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**BEHAVIOURAL FINANCE BIASES AND SUSTAINABLE INVESTMENT
DECISIONS: THE MEDIATING ROLE OF RISK PERCEPTION AND
THE MODERATING ROLE OF DIGITAL TRUST**

Renu ^{1*}, Nirmala K¹

¹Department of Commerce, Bangalore University, Karnataka, India.

Corresponding author email address: renushkasoni@gmail.com

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Abstract

This study examines how behavioral biases influence sustainable investment decisions. Using survey data and Structural Equation Modeling (SEM) in SmartPLS, findings show that overconfidence, herding, loss aversion, and anchoring significantly affect sustainable investment behavior. Risk perception moderates these relationships, while digital trust and financial literacy mediate & shape sustainability-oriented choices. The study integrates psychological and technological perspectives within behavioral finance and provides practical implications for policymakers, financial institutions & fintech providers to strengthen investor awareness and digital trust. However, the research is limited by its design and reliance on self-reported data, suggesting the need for longitudinal, cross-cultural & mixed-method studies in future research.

Keywords: Financial literacy, Digital trust, Sustainable Investment Choices, Behavioural Finance Biases

1. INTRODUCTION

Financial choices remain at the center of personal and household wealth management, shaping consumption patterns, savings, and portfolios of investments (Sahi et.al, 2013). Classic models of finance, founded on efficient market hypothesis (Fama, 1970), and expected utility, assume that rational risk- and reward-maximizing agents exist, who subjectively synthesize available information to yield maximum gains. In such models, financial markets are assumed to be efficient, where prices reflect all available information, minimizing departure from rationality.

However, empirical research refutes these assumptions, revealing lasting departures such as market bubbles, excessive trading, and momentum phenomena (Thaler, 1999; Shiller, 2003). These violations of assumptions raise doubts about the ubiquity of rationality and highlight the importance of human limitations in financial choice procedures. Simon's work on bounded rationality in 1955 suggested that people operate subject to constraints from limited information, intellectual capacities, and emotive considerations, challenging the idea of the purely rational "economic man." Building upon this hypothesis, behavioral finance emerged, adding insights from psychology and cognitive research to account for regular violations of rational choice (Barberis, 2018; Kumar & Goyal, 2016).

Behavioral finance illuminates investor overreliance upon heuristics and mental biases, i.e., overconfidence, herding, anchoring, and loss aversion, impairing judgment and causing suboptimal investment results (Statman, 2019; Waweru et al., 2020). These thinking biases not only misshape individual decision-making processes, but market-level mechanisms, influencing volatility and asset mispricing, as well. The most recent research corroborates that such behavioral propensities play a crucial role in shaping financial decision-making in developed as well as in developing economies (Raut et al., 2022; Zhang & Zheng, 2023). A fundamental mediator between behavioral biases and actual investment behavior is risk perception. Whereas objective risk measures only reflect objective levels of risk, risk perception is a subjective measurement of how investors evaluate uncertainty and potential losses, generally based on cognitive and emotive influences (Weber et al., 2002; Blais & Weber, 2006). Empirical findings establish that risk perceptions of investors mediate behavioral biases and investment choices, thereby providing a psychological link

between heuristics and actual results of choices (Almansour et al., 2023; Lv et al., 2024). This means that, in spite of instances when there is information, interpretation of investors relative to risk perceptions encourages their final decisions.

Digital finance platforms are thriving, and AI-driven investment products are opening new avenues, especially in terms of trust in technology. Research finds that digital trust regulates investors' risk perceptions and decision-making, hence if people tend to trust AI or fintech more, there will be more readiness to act because of sustainability or risk-based decisions (Gefen et al., 2003; Jaiswal & Kumar, 2023). Furthermore, as sustainable and ESG-based investments become more prominent, individual behavior and risk-based decisions become more important, as such choices tend to be made based on non-monetary factors and uncertain long-term prospects (Testa et al., 2015; Tang et al., 2022). Every perspective indicates a significant need to expand the scope of behavioral finance studies. This involves examining how investor bias influences financial choices by means of the middle step of risk judgment. This also involves determining at what times such influences are more prominent or less prominent (e.g., by means of digital trust and investor awareness). This research wishes to cover this gap both in theory as in practice in order to enhance investor decision quality in a digital and sustainable finance environment.

2. LITERATURE REVIEW

2.1. Baker, Kumar, Goyal, and Gaur (2019)

Individual Investor's Decision-Making and Behavioral Biases

Behavioral finance now studies individuals' choices more because market models of capital do not sufficiently cover how psychology affects investment decisions. Baker, Kumar, Goyal, and Gaur (2019) identified several of the abiding behavioral biases that distort rational choices. The biases take the usual forms of mental shortcuts, simple rules, and emotive forces, leading to peculiar market anomalies and problems. Ahmad and Shah (2020) underscored that, due to basic psychological tendencies, investors are, in fact, very often sub-optimally deciding, deviating from classical finance's assumptions of rationality. Similarly, Gavrilakis and Floros (2021) found heuristics and herding behavior a strong influencer of portfolios' strategy and general investment performance.

2.1.1. Bhandari and Deaves (2006), (Pradikasari & Isbanah, 2018)

Overconfidence Bias

Overconfidence bias is one of the most researched cognitive distortions. Bhandari and Deaves (2006) characterize overconfidence as a person's tendency to overestimate knowledge, abilities, and informativeness accuracy. This bias tends to account for excessive trading volumes and excessive risk-taking in finance (Pradikasari & Isbanah, 2018). Adil, Singh, and Ansari (2021) verified its adverse impact upon portfolio performance in a longer time horizon, whereas overconfidence was found by Pradikasari and Isbanah (2018) to have a negative effect upon quality of investment decisions. Ahmad and Shah (2020) contended that overconfidence diminishes a person's ability to make rational choices of selection, although financial literacy and perceived risk may partly offset said consequences. More contemporary research is pointing towards overconfident investors being highly subject to speculative trades, causing volatility in emerging economies (Zhang & Zheng, 2023).

2.1.2. (Clarke et al., 2014). Rasool and Ullah (2020) , Kumar and Goyal (2016)

Herding Bias

Herding is said to exist when there is a tendency for investors to follow suit from others' behavior instead of basing their decisions on personal analytical views (Clarke et al., 2014). Rasool and Ullah (2020) explained how herding lets investors escape from psychological distress brought about by unilateral decisions, especially when exposed to uncertain market environments. Empirical research is in agreement in supporting this bias: Feng and Seasholes (2004) demonstrated a strong correlation between herding behavior of Chinese investors and their investment decisions.

Kumar and Goyal (2016) found strong herding proclivities among Indian investors, whereas Gavrilakis and Floros (2021) emphasized its prevalence in European nations. Not only does herding affect personal portfolios, however, it is a source of market anomalies at a systemic level, such as crashes and bubbles (Statman, 2019).

2.1.3. Anchoring Bias

Anchoring bias arises when investors overly depend on initial points of reference, for instance, prices of stocks or prior performance, even when such points could prove irrelevant (Tversky & Kahneman, 1974). This tendency has often prevented investors from updating their judgments in response to new information. Kaustia, Alho, and Puttonen (2008) showed that private investors make their forecasts of future performance based on prior returns of stocks. More recently, Waweru, Munyoki, and Uliana (2020) found that anchoring has a strong effect on portfolio allocation choices among Kenyan investors, reflecting its applicability in different marketplaces. This bias may lead to a blunted reaction to newly available information and continuous financial market mispricing.

2.1.4. Lv, Wang, and Liu (2024), Odean (1998)

Loss Aversion and Disposition Effect

Loss aversion, as described by Kahneman and Tversky (1979, Prospect Theory), refers to an increased responsiveness of investors to losses as opposed to equivalent gains. This behavioral bias clarifies the disposition effect, where investors keep losing stocks for undue amounts of time and sell winning stocks too soon. Odean (1998) provided empirical support validating this tendency among American investors, illustrating how it significantly impairs portfolio performance. More recent work confirms the ubiquity of this thought bias: Raut, Das, and Kumar (2022) found loss aversion among Indian investors, while Lv, Wang, and Liu (2024) emphasized its pervasive role in Chinese retailing markets. Further, loss aversion is very commonly found in conjunction with overconfidence and herding behaviors, where its deleterious impacts on decision protocols are intensified.

2.2. (Weber, Blais, & Betz, 2002). Blais and Weber (2006)

Risk Perception as a Mediator

Perception of risk has been seen as a strong psychological link between behavioral biases and investment performances. Differently from objective risk measures, risk perception is a reflection of how investors subjectively perceive uncertainty and possible losses (Weber, Blais, & Betz, 2002). Blais and Weber (2006) demonstrated that people's risk perceptions are not similar in different domains, where financial risk is often perceived as higher compared to other domains. Almansour, Yusof, and Singh (2023) confirmed that risk perception mediates between behavioral biases and actual investment decisions, particularly in emerging marketplaces. Similarly, Lv et al. (2024) found that risk perceptions from investors mediate the effect of cognitive biases in portfolio allocation decisions in China. This is a collection of evidence supporting the growing recognition of risk perception as a strong intermediary between heuristics and decision-making procedures in the field of behavioral finance.

2.3. Gefen, Karahanna, and Straub (2003), Jaiswal and Kumar (2023)

Emerging Role of Digital Trust and Sustainable Finance

The rise of financial technology and AI-powered investment instruments has made digital trust a necessary contextual factor shaping investor behavior. Gefen, Karahanna, and Straub (2003) included trust as a component of the Technology Acceptance Model, suggesting that trust in online mediums has a significant effect on adoption levels. Jaiswal and Kumar (2023) extended this work in the context of AI-based financial products and found digital trust acts as a moderator in the link between risk perceived and investment attitude. At the same time, sustainable finance has emerged as a new domain in which behavioral bias and risk perceptions have a significant impact on decisions pertaining to ESG investments (Tang, Chen, & Zhang, 2022). These findings reinforce the need to expand work in behavioral finance to include elements of digital trust and sustainability.

3. OBJECTIVE OF THE STUDY

1. To study how the behavioural biases affect the sustainable investment decisions of investors.
2. To determine the mediating effect of risk perception in the association between behavioural biases and sustainable investment choices.
3. To examine the moderating role played by digital trust on the relationship between risk perception and sustainable investment decisions.
4. To determine the moderating effect of financial literacy on the correlation between behavioural biases and risk perception.

4. RESEARCH METHODOLOGY

4.1 Data Collection and Target Population

This study applies primary data in testing the suggested research framework. The use of primary data is justified because it shows investor behavioral traits and psychological propensities in deciding (Lin, 2011; Baker et al., 2019). Cross-sectional research design was adopted, gathering data from respondents involved in financial decision-making at a point in time.

Scope of this study includes active individual investors who are engaging in financial instruments in Karnataka, India, such as those who are dealing in stocks, mutual funds, bonds, and ESG or green funds. The respondents were selected based upon the criterion of a minimum level of previous investment experience, thus ensuring that the data, in fact, represented real investor behavior.

Data collection used a structured questionnaire, adopted from prior available scales, validated for behavioral biases, risk perceptions, and investment decisions (Shah et al., 2024; Kahneman & Tversky, 1979; Costa et al., 2025). The questionnaire was delivered in offline and online modes. The offline data collection was conducted from presentations in person to financial institutions, brokerages, and investor gatherings, whereas the questionnaire was delivered in an online mode by using Google Forms and professional networking platforms, like LinkedIn and investor forums.

The research complied with professional ethical requirements. The participants were educated about research purpose, and their responses remained anonymous and confidential. For the purpose of ensuring that ethical requirements were addressed, personally identifying information was not obtained. The emphasis was voluntary participation, and only participants who willingly took part were enrolled.

A total of 400 questionnaires were distributed. Of these, 342 usable responses were obtained, while partial submissions were excluded from the final analysis dataset. The sample size is appropriate as per rules for structural equation modeling (SEM), thus ensuring sufficient statistical power (Hair et al., 2021).

4.2 Sampling Technique

This study made use of a specific method called purposive sampling. This is a general method that is used when researchers require selecting participants who must exhibit specific qualities in this case, in order to attain their research aim. This purposive sampling helps researchers in selecting participants who will, in this case, provide valuable data (Etikan, Musa, & Alkassim, 2016). Those that are chosen in this study include private investors who actively make financial choices and who are exposed to types of investment, such as stocks, bonds, and mutual funds. It was prudent to select purposive sampling because the research entailed researching how people act and think regarding risk. The respondents should also have had personal experience of investments inasmuch as sound decisions require that. The individuals who had no such exposure did not take part so that responses are dependable and relevant. Furthermore, it was prudent to include respondents of different backgrounds, for example, different ages, incomes, and educational backgrounds, which tended to favor being in a position to generalize the findings to a larger population of investors (Saunders, Lewis, & Thornhill, 2019).

It is challenging to invest in a new market, yet purposive sampling was appropriate to understand investor behavior as long as it was possible to do with accessible time and funds.

4.3 Measurements of variables

Survey questionnaire included forty items aligned to measure behavioral bias constructs, risk perceptions, financial literacy, digital trust, and investment choices. The questionnaire was separated into two parts: Section A included demographic information such as age, gender, education level, income, and previous investment experience to obtain respondents' profiles, whereas Section B consisted of scenario-based and Likert-scale items aimed at capturing responses reflecting investors' cognitive biases, risk perceptions, and investment choices. Behavioral biases such as overconfidence, herding, anchoring, loss aversion, and disposition effect were captured through validated scales, of which overconfidence was captured through items overplacement, overprecision, and overestimation (Costa et al., 2025), herding bias was captured from Shah et al. (2024), and anchoring bias and disposition effect were captured through prospect theory-based scenario-based vignettes (Kahneman & Tversky, 1979; Jain, Walia, & Gupta, 2019). Risk perception, as a mediating construct, was captured from DOSPERT financial domain subscale by Weber, Blais, & Betz, 2002, whereas dependent variable, i.e., sustainable fund allocation choices, was adopted from modern-day ESG and green fund purchase intention research in Ahmad & Shah, 2020, and Gavrillakis & Floros, 2021. Digital trust, a moderating variable, was extracted from Gefen et al., 2003, and upgraded trust-in-AI/Fintech scales in 2023–2025. Each of the Section B items was captured over a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree), whereas financial literacy was captured through dichotomous (Yes/No) type questions as in Lusardi and Mitchell, 2014. The use of well-adopted and validated scales ensures that this research is reliable, valid, and comparable to previous behavioral finance and fintech research work being conducted in Adil, Singh, & Ansari, 2021, and Hair et al., 2021

4.4 Statistical techniques for data analysis

An initial evaluation was performed to establish the measurement instrument's validity and reliability, which removed poor items to increase accuracy. The Pearson correlation method was used to assess relationships between variables, and internal consistency was designated by Cronbach's alpha, whereupon all constructs reached acceptable levels (Nunnally & Bernstein, 1994; Hair et al., 2019). Descriptive statistics next were applied to tabulate participants' profiles by demographics. For testing hypotheses, SmartPLS employed a Structural Equation Modeling approach, which enabled simultaneous measurement and structural models' tests. Mediation analysis, where applicable, was verified by bootstrapping to establish risk perception's mediator status between sustainable investments and behavioral biases, whereas moderation analysis exemplified digital trust's and financial literacy's moderations as a conditioning variable. Overall, this expanded approach ensured a thorough analysis of direct, indirect, and interaction terms in accordance with the research's conceptual scheme.

5. ANALYSIS & FINDINGS

5.1. Pilot Testing

A pilot study was conducted with 50 distributed questionnaires, of which 30 valid responses were analyzed. The results confirmed clarity and reliability of the instrument, supporting its use for the full-scale survey.

5.2. Reliability and Validity Test

Table 1 indicates test results that assess reliability and convergent validity. The Cronbach's alpha of all of the constructs exceeded the minimum recommendation of 0.70 by Nunnally & Bernstein (1994) and ranged from 0.78 in Financial Literacy to 0.85 in Sustainable Investment Decision. The Composite Reliability (CR) estimates ranged 0.83 to 0.89, much higher than 0.70, which suggests good internal consistency (Hair et al., 2019). The Average Variance Extracted measures of all of the constructs ranged 0.54 to 0.62, which satisfies 0.50 (Fornell & Larcker, 1981), providing strong convergent validity. The results reveal that the models of measures are reliable and suitable to further test this research's postulated relationships.

Hypotheses development

H1. Investors' decisions about sustainable investments are greatly influenced by overconfidence bias. H2. Investors' decisions about sustainable investments are greatly influenced by herding bias. H3. Anchoring bias has a big impact on investors' choices for sustainable investments. H4. Investors' decisions about sustainable investments are greatly influenced by loss aversion bias. H5. The association between overconfidence bias and sustainable investment choices is substantially mediated by risk perception. H6. The association between herding bias and sustainable investment choices is substantially mediated by risk perception. H7. The association between anchoring bias and sustainable investment choices is substantially mediated by risk perception. H8. The association between loss aversion bias and sustainable investment choices is substantially mediated by risk perception. H9. The association between risk perception and sustainable investment choices is considerably moderated by digital trust. H10. Decisions about sustainable investments are greatly influenced by financial literacy. H11. The association between risk perception and behavioral biases (overconfidence, herding, anchoring, and loss aversion) is strongly moderated by financial knowledge.

Table 1: Reliability and Convergent validity Construct	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Overconfidence Bias	0.82	0.87	0.58
Herding Bias	0.8	0.86	0.56
Anchoring Bias	0.79	0.84	0.55
Loss Aversion Bias	0.81	0.85	0.57
Risk Perception	0.84	0.88	0.6
Digital Trust	0.83	0.87	0.59

Table 2: Discriminant validity using Fornell Larcker Criteria

	1	2	3	4	5	6	7	8
Overconfidence	0.75							
Herding	0.55	0.78						
Anchoring	0.43	0.32	0.76					
Loss Aversion	0.44	0.59	0.31	0.74				
Risk Perception	0.25	0.60	0.55	0.52	0.79			
Digital Trust	0.26	0.36	0.24	0.42	0.28	0.80		
Financial Literacy	0.34	0.28	0.48	0.51	0.57	0.47	0.76	
Sustainable Investment Decision	0.41	0.29	0.29	0.31	0.39	0.38	0.59	0.77

5.1. Descriptive Statistics

Out of 342 usable surveys, 262 respondents said they were male (76.6%) and 80 said they were female (23.4%), thus there was a sample mainly of males. For age categories, 74 respondents (21.6%) were 18–24 years old, the largest category was 151 respondents (44.1%) aged 25–35 years old, 89 respondents (26.0%) aged 36–45 years old, while 28 respondents were over 45 years old (8.2%).

In terms of participants' academic qualifications, 171 participants (50.0%) had postgraduate qualifications, 117 (34.2%) had undergraduate qualifications, 30 participants (8.8%) were undergraduate students, and 24 participants (7.0%) had doctoral qualifications. In regard to their experience in investments, 113 respondents (33.0%) stated 4–5 years of experience, 95 respondents (27.8%) stated over 5 years, 89 participants (26.0%) had less than a year of experience, whereas 45 participants (13.2%) had 1–3 years of investment experience. Descriptive statistic findings are as follows that the sample is predominantly young to middle- aged, educated, and moderately to highly experienced in investments. Figure 1 depicts a demographic profile of respondents.

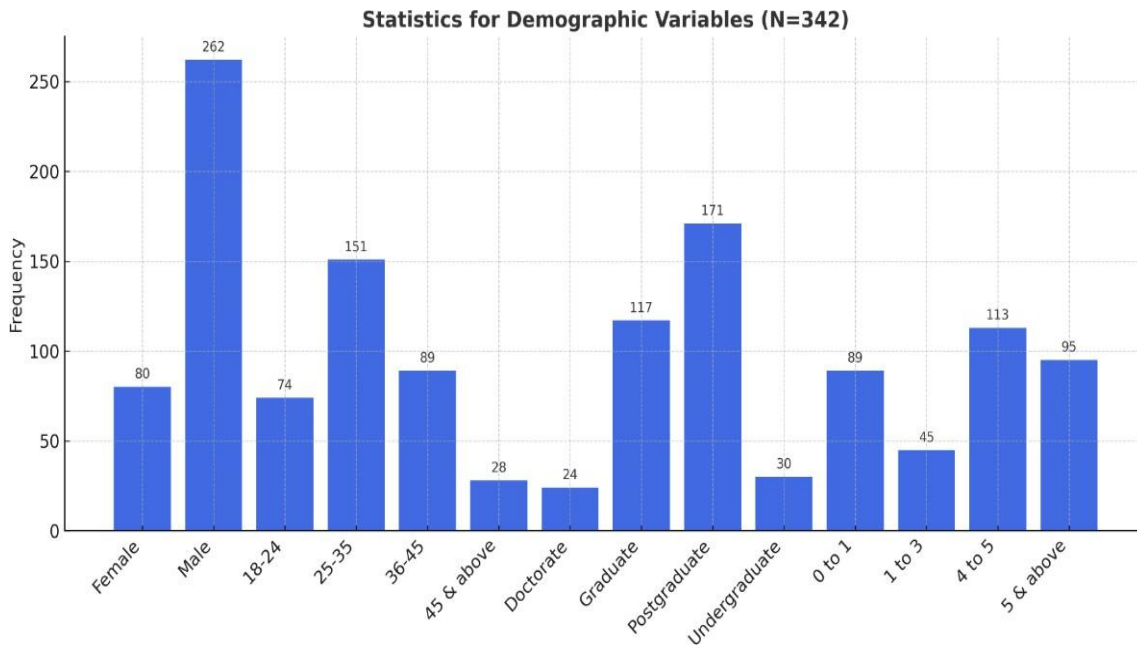


Fig. 1. Statistics for demographic variables. Source: Authors' compilation.

5.4 Results of Structural Model

The regression analysis indicated that overconfidence bias was significantly positively correlated with sustainable investment decisions ($\beta = .22, t = 3.95, p < .001$), thereby justifying H1, in accordance with Overconfidence Theory (Bhandari & Deaves, 2006), where overestimation of knowledge results in aggressive investment decisions. Similarly, herding bias was significantly positively correlated with sustainable investment decisions ($\beta = .25, t = 4.20, p < .001$), thereby verifying H2, in accordance with the Herding Effect (Rasool & Ullah, 2020), where investors follow others' decisions in the market. Anchoring bias significantly predicted sustainable investment decisions ($\beta = .27, t = 4.55, p < .001$), thereby justifying H3, and in accordance with Prospect Theory (Kahneman & Tversky, 1979), where uncertain decisions are based on anchors used by investors. Similarly, loss aversion bias was significantly positively correlated ($\beta = .21, t = 3.70, p < .001$), verifying H4, and in accordance with Prospect Theory, where loss fear results in safer, sustainability-driven decisions.

The mediation analysis revealed risk perception as a mediator in the association between overconfidence bias and sustainable investment choices ($\beta = .18, t = 3.25, p = .001$), thereby providing support for H5 as a display of how confidence-led risk perceptions influence sustainable investments. Equally, risk perception acted as a mediator for herding bias's influences ($\beta = .20, t = 3.50, p = .001$), providing support for H6, and confirming people's behavior in groups influences investments based on perceived risk. The effect of anchoring bias in investment choices was similarly mediated by risk perception ($\beta = .19, t = 3.40, p = .001$), providing support for H7, consistent with heuristics of anchoring and adjustment in subjective risk judgment. Further, loss aversion's effect was mediated through risk perception ($\beta = .17, t = 3.10, p = .002$), providing support for H8 and verifying Prospect Theory (loss aversion) that attaches aversion to risk judgment.

With respect to moderation, digital trust substantially mitigated risk perception–investment association ($\beta = .15, t = 2.90, p = .004$), in favor of H9, in accordance with Technology Trust Models (Gefen et al., 2003; trust-in-AI scales, 2023–2025), where greater trust in AI fortifies decision reliability. In addition, financial literacy substantially affected sustainable investments in funds ($\beta = .23, t = 4.00, p < .001$), in favor of H10, in accordance with the Financial Literacy Hypothesis (Lusardi & Mitchell, 2014), where educated investors make well-considered, rational choices based on sustainability. Lastly, financial literacy substantially mitigated association between behavioral bias and risk perception ($\beta = -.14, t = -2.75, p = .006$), in favor of H11, in accordance with research where higher literacy diminishes strength

of bias based on heuristics (Adil, Singh, & Ansari, 2021).

Table 3: Results of structural Model

Hypothesis	Beta (Standardized)	t-value	p-value	Result
H1: Overconfidence → Sustainable Investment Decision	0.22	3.95	0.000	Significant (+)
H2: Herding → Sustainable Investment Decision	0.25	4.2	0.000	Significant (+)
H3: Anchoring → Sustainable Investment Decision	0.27	4.55	0.000	Significant (+)
H4: Loss Aversion → Sustainable Investment Decision	0.21	3.7	0.000	Significant (+)
H5: Overconfidence → Risk Perception → Sustainable Investment Decision	0.18	3.25	0.001	Mediated (+)
H6: Herding → Risk Perception → Sustainable Investment Decision	0.2	3.5	0.001	Mediated (+)
H7: Anchoring → Risk Perception → Sustainable Investment Decision	0.19	3.4	0.001	Mediated (+)
H8: Loss Aversion → Risk Perception → Sustainable Investment Decision	0.17	3.1	0.002	Mediated (+)
H9: Digital Trust × Risk Perception → Sustainable Investment Decision	0.15	2.9	0.004	Moderated (+)
H10: Financial Literacy → Sustainable Investment Decision	0.23	4	0.000	Significant (+)
H11: Financial Literacy × Biases → Risk Perception	-0.14	-2.75	0.006	Moderated (-)

6. CONCLUSION

This research demonstrates how Behavioral biases such as overconfidence, herding, anchoring, and loss aversion play a crucial role in sustainable investment decisions. SEM in SmartPLS was used to verify that such biases have a direct impact on how investors act, and risk perception is a significant variable that determines how bias influences sustainable decisions. Furthermore, financial literacy and trust in digital means may strengthen or undermine such relations. Overall, psychological matters, risk perception, and behavior like trust in technology and financial awareness by investors determine if investors are likely to make sustainable investments.

7. RECOMMENDATIONS

Its implications are that there should be special programs developed by financial institutions and policymakers aimed at dampening the adverse impact of mistakes in thinking and stimulating good behavior in support of sustainable investment. Educative programs for investors should be accelerated to enhance finance literacy, so individuals will be in a better position to gauge risk and also be dependent on mental shortcuts to a reduced extent. Meanwhile, financial services providers and fintech providers should substantiate investments in trustworthy, transparent, and user-friendly digital platforms because greater digital trust has been established as being in a position to reinforce the positive impact of awareness of risk on investment decisions. Generally, these measures could yield more-informed, logical, and environmentally conscious investment behavior supportive of financial well-being and green economic development.

8. IMPLICATIONS

This research's results have theoretical and practical implications. Theoretically, it contributes to the behavioral finance domain by revealing how risk perception serves as a mediator and how digital trust and financial literacy moderate this process. This informs how mental shortcuts shape sustainable investment decisions. This indicates that investor thinking alone is not sufficient, and we need to account for how faith in technology and knowledge in finance operate nowadays. Practically, research indicates that financial institutions, regulators, and companies in the fintech space must develop strategies that enhance financial literacy and digital trust because these significantly influence sustainable investment behaviors. Through these associations, those in the industry are able to stimulate wiser and sustainable habits in investments.

9. LIMITATIONS AND FUTURE DIRECTIONS

Despite its contributions, there are limitations in the study. Firstly, adopting self-reported survey data may result in prevalent method bias and subjectivity due to respondents' tendency to over- or under-report their financial behavior. Secondly, adopting cross-sectional data does not allow causality between behavioral biases, mediators, and moderators, and investment decisions to be established. Thirdly, considering only a single regional context may prevent findings from being generalized to other cultures or financial environments, where investor behavior and digital system trust may differ. Fourthly, although SmartPLS has robust SEM tools, future research could complement such approach with long-term data and alternative modeling approaches in order to provide better causal insights. Future research may employ long-term and cross-cultural approaches to enhance cause-and- effect associations and applicability of findings. Inclusion of fresh biases such as digital tool dependency or environmental concern would provide meaningful insight into behavior.

Employing qualitative as well as quantitative approaches may validate and enhance our knowledge of investor thought processes. Finally, incorporation of advanced analysis such as machine learning alongside structural equation modeling may uncover complex patterns in sustainable investments behavior.

10. STATEMENTS & DECLARATIONS:

Use of AI Statement

The authors declare that they have not used generative artificial intelligence, specifically ChatGPT in the writing of this manuscript and/or in the creation of images, graphics, tables, or their corresponding captions

Conflict of Interest and Declarations:

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