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Overtrading as an Expression of Investor FOMO in Cryptocurrency Markets: Insights from the Monkey Business Perspective

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ABSTRACT: This study analysed overtrading behaviour as a manifestation of FOMO, influencers, market sentiment, and crypto literacy in crypto traders. Additionally, it examined the moderating role of monkey business practices in these relationships. This phenomenon is interesting because the emergence of DEXs provides transaction freedom while increasing the risk of market manipulation and behavioural bias. This study represents the first comprehensive behavioural analysis of overtrading within decentralized exchange environments, addressing a significant gap in the cryptocurrency literature. While prior research has examined behavioural factors in general cryptocurrency markets, centralized exchanges, or DEX market structures, but no study has specifically investigated how FOMO, influencers, market sentiment, and crypto literacy interact with market manipulation practices to drive overtrading behaviour on DEX platforms. The method employed was a quantitative survey of 180 DEX traders in social media groups, utilizing purposive sampling techniques. Data were analysed using PLS-SEM to test the direct influence and moderation between variables. The results indicate that FOMO, influencers, and market sentiment have a positive impact on overtrading, whereas crypto literacy has a negative effect. In addition, monkey business moderates the influence of FOMO on overtrading but does not moderate the influence of influencers, market participants, and crypto literacy. These findings enhance understanding of how psychological and social factors influence trading decisions in decentralized markets. Specifically, the moderating role of monkey business practices provides new insights for behavioural finance theory. The implications of the study confirm the importance of caution when trading crypto on DEXs.

Keywords: Overtrading, FOMO, Influencer, Monkey Business, Market Sentiment, Crypto Literacy, DEX.

INTRODUCTION

Crypto assets are digital commodities that use information technology networks and distributed ledgers (Subkhi & Rustam, 2023). With the increasing popularity of virtual assets, such as cryptocurrencies, it is evident that millennials and Gen Z are more inclined to invest in these

instruments compared to other investment options, particularly as they are more open to digital technology and information(Patil & Gokhale, 2023). The ease of access to trading through centralized exchanges (CEXs) and decentralized exchanges (DEXs) fuels overtrading tendencies. Many DEXs allow trading of new or unverified tokens without oversight from the Financial Services Authority (OJK) or the Commodity Futures Trading Regulatory Agency (BAPPEPTI), exposing traders to higher chances of fraud and significant losses. Moreover, tokens lacking clear fundamentals often promise high short-term returns, encouraging high-risk, impulsive speculation and further driving overtrading behavior (Shahzad et al., 2022). Research by Xia et al. (2021) identified more than 10,000 fraudulent tokens on the DEX. Uniswap V2, which represented about 50% of all registered tokens, with victim losses reaching $16 million. (Victor & Weintraud, 2021)also show that trading on DEXs is vulnerable to manipulations such as wash trading, which is detrimental to retail investors, with a wash trading volume of $159 million. Benson et al. (2024)assert that decentralized and often anonymous DEX/DeFi is often a means of unattended transactions, thus increasing the risk of financial criminal activity.

These problems indicate that the condition of the crypto market, especially on DEX platforms, is not only fraught with risks of fraud and manipulation but also poses behavioral risks that have the potential to trigger overtrading. Overtrading is defined as the tendency for investors to overtrade without considering rational factors or conducting adequate fundamental analysis(Ady et al., 2024). This research defines it as a psychological symptom carried out by a trader or investor. These behaviors are driven by psychological biases, such as overconfidence, which decreases profitability(Bregu, 2020), and the fear of missing out (FOMO), which triggers impulsive decisions(Friederich et al., 2024). Overtrading behavior is also closely related to addictive behavior and real negative risk.

Many traders exhibit behavioral symptoms such as addiction, compulsively making transactions even when it leads to financial losses(Jain et al., 2025). In fact, research by Lyn et al. (2025)explains that individuals who engage in excessive trading (overtrading) have characteristics similar to problem gambling.

These addictive tendencies make traders more susceptible to monkey business practices, where manipulative in the crypto market intensify the urge to overtrade. Monkey business is a cunning and dishonest business strategy employed to generate profits, typically through market manipulation(Subkhi & Rustam, 2023). This practice is often characterized by an unnatural increase in asset prices over a short period, which then returns to normal prices, creating speculative cycles that are detrimental to investors(Purba, 2022).

The phenomenon bears a striking resemblance to the pump-and-dump scheme, where a group of coordinated actors inflate the price of coins through massive promotions, then sell them simultaneously for quick profits. Research by (Kamps & Kleinberg (2018)indicates that the scheme begins with a spike in price and volume for small-cap tokens traded against other cryptocurrency pairs. In contrast, Clough & Edwards (2023)found that the price of pump-and-dump targeted assets can drop by an average of up to 30% over the long term. Nizzoli et al. (2020)found that the practice of manipulating crypto assets on online platforms involved more than 56% of Twitter

accounts spreading invitations to crypto-related Telegram channels, with bots accounting for a significant proportion.

Additionally, approximately 20% of Telegram channels were found to be involved in pump-and-dump schemes and Ponzi schemes. Monkey business is a moderating variable that can strengthen or weaken the influence of independent variables such as FOMO, influencers, crypto literacy, and market sentiment on overtrading behavior. Referring to the moderation framework of(Baron & Kenny, 1986), this variable has the potential to change the direction and strength of the relationship between the independent variable and the bound variable(Nindyati, 2020). This type of market manipulation makes investors more susceptible to being influenced by subjective or misleading information, reinforces the fear of missing out, and encourages risky, impulsive decisions (Semenog et al., 2025).

This study identified several research gaps from previous research. Research by Gerrans et al. (2023)examined S1 student respondents at the University of Western Australia, with the results indicating that the measured risk tolerance concept can be an indicator of why investors engage in excessive transactions. Individuals with a high-risk tolerance tend to be more active in taking positions in the market, which, in the context of volatile assets such as crypto, can lead to overtrading behavior. However, the study has not directly examined overtrading behavior, nor has it distinguished general financial literacy from more specific crypto literacy.

Research by (Deb & Deb (2024)has examined student respondents (from Computer Science and MBA programs) in Agartala, India, with the results showing that FOMO has a significant effect on crypto investment and awareness of blockchain technology. However, there has been no testing of the role of influencers and market sentiment, nor an exploration of the relationship between these variables and overtrading behavior. In fact, with a highly volatile cryptocurrency market, overtrading is often triggered by a combination of limited technological understanding, FOMO, and media exposure (Waghmare et al., 2022).

Research by Delfabbro et al. (2021)has examined cases in Australia and globally, yielding a result that over-frequency and compulsive trading behavior in cryptocurrency have the potential to result in significant losses. There is a research gap in that there is no empirical measurement to test the extent to which psychological and social factors influence these behaviors. The research of Friederich et al. (2024)and Lyn et al. (2025)suggests that overtrading is triggered by overconfidence, sensation seeking, and the addictive nature of the crypto market. However, the study has not analyzed protective factors, such as crypto literacy, or external influences, including influencers and market sentiment.

The research of Kamps & Kleinberg (2018)examined the trading data of Bittrex and Cryptopia (international exchanges) with planned pump and dump results. This scheme triggers repetitive, fast trading behavior in traders attempting to capitalize on price spikes. There is a gap in research that has not empirically tested how psychological factors (such as FOMO), external influences (influencers, market sentiment), and crypto literacy levels affect participation or loss in the scheme. Finally, Subkhi & Rustam (2023)research focuses on legal aspects related to monkey business in crypto transactions, but does not integrate investor behavior perspectives, such as FOMO and overtrading as triggers or impacts of such manipulative practices.

Despite growing insights into individual components, a comprehensive examination of how psychological biases (FOMO), external influences (influencers, market sentiment), and crypto literacy interact—and how monkey business moderates these relationships—to drive overtrading on DEX platforms remains unexplored. The research model used is shown in the following figure:

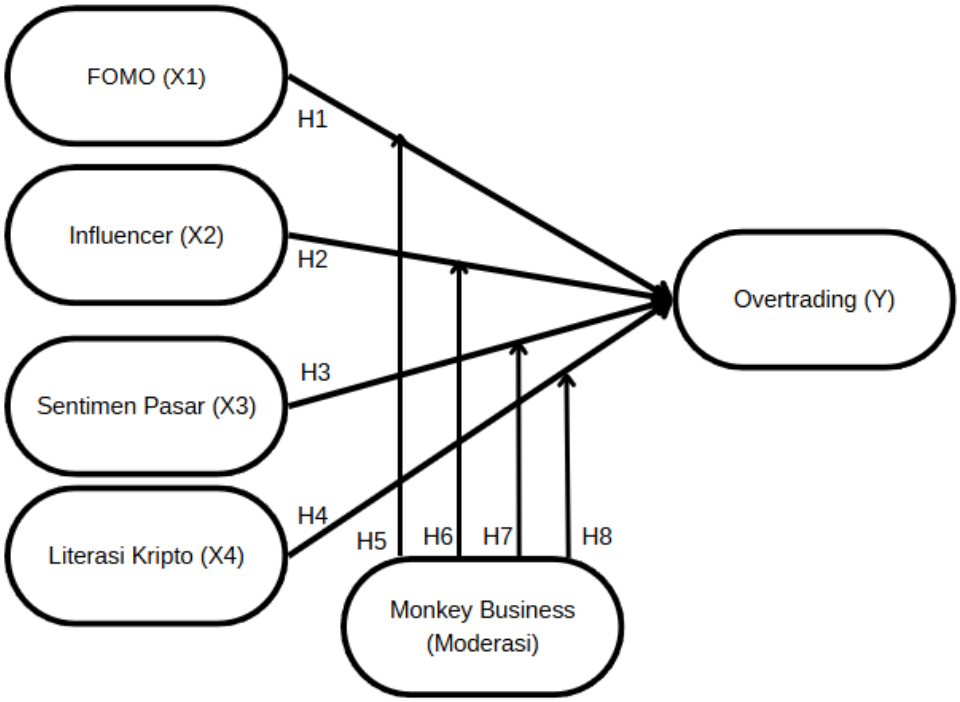

Figure 1. Research Model

Research Hypothesis

H1: Investor FOMO has a positive effect on overtrading behavior

FOMO acts as a catalyst for overtrading, manifesting both as an impulsive reaction and as a persistent tendency that drives investors toward riskier decisions(Gupta & Sharma, 2021). Investors who experience high levels of FOMO often resemble addicts, compelled to trade repeatedly in pursuit of instant gratification and to feel connected in fast-moving markets(Delfabbro et al., 2021).

H2: Influencers have a positive influence on overtrading behavior

Parasocial relationships with followers encourage the tendency to imitate influencer behavior(Yuan & Lou, 2020). Within Behavioral Finance theory, which combines psychology and economics to explain investor behavior, influencers have been proven to significantly affect investment decisions, including among university students (Panggabean & Adib, 2025).

H3: Market sentiment has a positive effect on overtrading behavior

Yifeng (2024)emphasizes that both positive and negative sentiment can drive investors to trade excessively, particularly in the short term. Meanwhile, (Pradnyadewi et al., 2025)demonstrate that

uncertainty triggers price fluctuations, high volatility, and shifts in market sentiment, which encourage herding and speculative behavior.

H4: Crypto literacy negatively affects overtrading behavior

Strong financial literacy enhances both the intention and ability to make sound investment decisions(Deb & Deb, 2024)and encourages investors to view professional guidance as a complement to their digital asset knowledge(Jones et al., 2024).

H5: Monkey business moderates the influence of FOMO on overtrading behavior

H6: Monkey business moderates influencers' influence on overtrading behavior

H7: Monkey business moderates the influence of market sentiment on overtrading behavior

H8: Monkey business moderates the influence of crypto literacy on overtrading behavior

This practice intensifies FOMO as investors fear missing profit opportunities amid cryptocurrency volatility, leading them to engage in impulsive overtrading without conducting fundamental analysis (Rahayu et al., 2024); (Gupta & Sharma, 2021).Monkey business leverages influencers through positive messaging that drives buying interest. Influencer effects cause investors to replicate impulsive investment actions due to social pressure and parasocial bonds ((Friederich et al., 2024);(Yuan & Lou, 2020). It also engineers market sentiment, creating buying euphoria or panic selling that both amplify overtrading ((Yifeng, 2024);(Sriasih et al., 2025)). Yet literacy's protective effect diminishes when monkey business induces strong FOMO and uncertainty (Hasan et al., 2024)Poor literacy leaves investors susceptible to addictive patterns, including persistent investing despite losses (Almeida & Gonçalves, 2023)

METHOD

This study employs a quantitative approach to investigate how the variables FOMO, influencers, market sentiment, and crypto literacy influence overtrading behavior in the cryptocurrency market, while taking into account the moderating effect of monkey business. Data collection was conducted through an online survey using a Google Form, which was distributed to various cryptocurrency groups on social media. The research instrument contains structured statements that measure each research variable based on the indicators that have been determined. This method was chosen because it allows for efficient data collection, reaches a wide range of respondents, and minimizes cost and time.

The study population was active crypto traders trading on DEXs, the exact number of which is unknown. The calculation of the number of samples is based on the reference by Hair et al. (2019), which states that if the population size is unknown, the representative sample size depends on the number of indicators, typically ranging from 5 to 10. The total number of indicators in the study is 30, and this study uses a multiplication factor of 6, so that a total of 180 samples was obtained.

The sampling technique employed in this study is a non-probability sampling method, specifically purposive sampling. Purposive sampling is used to screen respondents based on specific criteria that are considered relevant to the research objectives.

The sample criteria chosen by the researcher in this study are:
1. Crypto DEX traders aged 18 years or older,
2. Actively making at least five crypto transactions per week on DEX platforms, and
3. Being a member of one or more crypto groups on social media.

Table 1. Operational Definitions of Variables

Variable	Short Operational Definition	Indicators	Measurement Scale
FOMO	Anxiety or fear when one feels they miss opportunities or experiences enjoyed by others (Zhang et al., 2020).	a) Fear of missing out on crypto asset investment opportunities b) Feeling uneasy when other investors successfully trade crypto c) Feeling regret after missing out on a crypto asset investment opportunity d) Desire to always follow the actions of other crypto investors e) The desire to always monitor crypto information so as not to be left behind	Ordinal
Influencer	Primary information source for many investors that shapes their expectations and inclinations in investing (Meyer et al., 2024)	a) Influencers are the main source of information related to crypto assets b) Influencers encourage investors in making investment decisions in the crypto market. c) Influencers create emotional value in crypto investors d) Influencers deliver crypto asset promotions convincingly and persuasively e) Influencers trigger investors' desire to continue trading crypto assets	Ordinal
Market Sentiment	Market sentiment reflected in news, opinions in mass media, online platforms, and social networks, all of which strongly influence crypto asset price movements (Susanto et al., 2024)	a) Response to positive or negative news about crypto assets b) Response to public opinion regarding crypto market sentiment. c) Emotional response to negative news circulating about crypto assets d) Tendency to follow the direction of crypto market sentiment e) Perception of changes in the price of crypto assets influenced by news in the media	Ordinal

Variable	Short Operational Definition	Indicators	Measurement Scale
Crypto Literacy	Awareness, understanding, and knowledge of blockchain technology and crypto assets, including how they work, benefits, and associated risks (Deb & Deb, 2024).	a) Level of understanding of how blockchain works.. b) Level of knowledge of the functions and uses of crypto c) Ability to assess the benefits and risks of crypto investment d) Ability to analyze information before making decisions e) Awareness of the security aspects of crypto transactions	Ordinal
Monkey business	Practices marked by unnatural short-term price spikes followed by returns to normal levels, creating speculative cycles that harm investors (Purba, 2022).	a) Rising crypto asset prices without clear fundamental support b) Excessive and misleading promotion of crypto assets c) Unilateral profit motives that harm small investors d) Manipulation of the price of crypto assets by certain groups e) Inequality of access to information between initial investors and general investors	Ordinal
Overtrading	Overtrading is the activity of buying and selling financial assets excessively and irrationally (Yifeng, 2024).	a) Excessive frequency of crypto asset trading transactions b) Tendency to trade without in-depth analysis c) Overly reactive response to information around d) There is an emotional drive-in making trading decisions e) Tendency to continue trading despite losses	Ordinal

Source: Primary Data

The data analysis method used was Partial Least Squares Structural Equation Modeling (PLS-SEM) with Smart PLS. This technique was chosen because it can handle large models with many variables and assess the direct and indirect correlations between variables. The analysis was conducted through two stages: the outer model and the inner model. The outer model was used to test the validity and reliability of the constructs, while the inner model assessed the relationships between variables, including tests for multicollinearity using the Variance Inflation Factor (VIF) and the explanatory power of the model through the coefficient of determination (R^2).

RESULT AND DISCUSSION

From the distribution of questionnaires conducted in this study to crypto traders in DEXs, the characteristics of the respondents can be explained as follows:

Table 2. Respondent Characteristics

Category	Items	Frequency	Percentage
Gender	Male	155	86,1%
	Woman	25	13,9%
	Total	**180**	**100%**
Year of Birth	1997- 2012 (Gen Z)	95	52,8%
	1981-1996 (Gen Milenial)	78	43,2%
	1965-1980 (Gen X)	3	1,7%
	1946-1964 (Boomer)	4	2,3%
	Total	**180**	**100%**
Crypto Trading Duration	Less than 3 months	5	2,7%
	3–6 months	16	8,9%
	7–12 months	24	13,3%
	More than 1 year	135	75,1%
	Total	180	100%
Crypto Trading Amount	5-10x	86	48%
	11-20x	76	42%
	21-30x	13	7%
	More than 30x	5	3%
	Total	**180**	**100%**
DEX	Pancakeswap	52	29%
	Uniswap	41	23%
	Raydium	9	5%
	*Hyper*liquid	20	11%
	Orca	9	5%
	Pumpswap	33	18%
	Dydx	5	3%
	Aerodrome	7	4%
	Lainnya	4	2%
	Total	**180**	**100%**
Reasons to Trade Crypto	Try out a variety of new trending tokens	81	45%
	Join friends or communities	20	11%
	Capitalizing on the hype of the token	58	32%
	FOMO (fear of missing out on opportunities)	17	9%
	Other	4	2%
	Total	**180**	**100%**
Reasons to Follow Crypto Influencers	Has a large following/is famous in the crypto community	58	32%
	Have a proven track record (profit, precise prediction)	49	27%

Category	Items	Frequency	Percentage
	The explanation is easy to understand	29	16%
	Often provides detailed technical/fundamental analysis	40	22%
	Other	4	2%
	Total	**180**	**100%**

Source: Primary Data

Most DEX traders are men (86.1%), born between 1997 and 2012 (Gen Z; 52.8%), have traded crypto for over one year (75.1%), execute 5–10 transactions per week (48%), use PancakeSwap (29%), pursue crypto trading on DEXs to explore trending tokens (45%), and follow crypto influencers for their extensive community reach (32%).

Convergen Validity

The results of the convergent validity test for the variables in the research configuration are compiled as follows:

Table 3. Measurement and Outer Loading

Construct	Items	Code	Loading Factor
FOMO	Fear of missing out on crypto asset investment opportunities	FOMO_1	**0,797**
	Feeling uneasy when other investors successfully trade crypto	FOMO_2	**0,716**
	Feeling regret after missing out on a crypto asset investment opportunity	FOMO_3	**0,785**
	Desire to always follow the actions of other crypto investors	FOMO_4	**0,765**
	The desire to always monitor crypto information so as not to be left behind	FOMO_5	**0,595**
Influencer	Influencers are the main source of information related to crypto assets	INFLU_1	**0,811**
	Influencers encourage investors in making investment decisions in the crypto market.	INFLU_2	**0,741**
	Influencers create emotional value in crypto investors	INFLU_3	**0,821**
	Influencers deliver crypto asset promotions convincingly and persuasively	INFLU_4	**0,659**
	Influencers trigger investors' desire to continue trading crypto assets	INFLU_5	**0,795**
Market sentiment	Response to positive or negative news about crypto assets	SP_1	**0,772**
	Response to public opinion regarding crypto market sentiment.	SP_2	**0,702**

Construct	Items	Code	Loading Factor
	Emotional response to negative news circulating about crypto assets	SP_3	**0,786**
	Tendency to follow the direction of crypto market sentiment	SP_4	**0,810**
	Perception of changes in the price of crypto assets influenced by news in the media	SP_5	**0,803**
Crypto Literacy	Level of understanding of how blockchain works..	LK_1	**0,849**
	Level of knowledge of the functions and uses of crypto	LK_2	**0,718**
	Ability to assess the benefits and risks of crypto investment	LK_3	**0,882**
	Ability to analyze information before making decisions	LK_4	**0,820**
	Awareness of the security aspects of crypto transactions	LK_5	**0,679**
Monkey business	Rising crypto asset prices without clear fundamental support	MB_1	**0,655**
	Excessive and misleading promotion of crypto assets	MB_2	**0,797**
	Unilateral profit motives that harm small investors	MB_3	**0,797**
	Manipulation of the price of crypto assets by certain groups	MB_4	**0,800**
	Inequality of access to information between initial investors and general investors	MB_5	**0,782**
Overtrading	Excessive frequency of crypto asset trading transactions	OVT_1	**0,725**
	Tendency to trade without in-depth analysis	OVT_2	**0,708**
	Overly reactive response to information around	OVT_3	**0,743**
	There is an emotional drive-in making trading decisions	OVT_4	**0,768**
	Tendency to continue trading despite losses	OVT_5	**0,690**

Source: Primary Data

For the FOMO variable, indicator FOMO_1 exhibits a loading of 0.797, evidencing reliable measurement of fear of missing out in the context of crypto investment. Within the Influencer construct, INFLU_3 shows the highest loading at 0.821, indicating that persuasive crypto promotion is particularly representative of this construct. The Market Sentiment variable's strongest indicator, SP4, has a loading of 0.810, confirming that following market trends is the most valid measure for this factor. For Crypto Literacy, LK3 stands out with a loading of 0.882, suggesting that the ability to critically analyze information before trading is the most robust indicator. In the Monkey Business variable, MB4 achieves a loading of 0.800, underlining that unequal access to information is most indicative of manipulative market practices. Lastly, within the Overtrading construct, OVT4 records the largest loading at 0.768, showing that "continuing to trade despite losses" is the most valid indicator of excessive trading behavior. All retained items display loading values above the 0.60 threshold, appropriate for exploratory research, except

FOMO_5, which was removed for not meeting this criterion (loading = 0.595) (Sürücü et al, 2022). These results confirm that the measurement model achieves convergent validity, supporting the suitability of the indicators for further reliability analysis

Table 4. Construct Reliability

Construct	Cronbach's Alpha	Composite Reliability	(AVE)
FOMO	0,767	0,850	0,587
INFLU	0,827	0,877	0,590
LK	0,878	0,894	0,630
MB	0,828	0,877	0,590
MB FOMO	1,000	1,000	1,000
MB INFLU	1,000	1,000	1,000
MB LK	1,000	1,000	1,000
MB SP	1,000	1,000	1,000
OVT	0,779	0,848	0,529
SP	0,835	0,883	0,602

Source: Primary Data

The Cronbach's Alpha values for each construct exceed the minimum threshold of 0.7, with Market Sentiment achieving the highest reliability at 0.835, followed by Crypto Literacy at 0.878, Monkey Business at 0.828, Influencer at 0.827, Overtrading at 0.779, and FOMO at 0.767. These values indicate strong internal consistency across all primary constructs. In terms of composite reliability, all primary constructs demonstrate excellent internal consistency with values ranging from 0.848 to 0.894. Crypto Literacy exhibits the highest composite reliability at 0.894, followed by Market Sentiment (0.883), Monkey Business (0.877), Influencer (0.877), FOMO (0.850), and Overtrading (0.848).

Regarding convergent validity, the Average Variance Extracted (AVE) values show acceptable results for most constructs. Crypto Literacy demonstrates the highest AVE at 0.630, followed by Market Sentiment (0.602), indicating that more than 60% of the variance is explained by these constructs. FOMO shows an AVE of 0.587, Monkey Business at 0.590, and Influencer at 0.590, all approaching the ideal 0.5 threshold. Overtrading records the lowest AVE at 0.529, though this remains within acceptable ranges for exploratory research. Overall, these results indicate that all constructs in the study have very good reliability and validity. Thus, this model can be relied on for further analysis and hypothesis testing.

Table 5. Discriminant Validity

	FOMO	INFLU	LK	MB	OVT	SP
FOMO	0,766					
INFLU	0,456	0,768				
LK	0,171	0,167	0,794			
MB	0,260	0,252	0,156	0,768		
OVT	0,500	0,501	0,143	0,464	0,727	
SP	0,358	0,252	0,248	0,228	0,444	0,776

Source: Primary Data

The FOMO construct has a square root of AVE of 0.766, which is greater than its highest correlation with Overtrading (0.500), as well as correlations with Influencer (0.456), Crypto Literacy (0.171), Monkey Business (0.260), and Market Sentiment (0.358), indicating clear discriminant validity. For the Influencer construct, the square root of AVE is 0.768, exceeding its strongest correlation with Overtrading (0.501) and other correlations with FOMO (0.456), Crypto Literacy (0.167), Monkey Business (0.252), and Market Sentiment (0.252), confirming that Influencer is distinct from the other constructs. Crypto Literacy achieves a square root of AVE of 0.794, which surpasses its highest correlation with Market Sentiment (0.248) and all other correlations (FOMO 0.171; Influencer 0.167; Monkey Business 0.156; Overtrading 0.143), demonstrating strong discriminant validity.

The Monkey Business construct's square root of AVE is 0.768, higher than its strongest correlation with Overtrading (0.464) and its correlations with FOMO (0.260), Influencer (0.252), Crypto Literacy (0.156), and Market Sentiment (0.228), supporting its uniqueness. Overtrading shows a square root of AVE of 0.727, exceeding its highest correlation with Influencer (0.501) and other correlations (FOMO 0.500; Crypto Literacy 0.143; Monkey Business 0.464; Market Sentiment 0.444), indicating clear construct separation. Finally, Market Sentiment's square root of AVE of 0.776 surpasses its strongest correlation with Overtrading (0.444) and all other correlations (FOMO 0.358; Influencer 0.252; Crypto Literacy 0.248; Monkey Business 0.228), confirming that each construct measures a distinct concept.

Model Estimate

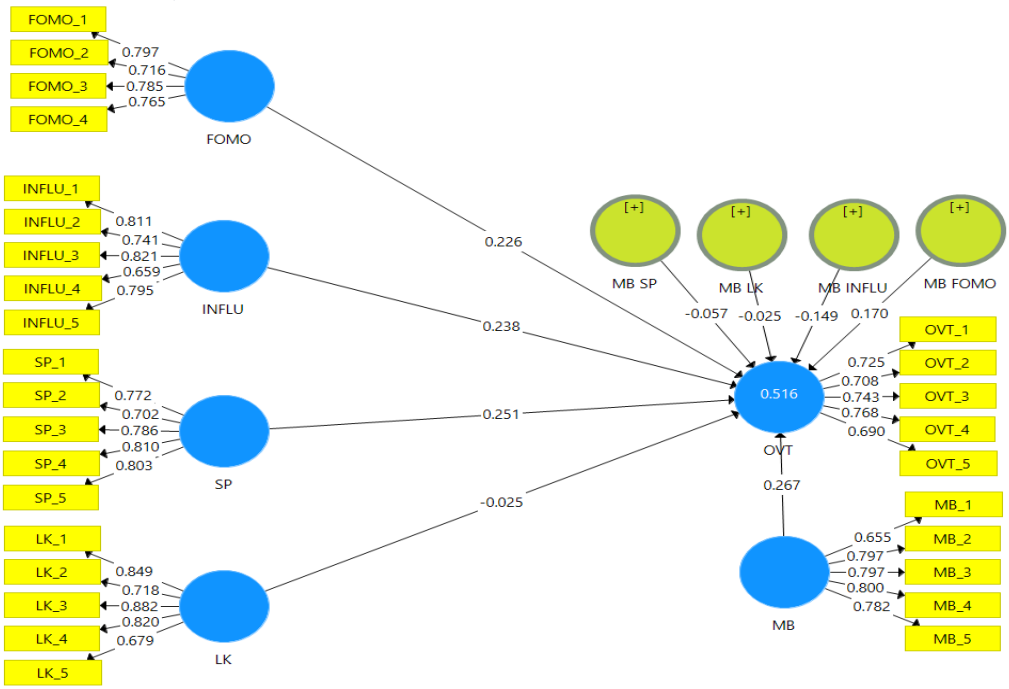

Figure 2. Model Estim

Collinearity Statistics (VIF)

Table 6. Collinearity Statistics (VIF)

Variable Code	VIF	Variable Code	VIF
FOMO * MB	1,000	MB_1	1,506
FOMO_1	1,636	MB_2	1,781
FOMO_2	1,375	MB_3	1,897
FOMO_3	1,724	MB_4	1,751
FOMO_4	1,379	MB_5	1,595
INFLU * MB	1,000	OVT_1	1,452
INFLU_1	1,760	OVT_2	1,435
INFLU_2	1,817	OVT_3	1,536
INFLU_3	1,876	OVT_4	1,477
INFLU_4	1,506	OVT_5	1,497
INFLU_5	1,870	SP * MB	1,000
LK * MB	1,000	SP_1	1,826
LK_1	1,897	SP_2	1,457
LK_2	2,460	SP_3	1,820
LK_3	2,138	SP_4	1,712
LK_4	1,883	SP_5	1,884
LK_5	2,382		

All indicator VIF values remain well below the threshold of 3, indicating that multicollinearity is not a concern in this model. FOMO indicators (FOMO_1 to FOMO_4) exhibit VIFs ranging from 1.375 to 1.724. Influencer indicators (INFLU_1 to INFLU_5) range from 1.506 to 1.876. Crypto Literacy indicators (LK_1 to LK_5) show VIFs between 1.883 and 2.460. Monkey Business indicators (MB_1 to MB_5) record VIFs from 1.506 to 1.897. Overtrading indicators (OVT_1 to OVT_5) range from 1.435 to 1.536. Finally, Market Sentiment indicators (SP_1 to SP_5) span 1.457 to 1.884. The highest VIF of 2.460 (LK_2) remains sufficiently low to ensure stable and interpretable parameter estimates. Overall, multicollinearity does not impair the reliability of the structural model.

R Square

Table 7. R Square

Variable	R Square	R Square Adjusted
Overtrading	0,516	0,490

The R Square value for the Overtrading construct is 0.516, indicating that 51.6% of the variance in overtrading behavior is explained by the independent variables in the model. This R Square falls within the moderate category, suggesting that the predictors collectively have a substantial influence on overtrading. The Adjusted R Square of 0.490 closely aligns with the unadjusted value, demonstrating that the model's explanatory power remains robust despite the number of predictors and does not suffer from overfitting. Overall, these results confirm that the structural model possesses good predictive ability for overtrading behavior.

Hypothesis Testing

The findings regarding the relationship between variables in the study framework are outlined as follows:

Table 8. Hypothesis Testing

Hypothesis	Variabel	Original Sample (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Information
H1	FOMO -> OVT	0,236	0,075	3,133	0,002	Accepted
H2	INFLU -> OVT	0,243	0,061	3,984	0,000	Accepted
H3	SP -> OVT	0,211	0,061	3,454	0,001	Accepted
H4	LK -> OVT	-0,012	0,093	0,125	0,900	Rejected
H5	MB FOMO -> OVT	0,168	0,081	2,077	0,038	Accepted
H6	MB INFLU -> OVT	-0,146	0,094	1,555	0,121	Rejected
H7	MB SP -> OVT	-0,046	0,076	0,607	0,544	Rejected
H8	MB LK -> OVT	-0,033	0,077	0,423	0,673	Rejected

Source: Primary Data

The results of the test with bootstrapping in this study from the PLS analysis are as follows:

H1 Testing: FOMO has a significant effect on overtrading

The influence of FOMO on overtrading shows a p-value of 0.002 or less than 0.05 (<0.05) with a t-statistical value of 3.133 or greater than 1.96 indicating that the relationship is significant and has an original sample of 0.236 indicating the direction of a positive relationship. It can be concluded that hypothesis 1 is accepted, where FOMO has a significant effect on overtrading.

H2 Testing: Influencers have a significant effect on overtrading

The influence of influencers on overtrading shows a p-value of 0.000 or less than 0.05 (<0.05) with a t-statistical value of 3.984 or greater than 1.96 so that it shows that the relationship is significant and has an original sample of 0.243 which indicates the direction of a positive relationship. It can be concluded that hypothesis 2 is accepted, where influencers have a significant influence on overtrading.

H3 Testing: Market sentiment has a significant effect on overtrading

The influence of market sentiment on overtrading shows a p-value of 0.001 or less than 0.05 (<0.05) with a t-statistical value of 3.45 or greater than 1.96 indicating that the relationship is significant and has an original sample of 0.211 which indicates a positive relationship direction. It

can be concluded that hypothesis 3 is accepted, where market sentiment has a significant effect on overtrading.

H4 Testing: Crypto literacy has a significant impact on overtrading

The effect of crypto literacy on overtrading shows a p-value of 0.900 or greater than 0.05 (<0.05) with a t-statistical value of 0.125 or less than 1.96, indicating that the relationship is not significant and has an original sample of -0.012 which indicates the direction of the negative relationship. It can be concluded that hypothesis 4 is rejected, where crypto literacy has no significant effect on overtrading.

H5 Testing: Monkey business moderates the influence of FOMO on overtrading

The results of monkey business moderating the influence of FOMO on overtrading showed a p-value of 0.038 or less than 0.05 (<0.05) with a t-statistical value of 2.077 or greater than 1.96 and had an original sample of 0.168 indicating a positive relationship. It can be concluded that hypothesis 5 is accepted, where monkey business practices can moderate the influence of FOMO on overtrading behavior.

H6 Testing: Monkey business moderates influencers' influence on overtrading

The results of monkey business moderating the influence of influencers on overtrading showed a p-value of 0.121 or greater than 0.05 (<0.05) with a t-statistical value of 1.555 or less than 1.96 and had an original sample of -0.146 indicating the direction of a negative relationship. It can be concluded that hypothesis 6 is rejected, where monkey business practices cannot moderate the influence of influencers on overtrading behavior.

H7 Testing: Monkey business moderates the influence of market sentiment on overtrading

The results of monkey business moderating the influence of market sentiment on overtrading showed a p-value of 0.673 or greater than 0.05 (<0.05) with a t-statistical value of 0.423 or less than 1.96 and had an original sample of -0.046 indicating the direction of a negative relationship. It can be concluded that hypothesis 7 is rejected, where monkey business practices cannot moderate the influence of market sentiment on overtrading behavior.

H8 Testing: Monkey business moderates the influence of crypto literacy on overtrading

The results of monkey business moderating the influence of crypto literacy on overtrading showed a p-value of 0.544 or greater than 0.05 (<0.05) with a t-statistical value of 0.607 or less than 1.96 and had an original sample of -0.033 which indicated the direction of a negative relationship. It can be concluded that hypothesis 8 is rejected, where monkey business practices cannot moderate the influence of crypto literacy on overtrading behavior.

The analysis demonstrates that FOMO exerts a robust and statistically significant effect on overtrading ($\beta = 0.236$, $t = 3.133$, $p = 0.002$), corroborating Delfabbro et al.'s (2021) conclusion that fear of missing out precipitates elevated trading activity among less experienced investors, while extending this effect to decentralized exchange (DEX) environments. Contrary to Friederich et al. (2024), who observed FOMO-induced social satisfaction primarily within centralized platforms, our findings indicate that the rapid token issuance characteristic of DEXs amplifies

speculative spikes prior to the detection of scams or rug pulls. This amplification suggests that the architectural features of decentralized infrastructures exacerbate impulsive purchasing beyond the scope reported by Lyn et al. (2025) in traditional markets.

Furthermore, Klepacki's (2025) assertion that anxiety-driven mechanisms underpin repeat transactions receives nuanced support: euphoric affect indeed motivates successive trades following losses, yet this cycle intensifies predominantly when impulsive individuals encounter heightened token hype. Similarly, Raghavendra's (2025) identification of pandemic-induced stressors as catalysts for extreme trading behavior finds conditional validation; increased trading frequency emerges only in conjunction with salient FOMO cues. Collectively, these findings imply that existing behavioral finance models require refinement to integrate platform-specific acceleration of hype, thereby providing a more comprehensive account of FOMO-driven overtrading in decentralized contexts.

Influencers markedly accelerate overtrading ($\beta = 0.243$, $t = 3.984$, $p < 0.001$), a pattern consistent with Meyer et al. (2024) but with important extensions. Whereas Meyer and colleagues documented price impacts of influencer endorsements, our findings show that influencers also stimulate trading frequency directly through FOMO appeals, confirming Shahzad et al.'s (2022) observation of tweet-induced speculative behavior and expanding it to community dynamics on platforms such as X, Telegram, and Discord (Kuusela, 2025). Notably, Jain et al. (2025) reported compulsive trading among followers, yet our results qualify this by revealing that influencer-driven trades persist even after losses only when social reinforcement remains high, suggesting that herd behavior in crypto groups exerts a stronger pull than isolated endorsements.

Turning to market sentiment, we observe a significant positive effect on overtrading ($\beta = 0.211$, $t = 3.450$, $p = 0.001$) that both corroborates and nuances prior evidence. López et al. (2020) conceptualized sentiment as investors' collective optimism or pessimism, and Yifeng (2024) linked sentiment fluctuations to short-term trading spikes. Our data extend these findings by showing that sentiment-driven overtrading occurs robustly across bullish and bearish phases, diverging from Yifeng's claim of a bias toward bull markets. Furthermore, Bowden and Gemayel's (2022) demonstration of Reddit sentiment effects on large-scale trading is echoed in PancakeSwap volume projections (Cointelegraph, 2024) but underscored here as an autonomous driver: sentiment influences trading intensity independently of social media signals. This autonomous role of market sentiment implies a pervasive emotional contagion within decentralized finance that traditional models have yet to fully capture.

The null effect of crypto literacy on overtrading ($\beta = –0.012$, $t = 0.125$, $p = 0.900$) challenges assumptions that financial knowledge alone curtails speculative behavior. While Hamurcu et al. (2025) observed knowledgeable traders still succumbing to risk due to emotional dysregulation, our findings extend this paradox: even high financial literacy fails to mitigate impulsivity-driven trading in crypto markets. This contrasts with traditional finance research that often reports a protective role of literacy, suggesting that non-cognitive factors—such as compulsion and sensation-seeking—dominate decision-making when market euphoria and social pressures are at play (Auer & Tercero L, 2022; Roza et al., 2024).

In contrast, monkey business distinctly magnifies FOMO's impact (interaction $\beta = 0.168$, $t = 2.077$, $p = 0.038$), confirming Xia et al.'s (2021) hypothesis that rapid token hype on DEXs exploits fear-based biases more effectively than in centralized venues. This moderation effect indicates that monkey business manipulation creates an environment where FOMO-driven traders behave compulsively, aligning with Delfabbro et al.'s (2021) addiction model but highlighting the unique acceleration enabled by decentralized infrastructures. Moreover, Rahayu et al. (2024) and Gupta and Sharma (2021) demonstrated manipulation's role in altcoin surges, yet our results specify that such practices intensify overtrading only in conjunction with strong FOMO cues. This nuanced interaction suggests that interventions aimed at reducing speculative behavior must address both emotional triggers and platform-specific design features.

The absence of a moderating effect of monkey business on influencer-driven overtrading (interaction $\beta = –0.146$, $t = 1.555$, $p = 0.121$) indicates that social influence operates independently of monkey business practices. This result contradicts Merkley et al. (2024), who proposed that contextual monkey business amplifies short-term price reactions to influencer content. Instead, our data suggest that the emotional salience of influencer messages—bolstered by hyperbolic language and perceived insider credibility—directly motivates trading behavior regardless of underlying price distortions (Meyer et al., 2024).

Similarly, market sentiment's effect on overtrading remains unmoderated by monkey business (interaction $\beta = –0.046$, $t = 0.423$, $p = 0.673$), reinforcing the notion that emotional contagion through sentiment functions as an autonomous driver of trading intensity. This finding aligns with Almeida and Gonçalves (2023) regarding sentiment-driven herding but diverges from Pradnyadewi et al. (2025), who observed stronger monkey business synergies under extreme bullish conditions. Our results imply that sentiment alone suffices to trigger impulsive transactions across market cycles, highlighting the pervasive influence of collective mood in decentralized finance.

Finally, crypto literacy's lack of moderation by monkey business practices (interaction $\beta = –0.038$, $t = 0.315$, $p = 0.753$) confirms the knowledge paradox observed in our main effects analysis. This outcome corroborates Auer and Tercero L (2022) and Carbo et al. (2023), who noted that higher financial literacy does not inoculate investors against speculative impulses. It further suggests that literacy-based interventions must address psychological and social dimensions—rather than solely improving technical understanding—to effectively mitigate overtrading in cryptocurrency markets.

This research has several limitations that need to be considered. First, the study only discusses decentralized exchanges (DEXs) in general without distinguishing the characteristics of individual blockchain ecosystems, such as BSC, Solana, Base, or Ethereum. In fact, each network has different mechanisms, liquidity, and a distinct trader community profile, which has the potential to influence overtrading behavior. Second, this research focuses more on psychological and social aspects, while the technical aspects of the token in the DEX itself, such as token liquidity and total supply, have not been analyzed. Third, the data collection in this study was conducted prior to the bull run or altseason phase, so the findings obtained tend to reflect the behavior of traders in bullish market conditions. There is a need for another study to examine the bearish phase.

Based on the research results, several suggestions can be considered by various parties. First, for crypto traders, it is recommended to constantly improve crypto literacy to enable a more critical assessment of information from the media, communities, and influencers. Next, investors should not only rely on market sentiment or momentary trends, but also pay attention to fundamental analysis and set clear risk limits to avoid overtrading. Furthermore, investors need to be more cautious about monkey business that often exploit the phenomenon of fear of missing out (FOMO) to encourage excessive trading activities.

CONCLUSION

This study demonstrates that FOMO, influencers, and market sentiment significantly drive overtrading in cryptocurrency markets, whereas crypto literacy exerts no mitigating effect. Additionally, the moderating role of monkey business was confirmed only for FOMO, revealing how manipulative token-launch practices amplify fear-based trading impulses.

By introducing monkey business as a novel moderating variable in decentralized trading contexts, these results advance behavioral finance literature and underscore the predominance of emotional and social triggers over rational knowledge. Regulators and platform designers should therefore implement behavioral safeguards—such as automated trade alerts and transaction limits—to mitigate hype-driven trading. Investors are advised to enhance crypto literacy for more critical evaluation of media, community, and influencer information; to integrate fundamental analysis with sentiment awareness; to establish clear risk limits; and to remain vigilant against monkey business tactics that exploit FOMO.

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