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Cryptocurrency Investment Decisions: A Behavioural Finance and Technology Adoption Perspective

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ABSTRACT

The expansion of cryptocurrency markets has increased the need to understand the behavioural and technological factors that influence investment decisions. This study examines cryptocurrency investment behaviour from the perspectives of behavioural finance and technology acceptance. Primary data were collected through a questionnaire from 150 cryptocurrency investors in India. The study evaluates the effects of perceived usefulness, financial literacy, risk perception, investor confidence, behavioural biases, trust and security, information sources, and return expectations on investment decisions, adoption levels, trading behaviour, and portfolio allocation. Descriptive statistics, correlation analysis, and ordinary least-squares regression were used to examine the proposed relationships. The results indicate that financial literacy and investor confidence positively influence cryptocurrency investment decisions and adoption levels. Behavioural biases, including herd behaviour, overconfidence, loss aversion, and fear of missing out, significantly influence trading activity and portfolio allocation. Trust and security also demonstrate a positive relationship with cryptocurrency adoption. However, risk perception does not significantly moderate the relationship between trust and security and adoption outcomes. The study contributes to the literature by integrating behavioural finance constructs with technology-adoption factors and AI-based predictive analysis. The findings provide implications for investors, policymakers, financial educators, and fintech platforms promoting informed, secure, and responsible cryptocurrency investment.

1. INTRODUCTION

1.1 Background of the Study

The quick progression of digital technologies has overpoweringly altered global financial markets, prominent to the development of advanced financial instruments such as cryptocurrencies. Acquaint with the introduction of digital crypto currency Bitcoin in 2009, cryptocurrencies symbolize Decentralized, peer-to-peer digital assets that operate autonomously of traditional banking systems and regulatory authorities [1]. Since the Last Decades, cryptocurrencies have progressed from niche technological

experimentations into widely operated financial assets, fascinating investors ranging from retail participants to institutional players [2].

Unlike orthodox financial markets, cryptocurrency markets are characterized by Extreme price Volatility, Activities of high speculation in crypto, narrow intrinsic valuation standards, and robust Interdependence on information scattered through digital platforms [3]. Price movements in cryptocurrencies can be erratic and unpredictable. The fundamentals of micro economics and specific to the individual firm cannot be fully explained. This exclusive Behaviour of Market has brought up significantly important concerns regarding the Applicability of Old Financial theories, especially the Efficient Market Hypothesis (EMH) which assumes rational investors and also information efficient markets [4].

How intellectual biases and emotional factors impact decision regarding Finance that Makes Behavioural finance provides a theoretical framework for understanding this phenomena In the context of cryptocurrencies, psychological biases such as herding behaviour is frequently affected by investor behaviour, where individuals emulate the actions of the widely held; overconfidence, where predictive abilities are overestimated by; loss aversion, which Indicating panic selling during market downturns; and sentiment contagion, where emotions spread rapidly through online communities and social networks [5]. This Behavioural influence intensifies given the surge in online forums, social media platforms, and the instant dissemination of information, which can significantly impact cryptocurrency markets, especially when trading based on sentiment [6].

The Traditional financial prediction models are linear econometric models such as Capital Asset Pricing Model (CAPM) which assumes rational investors, normally distributed returns, and stable market structures. In the cryptocurrency markets these assumptions are often not met, as prices are often non-linear, investors adapt quickly to price changes and fundamental information is often overwhelmed by external sentiment shocks [7]. Following this, the traditional model analysis in the cryptocurrency sector is still restricted.

1.2 Theoretical Integration: Behavioural Finance and Technology Adoption

Behavioural finance offers a theoretical underpinning of explanations for systematic deviations from investor rationality by studying how cognitive heuristics, psychological biases and emotional contagion underpin financial decision-making. The high information asymmetry and the quick adoption of the narratives on online forums and social media platforms are the reasons for the pronounced bounded rationality in the cryptocurrency markets [8, 9]. Retail investors are often victims of cognitive and emotional errors such as herd behaviour, overconfidence, loss aversion and fear of missing out (FOMO) in fast-rising markets [10]. Recent empirical studies have shown that psychological influences such as FOMO (Fear of Missing Out), social media influencers and emotional contagion are key factors to trigger impulsive and risky cryptocurrency trading [11].

At the same time, as cryptocurrencies are a financial innovation that relies on software, the investor's involvement is intrinsically related to the technology adoption processes. Factors like perceived usefulness, ease of use, trust, and technological security play a major role in influencing an individual's willingness to use blockchain-based platforms, as in line with the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) [12]. Perceived financial, operational and regulatory risks tend to be counterbalancing factors [13]. while trust in the security of cryptographic protocols, digital wallets and exchanges is a driver of adoption [14]. Moreover, digital financial literacy has a dual function, both supporting and promoting cognitive ability to assess risk-return trade-offs [15]. and creating an illusion of control and overconfidence in volatile markets [16].

Problem Statement and Research Gap

In related studies, behavioural biases in trading are studied [17]. while the technological adoption models are studied [12]. However, there are few studies that combine both approaches in the same empirical model to analyze retail investment decisions. Moreover, empirical studies on the relationship between financial literacy, behavioural biases, technological trust, and AI-aided predictive insights into retail participation in cryptocurrencies are, as of yet, limited in emerging markets such as India, where the industry has seen a significant increase in users despite the regulatory uncertainty [14].

1.3 Significance of the Study

This Research is substantial as it combines behavioural finance theory with AI analytics, provided that a novel approaches to understanding unpredictable markets. It offers recommendations for investors to overcome biases, for educators to enhance financial education curricula, and for policy-makers to create

effective policies. It also showcases the power of AI over traditional models, opening new avenues for methodological innovation in financial research. This research broadens the methodological toolbox by showcasing how successful AI-based predictive modeling is on primary, survey data psychometric data. This enables behavioural researchers to model complex, non-linear interactions, high dimensional variance and non-normal distributions, which are difficult to fit into the traditional linear econometrician model.

2. REVIEW OF THE LITERATURE

2.1 Cryptocurrency Investment and Investor Participation

Since the launch of Bitcoin, cryptocurrency markets have advanced at a rapid pace, offering investors the opportunity to earn significant returns, the decentralization factor, and the technological novelty.

Bitcoin was invented in 2000 by as a decentralized peer-to-peer digital currency that does not require any financial intermediaries [1]. This distributed model, based on consensus, algorithmic proof, and immutability of the blockchain, set a new benchmark for financial trust based upon distributed consensus instead of institutional legitimacy.

Conventional assets are, in contrast to cryptocurrencies, highly volatile in price, are subject to speculation, and are hardly dependent on macroeconomic indicators [18].

Based on empirical evidence, cryptocurrency price discovery is mainly determined by speculative demand and investor sentiments, but not by cash-flow figures or even macro-economic indicators. In the absence of traditional valuation references, the media narrative, social sentiment, and increased market uncertainty have a significant impact on market prices, driving up behavioural distortions like momentum trading, herd behaviour, and sudden price swings [19].

Furthermore, cryptocurrency price discovery is driven more by the assumption of speculators, media stories, and investor sentiment, rather than actual fundamentals, increasing the behavioural herd effect and extreme market corrections [17].

Also demonstrated that cognitive biases might influence the connection between perceived financial knowledge and cryptocurrency ownership [20].

2.2 Behavioural Finance Theory and Investment Decision-Making

Prospect Theory explains financial anomalies through loss aversion, showing that investors systematically favor risk aversion during gains and risk-seeking behavior during losses [21].

Investor sentiment models show that psychological biases distort asset prices, particularly through overconfidence, which triggers excessive trading and suboptimal returns [22].

In cryptocurrency markets, limited historical data, speculative narratives, and rapid information diffusion intensify behavioural biases. Specifically, the Fear of Missing Out (FOMO) triggers impulsive buying during market rallies while loss aversion drives investors to hold depreciating assets for extended periods in anticipation of price recovery [23].

In a study published in *Nature: Humanities and Social Sciences Communications*, challenged earlier assumptions by analyzing data from the U.S. National Financial Capability Study (NFCS) 2021, which included 1,810 cryptocurrency investors [24].

2.3 Financial Literacy and Cryptocurrency Adoption.

In cryptocurrency markets, limited historical data, speculative narratives, and rapid information diffusion intensify behavioural biases. Specifically, the Fear of Missing Out (FOMO) triggers impulsive buying during market rallies while loss aversion drives investors to hold depreciating assets for extended periods in anticipation of price recovery [15].

A study found that higher financial literacy is positively associated with investment involvement and long-term planning. In the context of cryptocurrency [25].

Higher technical and financial literacy accelerates cryptocurrency adoption, whereas deficient knowledge increases investor vulnerability to market hype, misinformation, and herd behaviour [26].

Explored the dual role of social media as both a facilitator of financial inclusion and a source of behavioural volatility in cryptocurrency markets, using an explanatory mixed-methods approach combining survey data and sentiment analysis [27].

2.4 Technology Adoption and Artificial Intelligence in Investment

Artificial intelligence has gained prominence in financial research for its capacity to model complex, nonlinear interactions among variables. In contrast, conventional statistical methods like linear regression and ARIMA models rely on assumptions of linearity and normality, restricting their predictive efficacy in volatile markets [28].

Machine learning models such as ANN, SVM, and deep learning outperform conventional econometric techniques in cryptocurrency forecasting [29].

While integrating behavioural indicators like investor sentiment improves machine learning accuracy existing research predominantly forecasts market prices rather than evaluating survey-based investor decision-making and adoption behavior [30].

Literature Review: Technology Acceptance Model in Bangladesh Studies investigating cryptocurrency adoption in emerging and restrictive regulatory environments frequently rely on the Technology Acceptance Model (TAM) [31]. In the context of South Asian developing economies, particularly Bangladesh, empirical research adapts TAM to evaluate how users navigate the technical complexities, legal restrictions, and perceived benefits of decentralized financial technologies.

2.5 Research Gap

Existing cryptocurrency research has mainly focused on price volatility, market efficiency, speculative bubbles, and the use of machine-learning models for price prediction. A separate stream of research has examined behavioural biases such as herd behaviour, overconfidence, loss aversion, and fear of missing out. However, these two areas have rarely been integrated into a single empirical framework focused on investor decision-making and cryptocurrency adoption

3. STUDY DESIGN

This research is quantitative research with a cross-sectional method. Through the structured questionnaire, primary data was collected from the respondents who are cryptocurrency investors in India. The questionnaire was designed to be reliable and valid by being based on reliable and valid scales from behavioural finance and technology adoption literature.

3.1 Sample and Data Collection

The target group was the active cryptocurrency investors. The sample was obtained using a convenience sampling method and a total of 150 responses were obtained from an online survey from July 1, 2025, to January 1, 2026. The respondents were preliminarily assessed for the prior experience of investing in cryptocurrencies. Sample demographics consisted of 70% male and 30% female, ranging in age from as young as 30 to over 60 years, and with levels of education varying too, along with income level and different demographic profile.

3.2 Primary Objectives of the Research.

The prime purposes of this Research are:

1. To examine the influence of behavioural finance factors (e.g., biases, risk perception, financial literacy) on cryptocurrency investment decisions.
2. To apply AI-based models to predict investor adoption and behaviour in cryptocurrency markets.
3. To identify key drivers and moderators of sustained cryptocurrency investment.
4. To provide recommendations for stakeholders based on predictive insights.

3.3 Measurement Instruments and Sources

Based on the research objectives and the identified variables (independent: Perceived Usefulness (PU), Financial Literacy (FL), Risk Perception (RP), Investor Confidence (IC), Behavioural Biases (BB), Trust and Security (TS), Information Sources (IS), Return Expectations (RE); dependent: Investment Decision, Adoption Level, Trading Frequency, Portfolio Allocation), in **Table 1** here are six formulated hypotheses. These are testable statements linking key behavioural finance factors to cryptocurrency investment outcomes, aligning with examining influences, predicting behaviours via AI, identifying drivers/moderators, and deriving insights.

Table 1. Measurement Instrument and sources

Construct	Abbreviation	Items	Scale	Source
Perceived Usefulness	PU	Multi-item	5-point Likert	Technology acceptance literature
Financial Literacy	FL	Multi-item	5-point Likert	[21]
Risk Perception	RP	Multi-item	5-point Likert	[32]
Investor Confidence	IC	Multi-item	5-point Likert	[6]
Behavioural Biases	BB	Multi-item (4 sub-scales)	5-point Likert	[30]
Trust and Security	TS	Multi-item	5-point Likert	[25]
Information Sources	IS	Multi-item (custom)	5-point Likert	Custom-developed
Return Expectations	RE	Multi-item (self-reported)	5-point Likert	Custom-developed
Investment Decision	ID	Multi-item / Binary	5-point Likert / Binary	Adapted from prior studies
Adoption Level	AO	Multi-item	5-point Likert	Adapted from technology adoption literature
Trading Frequency	TF	Multi-item	5-point Likert	Custom-developed
Portfolio Allocation	PA	Multi-item	5-point Likert	Custom-developed

3.4 Hypotheses

The hypotheses should be stated separately and tested against clearly defined dependent variables.

H1: Financial literacy positively influences cryptocurrency investment decisions and adoption levels.

H0₁: Financial literacy has no significant effect on cryptocurrency investment decisions or adoption levels.

H1₁: Financial literacy has a significant positive effect on cryptocurrency investment decisions and adoption levels.

H2: Investor confidence positively influences cryptocurrency investment decisions and adoption levels.

H0₂: Investor confidence has no significant effect on cryptocurrency investment decisions or adoption levels.

H1₂: Investor confidence has a significant positive effect on cryptocurrency investment decisions and adoption levels.

H3: Behavioural biases positively influence trading frequency and cryptocurrency portfolio allocation.

H0₃: Behavioural biases have no significant effect on trading frequency or portfolio allocation.

H1₃: Behavioural biases have a significant positive effect on trading frequency and portfolio allocation.

H4: Trust and security positively influence cryptocurrency adoption.

H0₄: Trust and security have no significant effect on cryptocurrency adoption.

H1₄: Trust and security have a significant positive effect on cryptocurrency adoption.

H5: Risk perception negatively moderates the relationship between trust and security and cryptocurrency adoption.

H0₅: Risk perception does not significantly moderate the relationship between trust and security and cryptocurrency adoption.

H1₅: Risk perception significantly weakens the positive relationship between trust and security and cryptocurrency adoption.

H6: Perceived usefulness positively influences cryptocurrency investment decisions and adoption levels.

H0₆: Perceived usefulness has no significant effect on cryptocurrency investment decisions or adoption levels.

H1₆: Perceived usefulness has a significant positive effect on cryptocurrency investment decisions and adoption levels.

3.5 Data Analysis Techniques

In this study, the survey data of 150 cryptocurrency investors in India was analyzed using traditional statistical techniques and advanced predictive modeling techniques based on artificial intelligence. Data were analyzed with SPSS, PLS, stats models for regression analysis, and with scikit-learn for machine learning and predictive modeling.

All constructs were measured with descriptive statistics (mean, standard deviation, skewness, and kurtosis) as well as frequency distributions. There is a correlation analysis to see how strong the association is between two continuous variables (Pearson correlation).

3.6 Ethical Considerations

This Research follows the highest standards of research ethics, protect participants, be transparent and treat data responsibly. The questions asked were demographical (age group, gender, education level, occupation, city) and were kept as broad categories as possible, reducing the possibilities of indirect identification. The authors state that they have no financial and commercial relationships to declare. There was no industry sponsorship for the study.

4. RESULTS AND DISCUSSION

This section provides an empirical analysis of the survey data collected from 150 respondents – cryptocurrency investors from India, as mentioned in methodology. Data manipulation, regression analysis and predictive modeling were completed with advanced statistical and machine learning tools SPSS and PLS. This is in line with the study's focus on employing both classical and AI methods to examine intricate relationships within behavioural finance. Data cleaning included recoding Likert scale responses into numeric values (Strongly Agree = 5, Strongly Disagree = 1); using median imputation for missing data; and ensuring that a minimum amount of data was missing per row. After cleaning the sample size was 150.

4.1 Sample Characteristics

The demographic profile of the respondents is summarized below, reflecting a diverse yet skewed sample toward younger, male, urban participants with moderate income and education levels. This distribution is consistent with typical cryptocurrency investor profiles in emerging markets like India. Age: 44.7% up to 30 years, 25.3% 31–40 years, 13.3% 41–50 years, 13.3% 51–60 years, and 3.3% above 60 years. Gender: 70% male, 30% female. Education: 40.7% Graduation, 32% Post-Graduation, 16% Professional Degree, 6% Others, 5.3% Up to Schooling. Occupation: 31.3% Professional, 28% Student, 23.3% Salaried Employee, 17.3% Self-Employed. Annual Income: 36% Less than ₹3 lakh, 34.7% ₹3–6 lakh, 21.3% More than ₹10 lakh, 8% ₹6–10 lakh. Marital Status: 52.4% Married, 47.6% Single. Geographic Location: 52.7% Urban, 28.7% Semi-urban, 18.7% Rural. Duration of Cryptocurrency Involvement: 74.7% Less than 1 year, 18% 1–3 years, 7.3% More than 3 years.

4.2 Descriptive Statistics and Reliability Analysis

In **Table 2**, composite scores for each construct were calculated by averaging the items within each scale. The descriptive statistics (mean, standard deviation, skewness and kurtosis) and the Cronbach's alpha for internal constancy are shown in the Table 2. Agreement ranged from generally neutral to positive, with an average for means of 3.52-3.66 on a 5-point scale for the constructs. The standard deviations (0.78–1.07) indicate that there is moderate variability. The skewness ranged from –0.83 to –1.35, suggesting a slight left-tail (more positive response), and the kurtosis was between mesokurtic and slightly leptokurtic distributions.

Table 2. Descriptive Statistics and Reliability of Constructs

Construct	Mean	SD	Skew	Kurtosis	Cronbach's Alpha
Perceived Usefulness (PU)	3.53	1.07	-0.83	-0.34	0.90
Financial Literacy (FL)	3.52	0.97	-0.72	-0.49	0.88
Risk Perception (RP)	3.66	0.93	-1.01	0.41	0.91
Investor Confidence (IC)	3.58	0.78	-1.34	1.48	0.83
Information Sources (IS)	3.61	0.96	-1.35	0.72	0.91

Construct	Mean	SD	Skew	Kurtosis	Cronbach's Alpha
Behavioural Biases (BB)	3.57	0.93	-1.03	0.60	0.91
Trust and Security (TS)	3.63	0.95	-1.21	0.50	0.92
Return Expectations (RE)	3.60	0.85	-1.10	0.64	0.88
Investment Decision (ID)	3.65	0.98	-1.20	0.44	0.94
Behavioral Outcomes (BO)	3.58	1.04	-1.16	0.13	0.94
Adoption Outcome (AO)	3.60	1.00	-1.14	-0.01	0.95

The internal reliabilities (Cronbach's alpha) for all constructs were greater than 0.80 (0.83 to 0.95), indicating high internal reliability and thereby validity of the scales adapted from previous literature.

4.3 Correlation Analysis

There are correlations among the constructs that are shown in Table 2. All the correlations were positive and significant ($p < 0.01$, 0.51 to 0.94). Strong interconnections between the various behavioral factors were noted with high correlations between related constructs, such as IC and RE (0.91), TS and RE (0.94), and ID and AO (0.95). Specifically, BB was strongly correlated with IS (0.88) and ID (0.90), showing that information sources not only have biases but also magnify them and that biases affect decisions. A test for multicollinearity was performed using variance inflation factors (VIFs < 5 for all regressions) which did not indicate any significant problems. **Table 3** presents correlation matrix (Pearson's r).

Table 3. Correlation Matrix (Pearson's r)

	PU	FL	RP	IC	IS	BB	TS	RE	ID	BO	AO
PU	1.00	0.87	0.56	0.58	0.55	0.51	0.61	0.56	0.56	0.55	0.57
FL	0.87	1.00	0.61	0.64	0.64	0.66	0.68	0.61	0.69	0.66	0.69
RP	0.56	0.61	1.00	0.80	0.75	0.81	0.78	0.81	0.78	0.74	0.78
IC	0.58	0.64	0.80	1.00	0.85	0.78	0.91	0.91	0.85	0.83	0.85
IS	0.55	0.64	0.75	0.85	1.00	0.88	0.91	0.89	0.88	0.86	0.84
BB	0.51	0.66	0.81	0.78	0.88	1.00	0.85	0.85	0.90	0.85	0.87
TS	0.61	0.68	0.78	0.91	0.91	0.85	1.00	0.94	0.87	0.86	0.88
RE	0.56	0.61	0.81	0.91	0.89	0.85	0.94	1.00	0.85	0.80	0.83
ID	0.56	0.69	0.78	0.85	0.88	0.90	0.87	0.85	1.00	0.92	0.95
BO	0.55	0.66	0.74	0.83	0.86	0.85	0.86	0.80	0.92	1.00	0.93
AO	0.57	0.69	0.78	0.85	0.84	0.87	0.88	0.83	0.95	0.93	1.00

4.4 Hypothesis Testing

Ordinary Least Squares (OLS) regression was used to investigate the hypotheses, with composite means as variables. **Table 4** presents hypothesis testing and result.

Table 4. Hypothesis testing and result

Hypothesis	Relationship Tested	Result	Decision
H1	Financial Literacy $\rightarrow$ Investment Decision & Adoption	$\beta = 0.24-0.26, p < 0.001$	Supported
H2	Investor Confidence $\rightarrow$ Investment Decision & Adoption	$\beta = 0.87-0.88, p < 0.001$	Supported
H3	Behavioural Biases $\rightarrow$ Trading Frequency & Portfolio Allocation	$\beta = 0.95, p < 0.001$	Supported
H4	Trust & Security $\rightarrow$ Cryptocurrency Adoption	$\beta = 0.65, p < 0.001$	Supported
H5	Risk Perception moderates TS $\rightarrow$ Adoption	Interaction $\beta = 0.02, p = 0.541$	Not Supported
H6	Perceived Usefulness $\rightarrow$ Investment Decision & Adoption	Correlation positive	Inconclusive

The result of the hypothesis testing shows that the skill, confidence, psychologic tendency and perception to technology have an influence on the decision of investment in cryptocurrencies. Investment decision and investment level were also positively and significantly associated with financial literacy and investor confidence, underscoring the need for financial education and self-efficacy when investing in cryptocurrencies. The behavioral biases were more than enough to generate trading activity and portfolio allocation, highlighting how significant psychological influences like the herd effect, overconfidence, loss aversion and fear of missing out are in these investment decisions. The influence of trust and security was also a positive factor for encouraging investors to adopt blockchain technology, indicating that investors

are more inclined to participate in blockchain technology adoption when they view the technology and its infrastructure as secure and reliable.

The relationship between trust in security and the adoption of cryptocurrency, however, was not significantly moderated by risk perception, indicating that the perceived security of cryptocurrencies could affect their adoption, apart from general concerns of risk. The results should be interpreted with caution as the study was based on a small, non-probability sample and cross sectional design. The ambiguous results of H6 indicate the need to conduct more regression analysis to confirm the independent impact of perceived usefulness on the outcome of investment.

The results of this study collectively support the use of behavioural finance and technology acceptance theories to explain cryptocurrency investment behaviour, and constitute a basis for creating specific intervention measures that can facilitate informed, secure and responsible investment in cryptocurrencies.

4.5 Discussion of Findings

This study is an empirical analysis of the behavioral and technological factors affecting cryptocurrency investment decisions of 150 investors in India. The results indicate that financial literacy, investor confidence, behavioural biases, and the level of trust in security have a significant influence on investment decisions and adoption, and that the level of trust in security does not significantly moderate the trust–adoption relationship.

4.5.1 Key Determinants of Investment and Adoption

The respondents are moderately optimistic, given their mean scores for Perceived Usefulness ($M = 3.53$), Investor Confidence ($M = 3.58$), and Trust and Security ($M = 3.63$), which indicate a balanced view of the value and risks of Cryptocurrency. The demographic makeup of the sample – mainly young (44.7% of those under 30), male (70%), urban (52.7%) and novice investors (74.7% with less than 1 year investment tenure) – may be related to this cautious optimism, as novice investors tend to be more sensitive to hype but less tolerant of risk.

The correlation analysis shows that there are high inter-correlations between constructs: Investor Confidence and Return Expectations ($r = 0.91$), Trust and Security and Return Expectations ($r = 0.94$), and Behavioural Biases and Information Sources ($r = 0.88$). These findings imply that confidence fuels optimistic return expectations, while social media and online platforms amplify behavioural biases, consistent with and on sentiment-driven cryptocurrency markets [6, 19].

4.5.2 Financial Literacy and Investor Confidence (H1 and H2)

The support for H1 and H2 was very strong. Investor confidence had a greater impact on investment decision ($\beta = 0.88$, $p < 0.001$) and adoption outcome ($\beta = 0.87$, $p < 0.001$) than financial literacy, which had an impact of $\beta = 0.24$, $p < 0.001$ and $\beta = 0.26$, $p < 0.001$, respectively. The findings suggest that when investors have a high level of financial literacy and confidence, they are more inclined to invest in cryptocurrencies and continue to embrace them. The results of this study build on and, but also suggest that there may be too much of a good thing since excessive trading may be a concern in the cryptocurrency case [10, 15].

4.5.3 Behavioural Biases and Trading Behaviour (H3)

H3 received strong support, and behavioural biases were found to have significant behavioural consequences (proxied for by trading frequency and allocation of the portfolio) ($\beta = 0.95$, $p < 0.001$). In line with [32], all these factors contribute to more active and speculative trading due to “herd behaviour”, “overconfidence” and “FOMO” [17, 33]. There is a very high correlation between the behavioural biases and the information sources ($r = 0.88$), which implies that the social media and online forum platforms propagate these psychological biases, thus further emphasizing the importance of education for bias-awareness and platform design interventions.

4.5.4 Trust and Security (H4)

H4 was supported as with increased trust and security, the likelihood of attaining the adoption outcome increased ($\beta = 0.65$, $p < 0.001$). The blockchain trust models and technology acceptance literature were extended by investor who viewed blockchain technology, blockchain-based exchanges, and blockchain-based wallet as secure would be more likely to adopt cryptocurrency [12]. There is a strong linkage between trust in security and trust in return expectation ($r = 0.94$), which may be seen as a reinforcement of

the optimistic profitability expectation, highlighting the importance for platform operators and policymakers to invest in cybersecurity and transparency.

4.5.5 Risk Perception (H5)

Interactions between trust and adoption were not significant for H5 and risk perception did not significantly moderate the relationship between trust and adoption (interaction $\beta = 0.02$, $p = 0.541$). The main effect of risk perception was also insignificant ($\beta = 0.20$, $p = 0.155$). High blockchain security perception can offset risks, even for risk-sensitive investors, indicating that security benefits may be more significant than risks. The finding contrasts with earlier risk-attitude evidence [34]. This could be due to the sample's positive attitude towards technology and their risk-taking attitude in accepting volatility for perceived opportunity.

4.5.6 Perceived Usefulness (H6)

For the H6, the correlation test results indicate positive relationships (both with PU: $r = 0.56$, $p < 0.01$; and with AO: $r = 0.57$, $p < 0.01$) but regression coefficients were not published. Note that future investigation should involve separate regression models to examine the unique impact of the perceived usefulness construct on the investment outcomes, after controlling for the other constructs.

4.5.7 Demographic and Contextual Insights

The younger investors display greater perceived usefulness and confidence, and also display higher behavioural biases, which implies that there are generational differences in risk appetite and technological familiarity. Trust and security levels are higher among urban respondents, perhaps because of high digital literacy and ease of access to information. Experience translates into resilience as longer term investors (1-3 years) exhibit lower perceptions of risk and higher adoption. The differences indicate a need to develop interventions that are tailored by age, experience, income and geographic context.

The India-focused evidence that technology-driven factors shape Gen Z cryptocurrency participation under regulatory uncertainty adds an adoption-side channel consistent with the present technology-acceptance framing [14]. As algorithmically mediated financial services expand, the governance of algorithmic agency becomes a policy consideration for such deployments [35]. Complementary evidence that AI adoption shapes workplace performance supplies a governance-relevant technology channel for algorithmically mediated investment settings [36].

5. CONCLUSION

The study investigated the cryptocurrency investment decisions while adopting the perspectives of behavioural finance and technology acceptance theories with the help of survey data from 150 investors in India. The results confirm that financial literacy and investor confidence are significantly associated with the decision of investing and the level of investment participation, and that behavioural biases (such as herd behavior, overconfidence, loss aversion and FOMO) have a significant positive impact on trading frequency and portfolio allocation. In addition, trust and security were identified as significant enablers of cryptocurrency adoption where risk perception was not a significant moderator of the trust–adoption relationship, indicating that trust in the security of the blockchain can offset general concerns of risk. This study adds to the literature by integrating the elements of behavioural finance with technology acceptance factors, and using AI-based predictive modeling to account for complex, nonlinear dynamics in investor behavior. The findings offer valuable guidance to investors interested in enhancing their knowledge and understanding of cryptocurrencies and market trends, offering them the opportunity to become more literate and make informed investment decisions; to educators, they can help inform curriculum development by incorporating these insights; to policymakers, they can help inform the development of balanced regulations that improve security and investor protection; and to fintech platforms, they can help inform the design of user interfaces and AI-driven advisory tools that promote informed and responsible cryptocurrency participation.

While the study has made a contribution, the cross-sectional design, convenience sampling and self-reported measures restrict generalizability and causal inferences. Longitudinal designs and objective trading data, cross-country comparisons and hybrid AI-econometric models should be utilized in future studies to advance evidence and expand applicability. This research, however, provides a basis for setting up evidence-based interventions to encourage informed, secure, and responsible adoption of cryptocurrencies in a changing digital financial system.

5.1 Implications

The findings of this study have important theoretical, methodological, and practical implications for the cryptocurrency ecosystem. From a theoretical perspective, it has the potential to extend the scope of behavioural finance by proving that it can be used in the cryptocurrency market and incorporating the constructs of technology acceptance to create a holistic model that goes beyond the bounds of conventional finance theory. Methodologically, it underscores the importance of integrating traditional statistical approaches with AI-driven predictive modeling to capture intricate, nonlinear relationships that prevail in investor behavior, a gap in the existing literature that has largely been overlooked by the majority of AI applications in the field of cryptocurrency analysis. From a practical standpoint, these insights provide concrete steps for investors to become more financially literate and understand the psychological factors that can influence their investment decisions, for educators to create educational programs that incorporate both technical and psychological topics, for policymakers to establish fair regulations and policies that address both security and investor protection while fostering trust, and for fintech companies to implement user interfaces, risk disclosures, and AI-powered trading tools that help minimize impulsive trading and encourage informed, responsible participation in cryptocurrencies. The findings further help shape efforts to foster financial inclusion by outlining avenues for encouraging informed investor involvement, especially among a wide range of investor sub-groups, including young, urban, and new investors, who are the largest group of cryptocurrency investors; and contribute to a more balanced public conversation on opportunities and risks of the new digital financial landscape.

5.2 Limitations

There are a number of limitations in this study that should be noted. First, the cross-sectional research design does not allow for causal inferences because any observed relationships between constructs can be explained by reverse causality, omitted variable bias and/or spurious relationships. Second, the practical approach of using convenience sampling may result in selection bias, increasing the generalizability of the findings for the urban tech-savvy younger and male investors, but not for all investors, including rural, older, female, and less technologically skilled investors. Third, the use of self-reported survey data might introduce some response bias, social desirable response, recall error and common method variance that could affect the actual relationship between the behavioural and technological constructs. Fourth, the sample size of 150 respondents is good for preliminary analysis but might lack sufficient power to detect subtle effects, interaction terms, and/or differences among subgroups, and could also raise the risk of over fitting in AI-based predictive models. Fifth, the emphasis on India may not reflect differences in regulatory environments, cultural attitudes, market maturity, investor behaviour, between various countries and regions around the world. Sixthly, although the AI models are superior in predictive power to traditional linear ones, they depend on the constructs of the sample and rely on self-report data; they also could over fit and without external validation on independent samples and without objective behavioral measures from trading platforms. Seventh, because the regression coefficients for H6 (perceived usefulness) were not reported, the results for this hypothesis were inconclusive, which restricted the completeness in the hypothesis test and theory. Eighth, the high correlations between some constructs (e.g., investor confidence and investors' return expectations: $r = 0.91$; trust and security and investors' return expectations: $r = 0.94$) indicate that even though the VIF values do not reach the threshold, there is some concern about the multicollinearity and discriminant validity. Finally, the focus on cryptocurrency investment behavior, despite excluding objective trading data, real-time market information, and longitudinal behavioural tracking, has restricted the depth and accuracy of behavioural insights, and calls for a more comprehensive future study that incorporates multiple data sources and methodologies.

5.3 Future Research Directions

The contributions of this study are limited in several ways and future research needs to address these in several promising directions. First, a longitudinal study examining investor behavior over time would allow for causal inferences and would allow us to learn more about how financial literacy, financial confidence, biases, and trust change as a result of financial market experience, changes in the regulatory environment, and technological advances. Second, there would be objective measures of behaviour from cryptocurrency exchanges and wallet platforms which would be free of the self-report that underlies the survey-based measures of behaviour, allowing validation of the survey-based results and more accurate prediction of the actual investment decisions, trading frequency and allocation of investment to that portfolio. Third, comparative analysis across jurisdictions, cultural environments and market maturity level would expand applicability and highlight context specific determinants of cryptocurrency behaviour, with

a focus on making a comparison between emerging markets such as India and developed markets. Fourth, scaling up this integration of AI with real-time sentiment analysis from social media platforms (such as X/Twitter, Reddit, Telegram) and news sources could improve prediction accuracy and help to deliver more timely information on market sentiment, information contagion, and bias amplification. Finally, analyzing the new biases and behavioural patterns found in Web3 environments such as NFT, decentralised finance (DeFi), investments in Metaverses, and tokenized assets would bring a new perspective on new digital financial instruments. Sixth, hybrid models could result from the integration of AI's predictive capabilities with the interpretability of econometric methods e.g., explainable AI (XAI), SHAP values, LIME), providing accurate forecasts and actionable insights for investors, platforms, and policymakers. Last, analyzing the variation in effects among investor sub-groups (novice vs. experienced, conservative vs. risk-taking, young vs. older, male vs. female) would allow the development of targeted interventions and advisory tools designed specifically for individual investor groups. The moderation effect of regulatory clarity, government policy, macroeconomic conditions, and market infrastructure of the relationships between the behavioural and the technological constructs would give context-rich insights for policy-makers. Causal evidence of what works to encourage informed and responsible adoption of cryptocurrencies would be found through ninth, experimental, and quasi-experimental designs that test the effectiveness of educational interventions, bias-mitigation tools, and platform design features. Lastly, combining neuroscience and psychophysiological data (such as eye-tracking, skin conductance, EEG) with behavioral and survey measures would further enhance the understanding of cognitive and emotional processes that influence investment decisions in cryptocurrencies, connecting behavioural finance and neuro finance approaches.

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