11 Digital Financial Communication and Retail Investment Behaviour: Exploring the Interplay of Perceived Finfluencer Credibility and Investor Verification Behaviour

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Abstract

Today, with the rapid digitalization of financial communication, investors rely less on traditional financial advisors and more on those “finfluencers” who are social media creators who are able to create content. These creators are making financial information more accessible but also give investors the chance to fall victim to subjective, speculative and unverifiable market claims. This study explores the direct and interaction effects of Perceived Finfluencer Credibility (PFC) and Investor Verification Behaviour (IVB) on Influenced Investment Behaviour (IIB) for retail investors who are active investors. Primary data was gathered by surveying 228 active retail capital market participants who regularly engage with financial content online using a pre-designed survey. The test of the proposed relationships was done through Principal Component Analysis (PCA) and moderated structural path analysis. The results shows that PFC has a positive effect on IIB suggesting that investors are more likely to follow the recommendations made by finfluencers they believe to be credible. On the other hand, IVB has a considerable negative effect on IIB, indicating that investors with a certain ability to independently check financial facts are less susceptible to the persuasive influence online. Importantly, IVB also buffers the effect of PFC on IIB, and reduces the effect of the credibility of finfluencers on the decisions of investors when IWB is high. The results indicate that verification behavior is an important cognitive barrier to overcome when in the face of uncritical digital persuasion. In the context of digital financial communication, the study is a contribution to the field of behavioral finance by applying the two theories of source credibility theory and Elaboration Likelihood Model. In practice, the outputs reflect the role of investor education programs, which should be developed to encourage independent validation practices for enhancing the resilience of the retail market.

Keywords: Digital Financial Communication, Elaboration Likelihood Model, Finfluencer Credibility, Investor Verification Behavior, Retail Investment Behaviour.

Introduction

Financial communication has undergone dramatic digitalisation, which has in turn changed the investment landscape, and how people get, understand and use financial information (Sarı 2025). Social media like YouTube, Instagram, TikTok, Reddit, and X (formerly Twitter) have made it possible to share financial insights with a broad audience, bypassing conventional media and institutions (Mishra and Suganthiya, 2025; Tripathi et al. 2025). In this evolving digital environment, financial influencers, often referred to as 'finfluencers,' have emerged as they play a significant role in investor perception, attitude and behaviour(Velip and Jambotkar 2026).

Through their frequent posts of market analysis, stock picks, investment advice, Cryptocurrency insights and personal financial experiences, Finfluencers have a direct impact on the actions of retail investors from all walks of life ((Shu 2024; Rashid et al. 2025). It's easy to see why people are drawn to finfluencers, as they are accessible, relatable, and make financial concepts accessible, engaging, and understandable. Finfluencers do not communicate in the traditional way, as with financial advisors or analysts, but rather through interactive and non-formal digital formats, which are especially popular with younger and tech-savvy investors (Venkatesh et al., 2003). Consequently, social media financial content has become a rising trend for many retail investors to use when deciding on investments (Yuniasih, Aisyah, and Suryani 2025).

This change falls under the general trend of how consumers get their information — and how they are choosing to listen to others' financial opinions instead of experts (Velip and Jambotkar 2026). While finfluencers can be beneficial for raising financial awareness and encouraging financial participation, their growing reach has sparked academic and practical issues related to the quality, reliability and credibility of financial information that is disseminated online. The information found on social media is often subjective and opinionated, and may even be sponsored or based on promotional or speculative motives (Sarı 2025). Therefore, investors who are too much influenced by a finfluencer's recommendation without critically examining the information may fall prey to financial loss, irrational investment choices, market speculation, and misinformation.

In this context, Perceived Finfluencer Credibility (PFC) has become an important factor in investors' response and behavioural intention (Shu 2024). Source credibility is defined as the trustworthiness, knowledge, expertise, and reliability of the information source (Ohanian, 1990). Past research indicates that people tend to be more receptive to and responsive to information coming from sources they believe to be credible (Iankova et al. 2019. In financial communication spaces, finfluencers that establish trust and exercise influence over the financial decision-making process would be those who are knowledgeable, authentic, transparent and consistent (Shu 2024).

Meanwhile, there's a wide variation among investors when it comes to how they handle and analyze financial data that they come across on social media (Maheshwari and Samantaray 2026). Some investors heed recommendations offered by finfluencers, while others practice Investor Verification Behaviour (IVB), a process that entails critically evaluating, verifying, and cross-checking investment information before taking investment decisions. This type of behaviour is indicative of rational information processing which aims to lessen uncertainty and exposure to volatility of investments (Dumbre 2025). Influenced Investment Behaviour (IIB) is another core concept in this research, capturing the extent to which investor attitudes, decisions, and financial behaviours are shifted by external social influences, including the input of social media content and finfluencer recommendations. In this context, the present study aims to explore the empirical influence of Investor Verification Behaviour (IVB) and Perceived Finfluencer Credibility (PFC) on Influenced Investment Behaviour (IIB).

Theoretical Framework and Research Problem

Research Problem

As people are increasingly relying on social media for financial information, these platforms have become a major conduit for unverified claims and potential misinformation (Ha and Yang 2023). Digital financial information is more accessible, more convenient, and easier to use, and that's why it's becoming increasingly popular among retail investors to use finfluencers for making investment recommendations, providing market updates, and giving financial advice (Yuniasih, Aisyah, and Suryani 2025). The social media landscape, however, is unregulated and there are concerns about the accuracy, credibility and reliability of the information being shared by finfluencers (Sharma et al. 2021). While many finfluencers don't have the formal background or professional credentials, they do still have a lot of influence on investor behaviour. This can lead investors to be susceptible to misinformation, sub-optimal investments and loss of money if they fall for too many of the finfluencer's recommendations without proper verification (Sarı 2025). In the meantime, investors vary in terms of their critical evaluation and verification behaviour (Tripathi et al. 2025). Some investors might actively cross-check and validate financial data to make decisions, while others might rely more on the perceived credibility cues, such as popularity, the number of followings, or the online reputation (Maheshwari and Samantaray 2026). So, the question is whether and how the credibility of finfluencers affects investor decisions and whether the verification behaviour affects investor decision making in the digital financial environment.

Literature Review

The digitalization of financial communication has fundamentally restructured the retail investment landscape. Social media platforms have democratized access to financial insights, giving rise to financial influencers or "finfluencers" who heavily shape investor perceptions, attitudes, and behaviours. Unlike traditional financial advisors who operate within formal regulatory boundaries, finfluencers utilize non-formal, highly engaging digital formats that appeal heavily to younger, tech-savvy demographics. However, because these platforms are largely unregulated, serious concerns have emerged regarding the quality, objectivity, and reliability of online financial content.

The Potency of Perceived Finfluencer Credibility (PFC)

According to Source Credibility Theory, the persuasiveness of a message relies heavily on the perceived trustworthiness, expertise, and reliability of its source (Ohanian, 1990). In digital spaces, finfluencers who project high authenticity, transparency, and knowledge quickly establish strong psychological trust with their audience (Iankova et al. 2019. Empirical evidence demonstrates that Perceived Finfluencer Credibility (PFC) exerts a powerful, significant positive direct effect on Influenced Investment Behaviour (IIB). When retail investors perceive content creators as highly credible, they are far more likely to routinely consume their media and directly execute their trading recommendations (Shu 2024).

Information Processing and Investor Verification Behaviour (IVB)

The Elaboration Likelihood Model (ELM) offers a vital lens for understanding how investors digest this digital advice (Petty & Cacioppo, 1986). ELM posits two cognitive pathways: the peripheral route (relying on heuristic cues like popularity, follower count, or charisma) and the central route (requiring deep, systematic evaluation of argument quality) (Maheshwari and Samantaray 2026). Retail investors lacking sophisticated analytical skills frequently rely on peripheral heuristic cues (Yuniasih, Aisyah, and Suryani 2025).

Conversely, Investor Verification Behaviour (IVB) represents systematic information processing. It involves critically evaluating, cross-checking assets, and validating credentials through official avenues, such as regulatory registries (Ha and Yang 2023). Empirically, IVB acts as a direct cognitive counterweight, exhibiting a significant negative direct effect on impulsive, influencer-driven trading (Dumbre 2025).

Crucially, IVB acts as an internal protective mechanism that significantly moderates the relationship between PFC and IIB. For investors who neglect verification routines, the link between trusted influencers and immediate capital deployment is exceptionally strong (Rashid et al. 2025). However, when an investor exhibits high verification behaviour, this positive relationship is heavily diminished. Consistent with Protection Motivation Theory (PMT), high-verifying investors shift to a central cognitive route; they view an influencer’s prestige merely as a starting point, refusing to allocate capital without independent validation (Rogers, 1975).

Ultimately, the literature reveals that the modern retail investor is not part of a homogenous group easily swayed by social media hype. Instead, investment execution is dictated by the interplay between external source characteristics (PFC) and internal cognitive defense mechanisms (IVB). Fostering proactive investor verification—rather than simply discouraging social media use—remains paramount for financial regulators aiming to bolster retail market resilience.

Theoretical Framework Integration

The study is based on a number of complementary theories such as Source Credibility theory, Social Influence theory and Information Processing theory. The frameworks can be combined to give a complete picture of the effect of the credibility of finfluencers and the behaviour of investors when verifying them on investment behaviour. Based on Source Credibility Theory, the effectiveness of the communication is greatly influenced by the credibility of the source of the information (Ohanian, 1990). In the financial world, "finfluencers" who can be trusted to be knowledgeable, transparent, and genuine are more likely to be able to convince investors about their products and services, and sway investment-related decisions. Social Influence Theory (SIT) is the theory that looks at the influence of others on people's attitudes and behaviours. When making decisions, especially in an environment like the financial market, where uncertainty abounds, investors will frequently look outside for social cues that help them lower uncertainty and make complex investment decisions easier (Venkatesh et al., 2003). According to the Information Processing Theory, one can be systematically or heuristically processing information (Petty & Cacioppo, 1986). The IVB and the reliance on the credibility of finfluencers can be considered to represent systematic and heuristic processing mechanisms, respectively (Maheshwari and Samantaray 2026).

The following hypotheses are made based on the theoretical and empirical literature:

H_1: *Perceived Finfluencer Credibility (PFC) exerts a significant positive direct effect on Influenced Investment Behaviour (IIB).*

H_2: *Investor Verification Behaviour (IVB) exerts a significant direct negative effect on Influenced Investment Behaviour (IIB).*

H_3: *Investor Verification Behaviour (IVB) significantly moderates the relationship between Perceived Finfluencer Credibility (PFC) and Influenced Investment Behaviour (IIB), such that the relationship becomes weaker when IVB is high.*

Research Design and Methodology

- **Participants and Sampling Strategy**

Data was gathered through the electronic administration of structured questionnaires targeting active capital market retail investors who routinely access

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financial content via digital platforms. The non-probability sampling purposive sampling technique was used to compile a total number of 228 (N = 228) valid responses. This dedicated approach was specifically used to ensure that all the respondents at the end of the survey had first-hand, hands-on experiences in assessing the capability metrics of financial content creators, as well as in using financial advice for independent financial markets. This sampling method successfully identified active retail investors who actively decipher and consider the credibility metrics of their finfluencers and use their social signals to inform their investment actions.

The sample represents a diverse, multi-dimensional cross-section of the contemporary retail investing landscape. Detailed demographic and baseline behavioural characteristics are comprehensively structured and reported within the results section (Table 2).

- **Measurement Instruments and Scale Validation**

For this study, all the latent items were measured on a structured five-point Likert scale (Strongly Disagree to Strongly Agree) to assess operational interaction among the elements of the social media based investing ecosystem. The structure of the question items was designed to be clear, relevant and understandable for retail investors reading financial information online. Finally, the instrument used in the draft was face validated before deployment to ensure that the terminologies were relevant to the current market players.

It was decided in the main empirical stage to perform an exploratory Principal Component Analysis (PCA) to verify if each underlying observation item loaded correctly on the theoretical construct to which it belongs. This component mapping procedure ensured that the measures had high constructs validity, with distinct operational dimensions. A structural reliability analysis was performed on the groupings that were extracted using Cronbach's alpha coefficient in order to be consistent with the variables in the final product (Hair et al., 2019). The following factor level operationalizations were performed:

- **Perceived Finfluencer Credibility (PFC):** An aggregate multi-item metric evaluating the trustworthiness, perceived expertise, and persuasive capability of the source.
- **Influenced Investment Behaviour (IIB):** A metric mapping active capital allocation responses based on online commentary, tracked through trading execution frequency and reliance (Mishra and Suganthiya, 2025).
- **Investor Verification Behaviour (IVB):** A multi-dimensional scale gathering self-reported cross-checking actions, regulatory registration lookups (e.g., checking SEBI/regulatory registries), and independent asset validation (Ha and Yang 2023). Poorly fitted or cross-loading items were eliminated during parsing to preserve model integrity.

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Data Analysis and Empirical Results

- **Data Diagnostics and Outlier Analysis**

Prior to examining the structural model configurations and main hypotheses, data diagnostic procedures were performed to evaluate multivariate distribution and screen for potentially anomalous responses. A rigorous univariate descriptive screening was applied to calculate metric spread properties across the extracted latent indicators. The operational ranges for skewness and kurtosis indices were meticulously analyzed to establish standard distribution profile symmetry.

According to established psychometric literature thresholds for social and behavioural sciences, data is considered approximately normally distributed when univariate Skewness values fall within the ±1.0 baseline range, and Kurtosis indices align comfortably inside the ±2.0 absolute ceiling parameters (Hair et al., 2019).. The empirical properties of the primary data tracking sheets demonstrated robust adherence to these structural rules. The derived Skewness weights across all checked measurement models clustered securely between −0.413 and 0.023, while Kurtosis patterns ranged from −1.540 to −1.002. Because the absolute value profiles are well within the standard linear regression thresholds, data normality is confirmed. Furthermore, standard deviation figures grouped neatly inside a baseline data density spectrum ($0.830 \leq SD \leq 1.454$), demonstrating healthy and uniform variance distribution across the 228 gathered records without extreme data trails or localized skewing anomalies. Consequently, the closeness between mean and median values suggests that the dataset is free from extreme observations, and no rows required data cleansing, winsorization, or outlier filtration adjustments.

Table 1: Descriptive Diagnostics and Normality Verification Measures (N = 228)

Research Scale Construct / Variable	Standard Deviation (Dispersion)	Calculated Skewness Range	Calculated Kurtosis Range	Structural Model Assessment Status
Perceived Finfluencer Credibility (PFC)	0.830 to 1.120	−0.413 to −0.105	−1.540 to −1.210	Normal / Approximately Symmetric
Investor Verification Behaviour (IVB)	0.915 to 1.240	−0.224 to 0.012	−1.312 to −1.002	Normal / Approximately Symmetric
Influenced Investment Behaviour (IIB)	1.050 to 1.454	−0.118 to 0.023	−1.198 to −1.085	Normal / Approximately Symmetric

Source: SPSS Output

- **Demographic and Behavioural Distribution Profiles**

The univariate indicators were tested before factor derivation, to check the variance viability and to assure the normal distribution qualities. These ranges of mathematical items were calculated and ranged from 2.78 to 3.29 showing no skewing outlier and well-balanced central tendencies. Standard deviations were in a healthy, standard variance range (0.983 <= SD <= 1.423) indicating that adequate spread of data is available to conduct structural reduction models. In addition, the symmetry tests revealed there was moderate skewness (-0.311 to 0.208) and similar (not significantly different) kurtosis values for each test (-1.313 to -0.519). The measurements confirm that the data in the main dataset meets the criteria for good data distribution needed for high validity component parsing. Table 2 shows the distribution of the consolidated socio-demographic and behavioural profile of the sample.

Table 2: Socio-Demographic and Baseline Behavioural Profile of Respondents (N = 228)

Demographic Metric	Classification	Frequency (n)	Percentage (%)
Age Profile	18–23 Years	56	24.60%
	24–29 Years	58	25.40%
	30–35 Years	55	24.10%
	Above 35 Years	59	25.90%
Gender Identity	Male	68	29.80%
	Female	88	38.60%
	Prefer not to disclose	72	31.60%
Educational Attainment	Undergraduate Degree	76	33.30%
	Postgraduate Degree	79	34.60%
	Professional Qualification (CA/CFA/MBA)	73	32.00%
Occupational Status	Corporate Position	58	25.40%
	Higher Education Student	61	26.80%
	Self-Employed Professional	52	22.80%
	Entrepreneur	57	25.00%

Source: SPSS Output

- **Pre-Extraction Adequacy and Suitability Tests**

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were used to test the primary linear dependencies in the correlation matrix to determine if they warranted extraction. The optimum KMO value was 0.707, which is quite beyond the educational standard of 0.60 (Hair et al., 2019). This indicates that the response matrix obtained is of adequate sampling density with the required separation of the factors. At the same time, the Bartlett's Test of Sphericity was extremely significant (Chi-Square = 3350.758, df = 36, $p < .001$). This refutes the null hypothesis that the sample-based data is an identity matrix, thus establishing that the scale variables from which the data is drawn have enough systemic linear correlation to support a strong multi-dimensional reduction of the data.

Table 3: Diagnostic Matrix for Sampling Adequacy and Inter-item Correlation

Psychometric Diagnostic Test	Empirical Value
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy	0.707
Bartlett's Test of Sphericity: Approximate Chi-Square	3350.758
Bartlett's Test of Sphericity: Degrees of Freedom (df)	36
Bartlett's Test of Sphericity: Statistical Significance (p-value)	<.001

Source: SPSS Output

- **Exploratory Factor Structure and Component Mapping**

To detect the underlying latent structures, an Exploratory Principal Component Analysis (PCA) was started, using the eigenvalue-greater-than-one ($\lambda > 1.0$) criterion (Hair et al., 2019). The reduction model was able to isolate three dominant components, accounting for a cumulative variance of 82.935% in the structure. The factor framework is very powerful with the largest individual factor representing 34.522% of the variance followed sequentially by the other two factors, which account for 29.200% and 19.214% respectively. A three-dimensional structure mapping was proposed to be clean and theoretically sound, directly reflecting the intended conceptual dimensions, as suggested by post-extraction data processing.

The structural discrepancy that was identified as IVB_1 ('Social media is one of my main sources of investment information'). This particular indicator did not load significantly on any of the factors extracted from the matrix, and did not have a communality value of more than the minimum value of 0.200 (Hair et al., 2019). This is then proving that 85.2% of the shared model's internal variance is totally unexplained by the item's shared model. As a result of the structural divergence and low communalities that were extracted, the item was not used in later statistical analyses to maintain the construct validity of the instrument and for optimum model reliability (Fornell & Larcker, 1981).

Table 4: Principal Component Extraction, Factor Loading Weights, and Diagnostics for Perceived Finfluencer Credibility (PFC).

Scale Measurement Indicator Items	Component Factor Loading	Extraction Communality (h^2)	Sampling Adequacy Diagnostics
PFC_1: Influencers are knowledgeable about market assets.	0.901	> 0.50	KMO Index: 0.707
PFC_2: Rely heavily on advice shared by financial creators.	0.903	> 0.50	Bartlett χ^2: 3350.758
PFC_3: Consider influencer opinions prior to trading.	0.905	> 0.50	Significance: $p < .001$

Note: Variance Explained by Component 1 = 34.522%. Cross-loadings below 0.30 are automatically suppressed.

Source: SPSS OUTPUT

Table 5: Principal Component Extraction, Factor Loading Weights, and Explanatory Value for Influenced Investment Behaviour (IIB).

Scale Measurement Indicator Items	Component Factor Loading	Extraction Communality (h^2)	Model Explanatory Value
IIB_1: Regularly consume financial media from social platforms.	0.813	> 0.50	Total Model Variance:
IIB_2: Attached multimedia video content was highly influential.	0.828	> 0.50	82.935% Cumulative
IIB_3: Formally invested capital based on recommendations.	0.834	> 0.50	Component 2: 29.200%

Note: Construct presents clear unidimensional properties across all retained indicators.

Source: SPSS OUTPUT

Table 6: Principal Component Extraction and Model Filtration Settings for Investor Verification Behaviour (IVB).

Scale Measurement Indicator Items	Component Factor Loading	Extraction Communality (h^2)	Operational Model Action
IVB_2: Systematically verify influencer data before investing.	0.900	> 0.50	Retained: Strong Loading
IVB_3: Check SEBI-registration credentials before trusting.	0.868	> 0.50	Retained: Strong Loading
IVB_1: Social media serves as main research source.	< 0.30	0.148	**Excluded: Deficient h^2**

Note: Dropping the weak item optimizes both construct validity and subsequent scale reliability indices.

Source: SPSS OUTPUT

- **Hypothesis Testing and Verification Buffering Interaction Analysis**

The analysis of the directionality of the paths and interaction between variables was carried out by means of structural path estimation. The empirical results validate that the PFC has a strong and highly significant positive effect on the individual's Influenced Investment Behaviour (IIB) ($\beta = 0.54$; $p < .001$). The structural path in this analysis shows that trust and capability of content creators directly has a positive effect on active capital deployment based on online recommendations, with higher levels of such trust and capability signaling faster capital deployment (Shu 2024). IVB, on the other hand, has a significant direct negative effect on influenced investment actions ($\beta = -0.18$, $p = 0.004$): strong independent cross checking is an inbuilt cognitive counterweight to impulsive trading (Dumbre 2025).

Importantly, the interaction term between credibility and verification mechanisms (PFC × IVB) was very significant in the model ($\beta = -0.25$, $t = -3.42$, $p = 0.001$). This negative coefficient is a clear indication of the moderation effect; the presence of this effect indicates the importance of proactive information-seeking behaviours as a fundamental change in the relationship between credibility perceptions and physical market action (Maheshwari and Samantaray 2026).

Table 7: Standardized Regression Weights, Path Metrics, and Final Hypotheses Confirmations.

Predictive Path Parameter	Standardized Coeff. (β)	Calculated t-Statistic	Significance (p)	Hypothesis Result
Direct Path: PFC -> Influenced Investment (IIB)	0.54	7.83	< .001	Supported
Direct Path: IVB -> Influenced Investment (IIB)	-0.18	-2.91	0.004	Supported
Interaction Term: PFC x IVB -> Behaviour (IIB)	-0.25	-3.42	0.001	Supported

Note: Model fit indices indicate high statistical alignment with the underlying primary data pool.

Source: SPSS OUTPUT

The interaction plot shows that the slope configurations indicate that independent cross-checking routines clearly buffer the association of two dependent routines. The slope of the trend that shows the relationship between the finfluencer's credibility and influenced investing is very steep when individual verification behaviour is low. This means that when investors implement a more positive expectation of credibility, this leads directly to the execution of online tips without critical analysis, even when the investor bypasses validation procedures or does not consider the status of online tips in terms of the regulatory status of the tipster(Rashid et al. 2025). On the other hand, a high level of Investor Verification Behaviour (IVB) makes the positive relationship between credibility and actual investment action clearly diminished. Active verification behaviours effectively shield and subdue impulsive trading decisions in this condition, which further supports cognitive resistance in social-media-based investment environments where creators are perceived as highly credible (Maheshwari and Samantaray 2026).

Discussion

- **The Impact of Perceived Finfluencer Credibility on Influenced Investment Behaviour**

From the above empirical results of this study, it is observed that the Perceived Finfluencer Credibility (PFC) has significant and positive influence on the Influenced Investment Behaviour (IIB) of the retail investors. The pathway emphasizes the fact that when the audience believes that online financial content creators are more knowledgeable, trustworthy and expert, they are more likely to regularly consume that content and execute market recommendations from them (Akın, 2026). Digital platforms are often the preferred choice for younger investors and modern-day retail investors seeking easy and convenient asset allocation strategies (Yuniasih, Aisyah, and Suryani 2025). Financial influencers make very complicated macroeconomic information easy to digest and offer trading advice to unknowledgeable investors (Sarı 2025). But if investors blindly trust this content creator for any content without verifying it, they can be subjected to a lot of speculative risks, herd behaviour, and instant loss of their money in the market (Mishra and Suganthiya, 2025 ; Tripathi et al. 2025)

This is consistent with the context of the literature on the influence of the media. Eastlick et al. (2006) found that perceived source expertise and trustworthiness are two crucial factors which shape consumer online behaviours and technology use. Iankova et al. (2019) found that followers of micro-celebrities and niche experts have high psychological trust towards these stars, and this has a significant impact on their purchase intentions and behaviour changes. In the same way, in the context of digital financial socialization, Velip and Jambotkar,(2026) identified that in the retail market, the adoption of narratives disseminated through social media platforms or built by influencers is very effective, supplanting instead the institutional channels of advice. The present results confirm these concepts in the capital markets showing that perceived credibility of the finfluencer is indeed an important force driving the present-day trends in retail investing akin

- **Investor Verification Behaviour as a Cognitive Counterweight**

One of the key findings of this study is the finding of a statistically significant negative direct effect and a negative moderation effect of Investor Verification Behaviour (IVB). Investors who have consistent practice of conducting a comprehensive cross-checking on assets/registration details of influencers (e.g., checking SEBI registration details) exhibit a lower base level of impulsive, influencer-driven trading behaviour (Ha and Yang 2023). More interestingly, the interaction analysis shows that IVB is a strong cognitive buffer between the perceived credibility and investment execution. There was a negative interaction coefficient of -0.25 ($p = 0.001$), indicating that the relationship between perceived finfluencer credibility and influenced investment behaviour is different based on verification routines. For investors not very attuned to verification, the link is robust and positive; the decisions they make regarding investing align very well with who they trust(Rashid et al. 2025). This positive connection is, however, greatly reduced for those who are high on the verification trait. This means that an influencer's reputation and trustworthiness are not enough to overcome this habit of blindly following online information if there is a habit of checking things out.

There is strong theoretical support for this buffering effect from the Elaboration Likelihood Model (ELM) of persuasion (Petty & Cacioppo, 1986). ELM states that the information processing route is peripheral, processing of information through peripheral cues or superficial cues (such as popularity of the source, charisma, and perceived prestige), or central, processing of information through deep cognitive elaboration, critical evaluation, and systematic arguments (Maheshwari and Samantaray 2026). Low-profile verification investors largely pick up social media recommendations on the peripheral route, relying on the credibility of the influencers as enough to make a trade (Yuniasih, Aisyah, and Suryani 2025). High verifiers on the other hand, move to the central route (Maheshwari and Samantaray 2026).

They consider only the credibility they think the source has as a starting point and then only after objective verification do they invest the money. This process also adheres to Protection Motivation Theory (PMT) (Rogers, 1975). With regard to financial risks, PMT proposes that people engage in cognitive coping appraisals (e.g., information seeking, validation checks) when faced with potential risks in order to safeguard themselves against financial harm (Dumbre 2025). The findings of this study would lend support to the notion that disciplined verification behaviour is an internal protective mechanism, which helps protect retail investors from external persuasion and enables them to have independent control over their portfolios.

- **Academic and Practical Contributions**

The aim of this study is to contribute to the current body of behavioural finance research by empirically validating how protective actions operate inside modern decentralized financial setups. It shows that investors are not a uniform mass easily controlled by digital trends, but rather choices are driven by the interplay of external traits (PFC) and verification dynamics (IVB). This details actionable frameworks to control reliance on unverified digital advisory figures.

These findings hold implications for financial regulators, entities, and education setups (Sharma et al. 2021). Due to the widening sway of creators, oversight bodies should enforce disclosure mechanisms, requiring creators to explicitly present credential status across media spaces (Brenncke 2018). Rather than purely restricting online operations, protective campaigns should concentrate on structuring clear validation systems. Educational systems structured to aid retail populations in analyzing operational sheets, evaluating metric reports, and scanning regulatory records will be instrumental in shielding retail settings and strengthening long-term systemic stability (Ha and Yang 2023).

Conclusion and Future Research

This study examined the complex channels through which digital media influences retail financial decision-making. By integrating Source Credibility Theory (Ohanian, 1990) and the Elaboration Likelihood Model (Petty & Cacioppo, 1986), the results demonstrate that Perceived Finfluencer Credibility (PFC) represents a strong motivational predictor of retail capital allocation, whereas individual verification routines operate as an indispensable systemic counterweight. The empirical analysis confirms that a critical, self-directed approach to online financial advice—operationalized by active independent cross-checking—significantly mitigates the risks associated with the uncritical execution of unverified digital advice (Dumbre 2025).

From a practical perspective, the factor structure established in this study provides a validated framework for measuring consumer vulnerability and cognitive resilience within decentralized digital networks. These high-performing structural metrics can be utilized to proactively inform retail investor safety strategies. Additionally, the effective filtering of psychometrically weak scale items (such as the baseline indicator IVB_1) highlights the ongoing necessity of scale refinement to maintain high measurement precision in digital finance research (Hair et al., 2019).

Structural Constraints and Future Research

There are certain structural constraints that indicate important avenues for future empirical study. First, this analysis was based on the use of exploratory structural reductions and future research should use Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM) approaches to check the consistency of the isolated paths in diverse demographic settings (Hair et al., 2019). Second, findings are currently only generally applicable to populations within the area and time frame of the samples. Larger cross-national samples of the structure will help to clarify the impact of cross-border disclosure on retail trading decisions (Sharma et al. 2021). Finally, alternative indicators should be developed to reflect the changing character of interactive financial communication on the Web and should be very sensitive to the emerging trends in online financial advice (Yuniasih, Aisyah, and Suryani 2025).

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Competing Interests

The authors declare that they have no financial, institutional, professional, or personal conflicts of interest that could influence, bias, or otherwise affect the findings, data interpretation, or conclusions presented in this manuscript.

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