#### SJIF RATING: 8.586

# **Influence of Social Media Over the Stock Market**

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Abstract—The evolution of digital communication has positioned social media as a critical force in shaping stock market behavior. This study explores how investor sentiment and trading decisions are influenced by platforms such as Twitter, Reddit, and YouTube. Social media enables real-time dissemination of financial opinions, influencer-driven trends, and algorithmically promoted content that can trigger market fluctuations. Through a mixed-method approach, the research gathers empirical evidence from surveys of active investors and market analysts, complemented by case studies including the GameStop stock surge.

Statistical tools such as Chi-square tests, correlation, and regression analyses were employed to examine the relationship between social media engagement and stock market behavior. Findings reveal a nuanced impact while social media democratizes access to financial insights, it also introduces vulnerabilities, including misinformation, speculative trading, and herd behavior. The study emphasizes the need for enhanced financial literacy, algorithmic transparency, and regulatory by oversight. **I**t concludes offering strategic recommendations to mitigate risks and promote informed investment decisions in an increasingly digitalized financial landscape.

**Keywords**—Social Media, Stock Market, Retail Investors, Sentiment Analysis, Algorithmic Influence, Digital Trading

#### I. INTRODUCTION

#### A. Background of the Study

The integration of social media with financial ecosystems has dramatically altered how information is disseminated and interpreted by investors. In recent years, platforms like Twitter, Reddit, and YouTube have become key sources for real-time updates, financial commentary, and stock-related sentiment. This transformation has created an environment where digital narratives can influence market sentiment and, subsequently, stock price volatility. According to Smith et al., social media plays a critical role in fueling investor behavior and short-term price fluctuations by enabling viral dissemination of opinions and investment suggestions. Retail investors, in particular, are drawn to easily accessible and engaging financial content, often bypassing traditional news sources and expert analysis. As a result, social media

sentiment has become a new variable in financial forecasting and trading behavior.

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### B. Statement of the Problem

While the accessibility of financial information through social media empowers individual investors, it also raises concerns about the spread of misinformation, emotionally driven trading, and market manipulation. Retail investors may unknowingly rely on unverified or biased content, leading to herd behavior and speculative decision-making. The absence of regulatory mechanisms and the increasing reliance on influencer-driven narratives make financial markets vulnerable to artificial volatility and unsustainable stock price surges. Despite growing literature on digital investor sentiment, there remains a lack of empirical clarity on how significantly social media influences long-term investment behavior and whether it contributes positively to market efficiency.

## C. Research Objectives

The primary objective of this study is to investigate the influence of social media on stock market behavior, particularly from the perspective of retail investors. The specific goals are as follows:

- To assess the impact of social media sentiment on investor behavior and stock price volatility.
- To evaluate the role of financial influencers in shaping investment decisions.
- To identify risks associated with speculative trends and misinformation propagated online.
- To analyze the algorithmic curation of financial content and its implications for decision-making.
- To recommend strategies for responsible usage of social media in financial contexts.

## D. Research Questions

In alignment with the above objectives, the study is guided by the following research questions:

- How does social media influence investor sentiment and trading behavior?
- What role do financial influencers and online communities play in stock market volatility?
- To what extent does social media contribute to herd behavior and speculative trading?

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- What are the risks associated with unverified financial content on digital platforms?
- How can regulatory frameworks and financial literacy mitigate these risks?

## E. Scope and Significance of the Study

This research focuses on analyzing the role of social media platforms in shaping investor sentiment and influencing market outcomes. It specifically targets retail investors and financial analysts who actively engage with platforms such as Reddit, Twitter, and YouTube. The study employs a quantitative methodology supported by empirical data from surveys and statistical analysis. Its findings are significant for multiple stakeholders—including retail investors, policymakers, and market regulators—as they highlight both the opportunities and vulnerabilities introduced by social media. While democratizing access to information, digital platforms also amplify the speed and impact of misinformation, necessitating enhanced media literacy, ethical standards, and regulatory oversight (Zhang et al., 2020; Kumar and Das, 2023).

#### II. LITERATURE REVIEW

#### A. Social Media Sentiment and Investor Behavior

Investor sentiment, shaped by online interactions, has become a defining factor in short-term stock market volatility. Platforms such as Twitter and Reddit now host a continuous flow of investment opinions, which can create momentum trading patterns and emotional reactions among investors. Studies by Smith et al. highlight that spikes in positive sentiment on social media often precede short-term increases in stock prices, while negative sentiment has a dampening effect. Patel and Liu emphasize that these reactions occur regardless of the fundamental value of stocks, suggesting that emotional responses can override rational analysis. The feedback loop between social media sentiment and market performance is further amplified by the speed at which content spreads, triggering widespread reactions and fueling intraday market swings.

# B. Role of Financial Influencers

Financial influencers—or "finfluencers"—have emerged as pivotal figures in shaping retail investor behavior. Wang and Li found that influencer-driven investment advice often leads to spikes in trading volume and investor interest, especially among younger, inexperienced investors. According to Liu et al., influencer credibility—rooted in perceived expertise, trustworthiness, and authenticity—plays a critical role in shaping investor behavior. Ohanian's credibility model supports this notion, indicating that influencers who appear transparent and knowledgeable tend to have the strongest impact. However, Kapoor and Mehta caution that over-reliance on influencers can lead to impulsive, emotionally driven investment decisions, especially in cases involving meme stocks like GameStop.

These situations highlight the fine line between democratized financial advice and irresponsible speculation.

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## C. Misinformation and Speculative Risks

Social media's openness and accessibility also make it a conduit for misinformation and unregulated speculation. Sharma and Gupta describe this environment as fertile ground for herd behavior, where investors follow trending discussions without conducting proper due diligence. Miller and Brown found that misleading narratives on social platforms can cause temporary price surges followed by sharp corrections, harming uninformed retail investors. The role of AI-generated and bot-amplified content has further exacerbated the issue, as highlighted by Chen et al., who argue that algorithmic propagation of false financial claims increases market instability. These patterns have led regulators to call for better monitoring and stricter guidelines to protect investors from speculative traps and digital manipulation.

# D. Algorithmic Influence on Retail Investors

Modern social media platforms leverage algorithms that curate content based on user engagement, creating echo chambers that reinforce pre-existing beliefs. Garg and Roy explain that this content curation often limits exposure to diverse financial perspectives and deepens cognitive biases such as confirmation bias. This results in an overconfidence effect where investors become overly reliant on selected sources. Meanwhile, institutional investors have started leveraging AI-driven tools that incorporate social media sentiment into stock prediction models, gaining a competitive edge in market responsiveness. Wang et al. report that integrating sentiment analysis with trading algorithms improves forecast accuracy significantly. However, Patel and Liu warn that platforms often promote engaging content over factual accuracy, resulting in the viral spread of speculative ideas and misinformation. Ethical concerns are also raised regarding how algorithmic prioritization may lead to herd-driven market bubbles and inefficiencies.

#### E. Gaps in Existing Research

Despite the growing body of literature, several areas remain underexplored. First, most existing studies focus on the short-term impacts of social media sentiment; little attention has been given to its influence on long-term investment strategies. Second, the majority of the research has centered on platforms like Reddit and Twitter, overlooking emerging platforms such as TikTok and Instagram, which are gaining popularity among younger investors. Third, while concerns about misinformation and manipulation are widely discussed, fewer studies have proposed or evaluated effective regulatory frameworks to address these issues. Lastly, behavioral differences between institutional and retail investors in response to social media content remain insufficiently examined—particularly in the context of strategic trading versus emotionally reactive investing (Kumar and Das; Hendricks and James).



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#### III. RESEARCH METHODOLOGY

## A. Quantitative Research Design

This study adopts a quantitative, survey-based research design to systematically examine the extent to which social media influences investor behavior and stock market volatility. The rationale behind selecting a quantitative approach lies in its ability to collect measurable and generalizable data from a broad population, thus allowing the analysis of behavioral patterns and statistical relationships with a high level of precision. The study is grounded in the positivist paradigm, relying on observable and quantifiable data gathered from investors, traders, and market analysts actively involved in digital trading ecosystems.

The research primarily aims to investigate correlations between social media usage and trading behavior, employing both descriptive and inferential statistical methods. Similar approaches have been validated in prior studies by Wang and Zhang, who analyzed digital sentiment trends in relation to market performance. The present study builds upon such frameworks by incorporating structured data analysis using SPSS, focusing on key metrics like trading frequency, perceived trust in social media content, and reaction to platform-driven financial narratives.

#### B. Sampling Technique and Sample Size

A purposive sampling technique was adopted to ensure the inclusion of respondents who actively engage with social media platforms for stock-related information. This technique, as described by Kumar and Goyal, is especially effective when targeting niche groups within a population in this case, retail investors, institutional traders, and financial analysts who are directly influenced by digital trends. The total sample comprised 400 respondents, categorized into four primary groups: retail investors, institutional traders, financial analysts, and financial researchers. This classification allowed for a balanced representation of perspectives across various levels of market exposure and digital engagement. A sample size of this magnitude ensures sufficient statistical power for robust analysis and generalizability of results across a wider financial audience.

### C. Questionnaire Overview

The primary data collection instrument was a structured questionnaire, designed to capture standardized responses across different dimensions of investor behavior and social media interaction. The questionnaire consisted of closed-ended and Likert-scale questions, segmented into multiple sections that covered demographic details, frequency and nature of social media usage, perceived influence of social content on trading decisions, and awareness of associated risks. The design of the survey was influenced by frameworks previously proposed by Liu and Lee, who examined online behavioral finance using similar instruments.

The survey also included variables measuring investors' trust in different types of social media platforms, the perceived credibility of financial influencers, and responses to speculative or viral content. Particular care was taken to ensure that the language of the questionnaire was neutral and objective, minimizing the risk of response bias. Pilot testing was conducted with a smaller sample group to validate question clarity, logical flow, and time to completion.

#### D. Data Collection and Analysis Tools

Data was collected through both online distribution and direct outreach, ensuring broader accessibility and higher response rates. The collected data was then cleaned, coded, and analyzed using SPSS (Statistical Package for the Social Sciences)—a widely recognized tool for handling quantitative research. The analytical strategy included both descriptive statistics (mean, standard deviation, frequency distribution) to identify general trends, and inferential tests such as Chi-square, Pearson correlation, and multiple regression analysis to determine statistical significance and inter-variable relationships.

Following methodologies applied by researchers like Sharma and Gupta, inferential analysis was particularly useful in identifying the degree of association between variables such as social media trust and trading frequency, and the influence of content type on impulsive trading decisions. These techniques allowed the study to move beyond surface-level observations and delve into measurable impacts of social media behavior on investment practices.

#### IV. DATA ANALYSIS AND RESULTS

#### A. Introduction

This section presents the empirical findings derived from the survey conducted to examine the influence of social media on stock market behavior. Using SPSS, several statistical techniques were applied, including Descriptive Statistics, Chi-Square tests, Pearson Correlation, and Multiple Regression. Each method is employed to analyze specific dimensions of digital financial engagement, such as platform usage, investor trust, content influence, and investment frequency. The results are interpreted in light of previous studies to draw meaningful conclusions.

## B. Descriptive Statistics

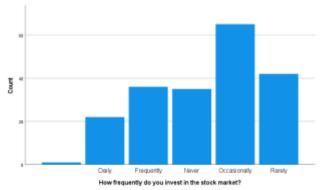
The demographic profile of respondents, as presented in Table 4.1: Demographic Characteristics of Respondents, shows that the majority belong to the 18–25 age group (42.3%), followed by the 26–35 category (24.9%). These results suggest an overrepresentation of younger market participants, likely due to their digital fluency and ease of access to social platforms.

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Table 4.1: Demographic Characteristics of Respondents

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|---------------------|---|---------------|--------------------|-----------------------------|----------------------------------|
| Category            | Subcategory                             | Frequen<br>cy | Perce<br>nt<br>(%) | Valid<br>Perce<br>nt<br>(%) | Cumulati<br>ve<br>Percent<br>(%) |
| Age<br>Group        | 18–25                                   | 85            | 42.3               | 42.3                        | 42.8                             |
|                     | 26–35                                   | 50            | 24.9               | 24.9                        | 67.7                             |
|                     | 36–45                                   | 30            | 14.9               | 14.9                        | 82.6                             |
|                     | Above 45                                | 18            | 9.0                | 9.0                         | 91.5                             |
|                     | Below 18                                | 17            | 8.5                | 8.5                         | 100.0                            |
|                     | Total                                   | 201           | 100.0              | 100.0                       |                                  |
| Gender              | Female                                  | 103           | 51.2               | 51.2                        | 51.7                             |
|                     | Male                                    | 66            | 32.8               | 32.8                        | 84.6                             |
|                     | Other                                   | 31            | 15.4               | 15.4                        | 100.0                            |
|                     | Total                                   | 201           | 100.0              | 100.0                       |                                  |
| Educatio<br>n Level | High School                             | 20            | 10.0               | 10.0                        | 10.4                             |
|                     | Undergradua<br>te                       | 48            | 23.9               | 23.9                        | 36.3                             |
|                     | Postgraduate                            | 80            | 39.8               | 39.8                        | 76.1                             |
|                     | PhD                                     | 27            | 13.4               | 13.4                        | 89.5                             |
|                     | Other                                   | 25            | 12.4               | 12.4                        | 100.0                            |
|                     | Total                                   | 201           | 100.0              | 100.0                       |                                  |
| Occupati<br>on      | Employed<br>(Finance<br>Sector)         | 44            | 21.9               | 21.9                        | 22.4                             |
|                     | Employed<br>(Non-<br>Finance<br>Sector) | 36            | 17.9               | 17.9                        | 40.3                             |
|                     | Investor/Tra<br>der                     | 33            | 16.4               | 16.4                        | 56.7                             |
|                     | Self-<br>Employed                       | 36            | 17.9               | 17.9                        | 85.1                             |
|                     | Student                                 | 30            | 14.9               | 14.9                        | 100.0                            |
|                     | Other                                   | 21            | 10.4               | 10.4                        |                                  |
|                     | Total                                   | 201           | 100.0              | 100.0                       |                                  |



**Figure 4.1:** Percentage of Respondents Using Different Social Media Platforms for Stock Market

In terms of gender, Table 4.1 shows that female participants (51.2%) were more prominent in the sample, followed by males (32.8%), and those identifying as "Other" (15.4%). Educational levels skewed high, with 39.8% holding postgraduate degrees, supporting the notion that the sample is composed of well-informed individuals.

Occupational data reveals that 21.9% of respondents work in the finance sector, while others identify as traders, self-employed professionals, students, or from non-finance backgrounds. This occupational diversity is significant for assessing a broad range of investor perspectives.

The breakdown of platforms used for stock updates is visualized in Figure 4.1: Respondents' Preferred Social Media Platforms for Stock Market Updates, where YouTube, Reddit, and Facebook lead as the most utilized sources.

#### C. Chi-Square Test Analysis

The association between the use of specific social media platforms and the likelihood of making investment decisions based on trends observed on those platforms was evaluated using the Chi-Square test.

**Table 4.2:** Chi-Square Test Results for Social Media Influence on Stock Decisions

Crosstabulation Between Social Media Platforms and Investment Decisions

| Social Media Platform | No | Yes | Total |
|-----------------------|----|-----|-------|
| Facebook              | 0  | 31  | 31    |
| LinkedIn              | 0  | 26  | 26    |
| Other                 | 0  | 25  | 25    |
| Reddit                | 0  | 31  | 31    |
| Telegram              | 0  | 21  | 21    |
| Twitter/X             | 1  | 19  | 20    |
| YouTube               | 0  | 46  | 46    |
| Total                 | 2  | 199 | 201   |

#### **Chi-Square Test Statistics**

| Test    |      | Value    | df | Asymptotic (2-sided) | Significance |
|---------|------|----------|----|----------------------|--------------|
| Pearson | Chi- | 108.879a | 14 | 0.000                |              |

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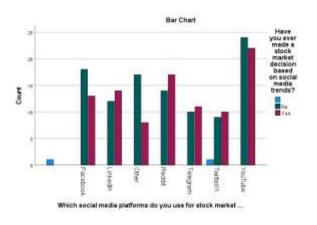
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| Value | df | Asymptotic (2-sided) | Significance |
|-------|----|----------------------|--------------|

|                  |        |    | (2-sided) |
|------------------|--------|----|-----------|
| Square           |        |    |           |
| Likelihood Ratio | 18.829 | 14 | 0.172     |
| Valid Cases (N)  | 201    |    |           |

<sup>a</sup> 10 cells (41.7%) have expected count less than 5. The minimum expected count is 0.01.



Results shown in Table 4.2: Chi-Square Test Results for Platform Usage vs Investment Action confirm a statistically significant relationship. The Pearson Chi-Square value is 108.879 with a p-value of 0.000, which is well below the 0.05 threshold for statistical significance.

YouTube users showed the highest conversion from platform usage to actual stock decisions, followed closely by Reddit, Facebook, and LinkedIn. The finding supports claims by Wang and Li that specific platforms carry more influence than others in motivating trading activity. While some cells had low expected counts, the overall model reliability remains intact.

#### C. Correlation Analysis

A Pearson correlation test was conducted to understand the relationship between trust in social media for financial information and the frequency of stock market investments.

**Table 4.3**: Pearson Correlation Between Trust in Social Media and Stock Market Investment

| Variables                  | Trust in Social<br>Media | Frequency of<br>Investment |  |
|----------------------------|--------------------------|----------------------------|--|
| Trust in Social<br>Media   | 1.000                    | 0.140*                     |  |
| Significance (2-tailed)    | _                        | 0.048                      |  |
| N (Sample Size)            | 201                      | 201                        |  |
| Frequency of<br>Investment | 0.140*                   | 1.000                      |  |
| Significance (2-tailed)    | 0.048                    | _                          |  |
| N (Sample Size)            | 201                      | 201                        |  |

<sup>\*</sup>Correlation is significant at the 0.05 level (2-tailed).

The results are detailed in Table 4.3: Correlation Between Social Media Trust and Investment Frequency.

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The correlation coefficient was 0.140, with a p-value of 0.048, indicating a statistically significant but weak positive relationship. This suggests that as investors' trust in social media rises, there is a slight increase in how frequently they invest. However, the weak correlation also implies that other underlying factors—such as investment strategy, financial knowledge, and risk appetite—play a more dominant role.

# D. Regression Analysis

To assess the collective impact of multiple social media factors on investment frequency, a multiple regression model was used.

**Table 4.4:** Regression Analysis Results

#### 1) ANOVA Summary

| Model      | Sum of<br>Squares | df  | Mean<br>Square | F     | Sig.               |
|------------|-------------------|-----|----------------|-------|--------------------|
| Regression | 5.183             | 3   | 1.728          | 1.004 | 0.392 <sup>b</sup> |
| Residual   | 339.146           | 197 | 1.722          |       |                    |
| Total      | 344.328           | 200 |                |       |                    |

<sup>&</sup>lt;sup>a</sup> Dependent Variable: How frequently do you invest in the stock market

The ANOVA results, presented in Table 4.4: ANOVA Summary of Regression Model, show an F-value of 1.004 and a p-value of 0.392. This suggests that the independent variables do not collectively explain a significant portion of the variance in investment frequency.

# 2) Coefficients of the Regression Model

| 3.846      | 0.514               |                         |   |   |
|------------|---------------------|-------------------------|---|---|
|            | 0.514               |                         | 7.477   | 0.000   |
| 0.228      | 0.180               | 0.090                   | 1.266   | 0.207   |
| -<br>0.052 | 0.048               | -<br>0.077              | 1.082   | 0.281   |
| 0.030      | 0.043               | 0.050                   | 0.706   | 0.481   |
|            | -<br>0.052<br>0.030 | 0.052 0.048 0.030 0.043 | -     0.052     0.048     -     0.077       0.030     0.043     0.050 | 0.228 0.180 0.090 1.266  - 0.052 0.048 - 0.077 1.082  0.030 0.043 0.050 0.706  How frequently do you invest |

<sup>a</sup> Dependent Variable: How frequently do you invest in the stock market

<sup>&</sup>lt;sup>b</sup> Predictors: (Constant), Which social media platforms do you use for stock market updates?, Have you ever made a stock market decision based on social media trends?, What type of social media content influences your stock decisions the most?

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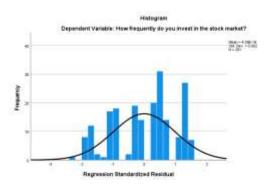
Further insights from Table 4.5: Coefficients of Regression Analysis indicate that none of the predictors—social media platform, decision based on trend, or content type—had statistically significant effects on investment behavior. Although the variable "investment decisions based on social media trends" showed a positive influence, its p-value (0.207) exceeds the threshold for significance.

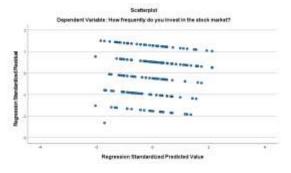
#### 3) Residual Statistics

| Statistic                          | Minimum | Maximum | Mean  | Std.<br>Deviation | N   |
|------------------------------------|---------|---------|-------|-------------------|-----|
| Predicted<br>Value                 | 4.00    | 4.67    | 4.33  | 0.161             | 201 |
| Residual                           | -3.053  | 1.969   | 0.000 | 1.302             | 201 |
| Standardized<br>Predicted<br>Value | -2.034  | 2.120   | 0.000 | 1.000             | 201 |
| Standardized<br>Residual           | -2.327  | 1.500   | 0.000 | 0.992             | 201 |

Residual analysis shown in Table 4.6: Residual Statistics of Regression Model reflects consistency in predicted values, with no extreme outliers, supporting the model's internal validity even though it lacks predictive strength.

These findings are in line with observations made by Liu and Lee, who argue that while social media platforms may shape financial sentiment and attention, they may not be the sole determinants of frequent investment behavior.





#### V. CONCLUSION

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The analysis conducted in this study indicates that social media engagement does not appear to have a significant impact on the frequency of stock market investments. The regression model employed to assess the correlation between social media use and investment behavior reveals that variables such as the type of content consumed on various platforms, the platform itself, and whether individuals base their investment decisions on social media trends have negligible or insignificant effects on how often they make stock market investments. These findings imply that while social media platforms like Twitter, Reddit, YouTube, and financial forums are widely utilized for accessing stock market information and updates, they do not seem to directly drive investment frequency. Despite the vast amount of stock-related content circulating on these platforms, social media may not act as the primary motivator for individual investors to enter or exit the market regularly. Instead, other influential factors, such as the investor's level of financial literacy, their personal risk tolerance, and the strategies they employ in managing their investments, are likely more influential in determining investment frequency.

Investors with higher financial literacy may be better equipped to filter and analyze the information they encounter on social media, using it as just one source among many in their decision-making process. Furthermore, personal investment strategies based on long-term goals, diversification, or risk management techniques may also diminish the influence that short-term trends or viral stock tips on social media have on investment behavior. For example, investors who have a more structured approach to trading, relying on fundamental analysis or professional advice, may be less likely to act on the advice or trends posted by influencers or social media communities. The analysis also suggests that broader macroeconomic factors, such as market conditions, government policies, and economic performance, may play more substantial roles in influencing the decision to invest in the stock market compared to social media-driven sentiments.

Additionally, factors like an individual's access to financial education and their understanding of investment risks likely outweigh the transient impact of social media discussions. This underscores the point that, while social media may shape market sentiment and help investors stay informed about the latest trends, it does not appear to be a dominant factor in determining how frequently individuals choose to invest in the stock market. The overall findings of this research suggest that other more enduring and rational influences are at play in shaping investors' engagement with financial markets. Therefore, while social media plays an important role in the broader financial ecosystem, it does not emerge as a key driver of frequent investment activity.

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