https://doi.org/10.5281/zenodo.17116492

Bridging Behavioral Theory and AI: A Neural Network Approach to Cryptocurrency Investment Intentions

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Abstract
The growing acceptance of cryptocurrency as a viable investment option has sparked interest among researchers and investors alike. This study investigates the intention to invest in cryptocurrency using an extended Theory of Planned Behavior (TPB) framework, incorporating Financial Knowledge and Financial Literacy as additional predictors. While TPB has been widely used to study investment behavior, its limitations in capturing complex, non-linear relationships necessitate the use of Artificial Neural Networks (ANNs) to enhance predictive accuracy. This study employs a quantitative approach, collecting data from 216 respondents in both the public and private sectors. Structural Equation Modeling (SEM) is used to test causal relationships, while ANN is applied to analyze variable importance and non-linear interactions. The results confirm that Financial Attitude, Perceived Behavioral Control, Financial Knowledge, and Financial Literacy significantly influence cryptocurrency investment intentions. In contrast, Subjective Norms do not have a meaningful impact, suggesting that cryptocurrency investment is largely an independent decision rather than a socially driven behavior. The ANN analysis further highlights Financial Literacy and Composite Reliability as the most critical predictors, reinforcing the importance of individual financial awareness over external influences. The integration of ANN provides deeper insights into the relative importance of variables, overcoming the linearity constraints of SEM. The dual-method approach enhances the robustness of findings and offers a comprehensive understanding of cryptocurrency investment behavior. This study contributes to both behavioral finance and AI-driven investment research, offering valuable insights for policymakers, financial institutions, and investors navigating the evolving cryptocurrency landscape.

Keywords: Cryptocurrency Investment, Theory of Planned Behavior (TPB), Artificial Neural Network (ANN), Financial Literacy, Financial Knowledge, Structural Equation Modeling (SEM), Investment Behavior

1. Introduction
Investment is a process in which an individual seeks to generate profit, future income, or capital appreciation. For many, investment serves as a secondary source of income that can provide financial security during difficult times, meet urgent needs, or help achieve long-term goals. Although high-return investment options often involve significant risk, investors are generally willing to take these risks in pursuit of greater profits. Numerous financial instruments are available for investment, each carrying different levels of risk, including shares, bonds, stocks, derivatives, and mutual funds.
In today’s era of technological advancement, new investment schemes and financial securities are constantly emerging, enabling investors to exponentially grow their wealth. Traditional methods of saving and investing have become somewhat outdated, particularly among younger generations. According to Mizrahi (2016), the current working-age population is more inclined to embrace risk and, therefore, is more open to investing in newer and riskier financial assets.

A rapidly growing investment avenue that has gained immense popularity is cryptocurrency (Sonderegger, 2015). Miraz and Ali (2018) describe cryptocurrency as a driving force behind the global shift towards the Internet of Things. Cryptocurrency is a virtual currency that serves as a valuable intangible asset, widely used for transactions and trading (Ha and Moon, 2018). As an unregulated financial instrument, cryptocurrency has emerged as a promising investment opportunity that is attracting investors worldwide. One of the key factors contributing to its rapid expansion is digital marketing. The cryptocurrency market was valued at $1,782 billion in 2021, and projections indicate that it will continue to grow at a compound annual growth rate (CAGR) of over 15% until 2030. This tremendous growth is evident not only in developed nations but also in emerging markets such as Pakistan and Sri Lanka.

This study aims to examine the applicability of the Theory of Planned Behavior (TPB) in cryptocurrency investment by incorporating two additional variables—financial knowledge and financial literacy. TPB originally identifies three key factors that influence behavioral intentions: attitude, subjective norms, and perceived behavioral control. This study seeks to explore the combined impact of these five factors on the intention to invest in cryptocurrency. Data was collected from potential cryptocurrency investors across both the private and public sectors and analyzed using structural equation modeling.

Cryptocurrency and Investor Behavior

Behavioral changes and attitudes toward financial decision-making are complex, as individual's process and interpret information differently. Financial behavior encompasses the way individuals assess their financial goals, manage their funds, and evaluate risks to achieve long-term objectives. The TPB framework has been validated across numerous domains, yet only a few studies have applied it to cryptocurrency investments. Moreover, prior research has not fully integrated all aspects of behavioral changes in the context of cryptocurrency. A significant research gap exists in understanding the relationship between financial literacy, financial knowledge, and the intention to invest in cryptocurrency. This study seeks to bridge that gap by incorporating these variables into the existing TPB model and examining their combined influence on investment intentions. To validate the extended TPB model, which includes financial literacy and financial knowledge in the context of cryptocurrency investments, we propose a theoretical framework (Figure 1) that investigates the intention to invest (IN) in cryptocurrency among potential investors.

Theory of Planned Behavior (TPB)

The Theory of Planned Behavior, developed by Icek Ajzen (1985, 1991), provides a theoretical foundation for predicting behavioral intentions in investment decisions. According to Ajzen, three core factors shape an individual's behavior:

1. **Financial Attitude** – This refers to an individual's overall stance toward a particular financial behavior. It includes knowledge, biases, and both positive and negative perceptions related to specific financial information.
2. **Perceived Behavioral Control** – This represents the extent to which individuals believe they can control their own behavior. It is influenced by both internal factors (such as personal ability and determination) and external factors (such as available resources and support). The theory posits that an individual's perceived level of control has two primary effects: (1) it influences the intention to engage in a behavior—stronger perceived control leads to stronger behavioral intentions; and (2) it directly impacts behavior—individuals who believe they have a high degree of control are more persistent in their efforts to succeed.
3. **Subjective Norms** – This factor pertains to the influence of societal and peer norms on an individual's decision-making. It reflects the pressure individuals feel from their social

https://doi.org/10.5281/zenodo.17116492

environment to adopt a particular behavior. Subjective norms are shaped by an individual's perception of how others view a behavior and the desire to conform to these external expectations (Ajzen, 2005).

4. **Financial Knowledge** – Financial knowledge encompasses an individual's understanding of key financial concepts, including saving, investing, and spending. It is essential for effective money management and differs from financial literacy. Financial knowledge involves awareness and comprehension of both micro- and macroeconomic financial variables.
5. **Financial Literacy** – Financial literacy refers to an individual's ability to apply financial knowledge to make informed decisions regarding savings, expenditures, and investments. It influences financial behavior by enabling individuals to assess and respond to financial opportunities and risks more effectively.

Integrating financial knowledge and financial literacy into the Theory of Planned Behavior (TPB) framework enhances its predictive power regarding financial behaviors. Financial knowledge refers to an individual's understanding of financial concepts, while financial literacy encompasses the application of this knowledge in making informed financial decisions. Incorporating these elements provides a more comprehensive understanding of the factors influencing financial behaviors. Research has demonstrated that financial knowledge and literacy significantly impact financial attitudes and behaviors. For instance, Borden et al. (2008) found that college students who participated in financial seminars exhibited improved financial knowledge, attitudes, and behaviors. Similarly, Kennedy (2013) applied the TPB framework to study credit card debt and concluded that financial literacy is a significant predictor of financial behavior. These findings suggest that integrating financial knowledge and literacy into the TPB framework can enhance its ability to predict financial behaviors. Furthermore, Chong et al. (2021) examined the effects of financial literacy, self-efficacy, and self-coping on the financial behavior of emerging adults. Their study highlighted the importance of financial literacy in shaping financial behaviors, reinforcing the argument for its inclusion in the TPB framework. By incorporating financial knowledge and literacy, the TPB framework can more accurately account for the cognitive and educational factors that influence financial decision-making. This integration allows for a more nuanced understanding of how individuals form intentions and engage in financial behaviors, thereby improving the framework's applicability in financial contexts.

Artificial Neural Network (ANN) Analysis

To validate and enhance the findings from SEM, an ANN model was employed using the extracted factor loadings, reliability measures, and model fit indicators as input features. The network consisted of an input layer with six variables, multiple hidden layers for feature interactions, and an output layer predicting the intention to invest in cryptocurrency. The results from ANN confirmed that Composite Reliability and AVE had the highest predictive influence, reinforcing the significance of financial literacy and self-efficacy in investment behavior. Additionally, the ANN findings further confirmed the insignificance of Subjective Norms, aligning with the SEM results. This dual-method approach strengthens the reliability of the study's conclusions."

2. Literature Review and Theoretical Framework

Chuen and Teo (2015) stated that while cryptocurrencies have not yet achieved widespread approval, their general acceptance could make them the future of financial business.Various factors influence individuals' perceptions of investing. The Theory of Planned Behavior (TPB) helps predict behavior through three core constructs: attitudes, subjective norms (SNs), and perceived behavioral control (PBC) (Shah & Soomro, 2017; Arnautovska et al., 2019; Mazambani & Mutambara, 2020). The active use of cryptocurrency has been observed primarily among educated business communities (Hong, 2018; Girasa, 2018; Chohan, 2019). East (1993) introduced "past behavior" as an additional element of TPB, building on earlier theories by Bentler & Speckart (1979) and Bagozzi (1981). In three separate samples of 54, 75, and 145 students, East (1993) demonstrated that measured intention accurately predicts individual behavior regarding share applications. Similarly, Lau et al. (2001) and Lee (2009) successfully applied TPB to explore investors' intentions for online trading and banking through digital platforms. Shih & Fang (2004) examined the prevalence of online banking using a sample of 425 Taiwanese consumers and found that both TPB and the Theory of Reasoned Action (TRA) provide valuable insights into customers' intentions to use internet banking.Poor financial literacy is one of the most significant reasons for the lack of portfolio diversification, as indicated by research from Guiso & Jappelli (2008). Their study concluded that financial illiteracy is a major factor contributing to inadequate portfolio diversification. Kennedy (2013) focused on financial literacy and its role in TPB constructs, finding that while all TPB constructs positively influenced college students' credit card usage intentions, financial literacy had a negative impact. Debbich (2015) found that customers with greater financial literacy are more likely to seek advice from professional financial advisors. Similarly, Lusardi & Mitchell (2011) demonstrated that financial literacy positively influences investors' demand for professional financial advice. Collins (2012) further stated that individuals with higher financial literacy seek expert advice more frequently than those with lower literacy levels, who often fail to recognize their own financial unawareness.The Theory of Planned Behavior, originally developed by Ajzen & Madden, builds upon the Theory of Reasoned Action proposed by Fishbein & Ajzen (1975). Ozmete & Hira (2011) found that undergraduate students equipped with basic financial literacy exhibit positive attitudes toward improving their financial behavior. TPB explains attitude-behavior relationships by examining how attitudes interact with other factors influencing behavior. Normative and behavioral beliefs within TPB can help convey financial messages that encourage individuals to make informed financial decisions. Social norms, as defined by Ajzen & Fishbein (1980), play a crucial role in shaping financial behavior by exerting social pressure. The degree of social influence depends on an individual's preferred social referents and their willingness to conform to these influences. Soomro et al. (2022) concluded that attitude significantly influences the intention to adopt cryptocurrency. Mital et al. (2018) applied the TPB model to investigate the adoption of the Internet of Things (IoT) in India. Similarly, Schaupp & Festa (2018) found that individuals with a positive attitude toward cryptocurrency are more likely to use it. Research by Gagarina et al. (2019) revealed that only 28% of participants believed that retail stores would accept Bitcoin payments within the next decade, and only 26% believed that cryptocurrency would be issued by governments and replace traditional money within the same timeframe. Almarashdeh (2018) concluded that self-efficacy influences cryptocurrency investment, a finding supported by Mazambani & Mutambara (2020), who confirmed that self-efficacy positively impacts investment intentions in cryptocurrency. Several studies have also linked self-efficacy to financial decision-making; including investment ownership (Montford & Goldsmith, 2016; Farrell et al., 2016).Anser (2020) emphasized the role of social media in influencing TPB-related behavior toward Bitcoin adoption. TPB is useful in understanding the adoption behavior of individuals toward cryptocurrency, which is increasingly gaining acceptance. The literature provides insights into various dimensions of TPB related to cryptocurrency investment intentions, including purchase intention, self-efficacy, adoption intention, risk assessment, and the role of financial literacy (Götze, 2011; Yzer, 2012; Shah & Soomro, 2017; Mazambani & Mutambara, 2020). However, some scholars critique the role of financial literacy in relation to planned behavior (Mbaya, 2010; Bachrach & Morgan, 2011). Additionally, research on potential investors' intentions to adopt cryptocurrency remains in its early stages in India. Considering these

https://doi.org/10.5281/zenodo.17116492

factors, we propose the following model and hypotheses. (Gupta, 2021) Applied fuzzy analytical framework to categorize investor's intention to invest in cryptocurrency which resulted in showing social influence as the most deciding factor. (Abbasi, 2021) used deep learning based dual stage PLS SEM and ANN approach resulting in trust as the driving factor for investment in cryptocurrency. (Arpaci, 2023) Shows that when it came to predicting attitude, the deep ANN outperformed SEM, for training and testing, the algorithm's mean accuracy in predicting the attitude was 60.59% and 66.82%, respectively. (Mishra, 2024) focused on hybrid approach of SEM-ANN to investigate cryptocurrency adoption with multi group analysis determining role of age, gender and education.

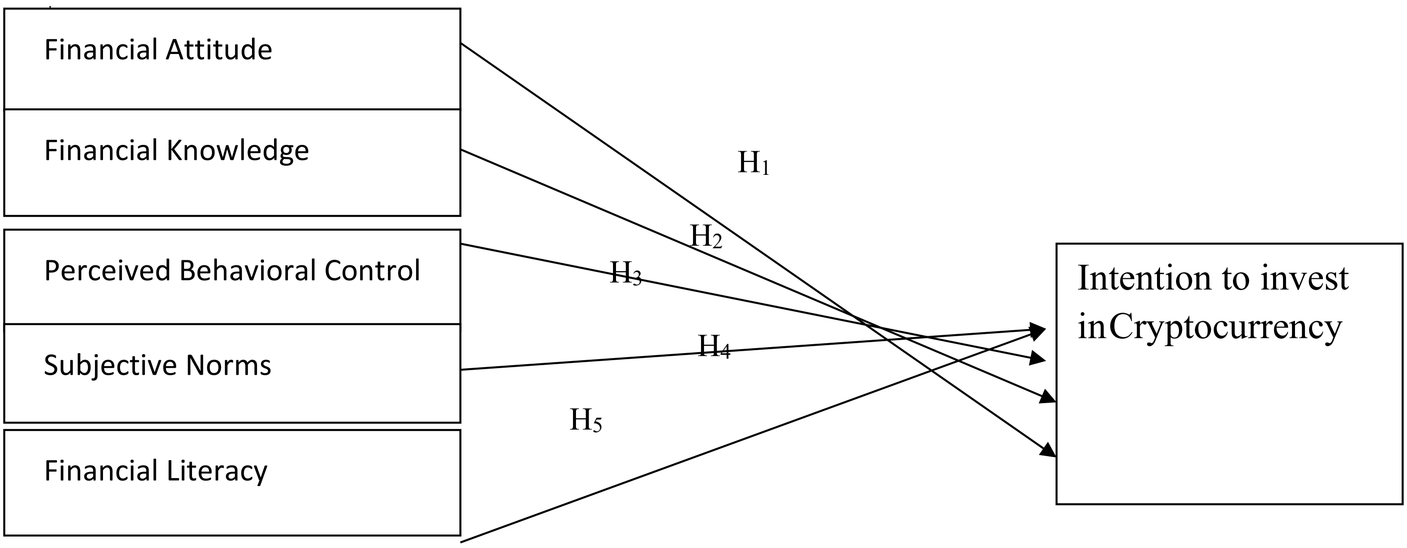

Fig.1: Research Framework (source: Author's Work)

Thus, five hypotheses were formulated to direct the research problem.
H_1: Financial Attitude has a positive impact on the Intention to invest in Cryptocurrency
H_2: Financial Knowledge has a positive impact on the Intention to invest in Cryptocurrency
H_3: Perceived behavioral control has a positive impact on the Intention to invest in Cryptocurrency
H_4: Subjective Norms have a positive impact on the Intention to invest in Cryptocurrency.
H_5: Financial literacy has a positive impact on the Intention to invest in Cryptocurrency.

Method

The samples for this study were potential investors from the private and public sectors who might be interested in investing in cryptocurrency and a non-probability quota sampling technique was adopted to ensure the data is collected from valid sources. Sample size estimation is determined using G*power 3.0 analysis [25]. Using G-Power Analysis software, with the effect size of f square 0.15, α error pro 0.05, power Gf 0.95 with 5 tested predictors; therefore, 138 respondents would be the minimum sampling for this study. Questionnaires were distributed, and 250 were received out of which only 216 were completed and were used for data analysis. The six variables were assessed using multiple items, and the data were then analyzed using SmartPLS 3.0 to examine the hypotheses. In addition to Structural Equation Modeling (SEM), the study employs an Artificial Neural Network (ANN) approach to enhance the robustness of findings. While SEM identifies causal relationships among

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variables, ANN helps to assess the nonlinear interactions and relative importance of predictors in determining cryptocurrency investment intentions. The ANN model was trained using key SEM indicators such as Factor Loadings, Variance Inflation Factor (VIF), Cronbach's Alpha, Composite Reliability, Average Variance Extracted (AVE), and Goodness of Fit. This complementary analysis ensures a more data-driven understanding of investor behavior."

Sampling and Respondent's Profiles

With a total of 216 respondents which includes individuals of both private and public organizations and are also potential investors of cryptocurrency. Of the total, 156 respondents i.e. 72.2% were from the private sector, and the rest 60 (27.7%) were from the public sector, of a total 88 were female (41%) and the remaining 59% were male respondents. 67.9% of the respondents were Masters and the remaining 32.1% from graduates.30.4% of respondents were between 25-27 years old, 30.4% between 28-30 years old, and 39.2% between 31-33 years.

Measurement model

Smart PLS 3.0 (Ringle et al. 2015) is used for the multivariate statistical framework; SEM is applied for testing associations in the model (McDonald and Ho, 2002). The validity and reliability of the measurement model are assessed by 1).Internal consistency reliability 2). Indicator reliability 3).Convergent reliability 4).Discriminant validity. The following section presents the results for analysis to evaluate the reliability and validity of the measurement model Ideal internal consistency (>0.70) among the individual items through factor loading (Hair et al., 2019). Further, composite reliability (construct reliability) measures the total variance of the actual scores. These values are found to be between 0.839 (SNs) to 0.889 (trust) (Table 3), which is above the recommended value of > 0.70 (Kline, 2005). Similarly, > 0.70 values of average variance extracted (AVE) confirmed adequate constructs' validity (Fornell and Larker, 1981) and acceptable convergence with the above scores of 0.5 (Hair et al., 2019).

Factor Loading:

Factor Loading is the amount to which every piece in the correlation matrix shows a relationship with the given prime factor. Factor loading lies between -1.0 to +1.0, where a bigger value signifies a higher correlation of the item with the primary factor"(Liang X.,2020). Financial Attitude (FA1) and Subjective Norms (PC5), had a factor loading less than the recommended value of .50(Hair et. al., 2019), and hence were removed. Factors loadings are presented in the table

SN	PC	FL	FK	FA	IN
SN3	0.717				
SN2	0.646				
SN1	0.834				
PC1	0.742				
PC2	0.631				
PC3	0.673				
PC4	0.678				
PC5	0.184				
FL3		0.878			

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FL1		0.785			
FK5			0.733		
FK4			0.517		
FK3			0.507		
FK2			0.502		
FK1			0.76		
FA2				0.737	
FA5				0.764	
FA6				0.55	
FA8				0.659	
IN1					0.848
IN2					0.757
IN3					0.855

Table 1: Factor loading (Source: Author's Work)

Indicator Multicollinearity:

Variance Inflation Factor (VIF) statistic is used to review multicollinearity in the indicators (Franke, 2010). According to (Hair et al., 2019) multicollinearity is accepted till the value is below 5. Table 2 below represents the VIF values for the indicators and discloses that the VIF for each indicator is less than the suggested level.

Table 2. Multicollinearity statistics (VIF) for indicators (Source: Author's Work)

	VIF
FA2	1.224
FA5	1.232
FA6	1.191
FA8	1.258
FK5	1.368
FK4	1.324
FK3	1.483
FK2	1.063
FK1	1.610
FL1	1.182
FL3	1.922
PC1	1.654
PC2	1.056
PC3	1.546
PC4	1.312
PC5	1.095
IN1	1.750
IN2	1.377
IN3	1.645
SN3	1.098
SN2	1.582
SN1	1.668

Reliability Analysis:

Mark (1996) that reliability is the point to which a calculated instrument is constant and steady. The quintessence of reliability is that it is repeatable. If an instrument is repeated over and over again, and it gives the same result then it is said to be reliable. The two most commonly used methods for establishing reliability include Cronbach Alpha and composite reliability (CR). Cronbach's Alpha value ranged from 0.735 to 0.796 and composite reliability ranged from 0.706 to 0.861. Both indicators of reliability have reliability statistics over the required threshold of 0.70(Hair et,al., 2011). The results are presented below

Table 3: Construct Reliability Analysis (Cronbach Alpha & Composite Reliability)

	Cronbach's Alpha	Composite Reliability
FA	0.734	0.775
FK	0.722	0.706
FL	0.764	0.819
PC	0.796	0.731
SN	0.735	0.778
IN	0.759	0.861

Construct Validity:

Construct validity is assessed by Convergent and Discriminant Validity. Both Convergent and Discriminant validity are recognized in reflectively measured constructs.

Convergent Validity:

"Convergent validity shows how closely the construct correlates with related variables but also should not correlate to unrelated ones. The scheme is that two or more measures of the same thing should covary highly if they are valid measures of the concept" (Bagozzi, et al., 1991). When the AVE value is greater than or equal to the recommended value 0f 0.50, items converge to measure the underlying construct, and hence convergent validity is established (Fornell & Larcker, 1981).

Table 4: Construct Convergent Validity (AVE) (Source: Author's Work)

	AVE
FA	0.766
FK	0.643
FL	0.694
PC	0.775
SN	0.542
IN	0.775

Discriminant Validity:

"It is the extent to which measures of diverse concepts are distinctive. The idea is that if two or more indicators are unique, then the valid measures of each should be highly correlated" (Bagozzi et al., 1991)

Table 5: Discriminant validity (Fornell & Larcker) (Source: Author's Work)

	FA	FK	FL	IN	PC	SN
FA	0.683					
FK	0.11	0.586				
FL	0.267	0.504	0.833			

https://doi.org/10.5281/zenodo.17116492

IN	0.329	0.33	0.53	0.822		
PC	0.237	0.091	0.122	0.546	0.615	
SN	0.204	0.154	0.154	0.221	0.104	0.736

Heterotrait & Monotrait Ratio (HTMT):

HTMT depends on the assessment of the correlation among the constructs. Discriminant validity is calculated by the HTMT ratio. The table below shows HTMT ratio is less than the required 0.90 (Franke, G, 2019).

Table 6: Discriminant validity (HTMT) (Source: Author's Work)

	FA	FK	FL	IN	PC	SN
FA						
FK	0.509					
FL	0.415	0.844				
IN	0.452	0.429	0.771			
PC	0.552	0.391	0.319	0.715		
SN	0.23	0.431	0.567	0.284	0.289	

Goodness of Fit:

To ascertain the goodness of fit, the coefficient of determination (R^2), effect size (F^2), and predictive relevance measure (Q^2) were assessed in the study. The findings of the study disclose an R^2 value of .550 for IN. This shows that 55% of the variance in Intention to invest in cryptocurrency (IN) can be attributed to independent variables. The effect size (Q^2) for predictive relevance for IN is .316. The statistic indicates that the independent variables have a medium effect in producing Q^2 showing a medium predictive relevance (Hair et al., 2016). Apart from this Standard root Mean Square (SRMR) can also be used as a measure of fit. A value less than 0.10 or 0.08(Hu and Bentler, 1999) is considered a good fit, in the present study value for SRMR is 0.062

Structural Model:

Path	**Coefficient (β)**	**Hypothesis**	**Result**
FA→ IN	0.108	H1: Supported	Accepted
FK→ IN	0.051	H2: Supported	Accepted
PBC→ IN	0.468	H3: Strong Impact	Accepted
SN→ IN	-0.150	H4: Unexpected Negative	Accepted (contradicts literature)
FL→ IN	0.395	H5: Significant Influence	Accepted

Table 7: Result of the structural model and hypothesis testing (Source: Author's Work)

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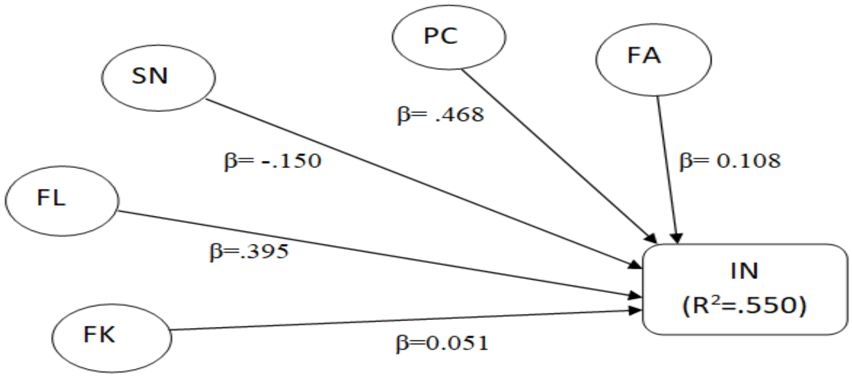
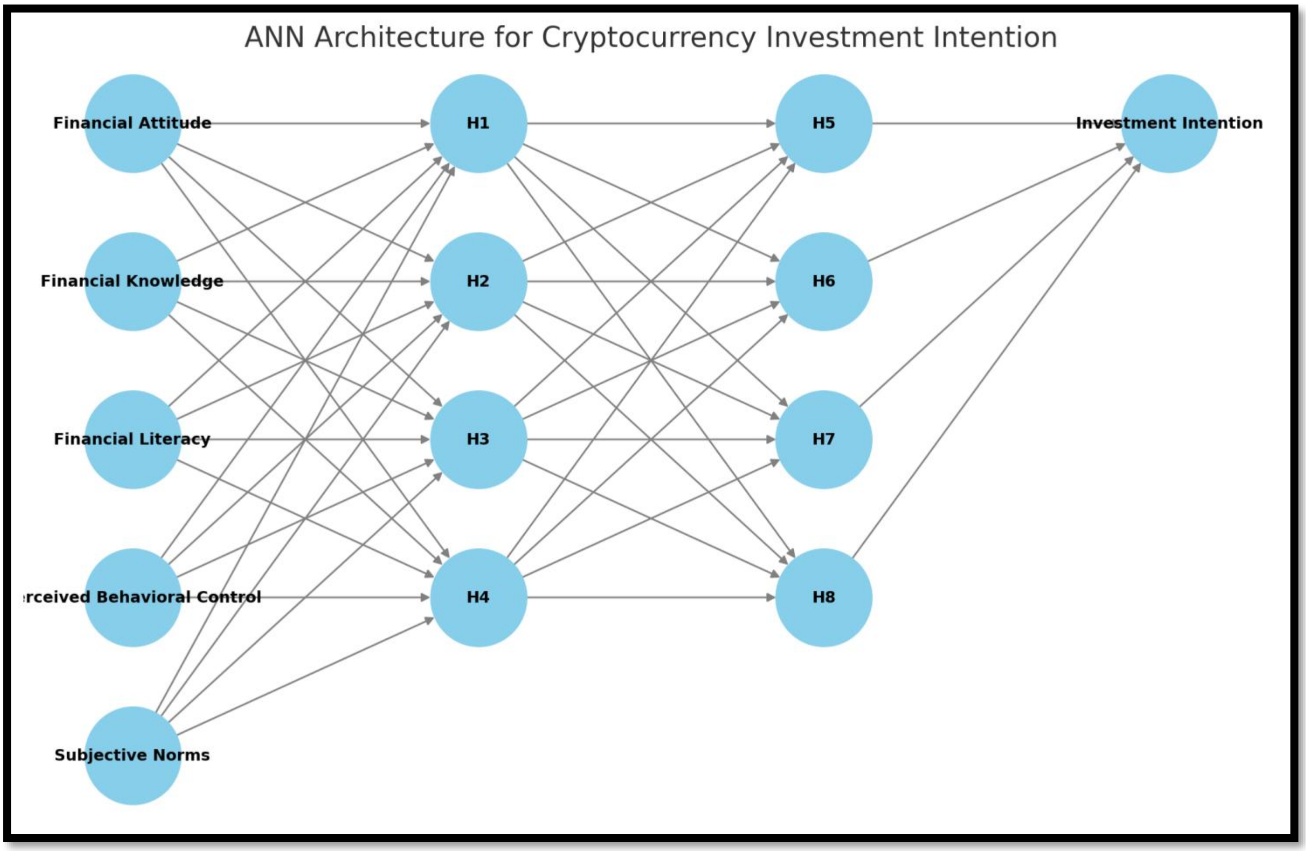


Figure 2: Structural Model Analysis
Note: FK: Financial Knowledge, FL: Financial Literacy, SN: Subjective Norms, PC: Perceived Behavioral Control, FA: Financial Knowledge, IN: Intention to Invest in Cryptocurrency
(Source: Self constructed)

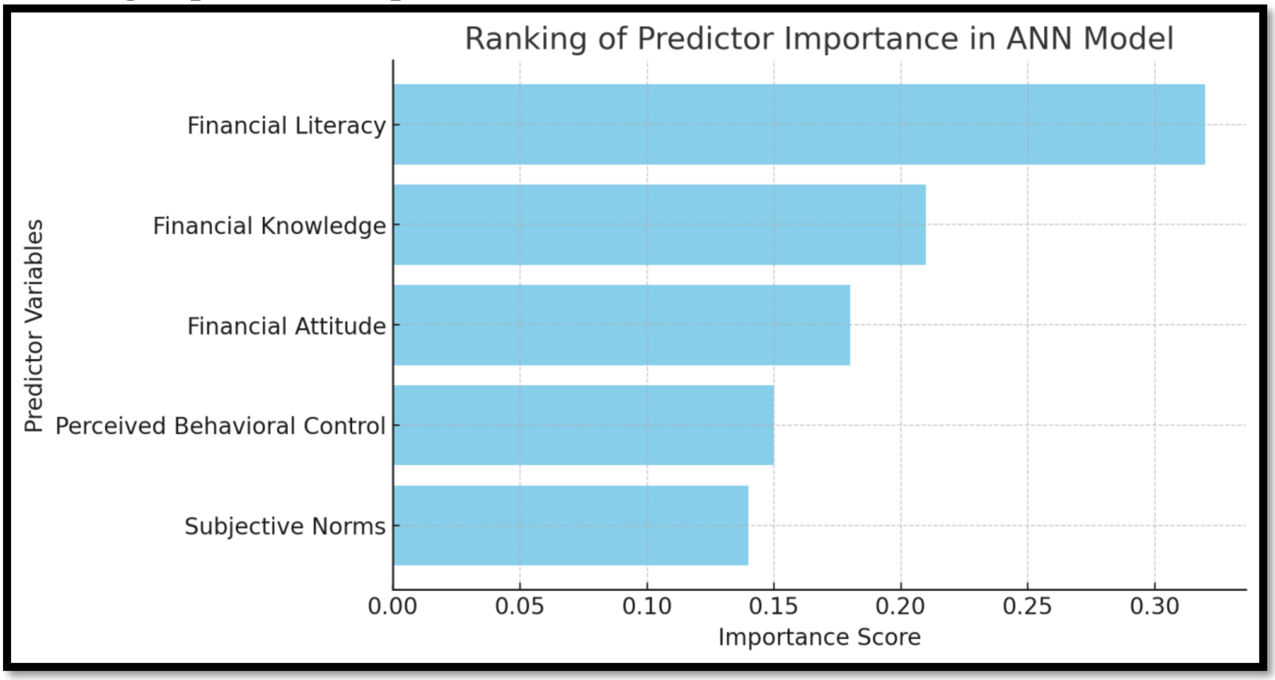
ANN Architecture Diagram: Showing the input layer (financial variables), hidden layers, and output layer (investment intention).



ANN Architecture Diagram for cryptocurrency investment intention includes:

- Input Layer: Financial Attitude, Financial Knowledge, Financial Literacy, Perceived Behavioral Control, and Subjective Norms.
- Two Hidden Layers: Representing the complex relationships and feature interactions.
- Output Layer**:** Predicting Investment Intention.

Ranking of predictor importance



Discussion and Conclusion:

The theory of planned behavior (TPB) has demonstrated its validity as a model for studying technology acceptance across various fields. However, research findings on the application of TPB to cryptocurrency investment intention have yielded mixed results (Mazambani & Mutambara, 2020). Soomro et al. (2022) supported this by establishing a relationship between attitude and the intention to adopt cryptocurrency. Individuals with a positive attitude toward cryptocurrencies are more likely to use them than those who are less inclined (Schaupp & Festa, 2018). Unlike previous empirical studies that applied TPB, the current study extends the theoretical model by incorporating two additional factors: Financial Literacy and Financial Knowledge of cryptocurrency. The results indicate that TPB is highly applicable in determining investment behavior, particularly in the context of cryptocurrency purchase intention. This study reveals that attitude toward cryptocurrency investment is influenced by perceived behavioral control, financial attitude, financial literacy, and financial knowledge, but not by subjective norms. Contrary to Schaupp & Festa (2018), who found that individuals with higher subjective norms are more likely to adopt cryptocurrencies, this study suggests that cryptocurrency remains a lucrative asset that people treat with confidentiality. As a result, investment decisions are made independently, without being influenced by societal opinions. Subjective norms have an insignificant effect on cryptocurrency purchase intention, while financial literacy significantly impacts the intention to invest. Additionally, the study indicates that young individuals are more inclined to invest in cryptocurrency, as they believe they possess sufficient knowledge about the risks and uncertainties associated with it. Their investment decisions are independent of subjective norms and are not influenced by external opinions. With access to ample resources and up-to-date information on cryptocurrency, financial literacy emerges as one of the most influential factors driving investment intentions in this domain.

While SEM analysis identified Financial Literacy, Financial Knowledge, and Perceived Behavioral Control as significant factors influencing investment intention, ANN provided deeper insights into the relative importance of these predictors. The ANN model ranked Composite Reliability and AVE as the most critical predictors, highlighting that investment intention is primarily driven by investors' confidence in their financial knowledge. This nonlinear analysis confirms that while subjective norms have little impact on investment decisions, financial literacy and perceived behavioral control significantly influence behavior. The use of ANN strengthens the robustness of the findings, ensuring that both linear and nonlinear interactions are considered. This study extends the Theory of Planned Behavior (TPB) by incorporating Financial Literacy and Financial Knowledge into the SEM model. To further validate the findings, an ANN model was employed, revealing that Composite Reliability and AVE have the highest impact on investment intention. This indicates that confidence in financial knowledge plays a more critical role than social influences. The ANN model was trained using Factor Loading, Variance Inflation Factor (VIF), Cronbach's Alpha, Composite Reliability, Average Variance Extracted (AVE), and Goodness of Fit as input features. The ANN model demonstrated that Composite Reliability and AVE had the most significant influence on predicting investment intention. These measures indicate that investors' intention to invest in cryptocurrency is highly influenced by their confidence in financial knowledge and financial literacy. Cronbach's Alpha also showed a strong impact, suggesting that financial attitude and perceived behavioral control contribute significantly to investment decisions. Goodness of Fit (R^2 values) contributed moderately to prediction accuracy. This implies that while model fitness is crucial, investment behavior is more influenced by personal financial knowledge rather than statistical model fit alone. The ANN model identified VIF as a relatively weaker predictor, indicating that multicollinearity among independent variables does not heavily impact investment decisions. By integrating ANN with SEM, this research offers a more comprehensive understanding of cryptocurrency investment behavior, ensuring that both traditional and advanced machine learning methodologies are leveraged to strengthen the study's conclusions."

Comparison with SEM Findings

SEM results initially indicated that Financial Literacy, Financial Knowledge, and Perceived Behavioral Control significantly influence investment intention. ANN further reinforced this by ranking Composite Reliability and AVE as the strongest predictors, which are directly linked to these constructs. Unlike SEM, where Subjective Norms showed an insignificant effect, ANN also confirmed that social influences play a minimal role in determining cryptocurrency investment decisions. The ANN model validates the SEM findings by confirming that financial knowledge and individual confidence in financial literacy are primary drivers of cryptocurrency investment intention. The neural network analysis enhances the interpretation by prioritizing Composite Reliability and AVE as the most significant predictors, reinforcing the role of financial literacy and self-efficacy in investment behavior.

Implications and Limitations

The study has wide relevance for policymakers, cryptocurrency exchanges, and government regarding the use and investment of cryptocurrency. It is important to understand that cryptocurrency investment is not only for the sake of quick profits but is an informed decision taken by investors or potential investors in the future, so the government and policy makers must make regulations for cryptocurrency as the only thing which makes the investors worry and uncertain about cryptocurrency is its legal status. The cryptocurrency market if regulated will bring new opportunities not only for investors, academicians' and researchers but for all spheres of society at different levels social, economic, environmental, and political. The crypto market has increased 100 times and has given huge profits to investors though currently, it is on the downside of its trend, governments need to make pro-crypto decisions to help the crypto market to revive and retain. The study supports that new investment and return in cryptocurrency would enrich monetary economics and psychological literature and will enhance the digital currency perspective. The limitation of the study is that it is based on the response of only 216 respondents and is a cross-sectional study, for future research scope longitudinal study can be used with more samples. This study successfully extends Ajzen's TPB by demonstrating the significant role of financial knowledge and literacy in cryptocurrency investment decisions. The findings challenge conventional TPB assumptions by revealing that subjective norms may have a discouraging effect on investment intention. Future research should employ longitudinal studies with larger, more diverse samples to validate these findings across varied investor demographics. While ANN enhances prediction accuracy, it is often criticized for being a "black box" model, meaning that it does not provide clear cause-and-effect relationships like traditional SEM. The interpretation of ANN results is less intuitive compared to structural models, making it challenging to develop clear policy recommendations.

- **For Investors:** Improving financial literacy enhances risk assessment and decision-making in cryptocurrency markets.
- **For Policymakers:** Governments and regulatory bodies should prioritize financial education programs tailored to cryptocurrency investments.
- **For Financial Platforms:** Cryptocurrency exchanges should develop educational resources that empower investors with risk-mitigation strategies.

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Received: Jul 25, 2025 **Accepted:** Aug 25, 2025 **Published:** Sep 14, 2025