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Article

From Followers to Traders: Finfluencer Credibility, Digital Trust, and Investment Decision-Making among Retail Investors

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Abstract: Purpose: The purpose of this study is to explore how financial content creators and social media influencers impact individual trading behaviours, especially among youth, by shaping risk perceptions, promoting online trading and betting apps, and influencing impulsive financial decisions through unverified advice, potentially increasing vulnerability to scams and financial missteps.
Design/Methodology/Approach: The study adopts a quantitative approach using primary data from 237 young individual traders and investors active on platforms like YouTube and Telegram. Responses were collected through purposive sampling. Data analysis was conducted using SPSS and AMOS, employing descriptive statistics, correlation, regression, factor analysis, and Structural Equation Modeling (SEM).
Findings: The findings reveal that frequent exposure to financial influencers on YouTube and Telegram significantly impacts individual trading decisions. Influencer promotion of betting/trading apps increases the likelihood of investing in high-risk platforms. Trust in unverified social media financial advice strongly correlates with impulsive, often misinformed, trading and betting behaviour among youth.
Conclusion: The study concludes that financial content creators and social media influencers significantly shape individual trading behaviours, especially among youth. Their promotions drive risk-taking and susceptibility to scams. Psychological factors like trust and frequent exposure to unverified advice contribute to impulsive and misinformed financial decisions, highlighting the need for regulatory oversight and financial literacy.
Originality/Value: This study provides valuable insights into the influence of financial influencers on individual traders' investment behaviours, particularly among youth. It highlights the psychological and behavioural factors driving impulsive decisions, offering critical implications for financial literacy, regulation, and investor protection strategies.
Keywords: Financial Influencers, Investment Behavior, Social Media Influence, Youth Traders, Impulsive Decision-Making

1. Introduction

Social media has become a significant force in shaping modern investment decision-making, providing investors with real-time information, peer insights, and direct interactions with financial influencers (Torrance et al., 2023). In today's world, the influence of social media has become a powerful tool and has influence on almost every facet of modern life, changing the way individuals communicate, access information and engage with various aspects of their lives (Riefel, 2024). In addition, the widespread emergence of user-friendly financial technology, such as app-based robo-advising and fee-free trading platforms, combined with the transparency of social media, has boosted financial engagement in the younger generations and turned personal finance, with investing in particular, into a trending topic suitable for discussion with a broader target audience (Gerritsen, & de Regt, 2025). Further, the social media has become a powerful influencing tool for financial decision making, reshaping global markets. Platforms like

Twitter, Reddit, and YouTube have transformed how people interact within financial markets, democratizing information access in the hands of retail investors (Singh et al., 2025; Keasey et al., 2025).

Finfluencers are helping to democratize financial literacy, providing an alternative opportunity for learning about finance. Finfluencers, by their very nature, are capable of distilling information in many different ways because they interpret financial speak and create easier to follow approaches for newcomers (Quang et al., 2023). They are able to also communicate on social media in real-time and can potentially give their message to millions of people quickly and/or cheaply. Gen Z feel more comfortable and connected to their finfluencer than their financial advisor, which creates trust and a camaraderie (Nag, & Shah, 2022). This peer relationship allows for momentum for youth to take financial action. Finfluencers also educate on moments that stem from financial technological and tool developments that facilitate self-directed learning. Their narratives serve as success stories that promote aspiration, confidence and engagement with financial markets (Dehestani et al., 2023). They normalize engagement as inclusive and fun and expand an awareness of finance in financially marginalized communities. Social media facilitates since social media is an open and inherently decentralized method of having conversations and learning can occur through peer dialogue (Mahalakshmi, & Munuswamy, 2022;Andrade & Newall, 2023).

Nevertheless, this emerging trend does have disadvantages. Finfluencers typically do not possess any formal qualifications in finance or investment, nor are they beholden to regulations, which raises the issue of misinformation. There is often a blurred line between paid promotion and sanctioned advice. Ethical issues arise when many fail to sufficiently disclaim the fact, high-risk trading platforms or betting apps, are being marketed (Oppong, et al., 2023; Epaphra, & Kiwia, 2021). Exploiting the inherent susceptibility of youth, it is easy to see how being influenced to watch emotionally-driven content can shift normal decision-making processes toward impulsivity about investment decisions. Content of this nature may exacerbate exaggerated expectations of performance without providing enough focus on risks. Many social media platforms exploit echo-chamber effects that do not help poor decision-making pathologies (Shaikh, & Khan, 2025). Additionally, an aspiration towards instant success may create informal gambling-like behaviour instead of informed investing behaviour. Unfounded financial information may increase exposure to potential frauds and scams. Also, the lack of potential accountability on social media reduces the efficacy of regulations that can be placed upon tradable influencers (Kubińska et al., 2023). Considering the expressed issues, the merit of conducting an empirical investigation into finfluencers' potential influence has never been more important (Steib, 2021).

This research studies the extent of financial influencers impact on the investment decisions of individual traders, especially young people and aims to understand how trust, exposure, and engagement with content inform risk perception and impulsive trading activity. The research uses a quantitative approach to analyze data from 237 young investors who follow influencers on YouTube and Telegram. The analysis uses statistical tools including correlational analysis, regressions, factor analysis, and Structural Equation Modelling (SEM) via SPSS and AMOS. The study also considers the connection between content curated by finfluencers and the use of high-risk betting or trading apps. To unpack the psychological dimensions related to risky behaviour, such as trust in unverified advice, and social proof, and to provide evidence of how influencer-driven content is adversely driving misinformed investor actions. The study fills a gap in investor protection and regulatory oversight in the digital financial advice ecosystem and hence offers empirical evidence. The objectives of study is provides as follows

- To examine the influence of financial content creators on platforms like YouTube and Telegram channels in shaping individual traders' stock market decisions and risk-taking behaviour.
- To analyse the role of social media influencers in promoting online betting and trading apps, and their impact on youth investment patterns and susceptibility to financial scams.
- To assess the psychological and behavioural drivers that lead individuals, particularly the youth, to trust unverified financial advice and promotions shared via social media, leading to impulsive or misinformed trading and betting decisions.

The study is set up as follows: Section 1 offers a general introduction and a synopsis of the study's goals. The second section of the literature study also discusses the idea. Section 3 gave the comprehensive approach and its analysis. The results of the investigation are then presented in Section 4. A discussion of the study is given in Section 5. The research is eventually concluded in Section 6, which also addresses the possible scope of the study.

2. Literature review

- ***Influence of Finfluencers on Investment Behavior***

Many studies have looked at finfluencer impact on investment decisions across markets and demographics. Gerritsen and de Regt (2025) examined and analyzed the 453 stock and cryptocurrency recommendations made by 21 Dutch finfluencers. They concluded that finfluencers often promote assets which appear to have performed well historically, but can be expected to have negative returns in the future. They suggest this reliance on social heuristics puts investors at risk and that disregarded financial advice on social media can have damaging consequences. Similarly, Kedvarin (2022) used VAR Granger causality to investigate the influence of the videos produced by the top finance influencers on YouTube. He found that finfluencer video activity had a high level of significant causality to cryptocurrency returns, but a negligible influence on the stock market—suggesting the finfluencer effect is stronger in less regulated areas prone to speculation like cryptocurrency. Zülch et al. (2024) compiled concerns surrounding finfluencers and their reliability, by conceptualizing the Finfluencer Quality Score (FinQ-Score) through a mixed-methods approach. Their framework provides consumers, platforms, and policymakers a way to assess the "quality" of finfluencers without implementing a highly regulated environment. Olajide et al. (2024) examined generational differences, noting that millennials who used platforms like Instagram and TikTok had a higher level of financial satisfaction than non-financial advice users. Interestingly, YouTube users showed the opposite pattern from TikTok and Instagram users. This represents some of the nuances platform and influencer characteristics can have on users.

- ***Role of Financial Literacy in Investment Decisions***

Thapa (2025) studied the increase in Nepali youth stock market involvement and found that while interest is increasing, most participants had low financial literacy and relied on friends and social media for choices, which is consistent with Rijanto and Utami (2024) who temporally examined financial technology utilization, influencer presence, and Indonesian youth new formulation, trading choices on cryptocurrency. While both influencers and financial technology use revealed a positive relationship with investment choices in competing assets (cryptocurrency), financial literacy was not a significant moderating variable, leaving open some concerns of assuming financial literacy acts as a buffer to social influences in high risk situations. However, reinforced the role(s) of financial literacy and digitalization in the shared growth of SMEs (Almuraqab et al., 2024) in brick nations, and while not individually linked with trading, there was a summary recommendation of its role in promoting sustainable active financial choices within developing areas, reinforced the notion that foundational financial knowledge as well as digital literacy mattered.

- ***Social Media as a Platform for Financial Information and Manipulation***

Social media usage in the investment landscape is well-established, and Aagruwal and Kaye (2022) referred to FinTok as a new means of investor education and regulatory knowledge. Through content analysis of TikTok, the authors illustrated the risks of "buy now, pay later" mechanisms and demonstrated some insights that regulators could use by following the trend in consumer finance that arises from social media platforms. Li et al. (2025) had a more empirical focus with their Bayesian model exploring how financial social media analysts (SMAs) respond to investor sentiment. Their case study on a Chinese financial platform determined that SMAs produce content purposely to match preferences of their audience, if only for monetization purposes rather than providing the information they espouse. This method appears to play a role in confirmation bias for retail investors while also showing the perils of being relying on the content component of the financial ecosystem.

- ***Regulation and Consumer Protection in the Finfluencer Economy***

A number of studies provide compelling reasons for regulation on finfluencer activities. Gerritsen and de Regt (2025) support regulatory intervention with their finding that finfluencers are inclined to endorse over-priced assets. Zülch et al. (2024) introduced the FinQ-Score, a practical substitute for the strict regulation of finfluencing, which aims to deliver a level of transparency in assessing the quality. Packin and Lev-Aretz (2023) highlighted decentralized credit scoring in a DeFi environment and sounded the alarm on the lack of regulation in lending protocols with the potential to exploit financially excluded individuals promoted by finfluencers. Their appeal for a more prominent role of the Consumer Financial Protection Bureau (CFPB) is evidence that regulatory institutions need to adapt to the most recent developments in a decentralized and influencer heavy financial world.

2.1Research gap

While previous literature has assessed how finfluencers shape asset outcome, content strategies, and investor sentiment across various platforms and markets, there is an important gap in the literature related to finfluencers influence the actual trading behaviour and/or psychological decision making of individual retail investors - particularly youth - across high-risk environments such as betting apps and crypto trading apps. Existing literature (e.g., Gerritsen & de Regt, 2025; Kedvarin, 2022; Zülch et al., 2024) has focused on asset market outcomes, influencer content quality and macro-level impacts of finfluencers, not micro-level behavioural outcomes such as impulsive trading decision-making and risk susceptibility. Moreover, literature such as Rijanto & Utami (2024) explore the influence without exploring how un-verified advice, and over-trust in social media channels for advice can lead to increased individual investor susceptibility to scams or errors. This study attempts to fill this under-explored intersection of psychology, channel-based influence, and financial behaviour in youth-led online trading ecosystems. This study will provide more behaviorally-rich, empirically-based insights into finfluencer-advised financial behaviour in the context of youth-based social trading apps, offering both micro and normative outcomes.

2.2 Research hypothesis

H1: The frequency of exposure to financial influencers on platforms like YouTube and Telegram channels positively influences the trading decision-making behavior of individual investors.

- **Independent Variable (IV):** Frequency of exposure to financial influencers (YouTube, Telegram) (FEFI)
- **Dependent Variable (DV):** Trading decision-making behavior (e.g., stock selection, risk tolerance, trade frequency) (TD-MB)

H2: Promotion of online betting and trading apps by social media influencers significantly increases the likelihood of investment in high-risk or scam platforms among Indian youth.

- **Independent Variable (IV):** Exposure to promotional content by social media influencers (EPCSMI)
- **Dependent Variable (DV):** Likelihood of investment in high-risk or scam platforms (LIH or SP)

H3: Trust in social media-based financial advice positively influences impulsive trading and betting behavior among individual traders.

- **Independent Variable (IV):** Trust in social media-based financial advice (TSM-BF)
- **Dependent Variable (DV):** Impulsive trading and betting behaviour (ITBB)

2.3 Conceptual framework

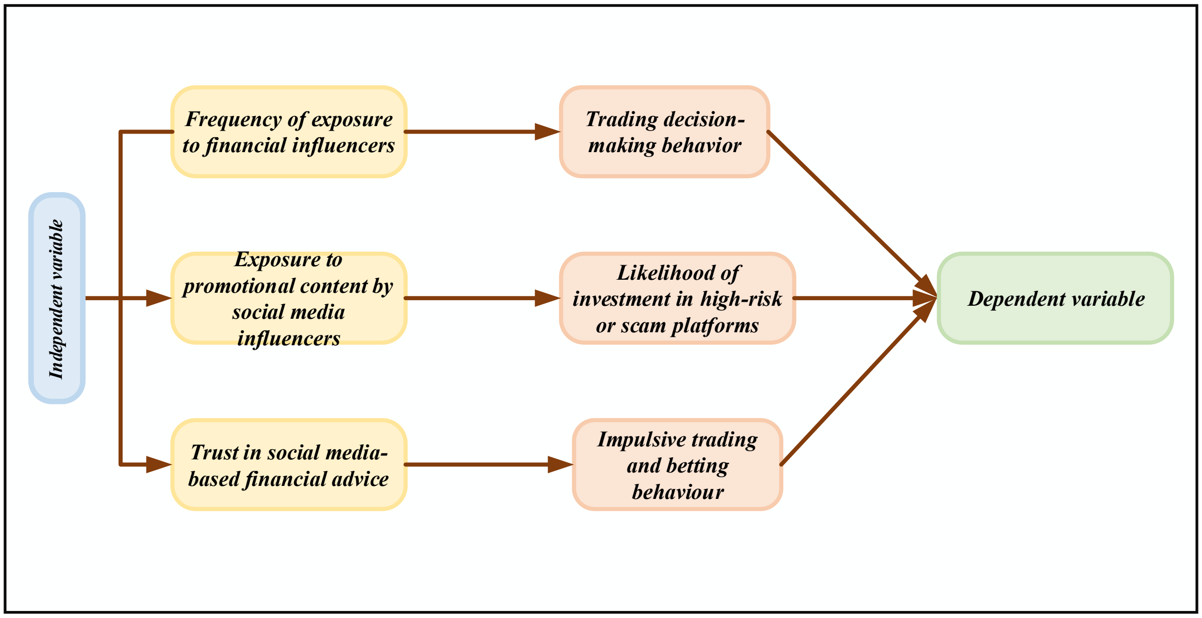

Figure 1: Conceptual frame work on variables

3. Research methodology

- ***Research design***

The study utilizes a quantitative, empirical research design to analyze the impact of financial influencers and financial influencers specifically on the trading activities of young people. The study is structured and deductive in nature, designed to confirm or reject hypotheses based on theoretical philosophies of behavioral finance and media studies. The researchers opted for a cross-sectional survey design to study a point in time capturing current trends, which includes investor trends and attitudes. This design allows for statistical analysis of the relationship between financial influencers and investment decisions. The entire study design is founded upon three theories of social learning, trust digital content, and financial behaviour, which can objectively develop cause-effect relationships.

- ***Data collection and sample size***

Primary data were obtained from an online questionnaire distributed to young individual traders and investors between the ages of 18–35 who actively consume financial content on YouTube and Telegram. A purposive sampling technique was employed to ensure that the participants had relevant experience with financial influencers, as well as personal experience with trading or investing. 237 valid responses were collected, providing sufficient data for analysis. The questionnaire consisted of closed-ended and Likert scale items where respondents were asked about parameters including the frequency of influencer engagement, the extent of trust in advice, if and how their trading decisions were impacted, and the use of apps related to betting/trading.

- ***Tools used***

The data used within this study was processed and analysed using SPSS and AMOS. Descriptive statistics were used to summarize the demographic and behaviour data, correlation and regression analyses were used to assess the strength and direction of variables and used to identify the latent constructs that influence behaviour, and structural equation modeling (SEM) was used to test the hypothesized relationships within the conceptual framework. The tools within SPSS and AMOS were robust enough to assist validating measurement models and test for path relationships which provided the empirical basis behind the influence of financial influencers on impulsive and high-risk trading decisions.

3.1 Data analysis

The data analysis was conducted utilizing descriptive and inferential statistics with the assistance of SPSS 26 and AMOS 24. Descriptive statistics included means, standard deviations, and frequency distributions, which were applied to describe the demographics of participants, the trading behavior, and the level of exposure to financial influencers. Inferential analysis included correlation analysis to explore the strength and direction of associations between engagement with influences, trust or distrust in financial content, and trading decisions. Furthermore, multiple regression analysis was utilized to consider variables such as exposure and trust or distrust in unverified advice as predictors of similar impulsive trades. was utilized to discover latent constructs or patterns of variables that were grouped together to better understand the relative influence on youth's investment decisions. Next, the newly created factors were used in a structural equation model (SEM) to test the proposed model and explore the direct and indirect influences of financial influencers on trading behavior. The model evaluation was undertaken using indices such as RMSEA and the Chi-square/df ratio. The analysis confirmed that being exposed to financial influencers contributed to impulsive and risky investing, with trust in unverified advice playing a co-mediator variable in this relationship.

3.2 Measures

Frequency test

A Frequency Table is an important statistical tool. In uses the data to put the data in categories and shows how often each category occurs. It gives you a quick way to visually see how many data points are in various categories. A Frequency Distribution goes beyond a Frequency Table. Rather than summarizing the data and plotting it in a table, a Frequency Distribution gives you an overall picture by organizing the information in a way that shows trends, patterns, and deviations. It helps you understand the data structure and to highlight the relationships and, in some cases, insight that may not be obtainable using the Frequency Table structure.

The demographic breakdown of the respondents shows that there is a heavy representation of youth. 61.6% of respondents identified themselves in the 18-34 age category. Not only is this demographic significant in this study, but it makes sense as the focus is on social media and social media use is very common among the younger crowd. The gender of the sample is skewed towards male with 62.9% of respondents identifying as male. This could indicate a gendered interest in online/trading activities. Educational attainment levels are high among participants. Over 92% of participants reported having at least a bachelor's degree. This indicates that this group is probably likely to be tech savvy and financially aware. The data on employment status was balanced. The majority of respondents were either full-time employees (32.5%), part-time employees (30.4%), or self-employed (28.7%). Even with good educational credentials, the majority of the respondents (89.1%) reported having a monthly income of less than ₹50,000. This suggests that these respondents have little disposable income, and they may be more acutely sensitive to financial risk. A high proportion of respondents (80.6%) use social media on either a daily or weekly basis, indicating that these respondents have a very high level of digital engagement.

Involvement with financial influencers is especially high on platforms like YouTube and Telegram, with over 79% of respondents claiming they view financial influencers regularly on YouTube with a very high rate of participation (over 81.9% being part of a financial discussion) on Telegram. This involvement suggests that respondents have an incredibly high level of trust, with high levels of trust with over 82% trusting YouTube advice, and over 83.1% finding Telegram content useful. These figures reflect, at surface level, the influential use of these platforms for financial information sources and also reflect significant trust in influencers relative to other sources..

This level of confidence translates to trading behavior, which was seen by 83.1% of the respondents who agreed that YouTube influencers impact their trading behavior. Promotion by influencers of trading apps is not uncommon, as 83.9% reported that they are frequently exposed to promotions of apps, and 81.4% said that influencers prompted them to use a trading app. An equal amount of exposure related to advertising is present, with 79.8% respondents frequently exposed to ads for high-risk trading platforms, with 79.4% observing that they were sponsored or promoted by influencers that they follow. Interestingly, 79.7% of the respondents trust this promotional content which may indicate greater trust in perceived authority than objective, data-driven investment strategies.

Psychological factors also show that influencer influence can be profound. Respondents overwhelmingly—81.4%—view social media advice as trustworthy as advice from professional financial advisors and 81.8% believe influencer content is more relatable. Although 78.9% stated they consider their risk tolerance, influencer recommendations significantly influenced their decisions, with 77% stating their stock decisions were influenced by influencers. Additionally, 79.3% reported trading more due to being exposed to influencers. The psychological immediacy created by influencer content was demonstrated with 80% stating they made quick buying and selling decisions and 76.8% reported impulsive trading behaviour, with 71.7% stating they experienced a greater sense of urgency after watching influencer content.

At last, investment behaviours reinforce this trend. A significant 79.3% of respondents were interested in investing in platforms discussed and promoted by influencers and exactly the same percentage of respondents invested . More concerning was the finding that 81% of respondents acknowledged ignoring the risks because the platforms were endorsed by trusted influencers. This highlights an extremely important weakness in digital financial behavior in which emotional and psychological drivers supersede rational analysis.

Demographic factors

The table outlines descriptive statistics on important demographic and behavior variables based on 237 participants. The mean age (M = 2.17, SD = 1.015) suggests that the majority of respondents classify as young adults. The mean gender (M = 1.37) suggests that the group is male-dominated, as lower coded values typically represent males. The mean education (M = 2.33) suggests that the group is relatively educated. The mean employment (M = 2.16) and income levels (M = 1.87) suggest moderate employment diversity and relatively low-income levels. The mean social media usage (SMU) of 1.81 suggests that the group is highly engaged with SUDA and social media in general. In terms of influencer effects, respondents reported strong agreement values overall for all measures related to influencers: Trust in Digital Media Behaviour (TDMB = 3.93), Following and Engagement with Financial Influencers (FEFI = 3.87), Likelihood to Invest in High-risk platforms (LIH = 3.86), Exposure to Promotional Content on social Media Influencers (EPCSMI = 3.83), Influence of Trading Behaviour of influencers (ITBB = 3.85), and Tendency for Social Media to Influence Financial Decision Making (TSMBF = 3.73). These high means suggest that there were substantial effects from influencers on respondent's trading behaviour.

Table 1: Demographic factors

	N	Mean	Std. Deviation	Std. Error Mean
Age	237	2.17	1.015	.066
Gender	237	1.37	.484	.031
Education	237	2.33	.613	.040
Employment	237	2.16	1.047	.068
Income	237	1.87	1.109	.072
SMU	237	1.81	.740	.048
TDMB	237	3.9342	.85255	.05538
FEFI	237	3.8793	.85417	.05548
LIH	237	3.8591	.82599	.05365
EPCSMI	237	3.8346	.84009	.05457
ITBB	237	3.8523	.86316	.05607

TSMBF	237	3.7308	.83500	.05424

4. Result

The research utilized quantitative statistical techniques to analyze how financial influencers and social media engagement influenced youth trading behaviour. The methods included descriptive statistics to describe the demographic characteristics; Cronbach's alpha to measure the reliability of the measurement scales; t-test to test the significance of the mean differences we observed; and, Pearson correlation determination to assess relationships between components such as the Trust in influencers and Impulsivity financial behaviour. A multiple regression, and ANOVA were used to assess predictive strength and variance of influencer exposures on trading decisions. The study also employed factor analysis and Structural Equation Modeling (SEM) for scale validation, and to establish relationships - observed and latent variables. Overall, the study emphasizes a rigorous methodological framework to safeguard findings from methodological weaknesses, and provides empirical evidence of the influential role played by finfluencers in people's financial decision-making. Referred to as 'finfluencers', this study adds significant insight into the impact of unverified content (such as YouTube and Telegram) as a choice for financial decision-making.

4.1 Reliability test

Table 2 outlines the reliability statistics and Cronbach’s Alpha for the scale derived from the 30-item scale, used for study 1 of the project. The Cronbach's Alpha of 0.969 (and 0.970 for standard items) for this scale indicates excellent internal consistency among all the items measuring the scale. It suggests that all the questionnaire items are correlated and consistently measuring the underlying constructs related to the impact of social media influencers on financial decision-making. A Cronbach’s Alpha score above 0.9 is typically viewed as extremely promising, and represents a study tool that has proven to be a reliable indicator and solid option for performing further statistical analysis and interpretation of these results in the context of the research presented here.

Table 2: Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.969	**.970**	**30**

The ANOVA findings are shown in Table 3. The ANOVA evaluates at the item level the variance in responses for the 30 items of the scale. The significant F-values (2.595, p = .000) in the Between Items row indicates there is a significant difference in the way participants responded to the various items which indicates the numerous items taken together represent a broader construct with different facets. There is also a non-additivity effect, which is significant (F = 9.940, p = .002) implying possible interaction effects or nonlinear relationships in the data In sum the sources of variance, validate the multidimensional nature of the instrument and the potential to model this or to pursue further factor analysis to explore underlying structures.

Table 3: ANOVA

			Sum of Squares	**df**	**Mean Square**	**F**	**Sig**
Between People			4154.756	236	17.605		
Within People	Between Items		41.198	29	1.421	2.595	.000
	Residual	Non-additivity	5.434^{a}	1	5.434	9.940	.002
		Balance	3741.168	6843	.547		
		Total	3746.602	6844	.547		
	Total		3787.800	6873	.551		

Total	7942.556	7109	1.117		

Table 4 displays the outcomes of Hotelling's T-Squared Test for difference of multivariate means which tests whether the mean vector of the items differ from a hypothesized mean population mean. The outcomes ($F = 1.370$, $p = .109$) is not statistically significant, thus indicating no meaningful multivariate difference across the set of measured variables.

Table 4: Hotelling's T-Squared Test

Hotelling's T-Squared	F	df1	df2	Sig
45.063	1.370	29	208	.109

The results of one-sample t-tests of the mean of each variable against a test value of zero were presented in Table 5. Each of the variables (demographic: Age, Gender, Education, Employment, Income, behavioural: SMU, psychological dimensions: TDMB, FEFI, LIH, EPCSMI, ITBB, TSMBF) had a statistically significant difference ($p < .001$). The t-values are all high, indicating strong deviations from the test value. For example, the mean of the Age variable (2.17) has a t-value of 32.887, meaning that respondents tended to be younger adults. In addition, the Gender variable has a mean of 1.37 ($t = 43.602$), meaning the respondents were more male. Considerably high mean values in the constructs reflected in TDMB (3.93), FEFI (3.87), LIH (3.86), and ITBB (3.85) suggest that respondents had similarly strong agreements with statements regarding trust in digital marketing behaviour, financial engagement, the influence of influencers, and impulsive trading. The narrow confidence intervals also provide further confidence about what was estimated.

Table 5: T-test

	Test Value = 0					
	t	**df**	**Sig. (2-tailed)**	**Mean Difference**	**95% Confidence Interval of the Difference**	
					Lower	**Upper**
Age	32.887	236	.000	2.169	2.04	2.30
Gender	43.602	236	.000	1.371	1.31	1.43
Education	58.604	236	.000	2.333	2.25	2.41
Employment	31.835	236	.000	2.165	2.03	2.30
Income	26.008	236	.000	1.873	1.73	2.02
SMU	37.593	236	.000	1.806	1.71	1.90
TDMB	71.041	236	.000	3.93418	3.8251	4.0433
FEFI	69.917	236	.000	3.87932	3.7700	3.9886
LIH	71.925	236	.000	3.85907	3.7534	3.9648
EPCSMI	70.270	236	.000	3.83460	3.7271	3.9421
ITBB	68.708	236	.000	3.85232	3.7419	3.9628
TSMBF	68.784	236	.000	3.73080	3.6239	3.8377

4.2 Hypothesis test

Hypothesis 1

The Pearson correlation displayed in Table 6 between TDMB and FEFI has a value of 0.817*. This suggests there is a strong positive relationship between both variables. This demonstrates that as trust in digital marketing is increased, people are more likely to engage with financial influencers. The strong degree of correlation supports showing H1 is confirmed that TDMB is positively associated with FEFI. Because the value is closer to 1.0, it indicates a high degree of positive association. This further shows that influencer-driven digital marketing has a strong association to how users' financial engagement behaviours are influenced on social media.

Table 6: Correlation H1

		TDMB	FEFI
Pearson Correlation	**TDMB**	**1.000**	**.817**
	FEFI	**.817**	**1.000**

Table 7 presents the regression results for Hypothesis 1, assessing the impact of TDMB on FEFI. The model shows a high R value of 0.817, indicating a strong correlation. The R Square value of 0.668 implies that 66.8% of the variance in FEFI is explained by TDMB. The F-statistic (473.107) with a significance level of .000 confirms the model is statistically significant. This demonstrates a robust predictive relationship, supporting the hypothesis that greater trust in digital marketing behaviour leads to increased financial engagement with influencers.

Table 7: Regression H1

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.817[a]	.668	.667	.49218	.668	473.107	1	235	.000

Table 8 shows the ANOVA results for Hypothesis 1. The analysis examined the TDMB may be associated with FEFI. There was a statistically significant F-value in the regression model of 473.107 with a p-value of .000. This indicates that there is a statistically significant relationship between the independent and dependent variables. The regression sum of squares (114.606) accounted for a much larger proportion of the total variability (171.533) instead of just the residual sum of squares (56.927). This demonstrates that TDMB does predict FEFI and is a strong supporter of the hypothesis**.**

Table 8: ANOVA H1

Model		Sum of Squares	df	Mean Square	F	Sig.
1	**Regression**	**114.606**	**1**	**114.606**	**473.107**	**.000[b]**
	Residual	**56.927**	**235**	**.242**		
	Total	**171.533**	**236**			

Table 9 presents the correlation coefficients for Hypothesis 1 between TDMB and FEFI. The correlation value of 1.000 indicates a perfect positive linear relationship between the two variables, suggesting that as TDMB increases, FEFI also increases proportionally. The covariance value of 0.001 indicates a very small degree of variability shared between the variables. While the correlation suggests a strong relationship, the covariance is very low, showing that the overall variance explained by the model is minimal.

Table 9: Coefficient Correlation H1

Model	FEFI

1	**Correlations**	**FEFI**	**1.000**
	Covariances	**FEFI**	**.001**

H2

Table 10 shows the Pearson correlation between LIH and EPCSMI. The correlation coefficient of 0.814 indicates a strong positive relationship between the two variables. This suggests that as the influence of LIH increases, EPCSMI also increases significantly. The correlation value of 1.000 for both variables indicates perfect internal consistency, meaning both LIH and EPCSMI are highly interconnected in the dataset. This strong correlation implies that influencer hype has a considerable effect on users' engagement with promotional content.

Table 10: Correlation H2

		LIH	**EPCSMI**
Pearson Correlation	**LIH**	**1.000**	**.814**
	EPCSMI	**.814**	**1.000**

Table 11: Regression H2

Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Change Statistics**				
					R Square Change	**F Change**	**df1**	**df2**	**Sig. F Change**
1	**.814[a]**	**.662**	**.661**	**.48099**	**.662**	**460.961**	**1**	**235**	**.000**

Table 11 presents the results of a regression analysis examining the relationship between LIH and EPCSMI. The R value of 0.814 indicates a strong positive correlation between the two variables. The R Square value of 0.662 suggests that approximately 66.2% of the variability in engagement with promotional content can be explained by the hype generated by lifestyle influencers. The Adjusted R Square of 0.661 accounts for model accuracy, showing that the regression model is well-fitted. The F Change value of 460.961 and a Sig. F Change of 0.000 indicate that the model is statistically significant, meaning the predictor variable (LIH) is a strong determinant of EPCSMI. The Std. Error of the Estimate of 0.48099 reflects the average distance between observed and predicted values in the regression model.

Table 12: ANOVA H2

Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	**Regression**	**106.645**	**1**	**106.645**	**460.961**	**.000[b]**
	Residual	**54.368**	**235**	**.231**		
	Total	**161.013**	**236**			

Table 13 presents the coefficient correlation between Engagement with EPCSMI. The correlation value of 1.000 indicates a perfect positive relationship between EPCSMI and itself, as expected for a single variable correlation. The covariance of 0.001 shows a very small variation, indicating minimal spread or variability in the values of EPCSMI. This suggests that EPCSMI is relatively consistent across the observed sample, with low variation. Since this is a self-correlation, the value is consistent and indicates no further complex relationships within this specific measure.

Table 13: coefficient correlation H2

Model			**EPCSMI**
1	**Correlations**	**EPCSMI**	**1.000**

	Covariances	EPCSMI	.001

H3

Table 14 displays the Pearson correlation between ITBB and TSMBF. The correlation value of 0.712 indicates a strong positive relationship between the two variables. As ITBB increases, there is a tendency for TSMBF to increase as well, suggesting that higher trust in influencers is associated with more frequent trading behaviors. A correlation of 0.712 suggests that while there is a strong relationship, other factors may also influence TSMBF, and the relationship is not perfectly linear.

Table 14: Correlation H3

		ITBB	TSMBF
Pearson Correlation	ITBB	1.000	.712
	TSMBF	.712	1.000

Table 15 presents the regression analysis for ITBB and TSMBF. The model shows an R value of 0.712, indicating a strong positive relationship between the variables. The R^2 value of 0.507 means that approximately 50.7% of the variance in TSMBF can be explained by ITBB, demonstrating a moderate to strong explanatory power. The F change value of 241.221 with a significance of 0.000 indicates that the model is statistically significant and ITBB is a strong predictor of TSMBF. The standard error of the estimate is 0.60764, indicating the typical deviation of the observed values from the regression line.

Table 15: Regression H3

Model	R	R^2	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.712[a]	.507	.504	.60764	.507	241.221	1	235	.000

Table 16 presents the ANOVA results for the regression model assessing the relationship between ITBB and TSMBF. The Sum of Squares for Regression is 89.064, and the Residual Sum of Squares is 86.767, indicating that the model explains a significant portion of the variance in the dependent variable. The F-value of 241.221 with a Sig. value of 0.000 indicates that the regression model is highly significant, meaning that ITBB is a strong predictor of TSMBF. The Total Sum of Squares is 175.831, reflecting the overall variance in the data**.**

Table 16: ANOVA H4

Model			Sum of Squares	df	Mean Square	F	Sig.
1	Regression		89.064	1	89.064	241.221	.000[b]
	Residual		86.767	235	.369		
	Total		175.831	236			

Table 17: Coefficient Correlation

Model			TSMBF
1	Correlations	TSMBF	1.000
	Covariances	TSMBF	.002

4.4 Factor Analysis

The table 18 presents the results of the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity, which assess the suitability of data for factor analysis. The KMO value is 0.925, which indicates excellent sampling adequacy (values closer to 1 suggest good suitability). Bartlett's Test of Sphericity tests the null hypothesis that the correlation matrix is an identity matrix. The test produces a Chi-Square value of 1511.350 with 15 degrees of freedom, and the p-value is 0.000, which is highly significant. This suggests that the correlation matrix is not an identity matrix, and factor analysis is appropriate for the data.

Table 18: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.925**
Bartlett's Test of Sphericity	Approx. Chi-Square	1511.350
	df	15
	Sig.	0.000

4.4 SEM analysis

The table 19 displays results from a regression model analysis, showing the relationships between latent variables. The regression coefficients (Estimates) for each path are provided along with their standard errors (S.E.), critical ratios (C.R.), and p-values (P). The path from FEFI to TDMB has an estimate of 0.816, with a standard error of 0.037, a critical ratio of 21.797, and a significant p-value (***). The path from EPCSMI to LIH has a similar estimate of 0.8, with a critical ratio of 21.516. The path from TSMBF to ITBB shows a slightly lower estimate of 0.736, with a C.R. of 15.564, all indicating strong statistical significance

Table 19: Regression Model

			Estimate	**S.E.**	**C.R.**	**P**	**Label**
TDMB	<---	FEFI	0.816	0.037	21.797	***	
LIH	<---	EPCSMI	0.8	0.037	21.516	***	
ITBB	<---	TSMBF	0.736	0.047	15.564	***	

The table 20 presents variance estimates for several variables (FEFI, EPCSMI, and TSMBF) along with their standard errors (S.E.), critical ratios (C.R.), and p-values (P). All variables show significant results with p-values marked as *** (indicating statistical significance). The estimate values for FEFI, EPCSMI, and TSMBF are 0.727, 0.703, and 0.694, respectively, with corresponding standard errors of 0.067, 0.065, and 0.064. The C.R. values are consistent across all variables at 10.863, indicating strong evidence of the model's validity. The variables (E1) associated with each measure are also highly significant with p-values.

Table 20: Variance

			Estimate	**S.E.**	**C.R.**	**P**	**Label**
FEFI			0.727	0.067	10.863	***	
E1			0.24	0.022	10.863	***	
EPCSMI			0.703	0.065	10.863	***	
E1			0.229	0.021	10.863	***	
TSMBF			0.694	0.064	10.863	***	
E1			0.366	0.034	10.863	***	

The table 21 provides the CMIN (Chi-Square) values for three groups (H1, H2, and H3) under different model conditions. For both the Default and Saturated models, CMIN is 0, indicating a perfect fit. In contrast, the

Independence model shows significant CMIN values. H1 and H3 have a CMIN of 166.686 with 1 degree of freedom (DF), yielding a CMIN/DF ratio of 166.686, while H2 has a CMIN of 256.227 with the same DF, giving a CMIN/DF ratio of 256.227. These high CMIN/DF values indicate poor model fit for the Independence model in all groups.

Table 21: CMIN

	Model	NPAR	CMIN	DF	P	CMIN/DF
H1	**Default model**	**3**	**0**	**0**		
	Saturated model	**3**	**0**	**0**		
	Independence model	**2**	**166.686**	**1**	**0**	**166.686**
H2	Default model	3	0	0		
	Saturated model	3	0	0		
	Independence model	2	256.227	1	0	256.227
H3	Default model	3	0	0		
	Saturated model	3	0	0		
	Independence model	2	166.686	1	0	166.686

The table 22 presents model fit indices for three groups (H1, H2, and H3) under various model conditions. For both the Default and Saturated models, RMR (Root Mean Square Residual) and GFI (Goodness-of-Fit Index) are 0 and 1, respectively, indicating perfect fit. In contrast, the Independence model shows non-zero values for RMR and GFI. Specifically, H1 and H3 have an RMR of 0.295 and GFI of 0.664, while H2 has an RMR of 0.325 and GFI of 0.602. The AGFI (Adjusted GFI) is negative for both H2 and H1, indicating a poor fit, while PGFI (Parsimony GFI) shows small values.

Table 22: RMR, GFI

	Model	RMR	GFI	AGFI	PGFI
H1	**Default model**	**0**	**1**		
	Saturated model	**0**	**1**		
	Independence model	**0.295**	**0.664**	**-0.009**	**0.221**
H2	Default model	0	1		
	Saturated model	0	1		
	Independence model	0.325	0.602	-0.195	0.201
H3	Default model	0	1		
	Saturated model	0	1		
	Independence model	0.295	0.664	-0.009	0.221

The table 23 presents data from a model comparison analysis. It includes three groups (H1, H2, and H3), each evaluated under three conditions: Default model, Saturated model, and Independence model. For all three groups, both the Default and Saturated models show a value of 0 across all variables (indicating no effect). The Independence model shows varying values: H1 and H3 have values of 165.686 (with a 90% confidence interval between 126.916

and 211.864), while H2 shows a higher value of 255.227 (with a confidence interval between 206.269 and 311.591). These results suggest a stronger association in H2 compared to H1 and H3.

Table 23: NCP

	Model	NCP	LO 90	HI 90
H1	Default model	0	0	0
	Saturated model	0	0	0
	Independence model	165.686	126.916	211.864
H2	Default model	0	0	0
	Saturated model	0	0	0
	Independence model	255.227	206.269	311.591
H3	Default model	0	0	0
	Saturated model	0	0	0
	Independence model	165.686	126.916	211.864

The table 24 presents FMIN values, which indicate the discrepancy between the hypothesized model and the observed data, for three hypotheses (H1, H2, and H3). For all three hypotheses, both the Default and Saturated models have FMIN, F0, and their 90% confidence intervals equal to zero, reflecting a perfect model fit with no deviation from the observed data. In contrast, the Independence models show much higher FMIN values—0.706 for H1 and H3, and 1.086 for H2—indicating a poor fit. Their confidence intervals further support this, showing wide ranges that suggest substantial misfit. Overall, the Default models outperform the Independence models substantially.

Table 24:FMIN

	Model	FMIN	F0	LO 90	HI 90
H1	Default model	0	0	0	0
	Saturated model	0	0	0	0
	Independence model	0.706	0.702	0.538	0.898
H2	Default model	0	0	0	0
	Saturated model	0	0	0	0
	Independence model	1.086	1.081	0.874	1.32
H3	Default model	0	0	0	0
	Saturated model	0	0	0	0
	Independence model	0.706	0.702	0.538	0.898

The table presents RMSEA (Root Mean Square Error of Approximation) values for the Independence models across three hypotheses (H1, H2, and H3). All RMSEA values are extremely high—0.838 for H1 and H3, and 1.04 for H2—indicating poor model fit. The 90% confidence intervals (LO 90 and HI 90) further support this, with all lower bounds well above the acceptable threshold of 0.08. Additionally, the PCLOSE values are 0 for all models, meaning the probability that RMSEA is less than or equal to 0.05 is effectively zero. These results confirm that the Independence models are an inadequate representation of the data.

Table 25: RMSEA

	Model	RMSEA	LO 90	HI 90	PCLOSE
H1	Independence model	0.838	0.733	0.947	0
H2	Independence model	1.04	0.935	1.149	0
H3	Independence model	0.838	0.733	0.947	0

The table 26 displays model fit indices—AIC, BCC, BIC, and CAIC—for three hypotheses (H1, H2, and H3), comparing Default, Saturated, and Independence models. For all three hypotheses, the Default and Saturated models yield identical and low values (AIC = 6), indicating excellent model fit. In contrast, the Independence models show significantly higher values across all indices, particularly in H2 (AIC = 260.227), reflecting poor model performance. The consistency between the Default and Saturated models suggests that the proposed structural models are well-specified and parsimonious. These results support the adequacy and efficiency of the Default models in representing the data accurately.

Table 26: AIC

	Model	AIC	BCC	BIC	CAIC
H1	Default model	6	6.077	16.404	19.404
	Saturated model	6	6.077	16.404	19.404
	Independence model	170.686	170.737	177.622	179.622
H2	Default model	6	6.077	16.404	19.404
	Saturated model	6	6.077	16.404	19.404
	Independence model	260.227	260.279	267.163	269.163
H3	Default model	6	6.077	16.404	19.404
	Saturated model	6	6.077	16.404	19.404
	Independence model	170.686	170.737	177.622	179.622

The table 27 presents fit indices—ECVI, AIC, BCC, BIC, and CAIC—for three models (H1, H2, and H3) across Default, Saturated, and Independence models. For all hypotheses, the Default and Saturated models have nearly identical and minimal values, indicating an excellent model fit. Specifically, H2 and H3 show exceptionally low values (~0.025), while H1's values are higher but still favorable compared to the Independence model. In contrast, the Independence models across all hypotheses have significantly higher values, reflecting poor model fit. These results confirm that the Default models are robust and represent the data structure much better than the Independence models.

Table 27: ECVI

	Model	AIC	BCC	BIC	CAIC
H1	Default model	6	6.077	16.404	19.404

	Saturated model	6	6.077	16.404	19.404
	Independence model	170.686	170.737	177.622	179.622
H2	Default model	0.025	0.025	0.025	0.026
	Saturated model	0.025	0.025	0.025	0.026
	Independence model	1.103	0.895	1.341	1.103
H3	Default model	0.025	0.025	0.025	0.026
	Saturated model	0.025	0.025	0.025	0.026
	Independence model	0.723	0.559	0.919	0.723

The figure 2 displays a structural equation model illustrating the relationship between the latent variables FEFI and TDMB. The path coefficient of 0.82 from FEFI to TDMB indicates a strong positive effect, suggesting that a one standard deviation increase in FEFI leads to a 0.82 standard deviation increase in TDMB. TDMB is influenced by measurement error, represented by E1 with a variance of 0.24, meaning 24% of TDMB's variance is due to measurement error. Additionally, the R^2 value of 0.73 for FEFI implies that 73% of its variance is explained by the model, indicating a strong explanatory power and a good model fit.

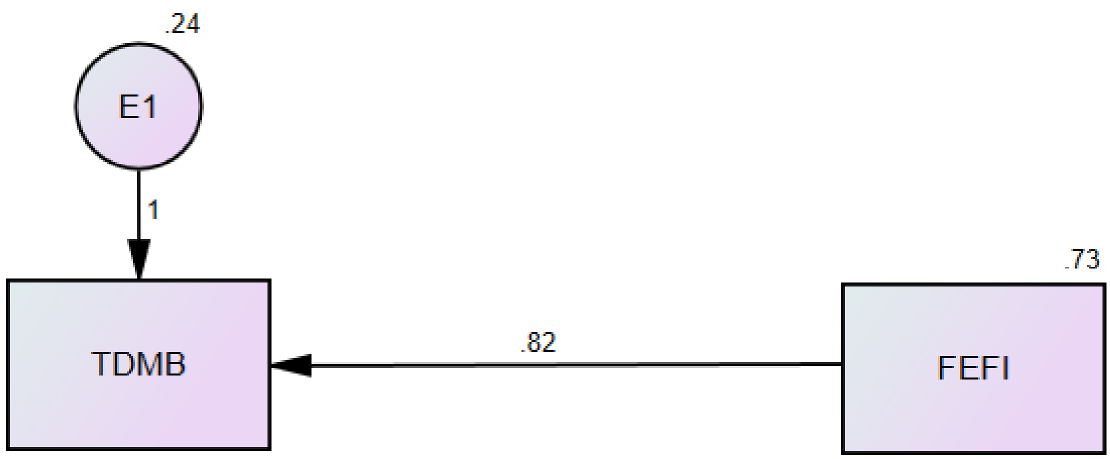

Figure 2: SEM analysis for H1

The figure 3 represents a structural equation model showing the relationship between the latent variables LIH and EPCSMI. The path coefficient of 0.80 indicates a strong positive effect of EPCSMI on LIH, suggesting that a one standard deviation increase in EPCSMI results in a 0.80 standard deviation increase in LIH. LIH is associated with a measurement error labeled E1, with a variance of 0.23, indicating that 23% of LIH's variance is due to error. The R^2 value for EPCSMI is 0.70, meaning 70% of its variance is explained by the model. This implies a good model fit and a significant predictive relationship

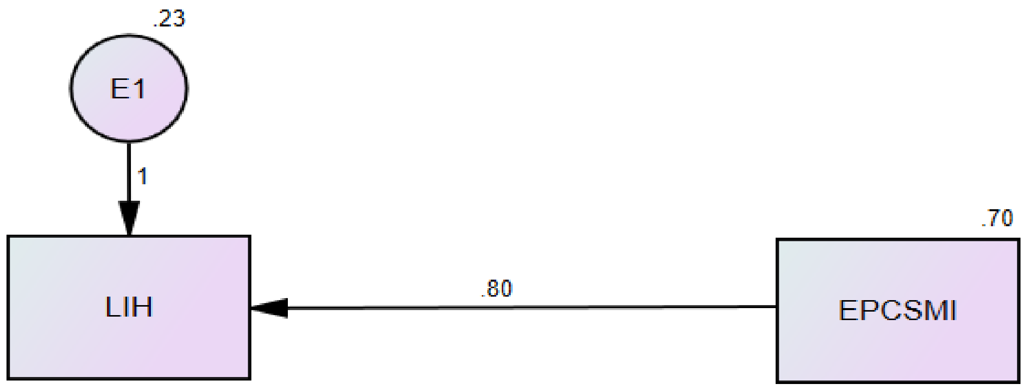

Figure 3: SEM analysis for H2

The figure 4 illustrates a structural equation model depicting the relationship between two latent variables: ITBB and TSMBF. A strong positive path coefficient of 0.74 from TSMBF to ITBB indicates that a one standard deviation increase in TSMBF leads to a 0.74 standard deviation increase in ITBB. The variable ITBB is influenced by measurement error, represented by E1, with a variance of 0.37, suggesting some degree of unreliability in its measurement. Additionally, the R^2 value of 0.69 associated with TSMBF implies that 69% of its variance is explained by the model, signifying a good overall fit and meaningful predictive relationship.

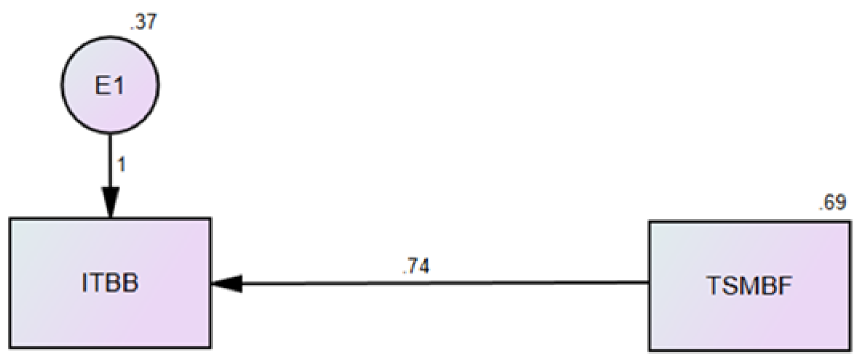

Figure 4: SEM analysis for H3

5. Discussion

The reviewed studies together indicate the multifaceted and at times problematic impact that financial influencers (finfluencers) have on investment behaviours. For example, Gerritsen and de Regt (2025) identified a tendency for finfluencers to endorse assets that had strong past performance which led to recommendations resulting in poor post-recommendation returns and presumably a financial loss for the investor after acting on the social heuristic-based recommendations. In addition, Kedvarin (2022) identified a strong influence of influencer activity on cryptocurrency returns as measured on YouTube, and that the impact on the stock market was minimal, implicit suggesting that crypto investments are more prone to volatility and susceptible to influencer activity to influence their prices. In contrast, Zülch et al. (2024) presented a FinQ-Score to provide avenues of evaluating the quality finfluencer, and strongly encouraged regulatory authorities to provide a measure of balance to provide consumer protections in the market while not stifling creativity and innovation. Collectively, the studies suggest that finfluencers impact financial behaviours (likely behaviours) and it is especially true in the crypto market. However, these impacts also suggest that finfluencer-based decision making is both speculative and risky. In light of the mixed evidence suggested by studies reviewed in this paper, there was an emerging need for indicators of quality and transparency to limit misinformation and to protect individual investors from acting impulsively upon the inappropriate use of information received from a finfluencer (or finfluencer based content).

The results in this study highlight the extent to which financial influencers affect traders' decisions, particularly among young individuals. The strong relationship between the exposure to finfluencers and impulsive trading behaviour indicates an emerging pattern of financial decision-making that is increasingly dictated by the narratives surrounding influences on digital platforms rather than by sound financial principles. Platforms such as YouTube and Telegram can be an environment of non-regulated and unverified advice leading traders to have a higher propensity to engage in high-risk trading and betting platforms. Trust in influencers—often influenced by their expertise and engaging content—can reduce the traditional risk assessment of younger traders. This behavioural shift highlights the need for education in financial literacy designed to build evaluation skills. To intervene at a systemic level, education must also be provided, but importantly, regulation must be adapted to follow and oversee the ever-evolving nature of digital financial services so that misleading promotions (Advertisements) are diminished. The study adds to the growing body of knowledge around the psychological and social contexts associated with investment behaviours that have been shaped by a culture of influences.

6. Conclusion

This study demonstrates that financial influencers on platforms like YouTube and Telegram have a profound effect on the trading behaviors of individual traders, especially among young investors. By promoting high-risk trading and betting apps, influencers increase the likelihood of impulsive and poorly informed investment decisions. The study found that trust in unverified financial advice leads to a significant shift in decision-making processes, emphasizing the psychological impact of influencer promotions. These behaviors, particularly among youth, make them more vulnerable to scams and financial missteps. The research underscores the necessity for increased regulatory measures to mitigate the risks posed by unverified advice. Additionally, it calls for enhanced financial literacy programs to equip individuals with the skills needed to critically assess the financial content they encounter online.

6.1 Limitations

This study has several limitations. First, the sample size of 237 young individual traders may not be fully representative of all demographics or geographical regions. Second, the study only focuses on YouTube and Telegram, potentially excluding other platforms where influencers are also active. Third, the reliance on self-reported data may introduce biases, as respondents may overstate or understate their actual behavior. Additionally, the study's cross-sectional design limits the ability to establish causal relationships over time. Lastly, the data collection period might not capture long-term shifts in behavior following exposure to financial influencers.

6.2 Future Scope

Future research could explore the influence of financial influencers across a broader range of social media platforms, such as Instagram and TikTok, to assess whether their impact varies by platform. Longitudinal studies could provide deeper insights into how influencer-driven behaviors evolve over time. Additionally, research could investigate the effectiveness of different types of financial education and regulatory interventions in mitigating the risks of impulsive trading. Exploring cultural and regional differences in influencer influence on investment decisions could also provide a more nuanced understanding of how these behaviors manifest in diverse populations. Finally, examining the role of emotion and behavioral biases in financial decision-making would be valuable.

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