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Strategic Financial Decision-Making Among Young Indonesian Investors: A Behavioral Perspective on Cryptocurrency Reinvestment

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ABSTRACT: This study investigates behavioral factors that shape the intention to reinvest in cryptocurrency among young investors in Jakarta, Indonesia. The research adopts a conceptual framework based on the Theory of Planned Behavior (TPB) and the Theory of Interpersonal Behavior (TIB), combining rational variables such as financial literacy and financial influencer with emotional variables including swift benefit and cognitive biases. A total of 528 valid responses were collected through an online survey and analyzed using PLS-SEM. The results indicate that positive sentiment ($\beta = 0.477$) and control belief ($\beta = 0.331$) have a significant impact on reinvestment intention. Emotional factors show stronger indirect effects through these mediators compared to rational factors. In addition, perceived technological advancement plays a moderating role by significantly enhancing the effect of control belief on reinvestment intention ($\beta = 0.208$), while reducing the influence of positive sentiment ($\beta = -0.458$). These findings suggest that emotional responses are more dominant than rational evaluations in guiding reinvestment decisions in volatile digital markets. The integration of TPB and TIB provides a theoretical contribution to the field of behavioral finance and offers practical recommendations for improving investor literacy, platform engagement strategies, and regulatory support in the cryptocurrency ecosystem.

Keywords: cryptocurrency, reinvestment behavior, behavioral finance, positive sentiment, control belief, Indonesia.

I. INTRODUCTION

The landscape of cryptocurrency investment in Jakarta, Indonesia has changed significantly over the past few years. In 2023, national figures indicated approximately 18.25 million individuals held crypto assets. That number rose to 20.16 million by 2024. A notable feature of this trend is the youth of the investors; more than half are under the age of 30, representing mostly Generation Z and Y [1, 2]. This demographic shift signals a generational transition in financial behavior, where digital assets are viewed not only as speculative tools, but also as gateways to financial independence. Nevertheless, participation in cryptocurrency does not eliminate its inherent risk. According to the Bank for International Settlements, nearly 75 percent of Bitcoin traders have experienced financial loss. The collapse of key platforms, including FTX and Terra Luna, revealed systemic flaws that extended beyond technical issues. They impacted trust, governance, and regulatory oversight factors that remain underdeveloped in many emerging markets. Existing literature has examined the psychological drivers behind initial investment decisions. Constructs such as control belief, perceived usefulness, and emotional sentiment have been studied in frameworks like the Theory of Planned Behavior (TPB) [3]. However, much of this research remains focused on first-time adoption. The question of what drives reinvestment particularly among young, emotionally driven investors in high-volatility markets has received limited empirical attention.

This gap becomes more apparent when considering the rapid, affect-laden nature of cryptocurrency environments. Investment decisions in such contexts often arise from a blend of rational appraisal and emotional stimulus. Immediate returns, financial narratives circulated via social platforms, and perceived technological sophistication influence not only intention, but also perception of risk and self-efficacy. In response to this complexity, the present study introduces a behavioral model that integrates multiple theoretical perspectives. In addition to TPB, it adopts constructs from the Theory of Interpersonal Behavior (TIB), Prospect Theory, and core principles of Behavioral Economics. The model investigates how swift benefit, financial literacy, influencer exposure, and cognitive biases shape investor control beliefs and emotional sentiment. These mediating variables are then examined in relation to reinvestment intention. Furthermore, the study tests whether perceived technological advancement moderates these relationships. By contextualizing reinvestment behavior in Jakarta, Indonesia's emerging digital economy, this study offers new insight into the intersection of behavioral finance and platform technology. The findings may help inform regulatory frameworks, enhance platform-user engagement strategies, and strengthen investor literacy efforts targeted at younger populations.

II. RELATED WORK

Although behavioral theories have been widely applied to financial decision-making, the combination of the Theory of Planned Behavior (TPB) and the Theory of Interpersonal Behavior (TIB) has not been thoroughly explored in the context of cryptocurrency reinvestment. This study adopts a theoretical framework that combines TPB [4–5] which emphasizes rational constructs such as attitude, subjective norms, and perceived behavioral control, with TIB [4–5] which accounts for emotional, habitual, and social components of behavior.

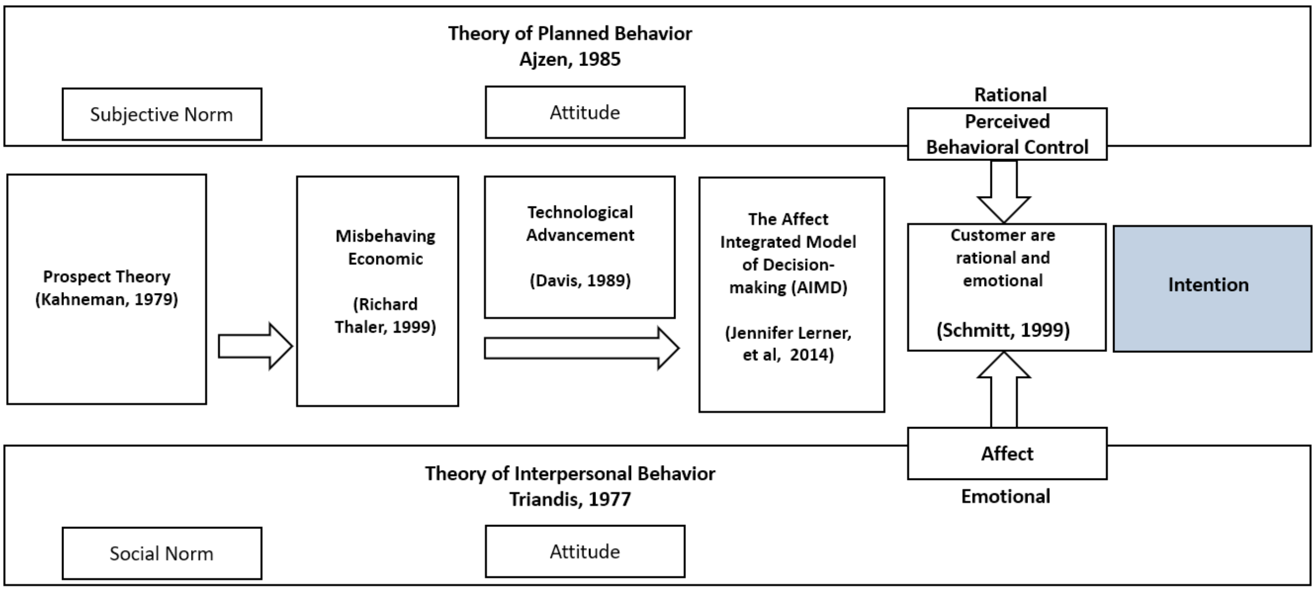

FIGURE 1. Theoretical framework.

While TPB has been extensively used to explain initial investment behaviors, it often overlooks emotional and situational drivers that are prominent in volatile markets such as cryptocurrency. TIB fills this gap by positioning affect as a primary determinant of behavior. This is particularly relevant for environments where decisions are frequently made under pressure and with incomplete information. Schmitt [6] has argued that individuals operate as both rational and emotional agents, highlighting the need for models that capture more than just cognitive reasoning. The integration of TPB and TIB allows for a more holistic view that includes deliberate thought and emotional reaction.

The combination of emotional and rational processes is further supported by Prospect Theory. According to this theory, individuals do not evaluate outcomes in absolute terms but instead compare them to subjective reference points [7–8]. As a result, losses are felt more strongly than equivalent gains. This distortion is particularly relevant in cryptocurrency trading, where dramatic price swings can provoke emotional reactions that override logic and strategic thinking. Behavioral Economics, especially as presented by Thaler, adds further depth to this understanding. It highlights systematic patterns of irrational behavior, including mental accounting and overconfidence [7–8]. For instance, profits from cryptocurrency investments are often treated differently from regular income. This perception, commonly referred to as the house money effect, makes investors more willing to reinvest those gains in riskier assets. Overconfidence can further reinforce this tendency by giving investors an exaggerated sense of control and predictive ability.

The Emotional Decision-Making framework developed by Lerner et al. also supports the role of emotion in shaping financial behavior. Emotions such as fear, anxiety, and excitement influence how information is processed and how quickly decisions are made, particularly in uncertain environments like cryptocurrency markets [3, 9, 10]. These theoretical insights collectively suggest that both rational constructs, such as control belief, and emotional constructs, such as positive sentiment, play significant roles in forming reinvestment intentions. Recognizing this dual process helps explain why some investors remain engaged despite high levels of volatility and risk. In addition, this study introduces perceived technological advancement as a moderating variable. Based on the Technology Acceptance Model [3, 9, 10] the perception that a platform is advanced, trustworthy, and user-friendly can enhance the investor's sense of control. At the same time, it may reduce reliance on emotion when making investment decisions. Previous studies have shown that technology can influence whether people rely more on intuition or analysis in financial contexts, which ultimately affects behavior [3, 9, 10]. In conclusion, this study proposes a comprehensive framework that integrates TPB and TIB with additional behavioral and technological insights. This approach is designed to better explain how young investors in emerging markets form reinvestment intentions in the cryptocurrency space, where both emotion and logic are deeply intertwined.

1. *HYPOTHESIS DEVELOPMENT*

Investment decisions within cryptocurrency markets are influenced by a combination of rational analysis and emotional factors. When facing uncertainty and rapid price fluctuations, investors typically engage in both cognitive evaluation and affective response processes. The Theory of Planned Behavior (TPB) [4, 5] primarily emphasizes rational dimensions such as perceived behavioral control and deliberate intent. On the other hand, the Theory of Interpersonal Behavior (TIB) [4, 5] highlights the importance of emotional and social determinants that frequently guide investor behavior, especially in volatile market conditions.

This study integrates these theoretical viewpoints to propose a comprehensive dual-pathway model incorporating both rational and affective elements. The proposed relationships between these constructs are illustrated visually in Figure 2. Based on this integrative theoretical approach, several specific hypotheses are proposed as follows:

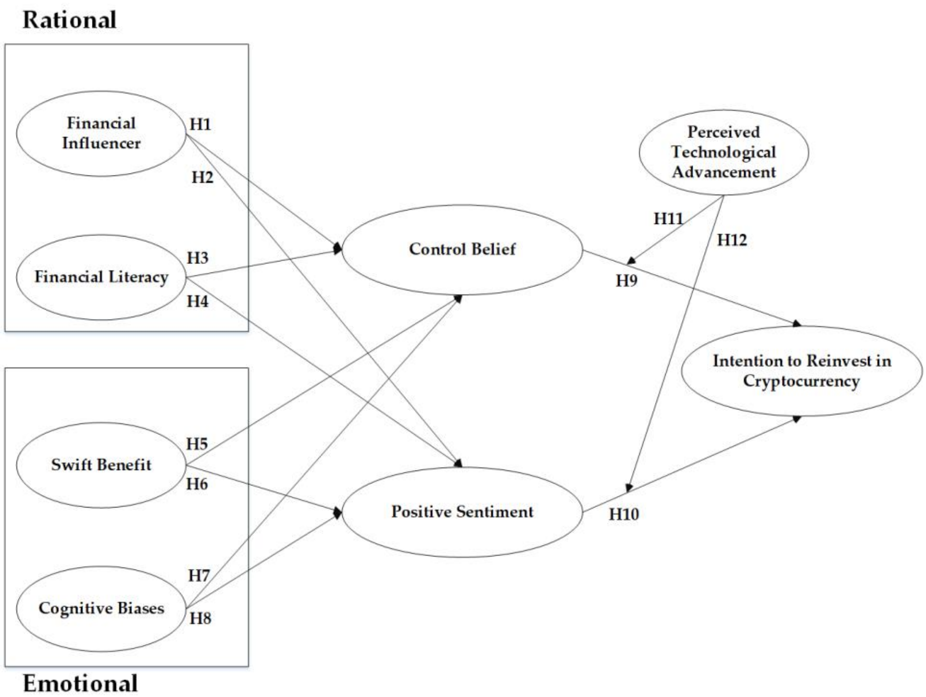

FIGURE 2. Conceptual framework.

- H1: Financial Influencer has a significant positive effect on Control Belief.
  Financial influencers provide credible insights, knowledge, and guidance to investors, thereby increasing their sense of capability and control over making effective investment decisions [11].
- H2: Financial Influencer has a significant positive effect on Positive Sentiment.

Information from financial influencers shapes investor optimism and emotional attitudes by framing investment opportunities positively, thus enhancing their emotional confidence in reinvesting [12, 13].

- H3: Financial Literacy has a significant positive effect on Control Belief.
  Greater financial literacy enhances investors understanding of market dynamics and their ability to manage investment risks, thereby increasing their perceived control over decision-making [14, 15].
- H4: Financial Literacy has a significant positive effect on Positive Sentiment.
  Investors with higher financial literacy experience increased optimism because of their enhanced capacity to evaluate potential returns accurately, thereby fostering positive emotional responses toward reinvestment [16].
- H5: Swift Benefit has a significant positive effect on Control Belief.
  Quick financial gains (swift benefits) provide immediate validation of investment decisions, thus reinforcing investors' confidence and perceived control over their subsequent investment actions [17].
- H6: Swift Benefit has a significant positive effect on Positive Sentiment.
  Immediate gratification from successful transactions significantly boosts investor optimism, enthusiasm, and positive emotions, increasing the likelihood of continued engagement in cryptocurrency reinvestment [18].
- H7: Cognitive Biases have a significant positive effect on Control Belief.
  Cognitive biases such as overconfidence make investors overestimate their ability to control or predict market outcomes, consequently enhancing their perceived control [8].
- H8: Cognitive Biases have a significant positive effect on Positive Sentiment.
  Investor biases, including overconfidence and herd mentality, foster emotional optimism, reinforcing positive sentiment toward cryptocurrency investments despite potential risks [19, 20].
- H9: Control Belief has a significant positive effect on the intention to reinvest in cryptocurrency.
  According to TPB, investors who perceive high levels of control over their investment decisions are more likely to form stronger intentions toward sustained reinvestment actions [4, 21].
- H10: Positive Sentiment has a significant positive effect on the intention to reinvest in cryptocurrency.
  In alignment with TIB, positive emotional responses such as optimism and enthusiasm toward cryptocurrency enhance investors' intentions to reinvest due to increased emotional attachment to potential future returns [13, 22].
- H11: Perceived Technological Advancement significantly strengthens the positive effect of Control Belief on the intention to reinvest in cryptocurrency.
  Advanced technological features in investment platforms strengthen investors' confidence in managing investments effectively, thus amplifying the relationship between control belief and reinvestment intentions [3].
- H12: Perceived Technological Advancement significantly strengthens the positive effect of Positive Sentiment on the intention to reinvest in cryptocurrency.
  When investors perceive cryptocurrency platforms as technologically advanced and reliable, their emotional optimism is further strengthened, reinforcing the influence of positive sentiment on the intention to reinvest [10].

III. MATERIAL AND METHOD

This study employs a causal-explanatory research design to investigate the relationships among variables proposed in the theoretical framework. A quantitative survey was used to gather numerical data suitable for hypothesis testing. Specifically, the study evaluates the influence of control belief, positive sentiment, and perceived technological advancement on reinvestment intentions among cryptocurrency investors. Partial Least Squares Structural Equation Modeling (PLS-SEM) was chosen to analyze these relationships statistically.

1. *DATA COLLECTION*

Primary data were collected through an online survey conducted from March to April 2024, targeting young cryptocurrency investors based in Jakarta, Indonesia. Participants were recruited from cryptocurrency investment communities and forums, ensuring respondents had at least one year of active investment experience in Bitcoin (BTC) and/or Ethereum (ETH). The sampling frame included verification methods such as unique email addresses and IP tracking to ensure no participant was surveyed more than once. A total of 528 valid responses were collected out of 870 distributed invitations, reflecting a response rate of approximately 60.7%. Only fully completed surveys were included, enhancing the reliability of the dataset.

The population targeted in this study consists of all cryptocurrency investors aged between 17 and 43 years (Gen Z and Gen Y) who reside in Jakarta, Indonesia and have invested in cryptocurrency within the last one year.

Furthermore, participants must have experience investing in major cryptocurrencies, particularly Bitcoin (BTC) and/or Ethereum (ETH). To ensure relevance and accuracy, the following inclusion criteria were applied:
1. Respondents were born between 1980 and 2007 (aged 17 to 43 at the time of the study).
2. Respondents had invested in cryptocurrency within the past 12 months.
3. Respondents had previously or currently invested in either BTC or ETH.
4. Respondents reside in Jakarta, Indonesia.

The required sample size in this study was determined through an a priori power analysis conducted using GPower version 3.1. The analysis was performed under the F-test family, employing a linear multiple regression model with a fixed structure and an R^2 deviation from zero as the statistical test. Key parameters included an anticipated small effect size ($f^2 = 0.04$), a significance level (α) of 0.05, statistical power set at 0.95, and a total of six predictors. Based on these criteria, the analysis yielded a minimum sample requirement of 521 participants. The final dataset as presented in Figure 3 comprised 528 valid responses, thereby exceeding the minimum threshold and ensuring sufficient statistical power for reliable estimation using Partial Least Squares Structural Equation Modeling (PLS-SEM).

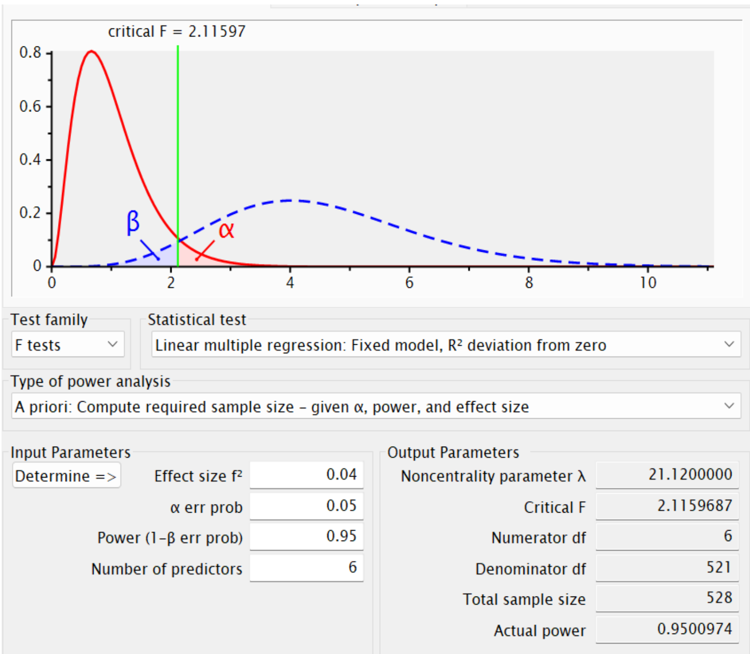

Figure 3. Sample size determination output from GPower 3.1.

The survey instrument comprised structured items measured on a 7-point Likert scale, capturing constructs such as control belief, positive sentiment, swift benefit perceptions, cognitive biases, financial literacy, financial influencers, perceived technological advancement, and intention to reinvest. Screening questions ensured that respondents actively managed their cryptocurrency portfolios rather than engaging in one-time speculative transactions. A total of 528 valid responses were collected. No missing data were observed, as all fields were mandatory for submission. The sample exhibited diversity in investment amounts, portfolio allocations, occupations, and education levels, providing a robust basis for analysis as seen in Table 1.

2. *RESEARCH DESIGN*

The analysis was conducted using SmartPLS 4 software. The measurement model was evaluated using Convergent validity that was evaluated through factor loadings (>0.70) and Average Variance Extracted (AVE >0.50), Internal consistency reliability that was confirmed via Cronbach's Alpha and Composite Reliability (both >0.70). And discriminant validity that was assessed using the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratios, ensuring distinctiveness among constructs.

The structural model analysis assessed by hypothesis testing that was conducted through bootstrapping with 10,000 subsamples to determine the significance of direct, mediating, and moderating effects. Cross Validated Predictive Ability Test (CVPAT) that was used to assess the model's predictive relevance. And Importance

Performance Mapping Analysis (IPMA) was used to identify priority factors influencing reinvestment intentions from a performance optimization perspective. This methodological approach aligns with contemporary practices for predictive behavioral modelling in investment research [23] ensuring relevance in cryptocurrency reinvestment behavior examinations.

IV. DATA ANALYSIS

1. SURVEY DEMOGRAPHICS

A total of 528 young investors from Jakarta, Indonesia participated in this study, all of whom had engaged in cryptocurrency trading involving Bitcoin (BTC) and/or Ethereum (ETH) for a minimum period of one year. The data revealed notable levels of investment: 68.94 percent of respondents held cryptocurrency assets valued at more than IDR 100 million. Furthermore, 53.22 percent had allocated between 51 and 75 percent of their investment portfolios to BTC, whereas 47.35 percent dedicated 25 to 50 percent to ETH. The participant pool was primarily composed of professionals and private-sector employees, with most holding either a bachelor's or postgraduate degree, as outlined in Table 1.

Table 1. Survey demographics (n=528).

Description	Category	Percentage (%)
Total Nominal Investment	Less than IDR 10 million	2.27
	IDR 10-50 million	4.17
	IDR 50-100 million	24.62
	More than IDR 100 million	68.94
BTC Allocation	Less than 25%	3.22
	25%-50%	10.23
	51%-75%	53.22
	More than 75%	33.33
ETH Allocation	Less than 25%	3.79
	25%-50%	47.35
	51%-75%	28.79
	More than 75%	3.79
Current Occupation	Civil servant	5.87
	Housewife	0.38
	Private employee	54.17
	Professional	10.61
	Self employed	28.98
Highest Education	High school or equivalent	0.19
	D1 (Diploma)	10.04
	S1 (Bachelor's)	56.63
	S2 (Master's)	26.89
	S3 (Doctoral)	6.25

1. MEASUREMENT MODEL

To evaluate the measurement model, convergent validity was assessed through item loadings, composite reliability (CR), and average variance extracted (AVE), in accordance with established PLS-SEM recommendations [24, 25]. All outer loadings reported in Table 2 exceeded the recommended threshold of 0.70, with values ranging from 0.836 (NI2) to 0.962 (TA2). These values indicate that each observed indicator contributes substantially to its corresponding latent construct, supporting indicator reliability. Composite reliability values also confirmed internal consistency across constructs. The CR values were 0.941 for Cognitive Biases (CBi), 0.930 for Control Belief (CBe), 0.949 for Financial Influencer (FI), 0.928 for Financial Literacy (FL), 0.909 for Intention to Reinvest (NI), 0.953 for Positive Sentiment (PS), 0.917 for Swift Benefit (SB), and 0.959 for Perceived Technological Advancement (TA), all above the recommended 0.70 threshold [24].

Furthermore, all constructs met the convergent validity criterion based on AVE, with values above 0.50. The AVE values ranged from 0.715 to 0.911, thereby confirming that more than half of the variance in observed indicators was explained by their respective constructs [24]. While the Financial Literacy construct showed high reliability and convergent validity (CR = 0.928; AVE = 0.810), caution is warranted in interpreting these results, as subjective assessments of financial capability may be inflated by overconfidence bias. This cognitive distortion has been well-documented in behavioral finance literature and may distort the relationship between actual and perceived financial knowledge [8, 14]. Future research should differentiate between objective financial knowledge and self-assessed financial confidence to minimize potential bias.

Table 2. Result of measurement model.

Variable	Ind.	Questionnaire Items	OL	CA	CR (rho_c)	AVE
Cognitive Biases (CBi)	CBi1	I feel afraid of missing investment opportunities if I don't act quickly	0.929	0.916	0.941	0.798
	CBi2	I tend to follow investment trends because I trust the majority opinion (peer investors).	0.876			
	CBi3	I am confident that my next investment will yield profits similar to my previous ones	0.883			
	CBi4	I invest because I am confident in the success will achieve	0.886			
Control Belief (CBe)	CBe1	I feel have full control over the cryptocurrency investment decisions I make	0.926	0.887	0.930	0.816
	CBe2	I feel capable of managing risks associated with cryptocurrency investments	0.895			
	CBe3	I understand the risks involved in cryptocurrency investments.	0.888			
Financial Influencer (FI)	FI1	Guidance from financial influencers affects my investment decisions	0.928	0.928	0.949	0.822
	FI2	I feel more confident in investing because of support from financial influencers	0.912			
	FI3	Financial influencers make me want to invest in cryptocurrency.	0.877			
	FI4	Financial influencers serve as references for determining cryptocurrency value	0.907			
Financial Literacy (FL)	FL1	I know how to manage risks in cryptocurrency investments	0.900	0.884	0.928	0.810
	FL2	I feel confident in making decisions about cryptocurrency investments	0.910			
	FL3	I understand the risks of failed investments and still choose to invest in cryptocurrency	0.891			
Intention to Reinvest (NI)	NI1	I will recommend cryptocurrency investments to friends and family	0.837	0.867	0.909	0.715
	NI2	I will continue investing in cryptocurrency in the future	0.836			

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	NI3	Invest in cryptocurrency based on my will	0.871			
	NI4	Social influences affect my intention to invest in cryptocurrency	0.837			
Positive Sentiment (PS)	PS1	I feel optimistic about the future of my cryptocurrency investments	0.908	0.865	0.953	0.911
	PS2	I am happy with my decision to invest in cryptocurrency	0.887			
	PS3	I am optimistic that cryptocurrency values will continue to increase	0.867			
Swift Benefit (SB)	SB1	The quickness of obtaining profits is the main reason I invest in cryptocurrency	0.922	0.943	0.917	0.788
	SB2	I invest in cryptocurrency because I have experienced quick profits	0.940			
	SB3	I can gain quick profits from cryptocurrency due to its rapid value changes	0.934			
	SB4	I invest in cryptocurrency because I can leverage its volatility for quick profits	0.899			
Perceived Technological Advancement (TA)	TA1	I understand that competition in the cryptocurrency influence my intention to invest	0.946	0.903	0.959	0.854
	TA2	I can make use of technological changes to decide whether to invest or not	0.962			

2. *RELIABILITY TEST*

Table 3 presents eight main constructs, Swift Benefit (SB), Financial Literacy (FL), Financial Influencer (FI), Cognitive Biases (CBi), Control Belief (CBe), Positive Sentiment (PS), Intention (NI), and Perceived Technological Advancement (TA), that were tested for reliability and validity. The reliability and convergent validity of the constructs were thoroughly examined to ensure the integrity of the measurement model used in this research. Given that the subject of this study cryptocurrency reinvestment among young Indonesian investors is highly influenced by perception, belief, and sentiment, ensuring internal consistency across psychological constructs was critical.

All latent variables demonstrated strong internal consistency, with Cronbach's Alpha values exceeding the 0.70 threshold. The lowest score was observed in Swift Benefit (0.865), while the highest occurred in Perceived Technological Advancement (0.943). These figures indicate that respondents interpreted and answered each set of questions in a coherent and consistent manner, supporting the use of these constructs in behavioral research involving digital assets [24]. Composite Reliability (CR) values were similarly robust. Ranging from 0.909 to 0.959, they confirmed that items within each construct shared a common conceptual foundation. Particularly, the high CR observed in Perceived Technological Advancement suggests that participants consistently associated technological features such as automation, security, and innovation with the ease or appeal of reinvesting in cryptocurrency. Meanwhile, slightly lower reliability in Reinvestment Intention may reflect the diverse psychological profiles of young investors, whose motivations include not only profit-seeking, but also social influence and speculative thrill.

To strengthen this interpretation, the study also incorporated Dijkstra-Henseler's rho_A values, which ranged from 0.868 to 0.944. These values are known to offer a stricter estimate of reliability than traditional methods, and their consistency across constructs adds further confidence to the stability of the measurement model [26]. Convergent validity was assessed using the Average Variance Extracted (AVE). All AVE values were above the recommended 0.50 threshold, ranging from 0.715 to 0.911. The construct with the highest AVE Positive Sentiment demonstrates that emotional responses to crypto market dynamics were captured with exceptional clarity. This is particularly relevant in the context of Indonesian Gen Z investors, where mood-driven behavior often overshadows fundamental analysis. In contrast, AVE for Reinvestment Intention, though lower, was still solid. This variation could point to the complex, multi-dimensional drivers of reinvestment decisions ranging from past profit experience to peer pressure. Collectively, these results confirm that the constructs used in this model are not only statistically reliable but also conceptually appropriate for capturing the nuanced psychological mechanisms behind cryptocurrency reinvestment behavior. Given the high volatility of the crypto market and the behavioral tendencies of young investors, ensuring measurement quality at this level is essential for producing credible and actionable insights.

Table 3. Reliability test.

Construct	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	AVE	Result
Cognitive Biases (CBi)	0.916	0.918	0.941	0.798	Reliable
Control Belief (CBe)	0.887	0.891	0.930	0.816	Reliable
Financial Influencer (FI)	0.928	0.933	0.949	0.822	Reliable
Financial Literacy (FL)	0.884	0.897	0.928	0.810	Reliable
Intention (NI)	0.867	0.868	0.909	0.715	Reliable
Positive Sentiment (PS)	0.903	0.922	0.953	0.911	Reliable
Swift Benefit (SB)	0.865	0.871	0.917	0.788	Reliable
Perceived Technological Advancement (TA)	0.943	0.944	0.959	0.854	Reliable

3. MEASUREMENT MODEL EVALUATION AND OUTER LOADINGS ANALYSIS

To confirm the validity and reliability of the constructs used in this study, an evaluation of the measurement model was conducted through the analysis of outer loadings, composite reliability, and average variance extracted (AVE). These assessments are essential to ensure that the latent variables, such as sentiment, belief, benefit perception, and technological orientation, are accurately represented in the context of cryptocurrency reinvestment behavior among young investors in Jakarta, Indonesia. The analysis followed established procedures in variance-based structural equation modeling [24, 25].

As presented in Figure 5, all outer loadings exceeded the recommended threshold of 0.70. The loadings ranged from 0.836 (NI2) to 0.962 (TA2), indicating that each observed indicator contributes significantly to its respective construct. Constructs measuring psychological and emotional aspects, including Positive Sentiment, Swift Benefit, and Cognitive Biases, showed consistently strong item loadings. This reflects that the survey items effectively captured the intended behavioral traits related to reinvestment tendencies.

Composite reliability (CR) values for all constructs ranged from 0.909 to 0.959, exceeding the minimum criterion of 0.70. These results indicate that the indicators within each construct demonstrated high internal consistency and measured the same underlying concept in a coherent manner [8, 24, 26]. The rho_A values, which provide a more conservative estimation of internal consistency, also supported the stability and reliability of the constructs [8, 24, 26]. Convergent validity was evaluated through the AVE scores. All constructs exceeded the accepted threshold of 0.50, with values ranging from 0.715 to 0.911. The highest AVE was observed in Positive Sentiment, which is consistent with the theoretical assumption that affective responses play a dominant role in shaping reinvestment intention, particularly within high-risk asset classes such as cryptocurrency [8, 24, 26].

Overall, the measurement model displayed in Figure 5 meets the statistical requirements for construct validity and reliability. These findings confirm that the selected constructs are suitable for investigating behavioral aspects of cryptocurrency reinvestment decisions, especially those driven by emotion, perceived benefit, and technological awareness, among young investors in Jakarta, Indonesia.

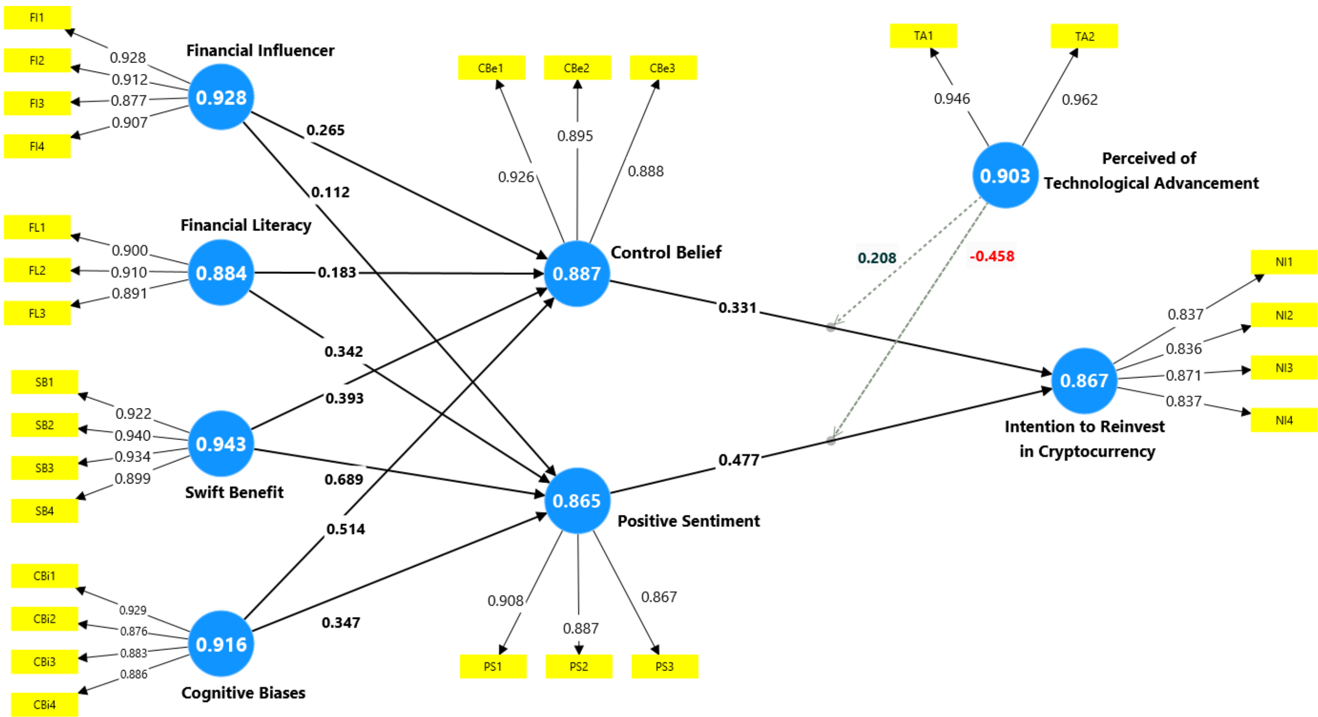

FIGURE 5. Outer model.

4. STRUCTURAL MODEL ASSESSMENT

Upon verifying the validity of the measurement model, the next logical step is to interpret the structural framework. Figure 6 illustrates the relationships among key variables influencing reinvestment in cryptocurrency, a financial decision increasingly popular among young investors in Jakarta, Indonesia. The model offers an insightful view into how emotions, perceptions, and psychological constructs interact to shape reinvestment behavior. A substantial portion of the variance in reinvestment intention is explained by the model ($R^2 = 0.654$). This result affirms the strength of the framework and its relevance in capturing how young investors make decisions in highly volatile crypto environments. Two factors stand out as direct predictors of reinvestment: Control Belief and Positive Sentiment. Control Belief reflects the confidence in handling crypto-related risks and accounts for a significant pathway (0.331). Meanwhile, Positive Sentiment shows an even stronger effect (0.477), suggesting that emotional confidence carries more weight than rational control. In a market dominated by unpredictability and hype, this emotional influence becomes even more pronounced [8, 20].

Looking deeper, Swift Benefit plays a foundational role. It is not only the strongest antecedent of Positive Sentiment (0.689) but also shapes Control Belief (0.393). Investors' attraction to fast gains often fuels excitement and perceived ability, reinforcing reinvestment patterns. This behavior is commonly associated with short-term orientation, which is widely observed among younger, risk-prone investor segments [8, 17]. Cognitive Biases also contribute notably to both sentiment and control. With coefficients of 0.514 and 0.347 respectively, biases such as overconfidence and fear of missing out appear to amplify both emotional optimism and perceived capability. This dual influence highlights the subtle ways in which heuristics affect decision-making beyond conscious awareness [8, 17].

Interestingly, external influences such as Financial Influencers and Financial Literacy had smaller effects on Control Belief (0.265 and 0.183). These findings suggest that while external input helps, internal psychological cues dominate the actual formation of confidence in investment management [24, 14]. One of the most compelling insights comes from the role of Perceived Technological Advancement. While it positively affects Control Belief (0.208), its direct effect on Reinvestment Intention is negative (-0.458). This contradiction implies a nuanced perception. Investors who understand technology may feel more capable, yet that same awareness might also make them more cautious. Possibly, they recognize underlying system volatility or fear unintended consequences from advanced trading platforms or algorithmic manipulation [27, 28]. Altogether, the structural model reveals that the decision to reinvest is not merely a financial calculation. It reflects a broader psychological framework where emotional responses, reward expectations, and cognitive shortcuts merge to drive behavior. Recognizing this interplay is essential for platforms, regulators, and educators who seek to engage younger investors in a more sustainable and informed way.

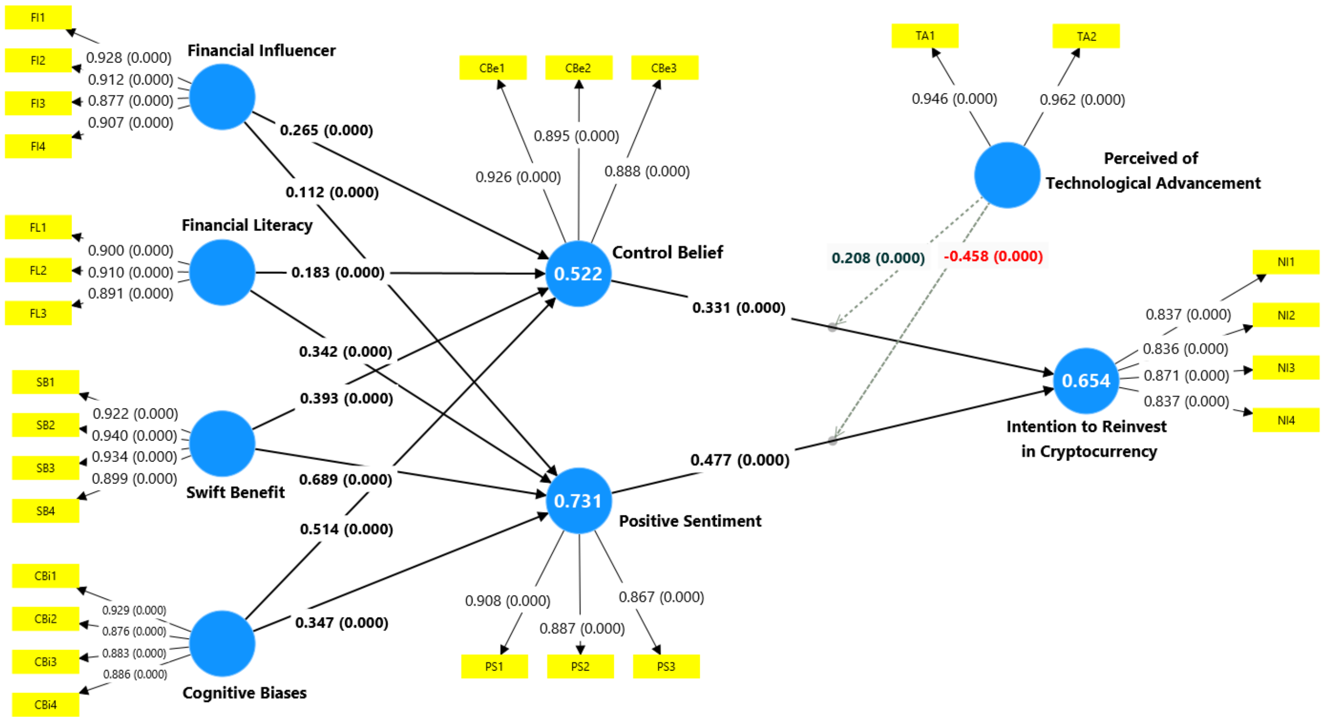

FIGURE 6. Inner model.

5. DISCRIMINANT VALIDITY ASSESSMENT

To ensure that each latent variable in the model represented a unique and conceptually distinct construct, discriminant validity was assessed using the Fornell–Larcker criterion and Heterotrait-Monotrait Ratio (HTMT) with bias-corrected confidence intervals. This analysis is crucial to confirm that variables such as Positive Sentiment, Swift Benefit, Control Belief, and others were not only reliable internally, but also sufficiently discriminated from one another in measuring distinct aspects of reinvestment behavior among young investors in Jakarta, Indonesia [24, 26].

As shown in Table 4, the diagonal values represent the square roots of the Average Variance Extracted (AVE) for each construct. In every case, these diagonal values were higher than the correlations between constructs in the corresponding rows and columns, which satisfies the Fornell–Larcker criterion [24, 26]. For instance, the square root of AVE for Positive Sentiment (0.877) exceeds its correlations with other constructs such as Swift Benefit (0.055), Financial Influencer (0.065), and Financial Literacy (0.366), indicating acceptable discriminant validity. In addition to this, HTMT ratios were further examined using 95% bias-corrected confidence intervals. None of the intervals included the critical value of 1.0, suggesting that there were no issues of multicollinearity or overlap among constructs [24, 26]. For example, the HTMT confidence interval between Control Belief and Cognitive Biases ranged from 0.533 to 0.641, staying well below the problematic threshold. Similarly, the HTMT CI between Swift Benefit and Positive Sentiment ranged from 0.022 to 0.129, further supporting discriminant separation between affective triggers and benefit-oriented motivation.

The importance of this step lies in the behavioral nature of the model. Constructs such as emotion, control, and perceived benefit often intersect in financial decision-making, particularly in high-risk environments like cryptocurrency markets. Ensuring discriminant validity confirms that each psychological and external factor was captured independently, which strengthens the internal logic of the model [8, 20]. By meeting both the Fornell–Larcker and HTMT confidence interval criteria, the constructs in this study can be interpreted as conceptually and statistically distinct. This finding reinforces the appropriateness of the theoretical structure and supports further analysis of the relationships among these drivers in shaping reinvestment intentions.

Table 4. Discriminant validity test.

	CBi	CBe	FI	FL	NI	TA	PS	SB
CBi								
CBe	0.587 CI:(0.533 0.641)							
FI	0.028 CI:(0.029 0.095)	0.252 CI:(0.180 0.322)						
FL	0.035 CI:(0.030 0.113)	0.179 CI:(0.098 0.258)	0.020 CI:(0.023 0.102)					
NI	0.419 CI:(0.358 0.480)	0.678 CI:(0.621 0.731)	0.155 CI:(0.081 0.235)	0.250 CI:(0.170 0.326)				
TA	0.024 CI:(0.023 0.091)	0.546 CI:(0.483 0.605)	0.042 CI:(0.024 0.120)	0.037 CI:(0.022 0.120)	0.131 CI:(0.053 0.227)			
PS	0.422 CI:(0.356 0.487)	0.681 CI:(0.629 0.730)	0.065 CI:(0.030 0.142)	0.366 CI:(0.299 0.431)	0.769 CI:(0.724 0.811)	0.063 CI:(0.032 0.139)		
SB	0.066 CI:(0.027 0.143)	0.443 CI:(0.372 0.510)	0.068 CI:(0.034 0.144)	0.043 CI:(0.529 0.636)	0.584 CI:(0.529 0.636)	0.055 CI:(0.022 0.129)	0.772 CI:(0.735 0.807)	

6. *PREDICTIVE RELEVANCE EVALUATION*

To verify the model's ability to generate accurate predictions beyond the estimation sample, a cross-validated prediction analysis was conducted. This evaluation provides an empirical test of how well the PLS-SEM model performs when applied to new data, which is essential when dealing with behavioral constructs that influence cryptocurrency reinvestment decisions among young investors in Jakarta, Indonesia [24]. The results presented in Table 5 compare the prediction accuracy of the PLS-SEM model with two benchmarks: the indicator average (IA) method and a linear model (LM). The analysis uses average prediction error (referred to as "loss") as a basis of comparison. Lower loss values indicate better predictive accuracy.

When compared to the IA method, the PLS-SEM model consistently showed lower prediction errors across all constructs. For instance, the PLS prediction loss for Positive Sentiment was 0.469, while the IA benchmark recorded 1.090, yielding a substantial loss difference of -0.621. Similar improvement was observed in predicting Intention to Reinvest, where the PLS model had a lower loss of 0.506 compared to 0.835 for the IA benchmark. In every case, the p-values were below 0.001, indicating that the differences were statistically significant.

The comparison between PLS-SEM and the linear model revealed more mixed results. While the linear model performed slightly better in predicting Intention to Reinvest and Positive Sentiment, the PLS model outperformed it in predicting Control Belief. The average loss difference for Control Belief was 0.230, with a p-value of 0.000, showing a clear advantage for the PLS approach in this construct. For Positive Sentiment, the loss difference was minimal (-0.011) but still statistically significant. This suggests that while both methods are viable, the PLS model captures certain dimensions of belief and affective response that may not be as effectively represented by linear models [29].

The final row of Table 5 summarizes the predictive performance across the full model. The average loss for PLS-SEM was 0.556, which is significantly lower than the IA benchmark (1.030), confirming the overall strength of the model's predictive ability. Compared to the linear model (0.514), the PLS model had a slightly higher average loss, but the difference was minor (0.042) and statistically significant. This result supports the view that PLS-SEM remains a valid approach for forecasting multidimensional behavior, especially in research settings where constructs are abstract and interdependent, such as financial behavior in high-risk digital asset environments [24, 29]. These findings indicate that the model not only explains reinvestment behavior well, but also offers practical predictive strength. This reinforces the relevance of behavioral constructs such as control belief, emotional responses, and quick-benefit perception in shaping actual decision-making among young cryptocurrency investors.

Table 5. Cross Validated Predictive Capability Test.

Variables	PLS SEM vs. Indicator average (IA)				PLS SEM vs. Linear model (LM)			
	PLS loss	IA loss	Average loss difference	p value	PLS loss	LM loss	Average loss difference	p value
Control Belief	0.710	1.228	-0.518	0.000	0.710	0.481	0.230	0.000
Intention to Reinvest in Cryptocurrency	0.506	0.835	-0.329	0.000	0.506	0.564	-0.058	0.000
Positive Sentiment	0.469	1.090	-0.621	0.000	0.469	0.480	-0.011	0.022
Overall Model	0.556	1.030	-0.473	0.000	0.556	0.514	0.042	0.000

7. *HYPOTHESIS TESTING RESULTS*

Upon analyzing the model, several psychological and informational elements appear to influence reinvestment behavior in cryptocurrency markets. Financial influencers, for instance, are linked to how investors perceive their sense of control (H1: $\beta = 0.265$) and their overall emotional stance (H2: $\beta = 0.112$). While not the most dominant factor, their presence seems to offer reassurance both in thought and feeling through accessible insights and motivational framing [11, 12, 13]. Similarly, financial literacy shows relevance in shaping investor behavior. Those with better understanding of economic principles tend to feel more in command of their actions (H3: $\beta = 0.183$) and display more confidence in terms of emotional outlook (H4: $\beta = 0.342$). This suggests that knowledge doesn't just improve analytical skills; it also helps reduce anxiety, creating a more positive investment mindset [14, 16].

Expectations of fast returns, labeled here as Swift Benefit, were among the strongest predictors in the model. The data show a clear connection between the promise of quick gains and feelings of control (H5: $\beta = 0.393$), but more strikingly, a heightened emotional state (H6: $\beta = 0.689$). It's plausible that investors, driven by past success or anecdotal wins, become energized and emotionally committed to reinvesting [18, 17]. Another set of variables cognitive biases also plays a central role. These biases were tied to an increase in perceived control (H7: $\beta = 0.514$) and positive sentiment (H8: $\beta = 0.347$). One could interpret this as evidence that psychological shortcuts like overconfidence and herd mentality create a distorted sense of mastery and comfort in otherwise unpredictable markets [8, 20]. Looking at the intention to reinvest, both control belief (H9: $\beta = 0.331$) and emotional positivity (H10: $\beta = 0.477$) mattered. Yet, the emotional component stood out as more influential. This isn't unexpected; after all, behavioral finance theories have long suggested that feelings often carry more weight than facts when individuals make choices involving uncertainty or risk [4, 21, 22, 13].

As for technological factors, investors who perceived crypto platforms as modern and reliable showed a stronger link between control and action (H11: $\beta = 0.208$). Interestingly, though, that same perception appeared to dampen the connection between sentiment and reinvestment (H12: $\beta = -0.458$). Perhaps the technology, while impressive, introduces complexity or uncertainty that weakens emotional motivation [3, 28]. Lastly, checks for multicollinearity confirmed that the relationships observed were not inflated by overlapping constructs. From a practical lens, the study points to the need for balance. Technological advancement alone is not enough users also need emotional clarity, intuitive interfaces, and a sense of psychological safety to continue reinvesting.

Table 6. Hypothesis Test.

Hipotesis		Std. Coeficient	P values	Confidence Interval 5.0% (lower)	Confidence Interval 95.0% (upper)	Result
H1	Financial Influencer -> Control Belief	0.265	0.000	0.217	0.315	Supported
H2	Financial Influencer -> Positive Sentiment	0.112	0.000	0.076	0.149	Supported
H3	Financial Literacy -> Control Belief	0.183	0.000	0.129	0.235	Supported
H4	Financial Literacy -> Positive Sentiment	0.342	0.000	0.301	0.384	Supported
H5	Swift Benefit -> Control Belief	0.393	0.000	0.342	0.444	Supported
H6	Swift Benefit -> Positive Sentiment	0.689	0.000	0.653	0.722	Supported
H7	Cognitive Biases -> Control Belief	0.514	0.000	0.470	0.557	Supported
H8	Cognitive Biases -> Positive Sentiment	0.347	0.000	0.309	0.385	Supported
H9	Control Belief -> Intention to Reinvest_ in Cryptocurrency	0.331	0.000	0.269	0.393	Supported
H10	Positive Sentiment -> Intention to Reinvest_ in Cryptocurrency	0.477	0.000	0.422	0.534	Supported
H11	Perceived of _Technological Advancement x Control Belief -> Intention to Reinvest_ in Cryptocurrency	0.208	0.000	0.158	0.254	Supported
H12	Perceived of _Technological Advancement x Positive Sentiment -> Intention to Reinvest_ in Cryptocurrency	-0.458	0.000	-0.514	-0.391	Not Supported

8. *IMPORTANCE-PERFORMANCE MAP ANALYSIS (IPMA)*

The Importance-Performance Map Analysis (IPMA) provides an extended interpretation of the structural model by identifying indicators that are not only statistically influential but also practically relevant in terms of performance. This approach helps to prioritize managerial interventions by revealing which variables exhibit both high importance (measured by total effects) and high or low performance (measured by average latent variable scores) [24]. As shown in Figure 7, the horizontal axis represents importance, while the vertical axis captures performance. The indicators are plotted across four quadrants, allowing for strategic interpretation.

Indicators such as TA2 (I can make use of technological changes to decide whether to invest or not) and FL3 (I understand the risks of failed investments and still choose to invest in cryptocurrency) are located in the high importance–low performance quadrant. This positioning suggests that although these items strongly influence Intention to Reinvest in Cryptocurrency, their current performance levels are below average. Therefore, these areas represent strategic leverage points where small improvements could yield large behavioral impacts. Enhancing user understanding of technological adaptability and long-term investment risks could lead to significant gains in reinvestment behavior. Conversely, indicators such as PS1, FI2, and CBi3 fall within the low importance–high performance quadrant. While these indicators perform well, their impact on reinvestment intention is relatively minor. Thus, maintaining their current quality is sufficient, but additional investment may not yield proportionally higher returns.

Several items including SB1, SB2, and CBi1 appear in the high importance–high performance quadrant, indicating that these drivers are both effective and impactful. These results affirm the influence of swift benefits and cognitive triggers in promoting cryptocurrency reinvestment among young investors in Jakarta, Indonesia [8, 17]. Indicators like FI1, CBi4, and CBe3 are mapped in the low importance–low performance quadrant, suggesting that they do not substantially contribute to the reinvestment intention and are currently underperforming. While improvement in these areas may be beneficial, they are not urgent priorities for immediate resource allocation. The insights from this map serve a practical function. For reinvestment platforms and fintech product designers, resources should be directed first toward indicators in the high importance–low performance quadrant. Enhancing TA2 through tutorials or intuitive tools, or boosting FL3 via tailored education content, may provide direct improvements in investor intention. These strategies can be executed alongside maintenance of high-performing, high-impact items such as SB1 and SB2. This IPMA analysis adds depth to the interpretation of the structural model by translating statistical significance into actionable performance insight. It supports both theoretical refinement and real-world decision-making in managing behavioral drivers of reinvestment.

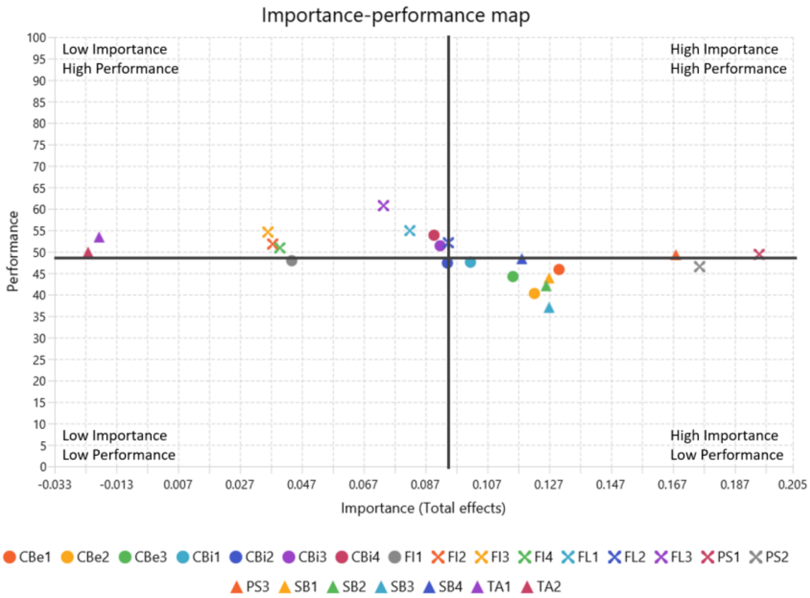

FIGURE 7. Importance performance map analysis (IPMA).

Table 7. Importance performance map analysis (IPMA).

Indicator	**Intention to Reinvest_ in Cryptocurrency**	**Performance (MV Score)**
CBe1	0.130	45.865
CBe2	0.122	40.278
CBe3	0.115	44.223
CBi1	0.101	47.569
CBi2	0.094	47.380
CBi3	0.091	51.389
CBi4	0.089	53.851
FI1	0.043	47.917
FI2	0.037	51.799
FI3	0.036	54.577
FI4	0.039	50.915
FL1	0.082	54.893
FL2	0.094	52.083

FL3	0.073	60.732
PS1	0.194	49.400
PS2	0.175	46.528
PS3	0.168	49.306
SB1	0.127	43.876
SB2	0.126	42.109
SB3	0.127	37.058
SB4	0.118	48.390
TA1	-0.019	53.441
TA2	-0.023	49.905

V. DISCUSSION

This study investigated the factors that influence cryptocurrency reinvestment decisions among young investors in Jakarta, Indonesia. Using an integrated framework that combines the Theory of Planned Behavior (TPB), the Theory of Interpersonal Behavior (TIB), and elements of Prospect Theory, this research revealed both rational and emotional mechanisms shaping investment intention. The use of PLS-SEM allowed for precise evaluation of latent constructs, mediation paths, and moderation effects.

1. COGNITIVE AND EMOTIONAL DETERMINANTS OF REINVESTMENT

The results confirm that Positive Sentiment has the strongest influence on Intention to Reinvest in Cryptocurrency. This finding demonstrates that emotional responses such as optimism, satisfaction, and enthusiasm are central to investment behavior in speculative markets. Rational considerations, such as Control Belief, also play a role, though to a lesser extent [4, 8, 17, 21]. This contrast aligns with studies in behavioral finance showing that emotional conviction often outweighs analytical reasoning when decisions involve high uncertainty [4, 8, 17, 21].

Cognitive Biases significantly affect both Control Belief and Positive Sentiment. This indicates that mental shortcuts, such as following trends or relying on past success, influence how investors judge their own capabilities and form emotional expectations [14, 17, 20, 24]. The influence of Swift Benefit further reinforces this tendency. When investors believe that profits can be achieved quickly, they experience stronger confidence and more positive emotions, which in turn lead to higher reinvestment intention [14, 17, 20, 24]. Although Financial Influencer and Financial Literacy were statistically significant, their effects were modest. This suggests that while external input and financial knowledge are valuable, the personal interpretation and emotional processing of these inputs are more decisive in shaping behavior [14, 17, 20, 24]. One interpretation of the limited effect of Financial Influencer is that young investors are becoming more selective and critical in assessing influencer content, relying more on personal judgment.

2. THEORETICAL CONTRIBUTIONS OF THE INTEGRATED MODEL

The integration of TPB and TIB offers a theoretical contribution by explaining how beliefs, emotions, and social cognition interact to influence behavior. While TPB emphasizes volitional control and intention formation, TIB adds an emotional and normative layer that better reflects real-world decision-making. In combining these two theories, the model provides a more comprehensive explanation of how intention is shaped in the context of cryptocurrency investment [4, 24]. This synthesis demonstrates that behavioral intention is not the result of planned reasoning alone. Instead, emotional reactions and perceived consequences also play significant roles. By applying this integrated framework, the study contributes to a deeper understanding of investor behavior within a financial environment that is often volatile, decentralized, and rapidly evolving.

3. IMPACT OF PERCEIVED TECHNOLOGICAL ADVANCEMENT

The moderation analysis yielded two important insights. When Perceived Technological Advancement interacts with Control Belief, it strengthens the influence on Intention to Reinvest. This suggests that investors who perceive technology as reliable and empowering are more confident in acting on their investment plans. In contrast, when this same construct moderates Positive Sentiment, the effect becomes negative. This pattern may reflect a reaction to rapid or complex technological changes. When updates or innovations are introduced without adequate explanation, users may feel overwhelmed. This can reduce their emotional engagement and weaken the link between sentiment and action [28]. These results suggest that while technology is essential, its perceived accessibility and clarity are equally important for maintaining investor trust and enthusiasm.

4. PREDICTIVE ACCURACY AND MEDIATION EFFECTS

The PLS model showed stronger predictive performance than the Indicator Average benchmark. However, differences with the Linear Model were marginal for some constructs, except for Positive Sentiment, which maintained stronger predictive value. This indicates that some aspects of investor behavior follow non-linear patterns, particularly in emotionally driven decisions [29]. The mediation analysis revealed that all mediating constructs act as partial mediators. This means that while they explain a portion of the effect from external factors to intention, additional variables may be influencing the decision-making process. This observation validates the inclusion of multiple theoretical dimensions and encourages future studies to explore complementary factors.

5. PRACTICAL IMPLICATIONS FOR INVESTMENT PLATFORMS AND POLICY

These findings offer practical value for platform developers, investor education providers, and regulators. First, enhancing emotional engagement may be more effective than focusing solely on information delivery. Design elements that promote feelings of security, achievement, and personal control such as progress indicators, portfolio summaries, and intuitive interfaces can reinforce positive sentiment. Second, improving perceived literacy, particularly in areas related to risk and self-directed decision-making, remains essential. Financial education campaigns should emphasize both conceptual understanding and practical application. Helping users interpret volatility or assess risk may improve their confidence and reduce reliance on biases [14]. Third, the role of technological perception suggests that innovation should not outpace users' ability to adapt. New features should be introduced with clear guidance, contextual explanations, and support systems that make investors feel confident in navigating changes. Finally, from a regulatory perspective, the results indicate that efforts to improve investor outcomes should include support for psychological readiness. Beyond safeguarding against fraud or market manipulation, regulators can help by encouraging best practices in platform design, promoting clear communication standards, and supporting digital financial education.

VI. CONCLUSION

This research examined the behavioral factors influencing cryptocurrency reinvestment intentions among young investors in Jakarta, Indonesia. By integrating the Theory of Planned Behavior (TPB), the Theory of Interpersonal Behavior (TIB), and Prospect Theory, the study proposed a comprehensive framework that captures both rational and emotional dimensions of financial decision-making in digital investment contexts. Empirical results confirmed that emotional constructs, particularly Positive Sentiment and Swift Benefit, exert the most substantial influence on the intention to reinvest. These findings indicate that young investors are not solely driven by rational cost–benefit analyses but are significantly shaped by perceived gains and affective responses. Such results validate the evolving role of emotions in shaping financial actions, especially in highly volatile and tech-driven environments such as cryptocurrencies [7, 8, 21].

The integration of TPB and TIB in this study represents a meaningful theoretical advancement. While TPB explains intention based on perceived control and rational evaluations, the addition of TIB accommodates affective, habitual, and experiential influences. This approach reflects the complexity of investment decisions in digital assets, where sentiment and immediacy of gain often supersede deliberative thought. The successful application of this hybrid framework marks a step forward in behavioral finance research [4, 5, 14, 30, 31]. From a managerial perspective, the findings offer actionable insights for cryptocurrency platforms, regulators, and financial educators. Platforms should prioritize user experience and emotional engagement, not merely transactional efficiency. Regulatory bodies are advised to complement financial literacy campaigns with programs that address emotional decision-making and digital trust [4, 5, 14, 30, 31]. Recognizing that trust and optimism can outweigh risk perception, strategic communication should be designed to reinforce positive investor sentiment and mitigate confusion stemming from technological complexity. However, the study also uncovers limitations in the influence of Financial Influencers and the moderation role of Perceived Technological Advancement. These outcomes may suggest a shift in investor attitudes toward independence and skepticism, possibly driven by overexposure to promotional content or disillusionment with speculative hype. Future system designs must be guided not only by innovation but also by clarity and psychological accessibility.

Several limitations should be acknowledged. The cross-sectional design constrains temporal insights, and self-reported measures may be influenced by bias. Moreover, while the study focused on intention, actual reinvestment behavior was not observed. Further longitudinal research incorporating behavioral tracking or experimental methods could enrich these findings. Additionally, extending this framework to diverse investor populations or regional comparisons may enhance generalizability. In conclusion, the study confirms that emotional evaluations are key predictors of cryptocurrency reinvestment intentions among young investors. It contributes a theoretically enriched model and presents practical guidance for improving platform design, investor support systems, and regulatory strategies in the evolving landscape of digital finance.

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Author Contributions

All authors made an equal contribution to the conceptualization, methodology, and planning of the study. Reddy Chandra contributed to the software, writing, visualization, and funding acquisition. Ferdi Antonio and Laurens Kaluge contributed to supervision and project administration. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data are available from the authors upon request.

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