When Security Meets Intelligence: Trust in AI, Blockchain Security, and Investor Behavior

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Despite the increasing integration of Artificial Intelligence (AI) into cryptocurrency trading environments, concerns remain regarding security, trust, and investor decision-making. Blockchain infrastructures are often described as trust-minimizing systems; however, AI-based trading tools increase reliance on opaque algorithmic outputs. This research study examines how blockchain security, AI accuracy, and AI experience shape trust in AI and behavioural intention in terms of use of an AI-based trading system. For achieving research outcomes, this research study recruited 215 cryptocurrency investors using a structured survey questionnaire and a model for testing trust, trading intentions, and system perceptions. The findings from this research study suggest that blockchain security and perceived accuracy enhance trust in AI. In contrast, AI experience negatively impacts trust in AI, as experienced users exhibit algorithmic scepticism. The findings further related that in the prediction of behavioural intention of users, perceived accuracy of AI and structural security have a direct impact on intention, and trust is not a key determining predictor in the research model. Therefore, structural assurance performs a key role in shaping investors' intentions in a financial market.

Keywords:
trust in AI,
blockchain security,
cryptocurrency trading,
behavioral intention,
algorithmic skepticism

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1 Introduction

The integration of deep learning and machine learning by use of Artificial Intelligence (AI)and blockchain technologies has transformed the financial markets, as traditional financial forecasting techniques and mechanisms have struggled to predict price fluctuations caused by changes in external sentiment and non-linear dynamics. Therefore, AI and blockchain technology have emerged as key analytical tools for financial analysis and investors (Alnami et al., 2025). AI-enabled trading algorithms facilitate investors by identifying patterns, analysing a large volume of data, and predicting changes due to a highly volatile environment. Similarly, blockchain technology enables secure digital infrastructure and transactions by providing algorithm-based decision support and cryptographic verification mechanisms (Ying et al., 2017). AI and blockchain together create a hybrid technological environment for financial users and investors (Lu, 2019).

Irrespective of technological advances and development in terms of blockchain and AI, the critical aspect of the human dimension of trust remains central for AI users. Blockchain is referred to as a system that minimizes the requirement of institutional and interpersonal trust levels due to a cryptographic verification mechanism (Kumar et al., 2023). However, an AI system requires users and investors to rely on such models and mechanisms that can not be easily interpreted due to complex language and mechanisms. While blockchain systems reduce the reliance of financial and AI users on social trust, it also results in algorithmic dependency and uncertainty for the users. Therefore, in complex trading environments that comprise cryptocurrency, there exist financial risks and high volatility for financial analysts and investors.

In financial decision environments and systems that are characterised by a high level of uncertainty and volatility, trust functions as a key mechanism that reduces underlying risk and enables decisions by AI users and analysts in an ambiguous environment. In digital financial ecosystems, measures including encryption, technological reliability, and safeguards ensure users' confidence in system output and reliability. Previous research, including Roger C. Mayer et al. (1995), provides a foundational model of trust formation, highlighting ability, benevolence, and integrity as key determinants of trust in uncertain environments. Although not specific to cryptocurrency, this framework is widely applied in digital and technological contexts to explain how users evaluate trust under risk. However, there exists a research gap in terms of addressing how structural measures in blockchain infrastructure form investors' intention in terms of AI performance and user experience. and the role of trust in an AI-enabled blockchain environment.

There also exists a research gap in terms of determining trust as the primary driver of adoption and how performance and structural measures directly impact the behavioural intention. Therefore, this research aims to address this research gap by examining how perceived AI accuracy, AI experience, and blockchain security impact trust in AI and behavioural intention of users for user AI-based cryptocurrency trading systems. For this purpose, To address this gap, the study uses survey data from 215 active cryptocurrency investors to examine how perceived AI accuracy, blockchain security, and AI experience influence trust and behavioral intention. This research tested a model by differentiating between blockchain security (structural assurance), perceived accuracy (cognitive accuracy), and AI experience (user characteristics).

The study is guided by the following hypotheses:

H_1: *Perceived accuracy of AI-based trading systems positively influences trust in AI.*

H_2: *AI experience negatively influences trust in AI.*

H_3: *Perceived blockchain security positively influences trust in AI.*

H_4: *Trust in AI positively influences behavioral intention to use AI-based trading systems.*

H_5: *Perceived accuracy positively influences behavioral intention.*

H_6: *AI experience negatively influences behavioral intention.*

H_7: *Perceived blockchain security positively influences behavioral intention.*

This research study contributes to the existing knowledge and research in Information Systems (AI) and blockchain in three different ways. Initially, it creates a difference between algorithmic performance and structural security as key drivers of user intention. Secondly, it analyses that the AI experience of a user may result in reducing trust level, which suggests that experienced users of AI are more prone to scepticism related to AI systems and mechanisms. Thirdly, this research study also relates that thought trust is critical in forming the perception of users, but it can not completely determine the adoption of AI by the users. Therefore, the findings of this research study provide key insights for AI developers, financial regulators, and analysts in AI-enabled trading systems in the financial ecosystem and environment, which are decentralised.

2 Theoretical foundation:

2.1 Trust Formation in Hybrid AI–Blockchain Environments

The integration of AI and blockchain creates a hybrid socio-technical environment in which AI provides predictive decision support, while blockchain ensures secure, decentralized, and verifiable transactions. The study by Lu et al. (2019) stated that in cryptocurrency-related trading, AI-based systems are capable of generating predictive recommendations, whereas blockchain infrastructure provides immutability, consensus mechanisms, and cryptographic verifications. In line with this, Kumar et al (2023) stated that blockchain is referred to as a system that reduces trust; therefore, AI users are recommended to use algorithmic outputs and results. Trust is characterised as a central determining factor in adopting technology and the digital environment. This is aligned with the research of Mayer et al. (1995), which stated that trust facilitates the overall decision-making process and reduces perceived uncertainty of AI systems. However, the research emphasised that trust in AI-enabled blockchain systems is different from the traditional level of systems, which comprises interpersonal trust and includes confidence level in algorithmic performance as cognitive trust and confidence in system infrastructure as structural assurance. In AI-enabled cryptocurrency trading systems, trust formation results from belief-based examination of system performance and security measures instead of the underlying behaviour intention model. Similarly, in high-risk systems, users' intention and evaluation of the AI system are based on the characteristics, including infrastructure security and predictive accuracy. This has also been supported by the study of McKnight et al. (2002), which stated that trust formation is influenced by structural assurance mechanisms and users' beliefs about system competence and reliability (McKnight et al., 2002), which relates to the way in which security measures and users' performance beliefs form trust and behavioural intention of users in decentralised financial systems.

2.2 Perceived Accuracy and Trust in AI

Perceived accuracy is a perception among users that there is trust in the reliability, precision, and consistency of predictions made by AI-based trading. Performance indicators especially become salient in risky financial markets like cryptocurrency markets. When results are seen to reflect market performance, the user is more likely to develop trust in AI systems. Studies on algorithmic decision-making indicate that perceived system competence is one of the key antecedents of trust development (Siau & Wang, 2018). The predictability of performance and reliability in the output of predictive analytics are cognitive indicators that create less uncertainty and build dependency (Dietvorst et al., 2015). Perceived system performance, according to a belief-based approach, plays a role in positive evaluative judgment, which subsequently defines the formation of trust. As long as investors believe that AI-generated suggestions are correct, they will consider using the system and trust it with its predictive power.

H1: Perceived accuracy of AI-based trading systems positively influences trust in AI.

2.3 AI Experience and Trust Formation

AI experience captures the extent to which users are familiar with AI systems and predictive tools. Traditional adoption models often assume that familiarity reduces uncertainty and increases positive evaluations. However, in algorithmic decision environments, experience may also increase critical awareness of system limitations. Experienced users may better understand model imperfections, biases, or predictive errors, potentially leading to more cautious evaluations. In financial markets characterized by volatility and high stakes, such skepticism may influence trust formation differently than in general consumer technology contexts. Studies on algorithm aversion indicate that exposure to algorithmic errors can reduce reliance on automated systems, particularly among knowledgeable users (Logg et al., 2019). Thus, experience may produce either familiarity-based trust or heightened critical scrutiny.

H2: AI experience negatively influences trust in AI.

2.4 Blockchain Security as Structural Assurance

Blockchain security reflects users' perceptions of integrity, transparency, and immutability of the underlying infrastructure (McKnight et al., 2002). In contrast to AI accuracy, which signals predictive performance, blockchain security signals structural assurance. Structural assurance refers to the perception that technical and institutional safeguards are in place to ensure safe transactions (McKnight et al., 2002). In cryptocurrency trading ecosystems, blockchain security reduces concerns about data manipulation, transaction fraud, and system tampering. Such assurances may strengthen confidence in AI-driven trading environments by reinforcing perceptions of system integrity (Tylcanaz-Prieto et al., 2023).

Therefore, blockchain security is expected to positively shape trust in AI-enabled trading systems.

H3: Perceived blockchain security positively influences trust in AI.

2.5 Trust and Behavioral Intention

Trust in AI is hypothesised to impact the behavioural intention of the users. When users trust AI-based trading systems, they are more likely to express an intention to rely on AI-generated recommendations.

H4: Trust in AI positively influences behavioral intention to use AI-based trading systems.

2.6 Direct Effects of System Perceptions on Intention

Beyond trust-mediated effects, system perceptions may directly shape behavioral intention. In high-risk financial contexts, investors respond directly to performance and security measures without completely relying on general trust evaluation.

Perceived accuracy may directly encourage intention by signaling expected utility and predictive advantage. Similarly, blockchain security may directly influence intention by reducing perceived transactional risk and reinforcing structural reliability.

H5: Perceived accuracy positively influences behavioral intention.

H6: AI experience influences behavioral intention.

H7: Perceived blockchain security positively influences behavioral intention.

3 Methodlogy

3.1 Research Model Development

These three streams together imply a conceptual framework for trust formation (Figure 1). Soomro et al. (2024) find that trust has a strong positive effect on cryptocurrency adoption intention. Thus, in our model, Trust mediates the effects of PA, BS, and AE on Behavioral Intention. Figure 1 (below) diagrams these hypothesised relationships.

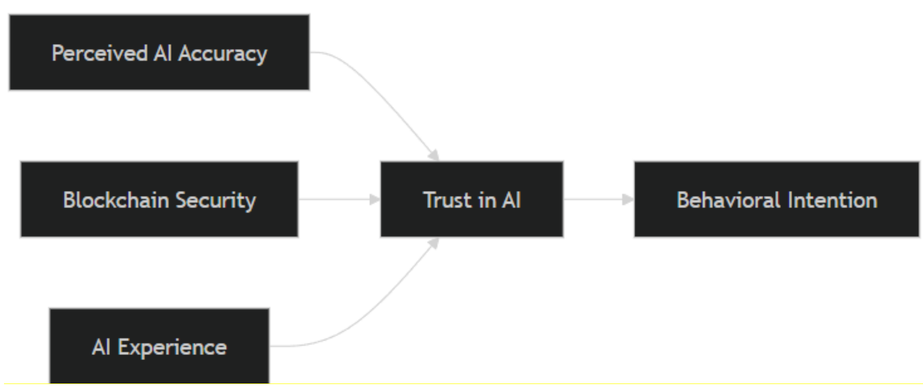

Figure 1: Research framework.

3.2 Research Design and Sample

In this research study, a quantitative survey design was utilised for examining the existing relationship in perceived AI accuracy, Blockchain security, trust in AI, AI experience, and behavioural intention of users for using AI-based cryptocurrency trading systems. For this purpose, data was collected from a sample of 215 active Bitcoin traders and cryptocurrency investors having sufficient knowledge and insights into trading and financial systems. Participants were recruited from online financial and cryptocurrency communities, including trading discussion groups, social media platforms, such as Telegram and Discord, and blockchain forums. The participation in the research study was voluntary, and all participants were informed regarding their voluntary participation and right to withdraw from the study. Participant Information Sheet (PIS) was distributed among the research participants, which included research purpose, confidentiality measures, and the right to withdraw from the research at anytime. PIS also included that no personal or identifiable information was included in the research process. The final research sample included research participants having different levels of trading frequency, gender, age, AI familiarity, and knowledge of the cryptocurrency market.

3.3 Measurement Instruments

All constructs were measured using multi-item scales adapted from established technology adoption and trust literature, contextualised to AI-based cryptocurrency trading. Responses were recorded using a **7-point Likert scale (1 = strongly disagree, 7 = strongly agree)**. Perceived Accuracy (PA), AI Experience (AE), and Blockchain Security (BS) are used as key constructs in the model.

The constructs included:

Perceived Accuracy (PA, 3 items)

Example item: "I believe the AI system provides accurate recommendations."

AI Experience (AE, 3 items)

Example item: "I have sufficient experience using AI systems in decision-making."

Blockchain Security (BS, 5 items)

Example item: "The blockchain ensures that my transactions are secure and tamper-proof."

Trust in AI (TA, 8 items)

Example item: "I can rely on the AI system to perform reliably."

Behavioural Intention (BI, 3 items)

Example item: "I intend to use the AI system frequently in the future."

Demographic variables such as age, gender, trading frequency, and trading history were also collected for descriptive purposes.

3.4 Data Analysis Procedure

In this research study, data analysis was performed in different stages by using R-Studio. A non-probability convenience sampling approach was used, as participants were recruited from online cryptocurrency communities such as Telegram, Discord, and blockchain forums. Initially, descriptive statistics including mean, minimum and maximum value, and standard deviation were calculated by evaluation of the distribution characteristics. Secondly, Cronbach's Alpha was utilised for the evaluation of internal consistency reliability for all the constructs of the research study. For examining the bivariate relationships existing among blockchain security, AI experience, trust in AI, and behavioural intention of users, the research study utilised the Pearson Correlation Coefficient. Afterwards, for a developed hypothesis, multiple regression was performed, and a regression model was developed and used for predicting the level of trust in AI from the perceived accuracy of the AI system, blockchain security, and AI experience. For examining statistical significance in data, standardised coefficients including p-values and t-values were used. Mediation analysis conducted under the research by use of Bootstrap (5000 samples) examined whether trust in AI mediates the relationship between the behavioural intention and system-level perceptions, including AI experience and perceived accuracy. Indirect impact was considered to be significant if the 95% confidence interval in the bootstrap did not include zero. Harman's single-factor-level test was conducted in the research to examine the common method bias existing in the model and data.

3.5 Analytical Rationale

In terms of analytical rationale, the research approach allowed analysis of both the direct impact of system perception on the behavioural intention of AI users and the indirect impact of operating through trust in AI. This system structure enabled researchers to differentiate the perceived accuracy (cognitive performance) and AI experience (user-related experience) in shaping the overall trust and AI users' trading intentions within AI-enabled blockchain and decentralised financial systems.

4 Empirical Findings

4.1 Descriptive Statistics and Correlations

Under descriptive statistics and correlation analysis, the research participants reported that there exists a high level of blockchain security (M=6.10) and the behavioural intention to use AI-based trading systems and platforms is (M=6.00). However, the research further reported that trust in AI (M=5.30) and perceived accuracy (M=5.80) were also high, which indicated that participants reported favorable perceptions of AI-enabled trading systems. The overall experience of AI was reported as moderate (M=4.60), which indicated that the level of participants' familiarity with the AI system varies.

4.2 Pearson Correlation among Constructs

The second finding of this research relates to the Pearson correlation among the constructs of the research. It has been analysed that perceived accuracy and blockchain security are positively related to the behavioural intention of the user and trust in AI. The overall AI experience of users has a negative relationship with the intention and trust of AI users, which suggests that AI users critically evaluate AI systems when they have a high level of experience. Therefore, there exists a significant level of correlation among the research constructs (Please refer to Appendix: 2).

4.3 Regression Analysis: Predicting Trust in AI

For examining predicting trust in AI and determinants of trust in AI, multiple regression analysis was performed by including AI experience, perceived accuracy, and blockchain security as predicting variables. The result of the analysis suggested that trust in AI is positively related to perceived accuracy, which supported Hypothesis 1 (H_1) of this research study. Secondly, blockchain security also resulted as a key predictor in the model, which supported Hypothesis 3 (H_3). AI experience has a significant negative impact on trust level, which supported Hypothesis 2 (H_2), which suggested that skepticism in AI-based trading systems results from experienced AI users (Please refer to Appendix: 3). Perceived accuracy significantly predicted trust ($\beta = 0.299$, $p < .001$), followed by blockchain security ($\beta = 0.423$, $p < .001$), while AI experience showed a negative effect ($\beta = -0.148$, $p < .001$).

4.4 Regression Analysis: Predicting Behavioral Intention

For predicting behavioural intention, regression analysis was carried out by examining predictors of behavioural intention in using an AI-based trading system. Blockchain security is a key predictor of behavioural intention in a single AI system, which overall supported Hypothesis 7 (H_7) of the research study. The regression analysis also resulted in the finding that perceived accuracy has a significant and positive impact on behavioural intention, which supported Hypothesis 5 (H_5) of this research study and results indicate that AI experience does not have a statistically significant effect on behavioral intention; therefore, H6 is not supported. Therefore, trust in AI does not result in significant prediction of behavioural intention when blockchain security and perceived accuracy are included in the analysis model. Therefore, the findings suggest that Hypothesis 4 (H_4) is not supported by the regression analysis in the model.

4.5 Mediation Analysis

This section of the research study discusses mediation analysis carried out to examine whether trust in AI mediates the impact of perceived accuracy and AI experience on behavioural intention. A bootstrap mediation analysis of 5000 samples was conducted, which resulted in trust in AI only mediating the relationship between the behavioural intention and perceived accuracy to a limited extent. The obtained results included an indirect effect (0.26), which represented a total of 38% of the overall mediation total effect. In terms of AI experience, the indirect impact of trust on negative but significant results indicates that a high level of user experience results in reducing the trust level, which results in reducing the overall behavioural intention. As given in the appendix section, the total impact of AI experience on intention is not significant, which further suggests that AI experience does not directly impact the adoption behaviour. The findings and analysis from mediation analysis indicated that trust acts as a key determiner in mediating the role in impacting perceived accuracy, but does not determine the overall behavioural intention when risk aversion and security factors are considered.

4.6 Hypothesis Testing Summary

Table 6: Hypothesis Testing Results

Hypothesis	Relationship	Result
H_1	PA → TA	Supported
H_2	AE → TA	Supported (negative effect)
H_3	BS → TA	Supported
H_4	TA → BI	Not Supported
H_5	PA → BI	Supported
H_6	AE → BI	Not Supported
H_7	BS → BI	Supported

5 Discussion and Contributions

5.1 Discussion of Findings

This research study examined how blockchain security, AI accuracy, and AI experience shape trust in AI and behavioural intention for using decentralised financial systems and AI-based cryptocurrency systems. The findings from this study indicate that there are distinct structures for forming user intention and trust in AI-enabled blockchain. The initial findings included that blockchain security and perceived accuracy positively impact trust in AI, resulting in enhancing the overall level of trust in AI by the users. Thus, blockchain security has emerged as one of the strongest predictor for determining trust level and suggests that in decentralised financial markets, structural assurance and system credibility perform a key role in shaping user confidence. This is supported by the existing research, including McKnight et al. (2002), which stated that structural-level security measures and system mechanisms result in minimising uncertainty in the digital environment. Therefore, perceived accuracy and structural security emerge as key antecedents of trust in AI systems. While transparency is often discussed in prior literature, it was not directly measured in this study and should be examined in future research.

The research findings further related that there is a negative relationship between AI experience and trust of users in AI. In contrast to the conventional assumption, confidence level is not impacted by familiarity. However, the more experienced AI users are, the more sceptical they are in actual terms of use of AI systems. The findings obtained from this research study align with the existing research on aversion, including Dietvorst et al. (2015), which suggests that users may reduce reliance on algorithm systems after identification of errors and inaccuracies. Therefore, in decentralised financial systems, including trading and cryptocurrency, AI users may apply stricter evaluation criteria and standards for system-level automation. Thirdly, in the prediction of behavioural intention of users, perceived accuracy and blockchain security and perceived accuracy are key determinants, whereas trust level in AI is not significant in the applied model. The results obtained suggested that investors are more likely to relate their behavioural intention to the characteristics of the system instead of generalised perceptions related to trust. The mediation analysis carried out under this research also relates that trust partially mediates the relationship between the perceived accuracy and behavioural intention. However, trust does not result in the explanation of adoption behaviour for AI users. Therefore, the findings of the research study suggest that trust is not the only driver for AI adoption in the cryptocurrency financial markets.

5.2 Theoretical Contributions

This research study contributed to research in information systems in three key ways. Firstly, the research study creates a distinction in terms of cognitive and structural drivers of users' intention. The research related to the past research of Mayer et al. (1995) in terms of technology adoption and how trust acts as a key variable in technology. The findings obtained from this research study demonstrated that mechanisms related to structural security directly impact the intention of the user and overall trust evaluation. The findings further suggested that in decentralised financial markets, structural level assurance is directed towards shaping the overall behavioural intention of the users. This study also contributed to reconceptualising the overall role of trust in the adoption of AI by suggesting that trust functions as a transmission mechanism linking performance perceptions to user intention. However, it can not be considered as the only determining factor in the adoption of a structurally secured environment. Thirdly, the research further strengthened the existing research work, including Dietvorst et al. (2015), in the context that AI-experienced users can not completely trust the recommendations provided by AI, as critical scrutiny is required due to familiarity with AI tools and systems. This also integrates user heterogeneity in AI adoption and suggests that user expertise does not directly contribute to improving overall acceptance of AI systems.

5.3 Practical Implications

In terms of practical implications, the findings of this research study suggest that technical developers and platform designers are required to emphasize the performance quality of AI systems and structural security. The user intention can be enhanced through carrying out a transparent audit, an encryption mechanism, and blockchain security. Similarly, trust of AI users and user adoption intention can be improved through testing of transparency and improving overall perceived AI accuracy. For experienced AI users, increased transparency may help contextualize algorithmic errors and improve understanding of system limitations, rather than directly eliminating errors.

6 Limitations and Future Research

Irrespective of its significant contribution in terms of research in blockchain security, investor behaviour, and trust in AI, this research study is subject to certain limitations. The cross-sectional survey design adopted under this research study did not allow causal inference in the research. Future research can address this limitation and use longitudinal or experimental research designs for examining trust calibration by AI users. The second key limitation in the research study was the online recruitment research sample from online cryptocurrency communities, which might have limited the generalisability of the research. Therefore, future research needs to recruit cross-national samples and institutional investors. The third limitation of the research related to the adopted research model is that it only considered antecedents of trust and intention. Additional variables and constructions, including explanation quality, social influence, perceived risk, and regulatory assurance, need to be taken into account in future research for improving understanding and implications of AI adoption in decentralised financial markets.

7 Conclusion

The findings and analysis performed under this research study conclude that perceived performance of the AI system and structural security are directly related to influencing the behavioral intention of AI users in a trading environment; however, trust acts as an evaluator and directs the impact of system-level perception on users' intention. Blockchain security has emerged as a key driver of user intention, and AI experience is related to algorithm checking. Thus, the overall findings of this research study enriched the underpinning theory and understanding in terms of the adoption of technology and trust in the hybrid AI-blockchain eco-system.

Proofreading statement:

The authors confirm that this manuscript has been carefully proofread and revised for language quality, grammar, and overall clarity prior to submission.

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Appendix: 1

Table 1: Descriptive Statistics of Constructs (N = 215)

Construct	Mean	SD	Min	Max
Perceived Accuracy (PA)	5.80	0.85	2.67	7.00
AI Experience (AE)	4.60	0.97	2.33	7.00
Blockchain Security (BS)	6.10	0.71	3.80	7.00
Trust in AI (TA)	5.30	0.72	3.38	6.88
Behavioral Intention (BI)	6.00	0.55	4.67	7.00

Appendix: 2

Table 2: Correlations Among Constructs

Variable	PA	AE	BS	TA	BI
PA	1				
AE	-0.23	1			
BS	0.80	-0.17	1		
TA	0.73	-0.35	0.73	1	
BI	0.65	-0.20	0.66	0.58	1

*p < .05, **p < .01.

Appendix: 3

Table 3: Regression Results Predicting Trust in AI ($R^2 = .63$)

Predictor	B	SE	t	p
Perceived Accuracy (PA)	0.299	0.060	5.02	< .001
AI Experience (AE)	-0.148	0.032	-4.67	< .001
Blockchain Security (BS)	0.423	0.070	6.01	< .001

The model explains 63% of the variance in trust in AI ($R^2 = .63$), indicating strong explanatory power.

Appendix: 4

Table 4: Regression Results Predicting Behavioral Intention ($R^2 = .49$)

Predictor	B	SE	T	P
Perceived Accuracy (PA)	0.189	0.057	3.28	.001
AI Experience (AE)	-0.027	0.030	-0.89	.373
Blockchain Security (BS)	0.277	0.069	3.99	< .001
Trust in AI (TA)	0.070	0.063	1.11	.268

The model explains 49% of the variance in behavioral intention ($R^2 = .49$).

Appendix: 5

Table 5: Mediation Results (Bootstrap, 5,000 samples, N = 215)

Path	Effect Type	Estimate	95% CI	p
PA → TA → BI	Indirect	0.26	[0.16, 0.38]	< .001
PA → BI	Direct	0.43	[0.25, 0.60]	< .001
AE → TA → BI	Indirect	-0.12	[-0.20, -0.05]	< .001
AE → BI	Direct	0.11	[0.00, 0.21]	.049