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Skewed by Design: Exploring How Short-Form Platform Algorithms Shape Behavioural Biases in Young Retail Investors

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ABSTRACT

This narrative literature review aims to understand how engagement-optimising recommendation algorithms on social media short-form platforms influence young and novice retail investors' psychology and shape behavioural biases by recommending emotionally amplified financial content. The paper is grounded in classical theories of cognitive psychology and behavioural finance across a proposed analytical chain linking platform algorithm design to investor behavioural outcomes. It analyses how financial and fin-fluencer content on social media might be coded for high-arousal emotional frames like fear, urgency, anger, excitement, etc., and how repeated exposure to this content creates a progressively narrowed "information cocoon". This emotionally framed content can affect investor psychology through heuristics and system 1 engagement, affecting trading behaviour (overconfidence, FOMO and herding, risk misperception, and anchoring). The texts analysed reveal a distinct pattern of vulnerability, especially amongst novice and young investors, exploring how social media can significantly affect retail

investors' trading behaviour. This review does not claim causation between links, as empirical evidence was not used.

KEYWORDS

Short-form social media | Financial content | Algorithmic recommendation | Emotional framing | Behavioural biases | Young investors | Investor decision-making

1 Introduction

As dependence on social media platforms for information grows, it is slowly becoming the primary knowledge source for the youth. Financial investment knowledge is not immune to this phenomenon, as social media is seeing the emergence of fin-fluencers and a growing sub-genre of financial content. A FINRA National Financial Capability Study from 2022 found that 60% of investors aged 18-34 rely on social media for investment advice compared with 35% of those aged 35–54 and only 8% of those aged 55 and older (Lin, Bumcrot, Mottola, Valdes, and Walsh, 2022). As such, exposure to social media financial content has the potential to significantly shape investment behaviour, especially for the youth who primarily rely on social media for investment advice.

Social media's algorithm may not support neutral financial advice, as it prioritises emotional content due to its higher engagement. A study analysing financial influencer activity on TikTok found that emotionally targeted language in financial content is positively and significantly associated with engagement (Haase et al., 2026). This emotional content can skew rational decision-making. As the algorithm repeatedly recommends this affective content, novice investors enter emotional contagion, prioritising "feelings-as-information " over rationality (Schwarz, N., 2012). Kahneman and Tversky's (1979) paper underscored how investors defy the axioms of expected utility theory and are prone to biases under risk. Proposed decades before social media existed, these biases may only be amplified in algorithmically curated environments, shifting from theoretical deviation to an observable norm among retail investors. Also, national surveys show that 61% of young retail investors follow social media tips to make investment decisions. This shows a dangerous knowledge-confidence gap, where subjective confidence surpasses objective financial knowledge (FINRA Investor Education Foundation, 2026).

Short-form media platforms' architectures might affect investor psychology in multiple ways. The condensed package of information engages cognitive processing modes that are fast and act as mental shortcuts, like System 1 thinking and heuristics over effortful System 2 evaluation (Kahneman, 2011). Through Albert Bandura's social learning theory (Bandura, A., 1986), investors are prone to herding, FOMO, and inflated self-efficacy, which can lead to overconfidence. This maps onto the five behavioural biases discussed in this paper, namely: overconfidence, FOMO, herding, risk misperception, and anchoring. These biases can cause panic selling, impulsivity, and other adverse trading behaviours. A study based on a sample of 134,013 individuals in the "Survey on Life and

Money" conducted jointly by Hiroshima University and Rakuten Securities found that non-panic sellers tend to have higher household income and assets (Homma et al., 2025).

While existing literature has analysed the effect of social media and fin-fluencers on investment decisions, the complete pathway linking affective financial content, platform architecture, and investor biases remains unexplored. This narrative literature review traces the conceptual pathway of how emotional investment content on short-form social media platforms is prioritised and recommended, and how that influences investor psychology and drives behavioural change. It analyses existing literature to answer the following questions:

R1	How do short-form content platforms' recommendation algorithms prioritise emotionally amplified financial content, and how do they rapidly reinforce it to young and novice investors?
R2	How does this content affect young and novice investor psychology?
R3	How are the investors' behaviours affected due to biases?

These research questions are addressed through three thematic areas: platform architecture and emotional content amplification, cognitive vulnerability in novice investors, and biases and behavioural outcomes.

2 Methodology

The methodology used is a narrative literature review, where the papers were organised thematically after the search and review. The process includes collecting existing literature on the selected research questions, synthesising the findings, and forming an interpretative description. A structured process for screening and extracting data was employed across the six search topics, after which the topics were analyzed thematically.

The themes and topics were decided after an initial exploratory search to understand the current discourse, patterns, and research gaps.

2.1 Search strategy

The papers were searched thematically on sites such as ScienceDirect, Google Scholar, JSTOR, SSRN, and Wiley Online Library, using predefined keywords. The first search strategy was based on the six topics that had been identified in the exploratory review of the literature.

The search strategy was improved as the literature search went on, with changes made in light of the terminology and the relevant studies found in the first results. Tools such as Elicit and Litmaps were used as auxiliary means of discovering the literature in order to find further relevant studies and to trace the relationships between papers. Backward citation searching (i.e., snowballing) was used to find studies which had not been picked up by the original keyword searches. The papers that were found using these supplementary methods were held to the same screening and inclusion criteria as those identified through the database searches. Some papers were used for multiple topics as they had overlapping themes.

This method was used since the review draws on literature from a number of different research fields such as financial behaviour, social-media algorithms, emotional framing and behavioural psychology.

The search terms used were organised according to the following topics, along with their sample keywords:

Table 1. Search topics, sample keywords and the papers screened for each.

TOPIC	DESCRIPTION	SAMPLE KEYWORDS	FOUND	DIRECT	ADJACENT	DISMISSED
Topic 1: Emotional framing in financial content on short-form media	This topic aimed to understand if and how financial videos are coded for fear, urgency, anger, excitement, etc.	`TikTok/instagram AND emotion, content curation AND "emotional content"`	4	4	0	0
Topic 2: Emotional framing of content leading to higher engagement	This topic looked for papers measuring emotional framing against watch time, completion rate, likes, comments, and shares.	`finfluencer AND fear, fear appeal AND "social media"`	6	2	3	1
Topic 3: Relationship between user engagement and subsequent algorithmic recommendation	This topic finds whether user interaction measurably increased exposure to similar content in the subsequent feed.	`"user engagement" AND "algorithmic recommendation", "content interaction" AND "recommendation systems"`	10	6	2	2

TOPIC	DESCRIPTION	SAMPLE KEYWORDS	FOUND	DIRECT	ADJACENT	DISMISSED
Topic 4: Repeated recommendation and information diversity	This topic measures repeated exposure measured alongside reduced content diversity or increased concentration of related content.	"algorithmic filter bubble" AND social media, repeated content exposure AND "information narrowing"	6	4	2	0
Topic 5: The cognitive mechanism	The psychology behind financial content on short-form media platforms influencing behavioural biases	"investment content" AND "social learning theory", "fear" AND "financial decision-making"	13	8	1	4
Topic 6: The behavioural effects due to biases	This topic measures biases linked to actual trading intention, trading behaviour, or portfolio decisions.	"retail investor" AND "panic selling", "young investor" AND "risk-taking".	12	9	3	0

Direct: studies a step in the review's proposed pathway. Adjacent: related evidence from another domain. Some papers served more than one topic. Source: the authors.

2.2 Inclusion and exclusion criteria

All papers selected were in the English language. No restriction on the date of publication was imposed.

The papers selected were filtered into three categories: Direct, adjacent, or dismissed based on selection criteria for each topic.

A screening process was followed to categorise the papers. The first screening question looks at whether or not the paper studied a mechanism in our proposed conceptual pathway of the review (emotional framing → engagement → algorithmic recommendation → information narrowing → investor bias and decisions). Papers not matching this condition were dismissed. Papers that answered yes or partially yes were then put through the second screening question, analysing them for contextual relevance: whether they addressed short-form video, financial content, young or retail investors, behavioural bias, or social media algorithms. Papers meeting this threshold were retained as direct evidence; papers studying the same underlying mechanism in the context of different domains (e.g., political content, climate content, or health misinformation) were categorised as

adjacent papers. Finally, to avoid redundancy, the papers were scanned to assess whether they added new information.

A total of 38 papers were finalised.

2.3 Thematic synthesis procedure

Papers meeting the inclusion criteria were extracted according to a standardised template for their category. For direct papers, the template recorded the study's aim, method (including sample size and population), key findings, the strongest citable statistic or conclusion, an explicit statement of how the finding connects to the review's proposed conceptual pathway, and the paper's most relevant limitation. For adjacent-evidence papers, a shorter extraction captured the mechanism studied, method, and key findings.

Synthesis paragraphs were prepared for each thematic section, bringing together the findings from all the extracted papers and highlighting areas of alignment, contradiction, and the most important gaps in the evidence. The synthesis paragraphs for each section served as the foundation for the narrative argument presented in the respective sections of this review. The initial screening was carried out independently by five researchers and was then verified by the lead researcher, who confirmed the inclusion and classification of the papers.

2.4 Methodological limitations

Since this paper was a narrative literature review, it can not establish a causal chain or causation between processes due to lack of empirical testing. While individual investigations provide empirical support for specific associations within the pathway, the connections among these associations have not been empirically tested as a single integrated mechanism. A narrative literature review is also dependent on the author’s own judgments, introducing subjectivity into the synthesis. Since this was a narrative rather than a systematic literature review, the search methodology was designed to identify literature relevant to the proposed conceptual framework rather than to identify all the existing studies. This approach may also cause selection bias, including inadvertent over-representation of findings that support the proposed framework.

3 Results and discussion

3.1 Platform architecture and emotional content amplification

3.1.1 *Emotional framing of short-form media content and how it leads to higher engagement*

In order to grasp how the transformation of complex information becomes viral content, there are two interdependent phases within the digital communication process that need to be examined. The first phase involves the content producers accommodating themselves to the requirements of the medium as well as social or market demands through the way in which information is framed. The second phase is where the information is now coded with particular emotional or linguistic cues, and the interaction between algorithms and human psychology determines how it is disseminated.

General subjects, which are broad by nature, tend to be semantically diverse. Given the fact that general guidance involves a vast lexicon of vocabulary and concepts, NLP classification tools and recommendation engines regard such broad subjects as semantically noisy. In contrast, very specialized or speculative subjects are characterized by tightly controlled jargon and terminology, with clear tags used. This semantically clean content is easy for recommendation algorithms to analyze, index, and target at the appropriate audience. Research into the classification speed of topics by platforms has shown that algorithms classify specialized content twice as fast as semantically diverse content. (Baumann et al., 2026)

This can be exacerbated when there is an increased degree of volatility in society or in the market, as people resort to using the platform for their emotional validation and instant clarity.

After complex messages are condensed and filtered through an emotional filter, particular behavioural and computational factors will determine the final extent of their spread and engagement. The main force of message dissemination through digital platforms is the autonomic transmission of high arousal. High-arousal emotions engage the human autonomic nervous system, which becomes a basic biological stimulus for the social transmission and active dissemination of messages (Berger, 2011). When people feel their increased physiological arousal, their willingness to respond, comment on, and disseminate the message grows manyfold in comparison with their reaction to neutral or low-arousal stimuli (Berger, 2011).

However, the triggering of high arousal has an uneven effect on all engagement indicators. Research into the behaviour of the audience shows that different emotional states create different behaviours:

- **Disgust and Anger:** High-arousal negative affective states act as the strongest drivers of active content dissemination. Disgust generates a large positive effect on active audience engagement in terms of increased comment posting (beta = 0.519) and video sharing (beta = 0.685). Anger acts as another driver that triggers active engagement, as it generates more likes (beta = 0.158) and shares (beta = 0.140). (Wang & Li, 2024).
- **Active Engagement per View:** On the contrary, low-arousal negative affect such as sadness hinders active participation by showing a negative correlation with comment density per view (beta = -0.052). In addition, positive affect such as hope also shows a non-significant, near-zero relation with active likes per view (beta = -0.001). (Wang & Li, 2024).
- **Performed Relatability and Authority Penalties:** The modern digital audience shows a high degree of sensitivity towards authentic voices and tones. Signs of institutional prestige or corporate power often suffer from the penalty imposed in the context of short visual content, as audiences prefer peer-like and informal experiences. On the other hand, the presence of a high degree of forced relatability imposes a negative reaction on engagement.

The influence of high-arousal emotional language in terms of operation is also moderated by the size of the content creator, which is evident from Persuasion Knowledge Theory (Friestad & Wright, 1994; Cascio Rizzo et al., 2024). Persuasion Knowledge Theory states that consumers actively defend themselves whenever they are aware of any persuasion or commercializing effort (Friestad & Wright, 1994).

In short-form videos, the follower count of the creator determines the way audiences perceive high-arousal linguistic signs. Cascio Rizzo et al. (2024) found that high-arousal language increased engagement for micro-influencers, but decreased it for macro-influencers.

3.1.2 *User engagement and subsequent algorithm recommendation*

Discourse shift from text-heavy forms of communication to predominantly visual communication inevitably results in the emergence of medium-driven knowledge compression. The content is stripped of its structural complexity and offered in a very simplified manner that is more visually oriented. Rather than presenting lengthy analysis, the creator creates a short hook that will hold attention. This is known as Knowledge Compression (Wang, Y., 2025). For novice retail investors with low financial literacy, quick information causes users to experience great Cognitive Overload (Wang, K., 2025). People often use tactile responses like pausing or rewinding as an automatic response to cognitive overload (Wang, Y., 2025).

Such an individual problem is then augmented by the recommendation algorithm of the platform. While the algorithm tailors the content feed according to the assumed user's preferences (like how much time a person spends viewing something), it does not do so according to stated preferences (Milli et al., 2025). Particularly, recommendation algorithms consider the watching time and dwell time as measures of positive utility. But when a novice investor pauses to decode the information from a complex stock chart or confusing disclaimer, the algorithm cannot differentiate whether a user is skeptical about the content or is convinced (Milli et al., 2025).

The platform registers this cognitive overload as engagement, thus triggering the mechanism called Algorithmic hijacking (Milli et al., 2025). Moreover, the lack of transparency in the recommendation algorithms makes users feel powerless and rely on viral social proofs (Chang & Yu, 2026). There is some empirical evidence proving the detrimental effects of such dynamics. Research shows that over 56% of financial influencers display anti-skill behaviour and earn negative abnormal returns, and the recommendation algorithms keep amplifying their reach, as speculation generates more engagement than cautious and reasonable posts (Kakhbod et al., 2024).

3.1.3 *Lower content diversity and the formation of an "information cocoon"*

Previously, the distribution of content in social networks was based on personal choice regarding following certain users (friend/follower graph). Nowadays, networks use the interests of the user (interest graph) and work with feedback loops. While the existence of algorithms is widely acknowledged, the process of content amplification and spreading remains partly unclear.

FILTER BUBBLES AND NETWORK POLARIZATION

Many theoretical models warn about informational isolation in digital information. One of the key terms is the filter bubble (Pariser, 2011), meaning the situation when algorithms form a personal content environment that corresponds to the user's views. Some empirical data show that even slight changes in the algorithm can significantly alter the flow of information within the network (Chitra & Musco, 2020).

MATHEMATICAL INSTABILITY OF BALANCED CONTENT

Some research proves that information narrowing is an inherent property of the engagement optimization system. The mathematical model of (Bakim, S, 2026) shows how opinions change with the amplification of some kind of content. According to the model, engagement-optimized content is inherently unbalanced. Thus, the algorithms constantly deprioritize balanced content in favor of the emotional, sensational, or extremist. Accordingly, the research indicates that information narrowing is the mathematical inevitability in the environments where the algorithms are optimized for engagement.

EXPLORATION DECAY AND THE “YOU LOOP”

Algorithms can limit exploration to improve personalisation; hence, the diversity of topics and hashtags seen by the user significantly drops (Baumann et al., 2026). According to the research, an algorithm needs an average of interaction with 13 videos of the same type for personalization to change the user feed (Baumann et al., 2026).

This finding supports the concept of "you loop" introduced by Pariser (2011), which means that user actions influence the selection of content that they see in the future, forming the "information cocoon".

3.2 Young and novice investor psychology, and the cognitive mechanism

DUAL PROCESS THEORY AT THE MOMENT OF FINANCIAL DECISION-MAKING

This section examines how consuming short-form financial content affects investor psychology and triggers biases. Internally, this content alters the viewer's emotions and how they process information. This shift can lead investors away from carefully evaluating information and toward inflated confidence, stopping them from checking their assumptions. Once the real investment decision comes, the investor arrives in a non-neutral state due to the affective residue left after consuming the emotionally charged content.

Emotional residue: After the short-form video ends, it leaves behind emotional residue, a process known as affect priming, that influences how the person reads information about the investment. Naturally, they cannot separate the emotion the content gave them from their own judgement of the investment, so feeling stands in for analysis as "feelings-as-information" (Schwarz, 1990).

The limits of deliberation: Even if the viewer attempts to differentiate their emotion from their judgement, their System 2 thinking, which is slow and effortful, does not correct the System 1

impression, which is fast and automatic. Instead, the effort unknowingly goes to justifying what they previously felt (bolstering), not verifying it, which is confirmation bias operating under the appearance of careful thought (Kahneman, 2003).

Probability insensitivity: Next, this emotional arousal focuses the viewer on whether the outcome could happen while leaving them blind to how likely it is (Loewenstein et al., 2001). The odds eventually stop mattering. Only possibility does, which is the possibility effect. The video's tone skews the viewer's judgement, though the direction is unpredictable. For example, reassuring tones made inflation forecasts go up, and alarming tones made inflation forecasts go down, which is backwards from what was expected (Zubiel et al., 2025).

HEURISTICS AND MENTAL SHORTCUTS

When situations become too complex or uncertain, deliberation ultimately fails. This leads people to often fall back on simple rules and mental shortcuts rather than working through everything properly, as made evident by frameworks like Herbert Simon's bounded rationality and Gerd Gigerenzer's adaptive toolbox framework (Simon, 1955; Gigerenzer & Goldstein, 1996). These heuristics are already established, but their use in short-form financial content has not been directly tested.

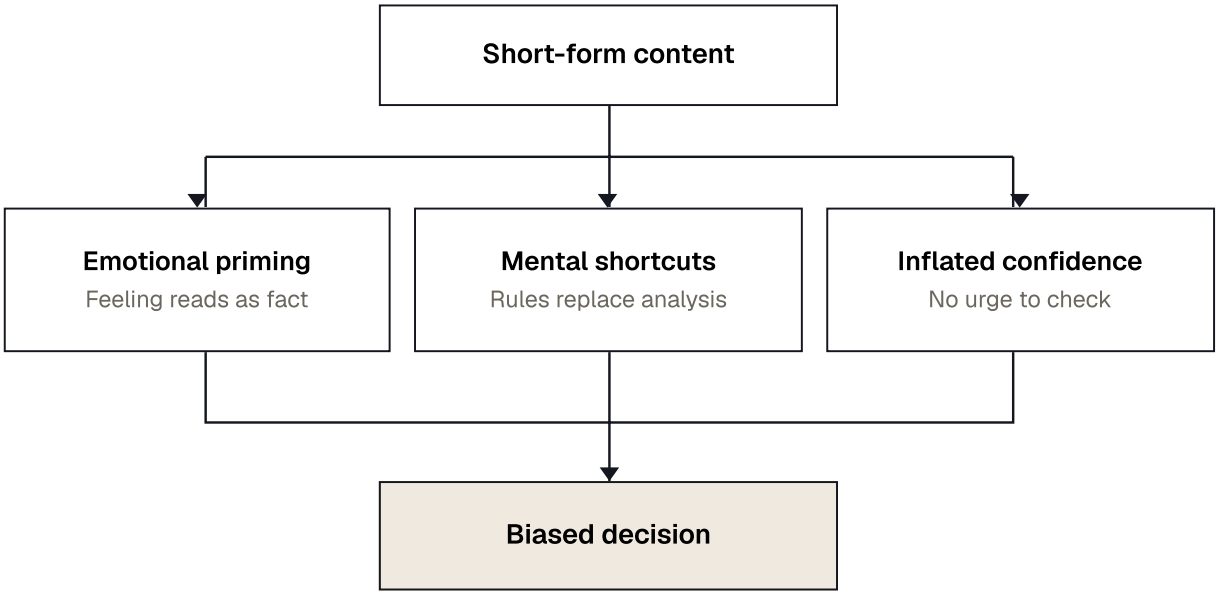
Availability and affect: Another shortcut is attribute substitution, where a person judges how likely something is based on how easily an example comes to mind (Tversky & Kahneman, 1974). Short-form content often shows dramatic wealth stories and large price increases. The emotion created by the content can then replace a proper assessment of the actual risk, leaving the viewer with availability bias rather than a considered judgement.

Take-the-best: The final shortcut is stopping the search for information once one signal seems strong enough to make a decision (Gigerenzer & Goldstein, 1996). Short-form content leaves little time for multiple signals, so a trend metric or creator endorsement becomes an anchor that the rest of the judgement is built around.

THE KNOWLEDGE-CONFIDENCE GAP

Both previous mechanisms assume the viewer might stop and check, and this section aims to explain why they do not. Consuming short-form content also creates a gap between what the viewer actually knows and what they think they know based on the content. This is created by how the content makes complex material feel easy to grasp. As confidence rises, the viewer feels the decision is within their reach, raising their perceived behavioural control and making them less vulnerable to losses. This lowers the hesitation that would normally make them stop and think before making a risky investment decision, leaving them with an illusion of control (Ajzen, 1991).

Figure 1. How short-form content can lead to a biased decision



Source: The authors.

3.3 Investor biases and behavioural outcomes

The following paragraphs discuss the behavioural biases that arise and what effect they produce.

OVERCONFIDENCE

This bias takes place in cases when a person experiences gains at least once and believes in their ability to continue gaining profits. This bias is more typical for novice investors. According to Gervais & Odean (2001), the peak of overconfidence takes place in the beginning since several successes may be interpreted incorrectly as one's talent instead of general market growth.

As was shown empirically, overconfidence manifests in the amount of trading. More frequent trading leads to poorer performance. As was demonstrated in the study by Barber & Odean (2000), the households which trade most actively achieved 11.4% of annual returns against 17.9% of the whole market return, which means that there is significant deficit caused by overvaluing of one's skills. The situation gets worse with fast apps because the move to the online environment was accompanied by higher trading volumes, increased risks, and poor performance compared to the market, which was beaten before (Barber & Odean, 2002). In the case of short-form videos, the problem increases due to mostly positive outcomes that people get to see. The winners share their experiences while the losers remain silent, which creates a false sense of winning rates and the efficiency of the bet.

In the survey of UAE cryptocurrency behaviour, 64% of respondents said they rarely or never check their facts before performing any actions (Dadhich, 2025). Additionally, overconfident people not only

overtrade in times of upward markets but also panic in times of downward markets. Elkind et al. (2022) have found that the people who considered their knowledge “excellent” were the first to sell off.

FOMO AND HERDING

FOMO and herding are often regarded as the same thing from different angles. FOMO, which is an anxiety about missing out on a profit while watching others profit, can cause someone to feel loss from under-trading, even though they haven't actually lost anything monetarily (Przybylski et al., 2013). In herd behaviour, individuals imitate the actions of the whole group; there's no participation of any individual trader, and they leave their analysis behind. The logic behind this strategy is simply that if many individuals are buying, they have insight, and so everyone should buy as well (Banerjee, 1992).

From a machine learning approach applied to YouTube Shorts, it was found that more than half of the comments on investment-related YouTube Shorts exhibited a singular sentiment consistent with herding behaviour (Singh et al., 2026).

However, there is one surprising outcome. According to a study by Rahmi et al. (2026), herding might have been a good idea for their group of investors. While this doesn't directly challenge the aforementioned point, it does show the importance of market conditions. In a bull market, people following the herd might bring success, but as soon as the market conditions start declining, it's herding that can cause trouble.

RISK MISPERCEPTION

Risk misperception is the perception that one might not experience big losses, but also that some profit may be possible - especially when the Internet is filled with positive or inspirational stories. This is similar to the perceived probability of winning a lottery, and short-form video feeds give the illusion of higher upside.

Evidence supporting this hypothesis is also given in the trading simulation performed by Andraszewicz et al. (2023) with a sample of 807 investors, where participants presented with the details of top performers exhibited behavior that is associated with riskier trades. They showed higher trading volume, became more aggressive, and were relatively less pleased with their results.

Risk awareness could arguably mitigate this behavior but is shown by the study from the UAE, where, according to Dadhich (2025), investors are aware that cryptocurrency is risk-laden but are not at all hesitant about investing impulsively, leading to losses.

ANCHORING

Once an investor buys an asset, the purchase price becomes a reference point against which later prices are judged. Anchoring may contribute to the disposition effect (Shefrin & Statman, 1985), which is a phenomenon in which investors sell profitable assets too early and hold onto poor-performing assets too long, because the acquisition price of an asset is used as a reference point for future price evaluation. The pattern is not specific to social media, and its connection to short-form content is a proposed link rather than a tested one. Still, it is consistent with accounts from UAE crypto investors who described holding positions through a decline (Dadhich, 2025).

For example, a trader might tweet that he believes a stock will "hit $500 by tomorrow", potentially leading followers and viewers to anchor to the number without any rationale behind it. Interviewees from the UAE admitted to buying tokens at the market high because they anchored to the $20k and $60k predictions spread through Telegram and Twitter, and holding through the decline (Dadhich, 2025). Thus, investors hold onto losers, anchor to arbitrary price points rather than intrinsic values, and consider stocks undervalued because they are below a high.

4 Conclusion

This narrative literature review has traced the conceptual pathway of exposure to emotional financial content on short-form social media platforms leading to behavioural biases in young and novice investors. It analysed studies from different domains like behavioural finance and economics, cognitive and social psychology, mass media and platform architecture studies, and computational social sciences.

The mechanism starts by explaining how compressed high-arousal content is prioritised over neutral or balanced financial information on social media platforms, since the algorithm uses watch time as an indicator for genuine interest (the watch time flaw); engagement can be optimised for the wrong metric. Finally, the collapse of exploration may occur as users get trapped in a digital "filter bubble".

The next piece of the mechanism looks at the cognitive vulnerabilities in young and novice investors. Fast and frugal heuristics, i.e., mental shortcuts, can get activated due to the conditions created by short-form platforms. Various psychological mechanisms, such as the knowledge-confidence gap, cause investors to mistake knowledge for mastery. Following the tenets of social learning theory, investors may be more inclined to follow their peers and fin-fluencers on media platforms, giving rise to feelings of FOMO and mass herding

Lastly, we examine how these psychological mechanisms might translate into biases that lead to maladaptive behavioural outcomes. Overconfidence may lead to excessive trading and poorer returns, where investors do not verify claims made on social media. FOMO and herding have been associated with panic-selling, copy trading, and suppression of private judgement. Risk misperception has been associated with riskier and more impulsive trading. Finally, anchoring effects can be of two types: reference-point effects around purchase prices that contribute to the disposition effect, and anchoring on arbitrary price targets provided by influencers. Much of this evidence is from neighbouring fields, survey or cross-sectional studies and speculative-asset contexts. These links should be interpreted as hypothesised pathways rather than causal effects.

5 Limitations and future research

The strength of the overall argument is uneven, as both adjacent and direct studies have been used. Some claims have direct empirical evidence supporting them, while others relying on evidence from other domains remain proposed mechanisms. The assumption that the mechanisms found in these areas also apply to financial content is theoretically justified, but has not yet been empirically tested.

The studies analysed are cross-sectional in nature—capturing momentary emotional states, making it difficult to rule out reverse causality— namely, whether exposure to fin-fluencer content causes mental biases, or whether people who are predisposed to impulsive trading choose to follow fin-fluencer content. Further, the evidence base of papers studied was skewed towards high-volatility and sentiment- driven assets like cryptocurrencies, meme stocks, and highly speculative tech assets.

This paper relies on dual process theory to describe investors' psychological framework. However, this theory has been critiqued for oversimplifying cognitive processing into two categories. In fact, cognitive processing is a continuum. The distinction between System 1 and System 2 is analytically helpful, but it may not be able to capture the complexity of investor decision-making.

It is necessary to carry out further empirical research to assess the effectiveness of various regulatory interventions. Research in the future should look at how platform-level design and short-form content can be regulated to reduce the biases discussed in the paper. Additionally, we need to understand how these biases might occur simultaneously and the effects for novice investors. The individual characteristics of investors, such as the level of financial literacy, cultural background, gender, and other demographic variables, can mitigate the relationships and behavioral outcomes that studies and other reviews can analyse and measure.

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