitimacy of FinTech platforms so fostering investor trust. Regulatory assurance affects technology adoption in emerging nations. Institutional support has always been related with increased trust in digital financial services (Lee & Shin, 2018). Recent studies revealed that regulatory quality, government-supported digital infrastructure, and consumer protection policies are crucial factors in enhancing public trust in digital financial ecosystems, especially in emerging economies where institutional support plays a vital role in FinTech adoption (Al Nawayseh, 2024; Dwivedi et al., 2023). Hence the hypothesis

H2: Government support (GS) positively influences FinTech trust (FT)

2.3. Perceived Risk and FinTech Trust

Perceived risk is still one of the biggest hurdles to the adoption of digital investment. Investors are typically concerned about financial, privacy, security and operational concerns while adopting FinTech services. High levels of perceived risk lower confidence in digital platforms and discourage investment activities. Existing research has continuously documented a negative association between perceived risk and trust in online financial services (Gefen et al., 2003; Rahi et al., 2021). While FinTech platforms are convenient and accessible, investors are nonetheless concerned about financial, cybersecurity, privacy and algorithmic risks. Recent empirical research continues to indicate that perceived risk considerably erodes trust and decreases the desire of investors to participate in digital financial services (Rahi et al., 2021; Singh et al., 2023). Hence, the hypothesis is as follows

H3: Perceived Risk negatively influences FinTech trust.

2.4. Perceived Algorithmic Transparency and FinTech Trust

Perceived Algorithmic Transparency (PAT) relates to investors' view of the transparency of digital platforms in providing explanations on the generation of investment recommendations, rankings, and risk assessments (Shin, 2021). PAT has become a crucial component of investor trust with the rise of AI-driven investment platforms offering tailored suggestions and automated financial guidance. Transparent algorithms give investors insight into the reasoning behind recommendations, eliminating the uncertainty that comes with black-box decision-making. Recent study on Explainable AI (XAI) shows that transparency has a vital role in encouraging user trust, acceptance and uptake of AI-enabled financial services (Shin, 2021; Haque et al., 2022; Yeo et al., 2023). Furthermore, explainable AI is gaining attention as a vital part of trustworthy financial AI systems as well as regulatory compliance. Thus, the hypothesis is as follows

H4: Perceived algorithmic transparency (PAT) has a positive effect on FinTech trust (FT).

2.5. FinTech Trust and Attitude

Trust is a key antecedent to positive sentiments towards digital financial technologies. According to Trust Theory, users who consider the FinTech platforms to be trustworthy, safe, and capable build positive assessments of the FinTech platforms. In FinTech (financial technology) environments, trust decreases uncertainty and promotes the

user acceptance of digital investment services (McKnight et al., 2002). Trust is one of the strongest predictors of positive opinions about digital financial technologies. Recent FinTech research confirms that users' opinions and continuing usage intentions are positively affected by perceived platform reliability, security and transparency (Shaikh et al., 2023; Glikson & Woolley, 2020).
H5: FinTech Trust (FT) positively influences investors' attitudes toward FinTech investment platforms (ATT)

2.6. Attitude and Investment Decision-Making
Attitude is a strong predictor of behavioural outcomes in the Theory of Planned Behaviour (Ajzen, 1991). Investors with a positive perception of FinTech platforms are more inclined to engage in digital investment activities. Numerous research have validated the strong influence of positive attitudes on the investment intentions and investment behaviour in the setting of digital finance (Venkatesh et al., 2003; Glikson & Woolley, 2020). Recent research in the field of AI-assisted financial decision-making has shown that positive attitudes towards digital investment platforms play a significant role in investment behaviour, especially when investors find digital technologies useful, trustworthy and reliable (Agarwal et al., 2024; Venkatesh et al., 2022). Therefore, the hypothesis is
H6: Attitude towards FinTech investment platforms (ATT) positively influences Investment Decision-Making (IDM).

2.7. Moderating Role of AI Advisory Trust (AIT)
AI-powered investment platforms are offering portfolio suggestions, risk assessments, and personalized financial advice. But there is a split among investors on how much they trust AI-generated advice. AIT is the degree to which investors feel AI-based financial advice is trustworthy, accurate and advantageous. According to the research on explainable AI, trust in AI decreases perceived ambiguity and increases confidence in automated decision-making, which in turn increases users' acceptance of algorithmic suggestions (Shin, 2021). Also, transparent AI explanations result in higher trust and acceptance of algorithmic financial advisors, which is supported by experimental evidence. As such, it is anticipated that investors with higher AIT will be more efficient than investors with lesser confidence in AI in terms of converting positive attitudes into actual investing decisions.
H7: AI Advisory Trust (AIT) positively moderates the relationship between Attitude (ATT) and Investment Decision-Making (IDM)

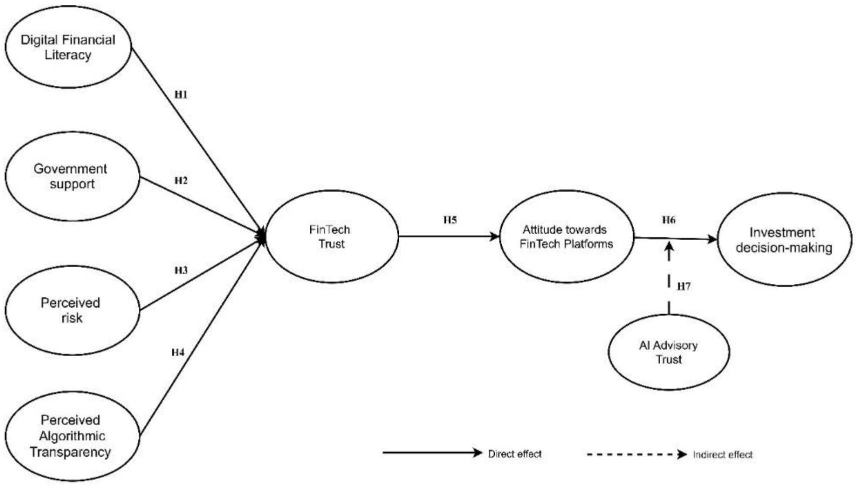

Figure 1. Research Model

3. Methodology
Analysing the factors that impact investment decision-making with FinTech users in India is the purpose of the present study, which is a combination of quantitative as well as cross-sectional research design. The conceptual model that has been provided may be tested using a quantitative method, and structural equation modelling can be used to study the causal relationships that exist between latent constructs (Creswell & Creswell, 2023). The

positivist research paradigm, which enables the testing of hypotheses via the examination of empirical data, serves as the foundation for this academic investigation.

Individual retail investors who are actively engaged in investment-related activities on FinTech investing platforms like as Groww, Zerodha, Upstox, INDmoney, and ET Money are the target demographic for this product. A method of intentional sampling will be used in order to guarantee that the individuals who are participating in the survey have prior experience working with investing programs that are based on FinTech. The data will be collected by a structured online questionnaire utilising a five-point Likert scale, ranging from strong disagreement to strong agreement. According to the 10-times rule and the latest guidelines on PLS-SEM, a minimum sample size of 425 valid responses is necessary to achieve sufficient statistical power and accurate parameter estimation (Hair et al., 2022; Kock & Hadaya, 2018).

To ensure the content validity and reliability of the questionnaire, it incorporates measurement scales that have been validated and adapted from prior research. Before the primary survey, a pilot study will be executed with approximately thirty participants to assess the instrument's clarity, reliability, and internal consistency. Utilising SmartPLS 4, we will do a data analysis employing the two-stage approach provided by Hair et al. (2022). The measurement model will be evaluated based on indicator reliability, internal consistency reliability (Cronbach's alpha and Composite Reliability), convergent validity (Average Variance Extracted), discriminant validity (HTMT criteria), and multicollinearity (Variance Inflation Factor) (Hair et al., 2022). The structural model will be assessed using bootstrapping with 5,000 resamples, focusing on path coefficients, the coefficient of determination (R2), effect size (f2), predictive relevance (Q2), and significance testing of direct, indirect (mediation), and moderating effects. These assessments will be conducted to ascertain the model's significance (Hair et al., 2022). PLS-SEM is especially advantageous as it accommodates complex research models, predictive objectives, and non-normally distributed data while simultaneously assessing multiple correlations across latent domains (Hair et al., 2022).

3.1. Demographic Profile

Out of the 425 respondents, men made up 60.7% of the total and women 37.9%, suggesting that males were more likely to invest in FinTech. Investors who are young and tech-savvy are prevalent, as 41.4% of respondents were in the 26-35 age bracket and 27.8% were in the 18-25 age bracket. The majority of respondents (52.0%) had a postgraduate degree, indicating a relatively well-educated group. The largest occupational category was private sector employees (40.7%) and 29.6% reported monthly income between ₹25,001 and ₹50,000. Experience of investment, 37.4% have been investing through FinTech platforms for 1-3 years. Groww was the most popular investment platform (40.2%) followed by Zerodha (27.8%). Mutual Funds (36.0%) and Equities (28.5%) were the most preferred investment tools, suggesting that respondents were mostly using FinTech applications for long-term wealth accumulation and equity investments. The demographic profile is summarized in the Table 1.

Table 1. Summary of the Demographic Profile

Demographic Variable	Category	Frequency	Percentage
Gender	Male	258	60.7
	Female	161	37.9
	Prefer not to say	6	1.4
Age (in Years)	18–25 Years	118	27.8
	26–35 Years	176	41.4
	36–45 Years	82	19.3
	46–55 Years	35	8.2
	Above 55 Years	14	3.3
Educational Qualification	Undergraduate	86	20.2
	Postgraduate	221	52.0
	Professional Degree	79	18.6
	Doctoral Degree	39	9.2
Occupation	Private Sector Employee	173	40.7

	Government Employee	56	13.2
	Business/Self-employed	84	19.8
	Student	71	16.7
	Others	41	9.6
Monthly Income (₹)	Below 25,000	73	17.2
	25,001–50,000	126	29.6
	50,001–75,000	98	23.1
	75,001–100,000	67	15.8
	Above 100,000	61	14.3
Investment Experience	Less than 1 year	72	16.9
	1–3 years	159	37.4
	3–5 years	109	25.6
	More than 5 years	85	20.0
Preferred FinTech Platform	Groww	171	40.2
	Zerodha	118	27.8
	Upstox	61	14.4
	INDmoney	42	9.9
	ET Money	18	4.2
	Others	15	3.5
Primary Investment Instrument	Mutual Funds	153	36.0
	Equities	121	28.5
	Exchange-Traded Funds (ETFs)	43	10.1
	Gold/Digital Gold	38	8.9
	Fixed Income/Bonds	29	6.8
	Cryptocurrency	19	4.5
	Others	22	5.2

Source: Researchers own compilation

4. Data Analysis and Result

4.1. Structural Equation Modelling (PLS-SEM)

The suggested theoretical framework was examined using the use of SmartPLS 4's PLS-SEM. Prediction-oriented studies with complex models involving several latent variables and mediation/moderation effects are well-suited to PLS-SEM (Hair et al., 2022). This study was able to analyse responses from 425 FinTech investors since PLS-SEM does not depend on multivariate normality and is resilient with moderate sample sizes (Hair et al., 2022). The two-stage analytical approach was used to verify the measurement model's validity and reliability before evaluating the structural linkages between the constructs.

Measurement Model

In accordance with the guidelines of Hair et al. (2022), the reliability and validity of the measurement model were evaluated. To assess the reliability of the indicators, factor loading was employed, with all indicators exceeding the required threshold of 0.70. Internal consistency reliability was assessed using Cronbach's Alpha (CA) and Composite Reliability (CR). A value exceeding 0.70 signifies strong internal consistency (Hair et al., 2022). Convergent validity was evaluated by Average Variance Extracted (AVE). All constructs exhibited AVE values exceeding 0.50, signifying that each construct accounted for more than half of the variance of its indicators (Fornell & Larcker, 1981).

Table 2. Reliability and Validity

Construct	Items	Cronbach's Alpha	Composite Reliability	AVE
Digital Financial Literacy (DFL)	4	0.921	0.944	0.808
Government Support (GS)	3	0.903	0.931	0.772
Perceived Risk (PR)	3	0.889	0.923	0.751

Perceived Algorithmic Transparency (PAT)	3	0.936	0.951	0.796
FinTech Trust (FT)	3	0.942	0.956	0.812
Attitude (ATT)	3	0.930	0.947	0.817
AI Advisory Trust (AIT)	3	0.914	0.939	0.793
Investment Decision Making (IDM)	3	0.918	0.942	0.801

Source: Researchers own compilation

4.2. Discriminant Validity

Discriminant validity was assessed using the Heterotrait–Monotrait Ratio (HTMT) and the Fornell–Larcker criterion, as advised by Henseler et al. (2015) and Hair et al. (2022). HTMT values below 0.85 indicate satisfactory discriminant validity. HTMT values below 0.90 are permissible for semantically related constructs. Table 3 illustrates that the HTMT values varied from 0.318 to 0.842, remaining below the recommended threshold. The results indicate that all concepts are empirically different and suitable for the subsequent phase of structural model analysis.

Table 3. Discriminant Validity (Heterotrait-monotrait ratio (HTMT) - Matrix)

Construct	ATT	PR	FT	IDM	DFL	GS	PAT	AIT
ATT								
PR	0.481							
FT	0.842	0.548						
IDM	0.776	0.391	0.798					
DFL	0.641	0.468	0.724	0.612				
GS	0.586	0.537	0.676	0.564	0.518			
PAT	0.688	0.431	0.816	0.658	0.679	0.593		
AIT	0.728	0.318	0.697	0.792	0.557	0.478	0.643	

Source: Researchers own compilation

4.3. Structural model

The structural model was evaluated utilising PLS-SEM in SmartPLS 4 to assess the proposed relationships among the constructs. The structural model was further evaluated for collinearity, coefficient of determination (R2), effect size (f2), and the relevance of the proposed relationships by a bootstrapping approach including 5,000 resamples (Hair et al., 2022). The path coefficients, t-values, and p-values were utilised to assess the relevance and robustness of the proposed hypotheses.

4.4. Collinearity statistics (VIF)

The Variance Inflation Factor (VIF) was employed to evaluate multicollinearity among predictor components prior to analysing the structural relationships. Hair et al. (2022) said that a VIF score below 5.0 indicates the absence of multicollinearity. The VIF values in this investigation varied from 1.284 to 2.746, much beneath the necessary threshold, indicating that multicollinearity is not a concern and the structural model is suitable for hypothesis testing. The coefficient of determination (R^2) was employed to evaluate the explanatory capacity of the endogenous constructs. The results indicate that the proposed model explains 69.1% of the variance in FinTech Trust, 78.2% of the variance in Attitude, and 74.1% of the variance in Investment Decision Making. The adjusted R^2 values closely resemble the corresponding R^2 values, signifying robust model stability and substantial explanatory power.

Table 4. R Square

Construct	R^2	Adjusted R^2
FinTech Trust (FT)	0.691	0.688
Attitude (ATT)	0.782	0.779
Investment Decision Making (IDM)	0.741	0.738

Source: Researchers own compilation

The effect size (f2) was utilised to examine the significance of each indicator to the endogenous constructs. Cohen (1988) proposed that impact sizes of 0.02, 0.15, and 0.35 represent mild, medium, and large effects, respectively. The results show that Perceived Algorithmic Transparency has the largest impact on FinTech Trust (f2 = 0.382) and FinTech Trust has a considerable impact on Attitude (f2 = 0.694). Similarly, Attitude has a strong effect on Investment Decision Making ($f^2 = 0.521$). Digital Financial Literacy and Perceived Risk have medium effects on FinTech Trust. The effects of Government Support and the moderating effect of AI Advisory Trust are relatively small but important.

4.5. Hypothesis testing

The presented hypotheses were examined through a bootstrapping approach including 5,000 resamples utilising SmartPLS 4. Standardised path coefficients (β), standard deviations (SD), t-values, and p-values were employed to evaluate the significance of the structural correlations. The hypothesis was validated if the t-value exceeded 1.96 and the p-value was less than 0.05 (Hair et al., 2022). The Direct Effects are presented in Table 5. The findings indicate that all six direct hypotheses are statistically significant ($p < 0.001$). Perceived Algorithmic Transparency ($\beta = 0.429$, $t = 9.750$) exhibits the most significant positive influence on FinTech confidence, emphasising the critical role of transparent algorithmic decision-making in enhancing investor trust. Perceived Risk adversely impacts FinTech Trust ($\beta = -0.214$, $t = 5.944$). A greater perceived risk correlates with diminished investor trust in FinTech platforms. FinTech Trust had a substantial positive influence on Attitude (β=0.884). Attitude exerts a positive and substantial influence on Investment Decision Making (β=0.731). The results offer empirical support for the proposed conceptual framework and underscore the significance of trust and attitudes in elucidating the investing decision-making processes of FinTech users.

Table 5. Direct effects result

Hypothesis	Relationship	β	SD	t-value	p-value	Decision
H1	DFL → FT	0.268	0.041	6.537	<0.001	Supported
H2	GS → FT	0.181	0.038	4.763	<0.001	Supported
H3	PR → FT	-0.214	0.036	5.944	<0.001	Supported
H4	PAT → FT	0.429	0.044	9.750	<0.001	Supported
H5	FT → ATT	0.884	0.021	42.095	<0.001	Supported
H6	ATT→ IDM	0.731	0.037	19.757	<0.001	Supported

Source: Researchers own compilation

4.6. Moderating effect analysis

The bootstrapping method in SmartPLS 4 was employed to examine the moderating effect of AI Advisory Trust (AIT) on the relationship between Attitude (ATT) and Investment Decision Making (IDM). The interaction term (ATT × AIT) was created by a two-stage approach, and its significance was evaluated using standardised path coefficients (β), standard deviation (SD), t-values, and p-values.

The results indicate that the interaction effect of Attitude and AI Advisory Trust is positive and statistically significant ($\beta = 0.137$, $t = 3.341$, $p = 0.001$). Consequently, H7 is affirmed. This research indicates that AI Advisory Trust strengthens the positive relationship between Attitude and Investment Decision Making. Investors possessing elevated AI Advisory Trust are more inclined to convert favourable views of FinTech platforms into tangible investment decisions compared to those with diminished AI Advisory Trust.

Table 6. Moderating effect results

Hypothesis	Moderating Relationship	β	SD	t-value	p-value	Decision
H7	AIT × ATT → IDM	0.137	0.041	3.341	0.001	Supported

Source: Researchers own compilation

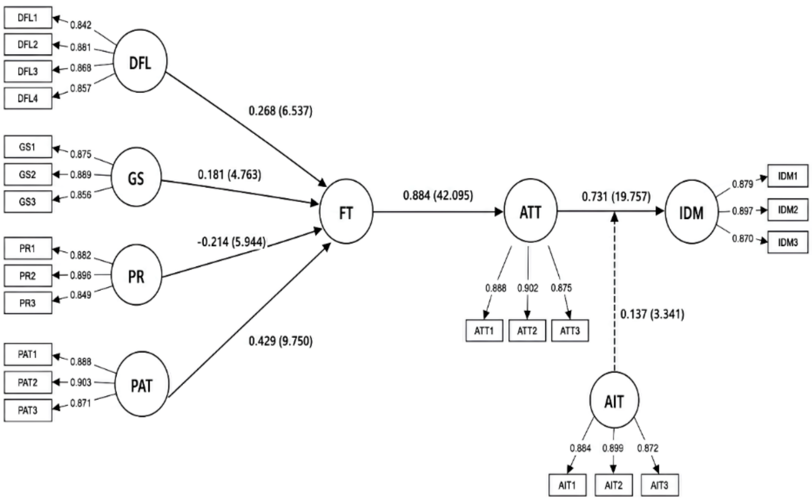

Figure 2. Structural model

5. Discussion

The findings indicate that Digital Financial Literacy (DFL) significantly and positively influences FinTech Trust ($\beta = 0.268$, $t = 6.537$, $p < 0.001$). This indicates that investors with advanced digital financial literacy are more likely to trust FinTech investment platforms, since they have the requisite knowledge and skills to effectively assess digital financial products and services. The discovery aligns with previous studies indicating that individuals with digital literacy exhibit greater confidence in utilising digital financial services and possess enhanced capabilities to assess the credibility of online investment platforms (Lusardi & Mitchell, 2014; Morgan et al., 2019; Nguyen et al., 2023). This study's results highlight the significance of digital financial literacy in fostering investor confidence across all artificial intelligence financial ecosystems.

The results show that Government Support (GS) has a positive effect on FinTech Trust ($\beta = 0.181$, $t = 4.763$, $p < 0.001$). The positive relationship between the two variables shows that positive government policies, regulatory institutions and investor protection measures build trust in FinTech platforms. This is compatible with institutional theory, which states that clear regulation lowers ambiguity and facilitates the acceptance of technical advances. The findings are in line with recent research that emphasizes the role of government actions in building trust and boosting the use of digital financial services (Lee & Shin, 2018; Al Nawayseh, 2024).

As expected, Perceived Risk (PR) has a substantial negative effect on FinTech Trust ($\beta = -0.214$, $t = 5.944$, $p < 0.001$). The research implies that concerns about financial loss, cybersecurity, privacy and transaction security limit investors' trust in FinTech platforms. The finding corroborates the previous studies which have shown that perceived risk continues to be a major challenge to the adoption of digital financial services (Gefen et al., 2003; Rahi et al., 2021; Singh et al., 2023). Thus, it is important to mitigate perceived risk through better security measures and transparent communication to build investor trust.

The data shows that Perceived Algorithmic Transparency (PAT) has the most beneficial effect on FinTech Trust ($\beta = 0.429$, $t = 9.750$, $p < 0.001$). The result suggests that investors are more likely to trust FinTech platforms when they can clearly see how the investment recommendations, rankings and risk assessments are formed. This result is in line with the ideas of Explainable Artificial Intelligence (XAI) which states that transparent AI systems contribute to increased user confidence and adoption by eliminating uncertainty in the decision-making of algorithms (Rai, 2020; Shin, 2021; Yeo et al., 2023). The importance of this link underscores the importance of algorithmic openness as a key component for trust in AI-based investment platforms.

The results show a significant positive link between FinTech Trust and Attitude ($\beta = 0.884$, $t = 42.095$, $p < 0.001$). This indicates that investors who consider FinTech platforms to be reliable, secure and trustworthy have more positive attitudes towards the use of these platforms for investing objectives. This finding is in line with Trust Theory and other studies which have found that trust has a major effect on users' attitudes towards digital financial systems (McKnight et al., 2002; Shaikh et al., 2023). The large effect size is also in support of the theory on the relevance of trust as a key psychological determinant in shaping favourable investor views.

The results show the positive and statistically significant effect of Attitude on Investment Decision Making (β = 0.731, t = 19.757, $p < 0.001$). From the above study, it can be assumed that good attitude of the investors towards FinTech platforms, the investors are more inclined to invest through those platforms. It is consistent with the Theory of Planned Behaviour (Ajzen, 1991) where attitude has been discovered as an important characteristic to predict behavioural intention.

The results of the moderating study indicate that AI Advisory Trust moderates the relationship between Attitude and Investment Decision Making (β = 0.137, t = 3.341, p = 0.001). It can be observed that investors that trust more in the recommendations of the AI regarding their investments will be able to translate positive emotions into action and make decisions related to the investments. At the same time, investors that do not trust AI advising systems can be scared even if they have a positive attitude towards FinTech platforms. These results are consistent with the current research in Explainable AI and human-AI trust, which states that when there is more trust in the recommendations of AI, there is more user acceptance and behavioral intention (Glikson & Woolley, 2020; Shin, 2021).

These results provide sufficient empirical evidence for the proposed conceptual model. From among the antecedent variables, it is observed that Perceived Algorithmic Transparency played an important part as the highest predictor of FinTech Trust, which brings forward the significance of explainability in AI for the digital era. FinTech Trust, in turn, had a substantial impact on the attitude of the investors and consequently played an important role in the decision of the investors. The high level of the moderating role of AI Advisory Trust indicates the rising need for trust in AI-based financial advisory system. These results are an extension of the Theory of Planned Behaviour, and thus provide a comprehensive understanding of the investor's decision making.

6. Conclusion

The study explored the factors influencing the process of investment decision-making in FinTech. Digital Financial Literacy, Government Support, Perceived Risk, Perceived Algorithmic Transparency, FinTech Trust, Attitude and AI Advisory Trust were some of the antecedent constructs in the proposed theoretical framework of the study. As per the findings based on the PLS-SEM analysis, FinTech Trust is positively affected by Digital Financial Literacy, Government Support, and Perceived Algorithmic Transparency but negatively impacted by Perceived Risk. Of all the mentioned factors influencing FinTech Trust, Perceived Algorithmic Transparency had the greatest impact. Moreover, FinTech Trust plays an important role in influencing the mindset of investors leading to effective investment decision-making. Besides, it was also confirmed that AI Advisory Trust has a moderating influence on the relationship between Attitude and Investment Decision-Making.

This research enriches the FinTech research stream by introducing Algorithmic Transparency and AI Advisory Trust in the Theory of Planned Behaviour and hence offering novel information on investment behavior in artificial intelligence-supported finance. As such, the conclusions drawn from this research suggest that FinTech companies need to enhance algorithm transparency, platform security, and digital financial literacy programs in order to encourage informed investment decision-making.

Limitations

This research has some drawbacks. The cross-sectional design restricts the ability to draw causal inferences. The second limitation of the study is its concentration on retail investors in India, thereby constraining the generalisability of the findings. The utilisation of self-reported data may lead to common method bias. Conclusion The established paradigm excludes additional components such as financial resilience, algorithmic justice, and AI literacy.

Future Research

Future research could employ longitudinal or cross-country methods for increased generalizability and investigation of changes in the behavior of investors over time. Furthermore, researchers could apply the proposed framework to the emerging factors like algorithmic justice, artificial intelligence literacy, financial well-being, digital privacy issues, and cyber resilience. Also, studying multiple categories of investors by considering their demographic characteristics and/or levels of experience in the field of investments would provide further information regarding differences between behaviors of different types of investors with respect to FinTech investments.

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