Artificial Intelligence and the Psychology of Influence in Investment Decisions: An Empirical Study

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Abstract

Artificial intelligence (AI) and Behavioral finance have come together to provide fresh insights into how social media influencers affect investor psychology and choices. Platforms like Twitter, YouTube, and TikTok are becoming more and more popular among retail investors for financial advice. On these sites, "influencers" provide information that has the potential to quickly alter trade activity and market sentiment. This empirical study examines the degree to which AI can identify and measure the psychological processes that underlie investing behaviour guided by influencers. Based on ideas of social proof, investor sentiment, and limited attention, the article synthesizes data from 30 empirical studies and creates an AI-driven pipeline for examining engagement metrics, influencer content, and market reactions.The use of transformer-based models for sentiment analysis, event investigations, and causal inference techniques shows that influencer postings have quantifiable effects on volatility, short-term anomalous returns, and retail trading flows. Confirming the behavioral character of such market movements, the results show regular patterns of attention-induced trading surges, short-term gains, and subsequent reversals. Furthermore, the strength of influencer involvement and trustworthiness considerably reduces the strength of these impacts. AI models do better than conventional lexicon-based methods in forecasting investor reactions, especially contextual sentiment analysis. According to the study, influencer-driven trading can increase herding behaviour and market volatility, while artificial intelligence (AI) allows for better monitoring and prediction accuracy. The significance of transparency, investor education, and AI-assisted manipulation campaign detection are emphasized in the policy implications.All things considered, behavioural finance's use of AI offers strong instruments for comprehending and controlling the psychology of influence in contemporary financial marketplaces.

Keywords: finfluencers, social media, investor psychology, AI, sentiment analysis, attention.

Introduction

Social media sites like Twitter (X), YouTube, TikTok, and Reddit have developed into significant informational conduits in today's financial environment, influencing the investing choices of individual investors. Millions of followers now receive stock suggestions, market commentary, and financial advice from an expanding group of "finfluencers," who frequently conflate promotion with education (CFA Institute, 2024; Pandey, 2025). Due to their reliance on these sources, retail investors—particularly novices—are susceptible to emotional appeal, persuasion, and herd mentality (BIS, 2021; Barber & Odean, 2008). This demonstrates the psychology of influence, wherein attention bias and social proof usually prevail over logical, basic reasoning when it comes to directing investing decisions (Shiller, 2003; De Bondt & Thaler, 1985).

Simultaneously, financial research has seen a revolution thanks to artificial intelligence (AI). Researchers can now methodically evaluate unstructured data, including text, photos, and videos from social media sites, thanks to developments in natural language processing (NLP), machine learning, and sentiment analysis (Kogan et al., 2009; Loughran & McDonald, 2011). According to Bollen et al. (2011), artificial intelligence (AI) makes it possible to extract emotion and attention signals at scale and connect them to observable investor actions and market results. Previous behavioural finance research demonstrates that restricted attention, media tone, and sentiment have a major impact on price dynamics and trade volume (Baker & Wurgler, 2006; Tetlock, 2007; Da, Engelberg & Gao, 2011).Influencer-driven postings have been shown to produce trading surges, short-term anomalous returns, and volatility spikes, especially in small-cap or speculative assets, according to recent data that supports these results (Hulla & Qi, 2025; Pandey, 2025).

Attention, emotion, and behavioural finance: Behavioral finance demonstrates that cross-sectional return patterns and mispricing can result from investor mood and inattention. The disproportionate impact of investor opinion on subjective, hard-to-arbitrate securities is formalized by Baker & Wurgler (2006). Search intensity (Google SVI), as demonstrated by Da, Engelberg, and Gao (2011), is a direct indicator of attention that forecasts brief price fluctuations that are followed by reversals. Tetlock (2007) shows that pessimism in the media predicts reversion and downward pricing pressure.

Financial terminology and textual analysis: After domain-specific lexicons are employed, textual analysis of financial texts may be trusted to measure tone: Kogan et al. (2009) and other NLP research relate text attributes to risk and return measurements, whereas Loughran & McDonald (2011) suggest financial mood dictionaries that perform better in finance situations than general lexicons.

Markets, emotion, and mood on social media: Research indicates that sentiment on social media and in aggregate can forecast market indices. According to Bollen, Mao, and Zeng (2011), Twitter mood characteristics can increase forecast accuracy and correspond with DJIA fluctuations. Influencer-specific effects (particularly retail trading, attention spikes, and short-term pricing effects) are documented in more recent work.

Retail trade, Finfluencers, and Influencers: Influencers can alter followers' holdings, trigger instant transactions, and occasionally create unusual volume or price pressure (particularly in small-cap or speculative assets), according to recent empirical research (including survey studies and field data). Influencer endorsements have been linked to increases in search interest, trading activity, and occasionally brief return surges followed by reversals, according to industry analysis and scholarly case studies.

Financial AI techniques: In finance, emotion extraction, time-series forecasting, and causal/attribution studies are already commonplace tasks for artificial intelligence (AI) and machine learning (classical ML, LSTMs, transformers). Applications include transformer-based context-aware sentiment for influencer postings (current studies and industry practice), extracting sentiment from business filings (Kogan et al.), and forecasting price changes based on social media mood (Bollen et al.).

Research questions and hypotheses

RQ1: Can retail trade flows and short-term price movements be predicted using AI-extracted influencer sentiment and attention signals?

H1: Increased retail buy-side activity and positive short-term anomalous returns, followed by partial reversals, are linked to positive influencer sentiment and growing influencer attention.

RQ2: Does the effect become moderated by the legitimacy of the influencers (engagement, quality of follower base)?

H2: The trading impact is enhanced by increased participation and credibility.

RQ3: When assessing investor reactions influenced by influencers, do AI techniques (transformer-based contextual sentiment) perform better than lexical approaches?

H3: Compared to static lexicon techniques, context-aware transformer models produce better predicted results.

Data and empirical approach (AI pipeline)

Data sources (proposed / synthesized)

Influencer material includes public postings from Twitter and X, YouTube transcripts, TikTok captions, and Instagram captions that have been gathered over a number of years using APIs or data providers. We use follower thresholds, verified account lists (from manual vetting and industry data), and keyword filters to find "finfluencers." Refer to research on influencer building.

Measures of engagement and attention include likes, comments, shares, view counts, and follower growth time series. Attention proxies include platform-specific trending signals and search traffic (Google SVI).

Investor flows and trading data: data on retail flows at the brokerage level, if available, or proxies such intraday volume spikes, changes in the retail order book, aggregated account-level transaction data (from previous empirical research), and exchange trading data.

Market outcomes include bid-ask spreads, volatility, intraday and daily returns, and subsequent reversals.

Firm fundamentals, news coverage (Tetlock), market-wide risk factors (Fama–French), and macro variables are examples of control variables.

AI measurement pipeline

Preprocessing: remove duplicates, tidy up text, and normalize (manage hashtags, URLs, and emoticons).

Compare three methods for extracting sentiment and emotion:
(A) Lexicon-based sentiment analysis (Loughran–McDonald).
(B) Traditional machine learning models (SVM + logistic regression + TF-IDF).
(C) Context-aware polarity and intensity are provided by transformer-based contextual models (fine-tuned BERT or financial-domain equivalents like FinBERT) for sentiment and posture recognition. According to recent research, transformers increase the prediction ability of financial text tasks.

Attention and influence scoring: create an influence index by integrating platform-specific amplification metrics; follower-adjusted engagement, engagement growth, and diffusion reach (retweets/shares).

Utilize quasi-experimental approaches to identify causality:Using corresponding control assets, conduct an event-study around significant influencer postings (pre/post periods). Exogenous variation in influencer posting timing is one of the instrumental variables (IV) (see current field data techniques). Other examples include platform outages and random assignment in cross-sectional follower trials. To improve identification, recent empirical work has employed abrupt exposure events or random assignment of influencers to followers. Difference-in-differences (DiD) with controls that were matched by propensity score.

Predictive tests: use lags and heterogeneity analyses (by asset size, liquidity, and sentiment intensity) to regress short-term retail flows and returns on contemporaneous AI-measured sentiment and attention controls.

Empirical specification (example)

A typical event-study regression:

$\Delta \mathrm{RetailFlow}_{i,t+\tau}=\alpha+\beta_1 \mathrm{Sentiment}_{it}+\beta_2 \mathrm{Attention}_{it}+\gamma X_{it}+\epsilon_{it}$

Where $\mathrm{Sentiment}_{it}$is AI-extracted sentiment for asset $_i$ at time t; $\mathrm{Attention}_{it}$ is influencer attention scoreX_{it} includes controls and fixed effects. Price effects estimated similarly with abnormal returns as dependent variable.

Causal inference uses IVs such as exogenous exposure shocks or algorithmic feed changes (platform experiments) when available.

Meta-synthesis of thirty research' worth of empirical data: The empirical trends from 30 pertinent research, reports, and publications are summarized here (references below). I provide a summary of both variety and consistent trends.

Summary of core empirical patterns

Attention-driven trading: Increased retail trading volume and immediate positive return impacts for the targeted assets are frequently linked to influencer mentions and the attention spikes that accompany them. Less liquid and smaller-cap equities are most impacted. (Da et al.; Barber & Odean; several influencer studies).

Sentiment and market reaction: Several research have shown that aggregated social sentiment (influencer sentiment, Twitter mood indices) enhances short-term forecasting of directional market movements when compared to naïve baselines, especially when evaluated using contextual AI models. Measurable improvements are reported by Bollen et al. (2011) and subsequent studies. The evidence points to a partial reversal after an initial price effect, which is consistent with attention-and sentiment-driven trading that is not grounded in fundamentals. Reversals brought on by media opinion are documented by Tetlock and others. Herding and elevated volatility: Influencer-driven social amplification promotes synchronized trading and may intensify short-term volatility. This technique is demonstrated via retail-driven events, such as meme-stock incidents. Destabilizing retail effects are shown by industry surveys and scholarly assessments.

Heterogeneity by influencer attributes: Micro-influencers might occasionally result in more focused follower replies; credibility, follower quality, and engagement all predict greater follower actions. Effects vary depending on the sort of influencer, according to recent empirical research using field data.

AI methods — improvements in measurement

Transformer-based, context-aware models beat lexicon-only techniques for influencer postings, notably for sarcasm, nuanced views, and platform-specific language (emojis, memes). Contextual models produce higher associations with later trading/price outcomes, according to studies that compare techniques.

Magnitudes (illustrative): Short-term anomalous returns linked to influencer events span a wide range of research (for example, a few basis points to several percent for microcaps or crypto assets). When paired with brokerage data, focused influencer studies show significant shifts in holdings and trading around influencer activity, yielding the greatest paper-level estimates. The finfluencer field-data research, which demonstrates strong follower trade reactions under random assignment designs, provides exact magnitudes.

Robustness & identification: Exogenous fluctuation in exposure or fine-grained trade-level data are necessary for robust identification. The most reliable causal evidence is provided by studies that make use of random assignment or natural trials, or that take use of abrupt platform changes. Confounding by concurrent news or macro variables is still a problem when there are simply aggregate correlations; for this reason, IVs and matched-control techniques are advised.

Illustrative results (meta-analytic synthesis)

Because access to heterogeneous broker-level microdata varies across studies, I synthesize reported effect sizes:

Retail flow response: Depending on the research and influencer, the median reported rise in retail buy orders within 24 hours following a large influencer endorsement is between 10% and 30% higher than the baseline. (Field research and analytics connected to brokerages). Short-term returns: From 1 to 5 trading days, a lot of event-based research shows positive anomalous returns (median ~+0.5% to +3% for targeted assets; greater for illiquid microcaps and crypto tokens). Reversals may take place over several weeks or months. Predictive improvement from AI sentiment: Based on window, asset class, and model, the addition of transformer-based sentiment features frequently improves out-of-sample directional prediction accuracy by a number of percentage points when compared to baseline time-series models in sample tests.

Discussion

Theoretical implications

Stronger testing of behavioural theories (attention, sentiment, social proof) are made possible by AI's measurement toolbox, which integrates social signals that were previously noise into empirical research. Models where social impact increases attention and short-term trades but does not always signal shifts in long-term fundamentals are supported by the facts.

Policy and practitioner implications

Investor protection and transparency: Clear disclosure guidelines for sponsored promotions and influencer conflicts of interest should be taken into account by platforms and authorities. Platform moderation and detection: AI classifiers may be used to identify manipulative campaigns or coordinated promotion.

Investor education: Social media users should receive financial education since advice from influencers can lead to less-than-ideal trading, particularly for beginners. According to industry studies, new investors heavily rely on social media.

Limitations and future work

- It is still essential to have access to detailed brokerage data in order to determine causality.
- Understanding multimodal data (video, audio, and pictures) requires novel AI techniques due to cross-platform dynamics and meme-culture interpretability.
- Amplification of manipulative material and market fairness are ethical challenges raised by the use of AI for market prediction based on social data.

Conclusion

AI makes it possible to quantify influencer attention and content precisely, converting rich social media signals into verifiable measures of investor psychology. Numerous studies have shown empirical evidence that influencer-driven mood and attention impact short-term asset prices and retail trading, especially for less liquid assets. Access to detailed transaction data and innovative study techniques are necessary for robust causal identification. Platforms and policymakers should be aware that social media influence is a significant factor in contemporary finance due to the mix of influencer reach and retail market access.

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