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Crypto Investment Psychology: Analysis of the Effect of Overconfidence and Financial Literacy with a Mental Budgeting Approach on Indonesian Retail Investors

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ABSTRACT

This study examines the psychological and cognitive mechanisms that drive cryptocurrency investment decisions among Indonesian retail investors by integrating overconfidence, financial literacy, investment interest, and mental budgeting within a serial mediation framework. As the adoption of digital assets accelerates in emerging markets, understanding the behavioral foundations of crypto participation becomes increasingly important. Using a cross-sectional survey of 350 active retail investors and Partial Least Squares Structural Equation Modeling (PLS-SEM), the study evaluates both direct and indirect effects across five key constructs. The findings reveal that overconfidence is the strongest predictor of investment interest and subsequent investment decisions, indicating that emotional overestimation of personal capability remains a dominant behavioral force in high-risk digital trading environments. Financial literacy also significantly influences investment interest and decision-making, although its effects are more rational and structured when compared to overconfidence. Investment interest and mental budgeting exhibit robust sequential mediation effects, demonstrating that investors' decisions are shaped through a multi-stage psychological process involving affective activation followed by cognitive fund allocation. This suggests that crypto trading behavior is neither purely rational nor purely bias-driven, but rather a hybrid mechanism shaped by interacting behavioral and cognitive paths. The study extends behavioral finance theory by positioning mental budgeting as a central mediator within crypto investment models and highlights limitations of traditional TAM/TPB frameworks in explaining speculative digital asset behavior. Practical implications emphasize the need for financial education that targets cognitive biases, emotional regulation, and high-risk budgeting practices. Overall, the findings contribute to a deeper understanding of psychological decision pathways in rapidly evolving digital financial ecosystems.

Keyword: *Overconfidence, Mental Budgeting, Crypto Investment Decisions.*

INTRODUCTION

Crypto investors in Indonesia have grown rapidly in recent years. Official data from the Indonesian Commodity Futures Trading Regulatory Agency (Bappebti) shows that the number of crypto asset investors has surpassed capital market investors, due to increased access to digital platforms and the perception that crypto offers the potential for high profits in a short time (BAPPEBTI, 2023). However, this surge is not entirely driven by rational considerations, but also by psychological factors such as behavioral biases, inaccurate risk perceptions, and a tendency to make impulsive decisions—characteristics often found among retail investors in markets with extreme volatility like crypto (Barber & Odean, 2001).

The core problem of this research stems from three phenomena:

(1) high overconfidence bias, where investors overestimate their ability to predict prices (Bai, 2023);
(2) poor budget planning (mental budgeting), resulting in investment decisions made without adequate self-control (Heath & Soll, 1996); and
(3) unequal financial literacy, which often leads investors to misjudge the risks of crypto assets (Lusardi & Mitchell, 2014).

The combination of these three factors makes crypto investment decisions in Indonesia susceptible to excessive risk-taking that is disproportionate to financial capacity and risk awareness.

From an academic perspective, there are significant research gaps. First, behavioral models such as the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) are widely used in technology adoption studies, but they are rarely applied to crypto investment decisions, a context inherently high in risk and rife with psychological biases (Venkatesh & Davis, 2000; Ajzen, 1991). Second, the concept of mental budgeting although important in behavioral finance is generally tested in the context of consumption or savings, not high-risk investments like crypto (Soman & Cheema, 2011). Furthermore, almost no research has examined mental budgeting as a layered mediator (serial mediation M1→M2) bridging the relationship between psychological biases, investment motivation, and investor final decisions.

Based on this gap, this research aims to address two main research questions:

(1) how overconfidence and financial literacy influence the interest and investment decisions of retail investors in Indonesia; and

(2) what is the mediating role of investment interest and mental budgeting in shaping investment decisions.

The aim of this research is to analyze the direct and indirect relationships between these variables, while also examining the psychological-behavioral pathways that shape crypto investment decisions.

This article's contributions are both theoretical and practical. Theoretically, this research expands the behavioral finance literature by presenting a serial mediation model that explains how interest and mental budgeting operate as layered mechanisms in high-risk investment decisions. Practically, the research findings provide an empirical basis for regulators, crypto platforms, and retail investors to design education and risk mitigation strategies that are more relevant to the behavioral patterns of Indonesian investors.

LITERATURE REVIEW

Overconfidence is one of the most dominant behavioral biases in modern investment decisions. This bias arises when individuals overestimate their analytical abilities, information accuracy, or market knowledge. With highly volatile crypto assets, overconfidence is even more likely to form because investors often rely on intuition and shallow experience to interpret rapidly fluctuating prices. Recent research shows that overconfidence increases trading frequency, risk tolerance, and the likelihood of engaging in high-risk assets like crypto (Kumar & Goyal, 2021; Chen et al., 2023). Another study on the digital asset market also found that overconfidence drives impulsive and excessive decisions when investors overestimate their personal abilities (Bai, 2023). This makes overconfidence a key psychological variable in research on crypto investment behavior.

Financial literacy serves as a cognitive foundation that determines the quality of financial decision-making. Individuals with high literacy are better able to understand risks, market mechanisms, and evaluate investment instruments. In the context of uncertain crypto assets, financial literacy has been shown to reduce behavioral biases, improve information processing, and improve risk judgment including among young investors who are the primary users of digital assets (Potrich et al., 2020; Morgan & Trinh, 2021). Recent research also emphasizes that digital literacy and financial literacy must be considered together to comprehensively explain crypto investment behavior (Awais et al., 2022).

Investment interest is the initial psychological drive that connects emotional and cognitive factors with actual actions. In behavioral models such as the TPB and TAM, interest is the most direct predictor of actual behavior. Recent research on crypto assets has found that interest is influenced by perceived usefulness, perceived risk, sensation-seeking, financial literacy, and behavioral biases (Tao et al., 2022; Wachira et al., 2023). In the context of high-risk markets, investment interest reflects not only interest but also psychological readiness to enter the market.

Mental budgeting is a self-regulation mechanism that involves creating mental financial categories that facilitates individual control over the allocation of funds. In recent years, this concept has gained attention in behavioral finance because it has been found to influence how individuals set loss limits, determine capital allocation, and maintain financial discipline (Bai, 2023; Lahti & Lagerkvist, 2020). Although mental budgeting has been widely studied in the context of consumption and savings, its

application to crypto assets remains very limited. The limited literature on mental budgeting as a sequential mediator makes this research a significant theoretical contribution.

Crypto investment decisions are influenced by emotional factors, cognitive factors, and individual control mechanisms. In highly volatile markets, investor decisions are more often driven by psychological biases than by in-depth fundamental or technical analysis. Recent empirical studies have shown that factors such as overconfidence, financial literacy, risk tolerance, and budgeting behavior simultaneously shape investors' decisions to buy, hold, or sell crypto assets (Kristjanpoller et al., 2020; Akhtar et al., 2023). This suggests that crypto investment behavior is the result of a combined interaction between emotional drives, cognitive capacity, and self-regulatory behavior.

This research's conceptual model integrates these three perspectives into a single structural framework. Overconfidence and financial literacy are assumed to influence investment intentions, which then encourages mental budgeting as a form of internal control before making investment decisions. This integration brings together behavioral finance, self-regulation theory, and the TPB approaches, while also providing a theoretical contribution by testing serial mediation in the context of crypto assets—a relatively new domain in academic research.

METHODS

This study uses a quantitative explanatory approach to analyze the influence of overconfidence and financial literacy on crypto investment decisions, with investment interest and mental budgeting as sequential mediators. This approach was chosen because it is appropriate for testing the causal relationship between psychological variables and financial behavior in the context of high-risk assets.

Research Design and Sample

The study employed an online survey method via Google Form distributed to retail crypto investors in Indonesia. The sampling technique used was purposive sampling, with the following criteria:

1. Domiciled in Indonesia,
2. Having active crypto assets or having conducted crypto transactions,
3. Being at least 17 years old.

A total of 350 respondents met the criteria, and their data were used in the analysis. This number meets the minimum standards for PLS-SEM analysis, which, according to Hair et al. (2021), requires ≥10 times the number of indicators in the largest path. With over 30 indicators, a sample size of 350 provides strong statistical power and high estimation stability.

Research Instrument

The research instrument was a 1–5 Likert-type questionnaire measuring five main constructs:

- Overconfidence
- Financial Literacy
- Investment Interest
- Mental Budgeting
- Investment Decisions (Crypto Asset Ownership)

All items were adapted from recent empirical literature (Nguyen et al., 2022; Bai, 2023; Heath & Soll, 1996; Lin, 2021; Gollwitzer, 1999) and adapted to the context of Indonesian crypto investors.

Data Collection Procedure

Data collection was conducted over two weeks through online distribution in Indonesian crypto trader Telegram and Discord communities, as well as digital asset education forums. Respondents were required to confirm that they understood the risks of crypto assets and were willing to participate voluntarily.

Data Analysis Techniques

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 software. The analysis was conducted in two stages:

1. Outer Model Evaluation

- Convergent validity: factor loading > 0.70 and AVE > 0.50

- Discriminant validity: cross-loading and Fornell-Larcker criterion
- Composite reliability: Cronbach's Alpha and Composite Reliability > 0.70

2. Inner Model Evaluation

- Test the significance of path coefficients using bootstrapping on 5,000 samples
- R^2 value to determine predictive power
- Effect size (f^2) to determine the contribution of each variable
- Predictive relevance (Q^2)

Research Ethics

All participants participated in the study voluntarily and anonymously. There were no financial incentives to avoid participation bias. This study did not collect sensitive data such as specific crypto assets held or portfolio value.

RESULT AND DISCUSSION

Respondent Descriptive Statistics

Respondent profiles were analyzed to provide a demographic overview of the crypto investors involved in this study. The distribution of respondents by gender, age, and investment experience is presented in Table 1.

Table 4.1. Descriptive Statistics of Respondents (n = 350)

Category	Classification	Count	Percentage
Gender	Male	239	68.29%
	Female	111	31.71%
Age	< 18 years	22	6.29%
	18–25 years	162	46.29%
	26–35 years	149	42.57%
	> 35 years	17	4.86%
Investment Experience	< 1 year	89	25.43%
	1–2 years	124	35.43%
	3–5 years	91	26.00%
	> 5 years	46	13.14%

Overall, respondents were predominantly male (68.29%), aged 18–35 (88.86%), and most had less than two years of investment experience (60.86%). This composition is consistent with the demographic dominance of Indonesian retail crypto investors, who tend to be young, digitally native, and risk tolerant.

Conceptual Model

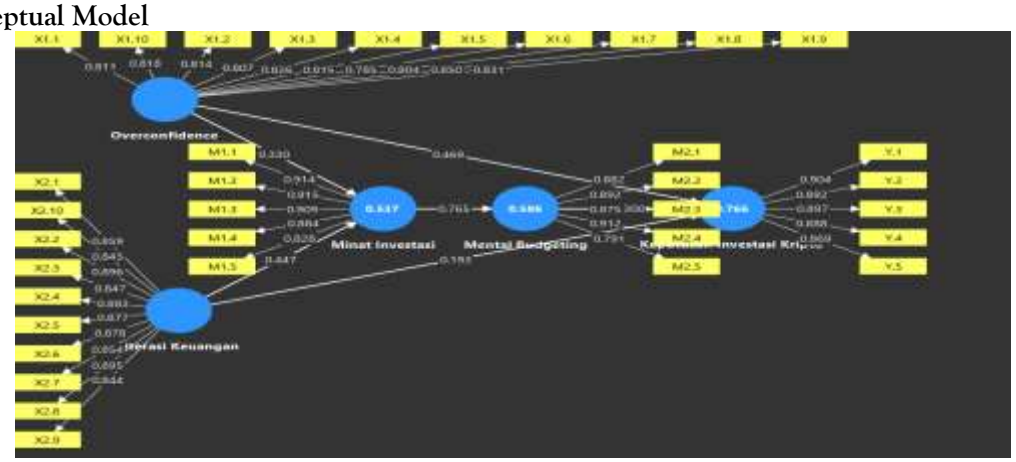

Figure 1. Conceptual model

The model illustrates the hypothesized relationships among Overconfidence (X1), Financial Literacy (X2), Investment Interest (M1), Mental Budgeting (M2), and Investment Decision (Y). Arrows indicate

structural paths; numbers adjacent to arrows are standardized path coefficients (β). The values inside circles are R^2 for endogenous constructs (Investment Interest = 0.537; Mental Budgeting = 0.586; Investment Decision = 0.766). Measurement items are omitted here for clarity. Source: SmartPLS output (2025).

The conceptual model tests both direct and indirect influences of psychological and cognitive variables on cryptocurrency investment decisions. Overconfidence (X1) and Financial Literacy (X2) are specified as exogenous predictors of Investment Interest (M1). Investment Interest subsequently predicts Mental Budgeting (M2), and both Mental Budgeting and Investment Interest feed into the final endogenous variable, Investment Decision (Y). Standardized path coefficients from the PLS-SEM analysis (as shown in the model graphic) indicate that Overconfidence positively affects Investment Interest (β = 0.330), while Financial Literacy also positively affects Investment Interest (β = 0.447). Investment Interest exerts a strong positive effect on Mental Budgeting (β = 0.765). Both Overconfidence (β = 0.469) and Mental Budgeting (β = 0.300) directly and positively influence Investment Decision. The model explains 53.7% of variance in Investment Interest (R^2 = 0.537), 58.6% of variance in Mental Budgeting (R^2 = 0.586), and 76.6% of variance in Investment Decision (R^2 = 0.766), demonstrating substantial explanatory power for investor decision-making in the sample.

Outer Model

The outer model evaluation aims to ensure that the indicators used in this study have an adequate level of validity and reliability to measure the latent constructs.

Convergent Validity

Convergent validity was assessed using three primary criteria: outer loadings, Average Variance Extracted (AVE), and Composite Reliability (CR). A construct is considered to have acceptable convergent validity when it satisfies the thresholds recommended by Hair et al. (2021):

- Loading factor ≥ 0.70 (the indicator is still acceptable at 0.60)
- AVE ≥ 0.50
- CR ≥ 0.70
- Cronbach's Alpha ≥ 0.70

Based on the SmartPLS output, all reflective constructs in this study successfully met these criteria, indicating strong convergent validity.

Table 4.2. AVE and Construct Reliability

Construct	Cronbach's α	Composite Reliability (CR)	AVE
Investment Decision (Y)	0.934	0.950	0.792
Financial Literacy (X2)	0.963	0.968	0.753
Mental Budgeting (M2)	0.920	0.940	0.759
Investment Interest (M1)	0.935	0.950	0.794
Overconfidence (X1)	0.944	0.952	0.666

Table 3. Outer Loadings of Indicators

Construct	Indicator	Outer Loading	Description
Investment Decision (Y)	Y1	0.904	Valid
	Y2	0.892	Valid
	Y3	0.897	Valid
	Y4	0.888	Valid
	Y5	0.869	Valid
Financial Literacy (X2)	X2.1	0.859	Valid
	X2.10	0.843	Valid
	X2.2	0.896	Valid
	X2.3	0.847	Valid
	X2.4	0.883	Valid
	X2.5	0.877	Valid
	X2.6	0.878	Valid

	X2.7	0.854	Valid
	X2.8	0.895	Valid
	X2.9	0.844	Valid
Mental Budgeting (M2)	M2.1	0.882	Valid
	M2.2	0.892	Valid
	M2.3	0.875	Valid
	M2.4	0.912	Valid
	M2.5	0.791	Valid
Investment Interest (M1)	M1.1	0.914	Valid
	M1.2	0.915	Valid
	M1.3	0.909	Valid
	M1.4	0.884	Valid
	M1.5	0.828	Valid
Overconfidence (X1)	X1.1	0.811	Valid
	X1.10	0.818	Valid
	X1.2	0.814	Valid
	X1.3	0.807	Valid
	X1.4	0.826	Valid
	X1.5	0.815	Valid
	X1.6	0.785	Valid
	X1.7	0.804	Valid
	X1.8	0.850	Valid
	X1.9	0.831	Valid

The results indicate:

- All indicators load strongly (>0.70) on their respective constructs.
- AVE values exceed 0.66, far above the minimum threshold, indicating that each construct explains more than two-thirds of the variance in its indicators.
- Composite Reliability ranges from 0.94 to 0.97, reflecting excellent internal consistency.
- The Overconfidence construct despite having slightly lower AVE still demonstrates strong convergent validity due to consistently high loadings and reliability.

Therefore, all reflective constructs meet the criteria for convergent validity and are suitable for further structural model evaluation.

Table 4.4. Fornell–Larcker Discriminant Validity

Construct	Y	X2	M2	M1	X1
Investment Decision (Y)	0.890				
Financial Literacy (X2)	0.773	0.868			
Mental Budgeting (M2)	0.764	0.719	0.871		
Investment Interest (M1)	0.757	0.703	0.765	0.891	
Overconfidence (X1)	0.827	0.776	0.693	0.676	0.816

All diagonal values (square roots of AVE) are higher than correlations between constructs. This confirms adequate discriminant validity.

Table 4.5. HTMT Matrix

Construct	Investment Decision (Y)	Financial Literacy (X2)	Mental Budgeting (M2)	Investment Interest (M1)	Overconfidence (X1)
Investment Decision (Y)	–	0.813	0.822	0.810	0.877
Financial Literacy (X2)	–	–	0.761	0.739	0.812

Mental Budgeting (M2)	–	–	–	0.824	0.739
Investment Interest (M1)	–	–	–	–	0.719
Overconfidence (X1)	–	–	–	–	–

All HTMT values are below the threshold of 0.90, indicating that discriminant validity is established for all construct pairs.

Inner Model

Coefficient of Determination (R^2)

Table 4.6. R^2 and Adjusted R^2

Endogenous Construct	R^2	Adjusted R^2	Interpretation
Investment Interest (M1)	0.766	0.764	Strong
Mental Budgeting (M2)	0.586	0.584	Strong
Investment Decision (Y)	0.537	0.534	Strong

The model explains a substantial portion of variance across all endogenous constructs. Investment Interest has the highest explanatory power (76.6%).

Predictive Relevance (Q^2)

Table 4.7. Q^2 Predictive Relevance

Construct	SSO	SSE	Q^2	Interpretation
Investment Decision (Y)	1750.000	692.316	0.604	Relevant
Mental Budgeting (M2)	1749.999	976.223	0.442	Relevant
Investment Interest (M1)	1750.000	529.563	0.697	Highly Relevant

All Q^2 values are above zero, indicating strong predictive relevance across the model.

Effect Size (f^2)

Table 4.8. Effect Size (f^2)

Relationship	f^2	Interpretation
X2 → M1	0.169	Medium
X2 → M2	0.171	Medium
X2 → Y	0.053	Weak
X1 → Y	0.338	Strong
X1 → M1	0.147	Medium
M1 → Y	1.413	Very Strong
M2 → Y	0.169	Medium

Investment Interest → Investment Decision has an exceptionally strong effect ($f^2 = 1.413$), confirming it as the dominant predictor in the model.

Table 4.9. Direct Path Coefficients

Hypothesis	Path	β	T-Statistic	P-Value	Result
H1	X1 → M1	0.330	5.791	0.000	Supported
H2	X2 → M1	0.447	7.774	0.000	Supported
H3	M1 → M2	0.765	27.692	0.000	Supported
H4	X2 → Y	0.193	3.588	0.000	Supported
H5	X1 → Y	0.469	8.068	0.000	Supported
H6	M2 → Y	0.300	6.082	0.000	Supported

All direct relationships are positive and statistically significant.

Indirect effects (Mediation)

Table 4.10. Mediation Effects

Hypothesis	Indirect Path	β	T-Statistic	P-Value	Result
H7	M1 → M2 → Y	0.230	5.731	0.000	Significant
H8	X1 → M1 → M2 → Y	0.076	4.151	0.000	Significant
H9	X2 → M1 → M2 → Y	0.103	4.438	0.000	Significant
H10	X1 → M1 → M2	0.252	5.419	0.000	Significant
H11	X2 → M1 → M2	0.342	7.337	0.000	Significant

All mediation pathways are significant, confirming both partial and serial mediation effects.

DISCUSSION

The empirical findings of this study confirm that overconfidence, financial literacy, investment interest, and mental budgeting play significant roles in shaping cryptocurrency investment decisions. These results align with a large and growing body of literature emphasizing the psychological, cognitive, and behavioral foundations of digital asset participation. Consistent with prior findings, overconfidence emerged as one of the strongest behavioral predictors of investment behavior. Studies have shown that cryptocurrency traders frequently display gambling-like tendencies, impulsive decision-making, and a persistent belief that they can outperform the market despite extreme volatility (Jain et al., 2025; Raghavendra, 2025). Overconfidence also influences investors' tendency to underestimate market risks, misjudge their analytical ability, and engage in excessive or high-frequency trading—patterns similarly documented in cryptocurrency users worldwide (Suriadi et al., 2023; Friederich et al., 2023). This reinforces the idea that crypto markets attract individuals who are emotionally driven and cognitively biased toward optimistic miscalibration.

The results also demonstrate that investment interest significantly predicts mental budgeting, which subsequently shapes investment decisions. This mediating effect indicates that investors who are enthusiastic about crypto tend to categorize their funds mentally into specific "crypto budgets," reinforcing risk-taking tendencies through emotional compartmentalization. Prior work supports this mechanism, suggesting that mental accounting modifies spending and investment behavior by segmenting financial resources into psychological categories that guide decisions (Schapsis et al., 2025; Gąsiorowska & Zaleskiewicz, 2021; Shah et al., 2025). In the context of digital assets, such mental segmentation allows investors to justify speculative behavior by allocating "high-risk money" toward crypto rather than treating it as part of their overall financial portfolio. This aligns with Suriadi et al. (2023), who found that mental accounting among cryptocurrency investors is strongly predicted by behavioral biases particularly overconfidence.

Financial literacy showed a substantial effect on investment interest and decision-making but not directly on mental budgeting. This distinction is consistent with evidence that financial literacy improves rational evaluations of financial opportunities but does not necessarily eliminate cognitive heuristics or emotional influences (Abramovich & Connell, 2021). Financially literate individuals are more capable of assessing risk–reward characteristics and navigating technological innovations (Abraham et al., 2019), but even these investors remain vulnerable to psychological factors inherent in crypto markets, such as FOMO, impulsivity, and social influence. As Kim (2021) notes, consumer beliefs and attitudes toward money significantly shape intentions to adopt emerging financial technologies, especially during periods of economic uncertainty. Similarly, Bai et al. (2025) demonstrate that individual financial satisfaction and macroeconomic sentiment shape perceptions of crypto as a portfolio alternative, reflecting how external stressors influence financial reasoning.

The psychological environment surrounding cryptocurrency trading further intensifies these dynamics. Social media, emotional contagion, and community-driven hype have been shown to strongly stimulate speculative motives (Jain et al., 2025), while FOMO remains one of the most powerful triggers of repeated investment regardless of prior losses (Friederich et al., 2023). These findings parallel the mediation structure identified in the present study: investment interest → mental budgeting →

investment decisions. When emotional stimuli are strong, traders mentally "assign" crypto investment as an independent category, enabling them to take higher risks or ignore portfolio-level rationality.

Broader theoretical perspectives also explain why these behavioral constructs strongly influence digital asset adoption. Research on cultural distance, societal norms, and psychological distance finds that individuals assess cryptocurrency not only through economic calculus but also through identity, national culture, and perceived novelty (Abraham et al., 2019; Swan, 2019). These socio-psychological inputs magnify behavioral biases and reinforce mental frameworks that guide financial choices. Additionally, crypto addiction research shows that addictive tendencies, impulsivity, and compulsive use patterns resemble pathological gambling, which further intensifies mental segmentation and emotional decision-making (Ucar, 2022). Taghva and Zaferani (2020) similarly describe a "cognitive ecosystem" of crypto involvement, combining personal cognition, environmental stimuli, and technological affordances all of which amplify the effects observed in this study.

Finally, the broader implications of these findings underscore the importance of improving financial literacy and psychological resilience among retail investors. Digital payments, instant-access trading platforms, and algorithmic engagement tools significantly increase the likelihood of overspending and speculative financial behavior (Shah et al., 2025). Without interventions targeting emotional regulation, cognitive biases, and risk perception, investors remain highly vulnerable to the psychological traps embedded in crypto markets. In combination, these findings highlight that cryptocurrency investment behavior is best understood as a convergence of rational evaluation, emotional impulses, cognitive biases, and mental frameworks precisely the dynamics revealed through the mediating model in this study.

CONCLUSION

This study discussed that cryptocurrency investment behavior is driven by the combined influence of cognitive factors, behavioral biases, and internal budgeting processes. Overconfidence emerged as the strongest predictor of both investment interest and investment decisions, confirming that psychological miscalibration plays a central role in speculative participation in digital assets. Financial literacy also significantly contributes to investment decisions, yet its effects are more rational and structured, and it does not fully counteract emotional or bias-driven tendencies.

Investment interest and mental budgeting function as critical psychological mechanisms linking investor traits to actual behavior. Interest intensifies engagement and motivates investors to allocate dedicated mental categories for crypto activities, while mental budgeting reinforces these choices by providing cognitive justification for higher risk-taking. These sequential mediators reveal that crypto investment decisions are shaped through a gradual psychological pathway rather than through direct analytical evaluation alone.

Overall, the findings show that cryptocurrency decision-making is neither purely rational nor purely emotional it reflects a hybrid behavioral–cognitive process. Even knowledgeable investors may act speculatively when overconfidence and affective interest interact with budgeting heuristics. This highlights the need for investor education programs that address not only financial knowledge but also psychological resilience, bias awareness, and emotional self-regulation.

By clarifying the joint roles of overconfidence, financial literacy, interest, and mental budgeting, this study contributes to a deeper understanding of digital asset participation in emerging markets. Strengthening both financial and psychological competencies among retail traders is essential for fostering more informed, disciplined, and sustainable engagement with the rapidly evolving crypto ecosystem.

Implications

This This study offers several key theoretical contributions to behavioural finance. It confirms that cryptocurrency investment decisions are shaped by both cognitive mechanisms (financial literacy) and behavioral biases (overconfidence), reinforcing the view that digital asset behavior cannot be captured by purely rational models. It also extends the literature by establishing investment interest and mental budgeting as serial mediators, showing that crypto decisions emerge through a psychological progression from motivation to structured budgeting rather than direct rational evaluation. Finally, the integration of overconfidence and mental budgeting into a TAM/TPB-oriented framework

demonstrates that classical technology adoption models are insufficient for high-risk financial technologies, which require behavioural and budgeting constructs for more accurate explanatory power.

From a managerial perspective, the findings highlight several actionable insights. Investor education must go beyond knowledge transfer and address psychological biases like overconfidence, FOMO, and impulsive trading. Crypto exchanges should adopt behavioural safeguards such as cooling-off periods or pre-trade warnings to reinforce budgeting discipline. Regulators need early detection tools for risky or addictive trading tendencies, supported by mental health–aligned interventions. Financial advisors should emphasize clear budget segregation to limit losses from high-risk assets. Lastly, public policy should expand digital financial literacy programs to incorporate crypto risk awareness and behavioural decision-making.

Limitations

This study has several limitations that should be acknowledged. First, its cross-sectional design captures investor behavior at only one point in time, which constrains the ability to generalize findings across different phases of crypto market volatility. Second, the reliance on self-reported data may introduce social desirability bias, recall inaccuracies, and subjective interpretations of trading behavior. Third, the sample focuses exclusively on retail investors, leaving out professional traders, institutional actors, and algorithmic trading systems, thereby limiting the applicability of findings to the broader crypto ecosystem. Fourth, the study is embedded in the Indonesian context, where cultural norms, regulatory frameworks, and technological adoption differ substantially from other regions, restricting international generalizability. Fifth, the model specification incorporates only four behavioral and cognitive constructs overconfidence, financial literacy, investment interest, and mental budgeting while excluding other potentially influential factors such as FOMO, trust, perceived risk, social influence, or emotional drivers, which may play significant roles in shaping crypto investment decisions.

Suggestions

Future research should extend this study by employing longitudinal designs to observe how investor psychology shifts across different crypto market cycles, and by integrating additional behavioral constructs—such as FOMO, herding, sensation seeking, fear, and gambling tendencies—to strengthen model explanatory power. Cross-country comparisons are also needed to clarify how cultural and regulatory differences shape crypto decision-making. More objective insights could be gained through experimental or neurobehavioral methods (e.g., trading simulations, eye-tracking, EEG, fMRI), complemented by mixed-methods approaches involving interviews with traders and industry actors to uncover deeper psychological drivers. Advanced machine learning predictive models may help identify behavioral indicators of excessive risk-taking, while future studies should also explore mental budgeting interventions to evaluate whether structured budgeting or digital self-control tools can effectively reduce harmful trading behaviors.

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