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From Attention to Financial Behaviour: Modelling the Influence of Finfluencer Credibility, Algorithmic Exposure and Social Proof on Gen Z Investment Risk-Taking

Akshay Puttabakula[1], Raghu Raja Mehra[2]

[1]Student Researcher, Amritsar, Punjab, India

[2]Faculty Mentor, Amritsar, Punjab, India

Abstract: ***A large share of Generation Z now meets financial markets for the first time on a social media feed rather than in a bank branch. Short videos by financial influencers, or 'finfluencers', reach millions of young viewers, and recommendation algorithms decide which of those videos a viewer sees. This study asks how three features of that environment - how credible the finfluencer seems, how often the algorithm shows financial content, and how many peers appear to be investing - relate to how much investment risk young people are willing to take. A questionnaire covering five constructs was designed from established scales, and a simulated response set of 268 respondents aged 18–26 was generated to demonstrate the analysis; the dataset is clearly labelled as artificial and is not a real survey. All scales showed good reliability (Cronbach's alpha 0.85 to 0.89). Multiple regression explained 58.8% of the variation in risk-taking. Social proof had the strongest standardised effect ($\beta = 0.39$), followed by perceived credibility ($\beta = 0.30$) and algorithmic exposure ($\beta = 0.19$), while financial literacy had a smaller negative effect ($\beta = -0.14$). Literacy did not moderate the credibility effect ($\beta = -0.02$, $p = 0.56$), which suggests that knowing more about finance reduces risk-taking directly but does not make a young investor resistant to a persuasive creator. Respondents in the top third of algorithmic exposure reported a risk-taking score of 4.30 against 3.49 in the bottom third. The findings support financial education that trains source evaluation, not only product knowledge.***

Keywords: finfluencer; social media; source credibility; social proof; recommendation algorithms; financial literacy; Generation Z; investment risk-taking

1. Introduction

For most of the twentieth century, a young person's first contact with investing came through a parent, a bank or a broker. For Generation Z, that first contact usually happens on a phone. A thirty-second video explains a stock, a mutual fund or a cryptocurrency, and the next video appears automatically. The people making these videos are known as finfluencers, and they now reach audiences that no traditional adviser could reach [1], [2].

This has clear benefits. Financial content that is free, short and in everyday language has brought many young people into markets who would otherwise have stayed out. It also carries risks. Most finfluencers are not licensed advisers, many are paid to promote products, and very few are required to explain what can go wrong [3]. Regulators have noticed. In 2024 the Securities and Exchange Board of India barred its regulated entities from associating with unregistered financial influencers, and in 2025 it further restricted the use of live market prices in content presented as education [4].

What is less well understood is the mechanism. Influence does not act only through the content of the advice. It also acts through how trustworthy the creator seems, how often the algorithm places such content in front of a viewer, and how many other people appear to be doing the same thing. This study separates those three channels and measures how each relates to willingness to take investment risk. It also asks whether financial literacy protects young investors from these effects.

The scale of the change is easy to underestimate. A single well-performing video about a stock or a cryptocurrency can be seen by more young people in a week than a bank branch would advise in a decade, and it costs the viewer nothing. Because the content is short and confident, it also removes most of the friction that used to slow a first investment down: there is no form to fill, no adviser to convince and no waiting period in which enthusiasm can cool. Opening an account and buying an asset can now happen inside the same hour as the video that suggested it.

This paper does not argue that finfluencers are harmful in themselves. Much of what they publish is ordinary financial education, and some of it is better explained than the material produced by regulated firms. The concern is narrower. Persuasion on a social feed works through cues- confidence, follower counts, visible profits, repetition- and those cues carry no information about whether an investment suits the person watching. If risk-taking rises with the strength of the cues rather than with the quality of the reasoning, then young investors are being sorted into risky assets by the design of the platform rather than by their own circumstances.

The paper is organised as follows. Section II sets out the problem and Section III reviews the literature. Section IV states the gap, the objectives and the hypotheses. Section V describes the method and Section VI the sample. Sections

VII to IX report the correlation, regression, moderation and group results. Sections X to XIII discuss the findings, their implications, the limitations and the conclusion.

2. Background and Problem Statement

Three ideas from earlier research shape the problem. The first is source credibility. Work going back to Hovland and Weiss [5] and later formalised by Ohanian [6] shows that a message is more persuasive when the speaker is seen as trustworthy and expert, even if the message itself does not change. Applied to finfluencers, this suggests that a confident, likeable creator can move behaviour without offering better information.

The second is attention. A viewer does not choose from all financial content available; the viewer sees what the recommendation system supplies. Barber and Odean [7] showed that investors tend to buy assets that catch their attention, and later work on app-based retail investing [8] found similar attention-driven trading. If an algorithm repeatedly shows a particular kind of asset, that asset becomes the visible choice.

The third is social proof. Cialdini [9] describes the tendency to treat the behaviour of others as evidence about what is correct. In finance this connects to herd behaviour and informational cascades [10], [11], where people follow the crowd even when their own information suggests otherwise. Comment counts, likes and screenshots of profits are all visible signals of what other people are doing.

These three ideas are not competing explanations; they describe three points in the same chain. The algorithm decides what reaches the viewer, credibility decides whether the viewer accepts it, and social proof decides how confident the viewer feels about acting. A study that measures only one of them will attribute the whole effect to that one channel, because the three move together in real life.

A fourth idea sits underneath all three. The elaboration likelihood model [16] distinguishes between decisions made by working through an argument and decisions made by reacting to surface signals. Scrolling a feed is close to the second case: the viewer is not comparing expense ratios, and the decision is made in seconds. This predicts that persuasion cues should matter more than the technical content of the advice- a prediction this study tests indirectly through the moderation hypothesis.

The problem this paper addresses is therefore: among Gen Z investors, how strongly is each of these three channels associated with investment risk-taking, and does financial literacy weaken those associations?

3. Literature Review

1) *Finfluencers and financial behaviour*

Research on finfluencers has grown quickly. The CFA Institute study by Espeute and Preece [1] surveyed young investors and found that finfluencer content is a major information source for them, often ahead of professional advice. Mölders et al. [12] studied how finfluencers see their own role and how brands partner with them. Hasanah et al. [13] analysed the content of leading finfluencers and found that specific investment products, including cryptocurrencies, dominate, while risk warnings are often thin. Guan [3] reviews the legal position and argues that the gap between entertainment and advice is where most investor harm sits. Singh and Sarva [14] describe the same shift in the Indian market.

2) *Credibility and persuasion*

Source credibility research [5], [6] is the foundation for measuring how a creator is perceived. Djafarova and Rushworth [15] applied it to Instagram and found that perceived credibility of an online personality strongly predicts the purchase decisions of young users. The elaboration likelihood model [16] adds a useful distinction: when a viewer has little knowledge or little time, persuasion runs through surface cues such as confidence and follower count rather than through the argument itself.

Two features of this literature are worth noting. First, most studies are either content analyses, which examine what finfluencers post, or market studies, which examine what happens to prices afterwards. Comparatively few measure what viewers themselves think and do. Second, where investor surveys do exist, they tend to record how often young people use social media for financial information rather than which feature of the content is doing the persuading.

3) *Literacy and risk-taking*

Lusardi and Mitchell [17] document how weak financial literacy is across populations and how strongly it predicts poor financial outcomes. Mohta and Shunmugasundaram [18] examined whether literacy moderates the link between risk tolerance and risky investing among Indian millennials, which is the closest published test to the moderation hypothesis examined here. Grable and Lytton [19] provide the standard approach to measuring financial risk tolerance.
Taken together, this literature establishes three separate mechanisms and leaves the interaction between them open. Table 1 shows how the studies map onto the three channels examined here.

Table 1: Selected studies and what they cover

Study	Focus	Cred.	Algo.	Social
Hovland [5]	Source credibility	✓	–	–
Ohanian [6]	Credibility scale	✓	–	–
Cialdini [9]	Social proof	–	–	✓
Banerjee [10]	Herd behaviour	–	–	✓
Barber [7]	Attention and buying	–	✓	–
Djafarova [15]	Influencer credibility	✓	–	✓
Barber [8]	App-based investing	–	✓	✓
Espeute [1]	Finfluencer use	✓	✓	✓
Hasanah [13]	Finfluencer content	✓	–	–
This study	Combined model	✓	✓	✓

Cred. = credibility, Algo. = algorithmic exposure, Social = social proof

4) *Recommendation systems and what gets seen*

A separate strand of work looks at the feed itself rather than at the creator. Recommendation systems are built to maximise watch time, which means they promote content that holds attention. Financial content that promises a large, fast gain holds attention better than content about index funds and patience, so the two are not equally likely to be shown. Barber et al. [8] document the market-level consequence of this kind of attention concentration among users of a popular investing app, where large numbers of small investors bought the same assets at the same time. The point for the present study is that exposure is not a personal choice in the way that following a creator is; it is a property of the system.

Content analyses of finfluencer material support the same concern from the other direction. Hasanah et al. [13] found that specific investment products, including cryptocurrencies, dominate the content of leading creators, and that risk warnings are frequently absent or brief. A viewer whose feed is filled with such material is not seeing a representative sample of investment options.

4. Research Gap, Objectives and Hypotheses

Two gaps stand out. First, most studies examine one channel at a time. Credibility research rarely measures algorithmic exposure, and studies of herd behaviour rarely measure how credible the source seemed. Because the three channels are correlated in real life, testing them separately over-states each one. Second, financial literacy is usually treated as a simple control variable, so it is not clear whether literacy protects young investors from persuasion or merely lowers their risk-taking on average.

The objectives are: (O1) to build a measurement model for the three channels; (O2) to estimate their combined effect on risk-taking; (O3) to test whether financial literacy moderates the credibility effect; and (O4) to compare risk-taking across levels of algorithmic exposure.

Five hypotheses follow, and the conceptual model is shown in Fig. 1.

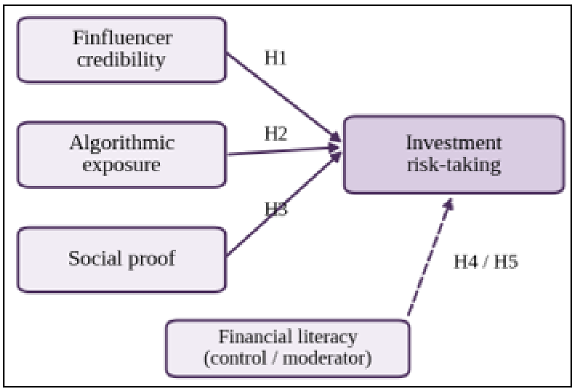

Figure 1: Conceptual model. The three social media channels are tested together; financial literacy enters both as a direct influence (H4) and as a possible moderator (H5).

H1: Perceived finfluencer credibility is positively related to investment risk-taking. H2: Algorithmic exposure to financial content is positively related to risk-taking. H3: Social proof is positively related to risk-taking. H4: Financial literacy is negatively related to risk-taking. H5: Financial literacy weakens the relationship between credibility and risk-taking.

5. Method

The response data used in this study are simulated. The questionnaire, the constructs and the analysis are real and reusable, but the 268 responses were generated by the authors so that the full analysis could be demonstrated end to end. No claim is made about any actual group of respondents, and the findings should be read as a worked demonstration rather than as evidence about Gen Z investors.

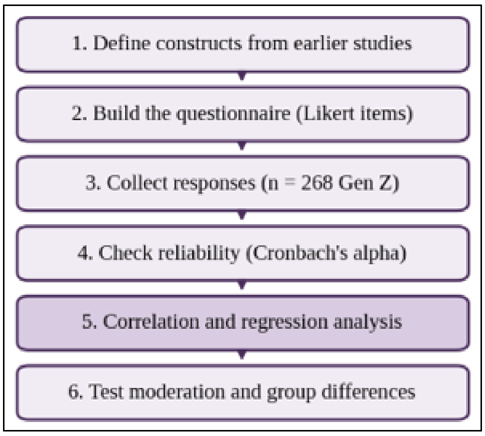

Figure 2: Steps followed in the study

Five constructs are measured. Finfluencer credibility uses five items adapted from Ohanian [6], covering trustworthiness, expertise and honesty. Algorithmic exposure uses four items on how often financial content appears in the respondent's feed without being searched for. Social proof uses four items on whether friends and visible online audiences appear to be investing. Investment risk-taking uses five items adapted from Grable and Lytton [19]. All of these use a five-point agreement scale. Financial literacy is measured separately as a score out of ten on basic questions about interest, inflation and diversification, following the approach of Lusardi and Mitchell [17]. Overconfidence, age, gender and investing experience are included as controls.

The questionnaire was designed to be short enough to complete in about eight minutes, since long instruments produce careless answers from younger respondents. Items are worded in plain language, and two items in each scale are reverse-worded so that a respondent who agrees with everything can be identified. The intended sampling frame is investors aged 18 to 26 who have used at least one investing application, recruited through college groups and online communities. Participation would be voluntary and anonymous, no personally identifying information would be collected, and respondents under 18 would be excluded at the screening question.

Reliability was checked using Cronbach's alpha, which measures whether the items in a scale move together. Values above 0.70 are normally considered acceptable. Table 2 shows that all four scales are comfortably above this level.

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Table 2: Constructs, items and reliability

Construct	Items	Adapted from	Alpha
Finfluencer credibility	5	Ohanian [6]	0.87
Algorithmic exposure	4	Barber et al. [8]	0.86
Social proof	4	Cialdini [9]	0.85
Investment risk-taking	5	Grable [19]	0.89
Financial literacy	10	Lusardi [17]	score /10

The analysis has four steps: descriptive statistics; a correlation matrix; multiple regression with risk-taking as the dependent variable; and two additional tests- an interaction term for moderation and a comparison of exposure groups. Standardised coefficients are reported so that variables measured on different scales can be compared directly. Three checks were run before interpreting the regression. Multicollinearity was assessed using variance inflation factors, all of which stayed below 2, so the three channels can be entered together without distorting the coefficients. Residuals were inspected for non-normality and for changing spread across fitted values. And the control-only model was estimated first, so that the additional explanatory power of the three channels can be reported separately rather than assumed.

$$\textit{Risk-taking} = a + b_1\,\textit{Credibility} + b_2\,\textit{Exposure} + b_3\,\textit{Social proof} + b_4\,\textit{Literacy} + \textit{controls} + \textit{error}$$

6. Sample and Descriptive Results

The sample has 268 respondents aged 18 to 26, with a mean age of 22.1 years. Women make up 42.9% of the sample and 53.0% are students. Median investing experience is 16 months, which confirms that most respondents are new investors. Fig. 3 shows where respondents mainly see financial content: Instagram and YouTube together account for about two-thirds.

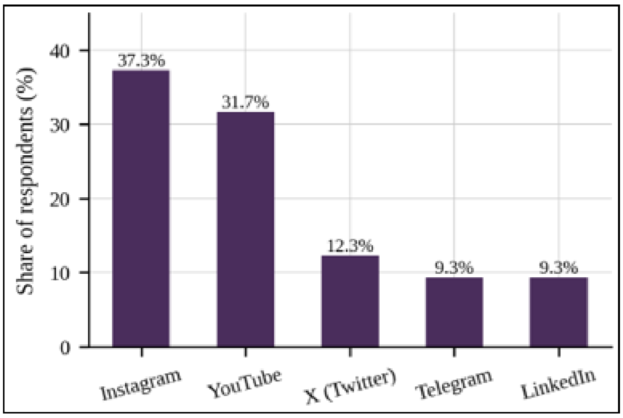

Figure 3: Main platform on which respondents see financial content.

Table 3: Profile of the sample (n = 268).

Characteristic	Value
Mean age (years)	22.1
Female	42.9%
Students	53.0%
Median investing experience	16 months
Main platform: Instagram	37.3%
Main platform: YouTube	31.7%
Acted on finfluencer advice	50.7%
Checked another source first	58.2%

Two behavioural figures are worth noting. About 50.7% of respondents say they have actually made an investment after seeing finfluencer content, and 58.2% say they usually check another source before investing. The gap between these two numbers is the space in which most of the risk sits.

Table 4 and Fig. 4 give the construct means. Algorithmic exposure scores highest (3.67 out of 5), which fits a sample that mostly encounters financial content without looking for it. Risk-taking averages 3.83, and respondents report holding about 41% of their portfolio in assets they consider high-risk. Financial literacy averages 5.62 out of 10, which is modest given the level of risk being taken- a mismatch also reported in the CFA Institute survey [1].

Table 4: Descriptive statistics

Variable	Mean	SD	Min	Max
Finfluencer credibility	3.37	0.76	1.57	5.0
Algorithmic exposure	3.67	0.77	1.75	5.0
Social proof	3.3	0.84	1.0	5.0
Overconfidence	3.18	0.81	1.05	5.0
Financial literacy (/10)	5.62	1.8	0.8	10.0
Investment risk-taking	3.83	0.77	1.57	5.0
High-risk share (%)	41.1	11.9	9.9	66.6

All constructs are measured on a 1–5 scale unless stated

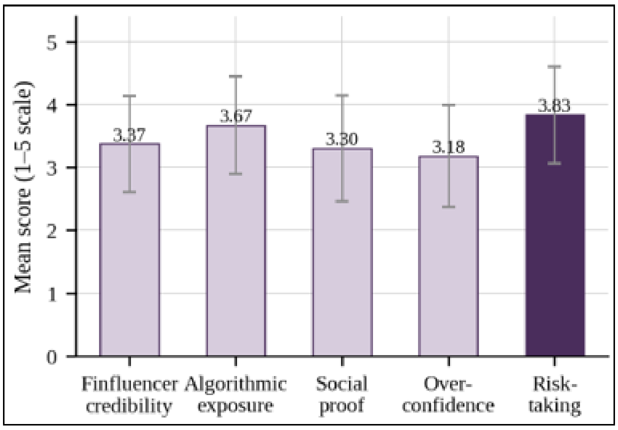

Figure 4: Average score on each construct. Bars show one standard deviation.

One pattern in Table 4 deserves attention. The standard deviation of algorithmic exposure is large relative to its mean, which means the sample contains both respondents who almost never see financial content and respondents who see it constantly. That spread is what makes the group comparison in Section IX possible: the sample effectively contains two different information environments.

7. Correlation Analysis

Table 5 and Fig. 5 report the correlations. All three social media channels are positively related to risk-taking, with social proof the strongest ($r = 0.62$), followed by credibility ($r = 0.57$) and exposure ($r = 0.45$). Financial literacy is negatively related to risk-taking ($r = –0.30$). The three channels are also correlated with each other ($r = 0.30$ to 0.42), which is exactly why they need to be tested together rather than one at a time.

The strongest correlation in the table is between the risk-taking score and the reported share of the portfolio held in high-risk assets (r = 0.78). This is a useful check: what respondents say about their attitude to risk lines up with what they say they actually hold.

Table 5: Correlation matrix

	FC	AE	SP	OC	FL	RT
Credibility (FC)	1.00					
Exposure (AE)	0.34	1.00				
Social proof (SP)	0.42	0.30	1.00			
Overconfidence (OC)	0.21	0.14	0.22	1.00		
Literacy (FL)	–0.19	–0.17	–0.15	–0.16	1.00	
Risk-taking (RT)	0.57	0.45	0.62	0.29	–0.30	1.00
High-risk share	0.47	0.29	0.50	0.22	–0.25	0.78

Correlations above 0.13 are significant at the 5% level for n = 268

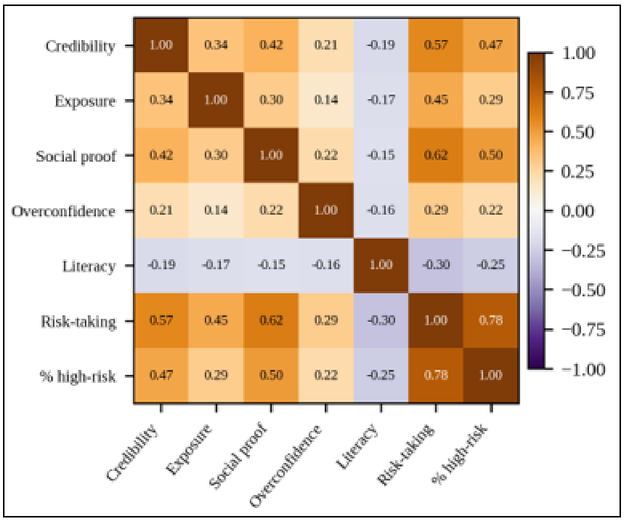

Figure 5: Correlation heat map of the main variables

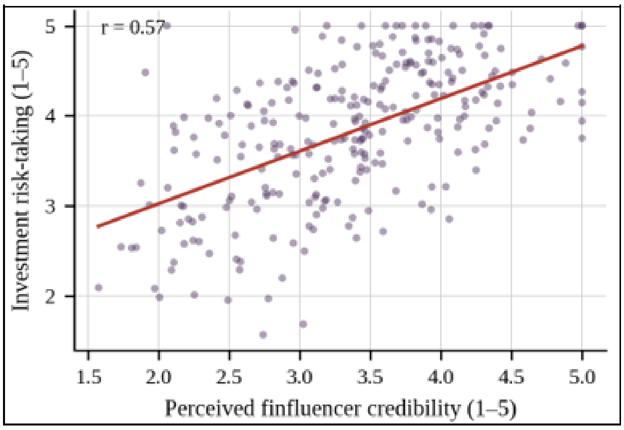

Figure 6: Perceived credibility against risk-taking. Each point is one respondent; the line is the best fit

It is worth stating what the correlations cannot show. A positive correlation between credibility and risk-taking is consistent with persuasion, but it is equally consistent with the reverse: young people who already enjoy taking risk may simply find risk-tolerant creators more credible. The regression that follows controls for other influences, but it cannot settle the direction either. This is a limitation of the design rather than of the analysis, and it is returned to in Section XII.

8. Regression Results

Two regression models were estimated. Model 1 includes only the control variables. Model 2 adds the three social media channels and overconfidence. Table 6 reports both, and Fig. 7 shows the standardised coefficients of the full model.

Table 6: Regression results (dependent variable: risk-taking).

Variable	M1 b	M2 b	M2 β	t	p
Finfluencer credibility	–	0.305	0.300	6.53	<.001
Algorithmic exposure	–	0.194	0.194	4.47	<.001
Social proof	–	0.359	0.389	8.55	<.001
Financial literacy	-0.131	-0.060	-0.139	-3.37	<.001
Overconfidence	–	0.109	0.114	2.73	.007
Experience (years)	-0.031	0.028	0.038	0.94	.350
Female	-0.187	-0.185	-0.239	-2.94	.004
R²	**0.109**	**0.588**			
Adjusted R²	0.099	0.577			
F statistic	10.82	53.10			

b = unstandardised coefficient, β = standardised coefficient. n = 268.

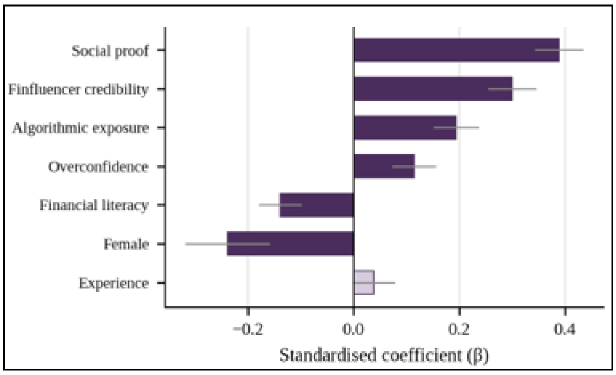

Figure 7: Standardised coefficients from the full model. Dark bars are significant at the 5% level; whiskers show standard errors

The full model explains 58.8% of the variation in risk-taking, against 10.9% for the controls alone (Fig. 8). Adding the three channels therefore accounts for roughly 48 percentage points of additional explained variation, which is the central quantitative result of the paper.

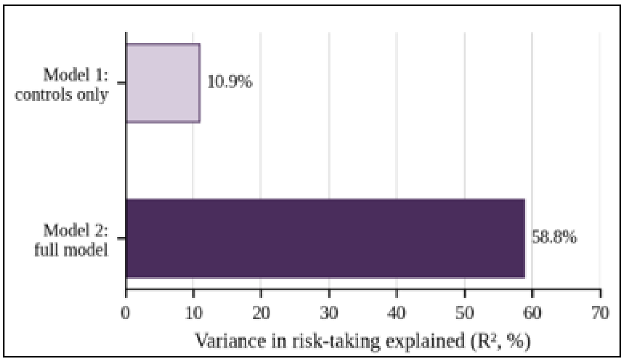

Figure 8: Variation in risk-taking explained by each model

Taking the hypotheses in turn: H1 is supported ($\beta = 0.30$, $p < .001$); H2 is supported ($\beta = 0.19$, $p < .001$); H3 is supported and is the strongest single effect ($\beta = 0.39$, $p < .001$); and H4 is supported, with financial literacy reducing risk-taking ($\beta =$

-0.14, p < .001). Overconfidence adds a small positive effect, and women in the sample report slightly lower risk-taking. Investing experience is not significant, which suggests that how young investors encounter markets matters more than how long they have been in them.

9. Moderation and Group Comparison

H5 predicted that financial literacy would weaken the credibility effect. The interaction term is small and not significant (β = -0.024, p = 0.56), so H5 is not supported. Fig. 9 shows the same result graphically: the two lines are almost parallel, with a slope of 0.60 for low-literacy respondents and 0.53 for high-literacy respondents. The high-literacy line sits lower, which is the direct effect already captured by H4, but it is not flatter.

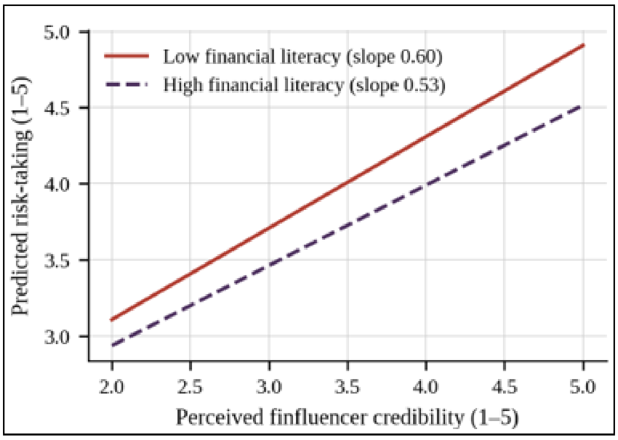

Figure 9: Credibility and risk-taking at low and high levels of financial literacy. The lines are close to parallel, so literacy shifts the level but not the slope.

This null result is arguably the most interesting finding in the study. It suggests that financial knowledge and resistance to persuasion are two different things. A young investor may know what diversification means and still act on a confident creator's recommendation, because the decision is being made through a trust cue rather than through analysis- which is what the elaboration likelihood model [16] would predict for a fast, low-effort decision.

Respondents were then split into three equal groups by algorithmic exposure. Table 7 and Figs. 10 and 11 show the comparison. Risk-taking rises from 3.49 in the lowest third to 4.3 in the highest, and the reported high-risk share rises from 37% to 46%. A one-way ANOVA confirms that the three groups differ (F = 32.71, p < .001).

Table 7: Comparison across levels of algorithmic exposure

Measure	Low	Medium	High
Respondents	89	90	89
Risk-taking (1–5)	3.49	3.69	4.3
High-risk share (%)	37.4	39.9	45.9
Acted on advice (%)	48.3	47.8	56.2
Checked a source (%)	52.8	63.3	58.4

One-way ANOVA on risk-taking: F = 32.71, p < .001.

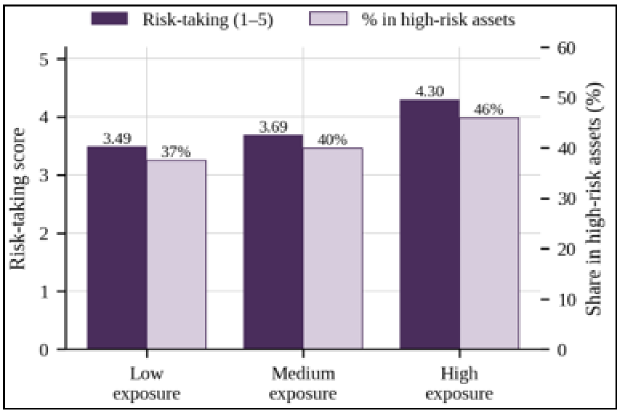

Figure 10: Risk-taking and high-risk holdings by exposure group

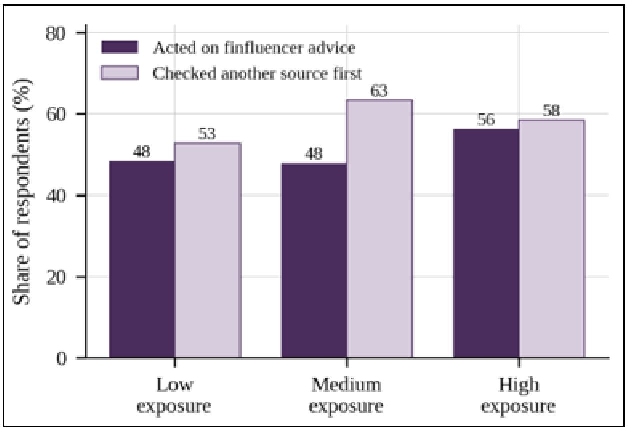

Figure 11: Acting on advice and checking another source, by exposure group.

Fig. 11 contains a warning that the regression does not show. The share who act on finfluencer advice rises with exposure, but the share who check another source does not rise with it. In other words, higher exposure produces more action without producing more verification.

Table 8: Summary of hypothesis tests.

Hypothesis	Result	Evidence
H1 Credibility → risk	Supported	β = 0.30, p < .001
H2 Exposure → risk	Supported	β = 0.19, p < .001
H3 Social proof → risk	Supported	β = 0.39, p < .001
H4 Literacy → lower risk	Supported	β = -0.14, p < .001
H5 Literacy moderates H1	Not supported	β = -0.02, p = 0.56

A final descriptive point strengthens the interpretation. Verification behaviour does not rise with exposure, but it does rise with financial literacy. That is consistent with the regression result: literacy changes what a young investor does before investing, while exposure changes how often the question of investing comes up at all. The two act on different parts of the decision.

A worked example

The size of these effects is easier to judge with an example. Take two respondents who are identical on every control variable. The first sits at the sample average on all three channels. The second sits one standard deviation higher on each of them — a plausible description of somebody whose feed is saturated with financial content, who follows a creator they trust, and whose friends are all discussing the same trade. Using the standardised coefficients, the second respondent's predicted risk-taking score is about 0.88 of a standard deviation higher, which on this scale is roughly the difference between the middle of the sample and the top quarter of it. The environment, in other words, is worth about as much as a large difference in personality.

10. Discussion

Three points follow from the results. The first is that social proof matters more than the creator. Social proof carried the largest coefficient, ahead of credibility. What appears to move young investors is not only the person speaking but the impression that a large number of peers are already acting. That fits the herd behaviour literature [10], [11], where visible action by others is treated as information in itself.

The second point is that exposure has an independent effect. Even after credibility and social proof are accounted for, simply seeing more financial content is associated with higher risk-taking. A recommendation algorithm is not neutral: by deciding what is visible, it decides what feels normal. This is the attention channel described by Barber and Odean [7], now operating through a feed rather than through newspaper coverage.

The third point is the null result on moderation. Financial literacy lowers risk-taking, but it does not blunt the effect of a persuasive creator. If this pattern held in real data, it would have a direct implication for financial education: teaching products and definitions is not enough. Students would also need practice in evaluating sources- checking whether a creator is registered, whether a promotion is disclosed, and whether past performance is being presented selectively. That is a media-literacy skill as much as a finance skill.

It is also useful to compare these patterns with what earlier studies report. The ordering found here- social proof ahead of credibility, and credibility ahead of raw exposure- is broadly consistent with influencer marketing research, where perceived credibility predicts purchase intention [15], and with the herd behaviour literature, where visible collective action is treated as evidence [10], [11]. The weak role of investing experience is the one result that runs against intuition. If it held in real data, it would mean that a young investor does not automatically become harder to influence after a year or two in the market.

The size of the explained variation should not be over-read either. A model that accounts for close to sixty per cent of the variation in a self-reported attitude is doing well by survey standards, but part of that performance comes from the fact that all the variables are collected from the same person at the same moment, which tends to inflate relationships. This is known as common method bias, and it is one reason why the coefficients should be treated as indicative rather than exact.

11. Implications

For educators, the results argue for adding source evaluation to financial literacy programmes, and for using the students' own feeds as teaching material. For platforms, the finding that exposure has an independent effect supports clearer labelling of paid financial promotions. For regulators, the results are consistent with the direction taken by SEBI since 2024 [4], although a rule that restricts registered firms from working with unregistered creators does not by itself change what a young viewer sees. For young investors, the practical message is simple: the number of people who appear to be buying something is not information about whether it is a good investment.

It is worth being concrete about what a source-evaluation lesson would contain. A short checklist would cover four questions: is the creator registered with the regulator; is the video a paid promotion, and is that disclosed; is the performance being shown selected from a longer period; and does the recommendation mention what would have to happen for the investment to lose money. None of these questions requires advanced finance, and all four can be practised on real content in a classroom.

For a school or college programme, the practical route is to teach the checklist alongside the usual content on saving, compounding and diversification rather than in place of it. The results here suggest the two are complementary: product knowledge lowers the level of risk-taking, while source evaluation is what would be needed to change how students respond to a persuasive creator.

12. Limitations

The limitations are important. The response data are simulated, so the coefficients demonstrate the method rather than measure the world; the same questionnaire would need to be administered to a real sample before any of these numbers could be quoted. The design is cross-sectional, so it shows association and not causation — it is equally possible that young people who already like risk seek out more finfluencer content. All measures are self-reported, which invites both memory error and a tendency to give socially acceptable answers. Algorithmic exposure is measured by perception rather than by platform data. And the study covers one age group in one country, so the results should not be generalised to older investors or other markets.

Two further points about measurement should be stated. Because all the constructs are collected in one questionnaire, a respondent who is generally enthusiastic may score high on every scale, which inflates the apparent relationships. A stronger design would collect the exposure measure separately- for example from screen-time data- or would separate the measurement of the independent and dependent variables in time. In addition, the risk-taking measure captures stated willingness rather than observed behaviour; the reported share held in high-risk assets is a partial check on this, but it is still self-reported.

Table 9: Limitations and their effect

Limitation	Effect on the findings
Simulated responses	Numbers demonstrate the method, not reality
Cross-sectional design	Direction of causation cannot be established
Self-reported measures	Recall and social desirability bias
Perceived exposure	No platform-level data on what was actually shown
Single age group	Results may not extend to older investors
Single country	Regulatory and market context differ elsewhere

Future work should collect real responses, ideally alongside screen-time or platform data so that exposure is measured rather than recalled. A short experiment, in which the same investment message is shown with and without visible social proof, would test the causal claim directly. Following the same respondents over a year would show whether early risk-taking driven by social media persists or fades with experience.

13. Conclusion

This study asked how finfluencer credibility, algorithmic exposure and social proof relate to investment risk-taking among Gen Z, and whether financial literacy protects against those influences. Using a five-construct questionnaire and a simulated sample of 268 respondents, the three channels together explained 58.8% of the variation in risk-taking. Social proof was the strongest single influence ($\beta = 0.39$), followed by credibility ($\beta = 0.30$) and exposure ($\beta = 0.19$). Financial literacy reduced risk-taking but did not weaken the credibility effect.

The wider conclusion is about the route rather than the size of the effect. Attention becomes financial behaviour through trust and through the visible behaviour of others, not mainly through analysis of the advice itself. That is why knowing more finance does not automatically make a young investor harder to persuade, and why financial education for this generation has to teach how to judge a source as well as how to judge an investment. Testing the same model on real survey data is the necessary next step.

References

[1] Espeute, S., & Preece, R. (2024). The finfluencer appeal: Investing in the age of social media. CFA Institute Research and Policy Center.
[2] Hayes, A. S., & Ben-Shmuel, A. T. (2024). Under the finfluence: Financial influencers, economic meaning-making and the financialization of digital life. Economy and Society, 53(3), 478–503. https://doi.org/10.1080/03085147.2024.2381980
[3] Guan, S. S. (2023). The rise of the finfluencer. NYU Journal of Law & Business, 19, 489–560.
[4] Securities and Exchange Board of India. (2024–2025). Restrictions on association of regulated entities with unregistered financial influencers; circular on use of market data in educational content.
[5] Hovland, C. I., & Weiss, W. (1951). The influence of source credibility on communication effectiveness. Public Opinion Quarterly, 15(4), 635–650.
[6] Ohanian, R. (1990). Construct validation of a scale to measure celebrity endorsers' perceived expertise, trustworthiness, and attractiveness. Journal of Advertising, 19(3), 39–52.
[7] Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies, 21(2), 785–818.
[8] Barber, B. M., Huang, X., Odean, T., & Schwarz, C. (2022). Attention-induced trading and returns: Evidence from Robinhood users. Journal of Finance, 77(6), 3141–3190.
[9] Cialdini, R. B. (2009). Influence: Science and practice (5th ed.). Pearson.
[10] Banerjee, A. V. (1992). A simple model of herd behavior. Quarterly Journal of Economics, 107(3), 797–817.
[11] Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy, 100(5), 992–1026.
[12] Mölders, M., Bock, L., Barrantes, E., & Zülch, H. (2025). Understanding finfluencers: Roles and strategic partnerships in retail investor engagement. Journal of Business Research, 198, 115462.
[13] Hasanah, E. N., Koesrindartoto, D. P., Wiryono, S. K., & Angelica, A. E. (2025). Who deserves to be the finfluencer? Journal of Open Innovation: Technology, Market, and Complexity, 11(2), 100553. https://doi.org/10.1016/j.joitmc.2025.100553
[14] Singh, S., & Sarva, M. (2024). The rise of finfluencers: A digital transformation in investment advice. Australasian Accounting, Business and Finance Journal, 18(3). https://doi.org/10.14453/aabfj.v18i3.14
[15] Djafarova, E., & Rushworth, C. (2017). Exploring the credibility of online celebrities' Instagram profiles in influencing the purchase decisions of young female users. Computers in Human Behavior, 68, 1–7. https://doi.org/10.1016/j.chb.2016.11.009
[16] Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. Advances in Experimental Social Psychology, 19, 123–205.
[17] Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. Journal of Economic Literature, 52(1), 5–44. https://doi.org/10.1257/jel.52.1.5
[18] Mohta, A., & Shunmugasundaram, V. (2024). Moderating role of millennials' financial literacy on the relationship between risk tolerance and risky investment behavior: Evidence from India. International Journal of Social Economics, 51(3), 422–440.
[19] Grable, J. E., & Lytton, R. H. (1999). Financial risk tolerance revisited: The development of a risk assessment instrument. Financial Services Review, 8(3), 163–181.
[20] Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.