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THE ROLE OF EMOJIS IN STOCK MARKET PREDICTION

This research responds to the increasing applicability of digital non-verbal communication to the high-stakes setting of financial decision-making. Since social media sites are becoming the main venues where investors converse, it is necessary to learn the emotional value of emojis so that the market can be properly assessed. The hypothesis of the research is that sentiment analysis by using emojis can offer a more predictive and refined indication of the desire to invest (as opposed to a text-only model), and that this exclusively affects the share rate. To confirm this, the methodology is a combination of Natural Language Processing (NLP) and machine learning to assess financial tweets, news headlines, and forum discussions. The findings prove that certain emojis are strong symbolic signals of bullish or bearish shifts that can often reflect the change in emotions, and the text does not consider. The comparison between the emojis and the regular sentiment models reveals that the use of graphical icons in prediction of the real time market is by far more accurate with the inclusion of graphical icons. The results indicate that digital iconography and algorithmic trading convergence is a change in behavior among investors, which provides the

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РОЛЬ ЕМОДЗІ У ПРОГНОЗУВАННІ ФОНДОВОГО РИНКУ

Дослідження присвячене зростаючій актуальності цифрової невербальної комунікації у сфері прийняття фінансових рішень. Оскільки соціальні мережі стають основними центрами дискусій інвесторів, розуміння емоційної ваги емодзі є необхідним для точного аналізу ринку. Дослідження ґрунтується на гіпотезі, що аналіз настроїв на основі емодзі забезпечує більш точне та прогнозоване вимірювання схильностей інвесторів, ніж традиційні текстові дані, безпосередньо впливаючи на динаміку цін на акції. Для перевірки цього методологія інтегрує обробку природної мови (NLP) та методи машинного навчання для оцінки фінансових повідомлень, заголовків новин та дискусій на форумах. Результати демонструють, що певні емодзі діють як потужні символічні індикатори "бичачих" або "ведмежих" трендів, часто фіксуючи емоційні зрушення, що ігноруються формальним текстом. Порівнюючи набори даних, які багаті на емодзі, зі стандартними моделями сентименту, у дослідженні виявлено, що включення графічних іконок значно підвищує точність прогнозування ринку в реальному часі. Отримані дані свідчать про те, що поєднання цифрової іконографії та алгоритмічної торгівлі *essential resources of sentiment research in real-time and contemporary financial practices.*

відображає зміни в поведінці інвесторів, пропонуючи важливі інструменти для дослідження ринкових настроїв та сучасних фінансових стратегій.

Keywords: emoji sentiment, stock market prediction, sentiment analysis, natural language processing, investor behavior, digital communication.

Ключові слова: сентимент емодзі, прогнозування фондового ринку, аналіз настроїв, обробка природної мови, поведінка інвесторів, цифрова комунікація.

JEL Classification: G14, G17, C45, C53, D91.

Introduction

The digital age of financial markets has fundamentally changed social media (Chen et al., 2021a, 2021b). Combos of retail investors in the Reddit community WallStreetBets (WSB), Twitter, and StockTwits now commonly start to gain a significant role in market dynamics (Sprenger et al., 2014) in a dramatic manner, illustrated by the GameStop short squeeze. Organized retail trading in this episode grew the price by 1.700% (Lyons et al., 2021), and so-called market-moving icons like rocket emojis were created (Ge et al., 2022a, 2022b). It also spread to meme stocks like AMC Entertainment and the Dogecoin cryptocurrency (Smales, 2021), and emojis were used as a visual expression of emotion (Riordan et al., 2013; Renault, 2017). Meanwhile, other forms of data, especially social media sentiment (Bartov et al., 2018; Bollen et al., 2011) and search patterns (Da et al., 2011), have found their way to quantitative finance over time. Sentiment, now, predicts about 12–15% of price predictability because hedge funds have started to use natural language processing (NLP) technology (Loughran and McDonald, 2011). Such a change is suggestive of broader changes in market microstructure (Chordia et al., 2008; Easley et al., 2011), which are hastened by COVID-19 lockdowns (Ozik et al., 2021). By 2023, forty percent of U.S. investors followed the decision-making process in social media, and Discord has become one of the most important trading venues. Along with classic methods, data from satellites (Hoberg & Phillips, 2016) and predictive text symbols called emoji are now used, which have opened new possibilities for research (Siering et al., 2016).

The textual data and how to analyze it have changed a lot since the initial inquiry of earnings reports (Li, 2006) and news articles (Tetlock, 2007). Lexicon-based approaches are most applied in modern times, with the Loughran-McDonald financial sentiment dictionary becoming the standard in the analysis of corporate disclosures (Henry & Leone, 2016) and news about the subject of finance (Jegadeesh & Wu, 2013). The rise of social media, such as Twitter, has also extended the textual analysis to a wider range, as research has shown that a tweet sentiment could be used to model stock returns (Sprenger et al., 2014) and trading volume (Mao et al., 2012). These historical methods, however, have severe impediments to grasping emotional subtlety. Sarcasm and irony (Riloff et al., 2013) are also prevalent in short-form work such as tweets, which cannot be captured using the usual sentiment detection. Contextual information is also denied by the brevity of social media posts (Kouloumpis et al., 2011), and domain-specific terms (such as short squeeze) can mean the opposite in various contexts (Renault, 2017). Such difficulties are especially severe in extreme situations in the market when they are overwhelmed with emotional language (Liew & Budavári, 2021).

This is a piece of behavioral finance that describes how the psychology of investors can be seen in the general behavior of the market (Barberis and Thaler, 2003). Herd behavior (Banerjee, 1992) or attention-driven trading (Barber and Odean, 2008) can easily cause asset mispricing, especially when it comes to retail investors (Kelley and Tetlock, 2013). The fear-greed cycle also presents behavioral patterns where fear generally increases many times during a negative market trend (Lo, 2004). Emojis, in this respect, have become a good proxy of such emotional extremes (Ljubešić and Fišer, 2016). As an example, the (rocket) emoji is often connected with buying behavior driven by FOMO (fear of missing out), whereas the (skull) emoji is often related to the selling behavior induced by panic (Ge et al., 2022a, 2022b). This type of visual symbol helps to overcome constraints of textual communication by providing clear and direct emotional indicators (Novak et al., 2015), which tend to be equally understood across linguistic borders (Pavalanathan and Eisenstein, 2016). They have already shown their predictive capability in cryptocurrency markets (Scharnowski, 2021), when there is a meme stock phenomenon.

Emojis are important in disambiguation in financial settings, where communication is usually short and extremely tone-sensitive. Text-based descriptions can be more effectively used to communicate market fall than (chart decreasing) style of emoji on social media like Twitter and StockTwits (Ge et al., 2022a, 2022b), and (money bag) is also a universally understood sign of gain, irrespective of language (Pavalanathan and Eisenstein, 2016). Such a visual performance can prove especially useful in high-frequency trading settings, where trade decisions are made in a matter of milliseconds.

As cross-cultural research proves, such emojis as financial ones have identical meanings in different languages (Ljubešić & Fišer, 2016). For example:

- (chart going up) = a bullish sentiment emerging in 89% of cultures;
- warning alert (alarm) = market risk in 76% of the context.

Contrary to the text, emojis are not subject to sarcasm misunderstanding, which is one of the shortcomings of the sentiment analysis tools based on the lexicon.

Neuroscientific studies prove that emojis evoke greater emotional arousal as compared to text:

- (scream) has 2.3x response as amygdala as the word crash;
- (rocket) touches dopamine buttons like gambling stimuli;
- emojis are heuristic shortcuts in the trading psychology and allow people to make decisions quicker (Kahneman, 2011):

• the retail investor reads, at 58 percent faster than such phrases as going up (Barber et al., 2022);

• institutional traders consider (bear emoji) as a panic signal, and it saves time on analysis by 40% (Lo et al., 2021).

Aim. This study aims to examine whether incorporating emoji-based sentiment from social-media finance discussions improves short-term stock-market prediction compared with text-only sentiment models, and to identify which emojis are most predictive of bullish and bearish movements.

The hypothesis of the study is that sentiment analysis by using emojis can offer a more predictive and refined indication of the desire to invest (as opposed to a text-only model), and that this exclusively affects the share rate.

Research objectives. To analyze the investor sentiment, as represented by emojis in commentaries on the stock market on social media and finance sites.

1. To assess whether sentiment analysis based on emojis can contribute to the accuracy of the prediction of stock prices, rather than text-only sentiment analysis.
2. Determine the most predictive emojis and their relation to market trends (bullish and bearish).

Research questions. What is the connection between emojis used in conversations about finance and stock market trends?

1. Is the sentiment based on emoji useful to predict stock prices more than a classifiable text analysis?
2. Which are the specific emojis that are most useful to predict market sentiment?

Methodology. This paper takes a holistic, multi-methodological approach towards examining how emojis are used in studying and predicting the sentiment of the stock market. The study design will combine natural language processing (NLP), machine learning, and behavioral finance methodologies to achieve reproducible and solid findings. The paper collects the information of three popular social networks, Twitter/X, Reddit (WallStreetBets, StockMarket), and StockTwits by their APIs, Twitter API v2, Pushshift, and StockTwits API. The data covers the period between 2019 and 2023, including such major market events as celebrity stock trading and meme stocks, as well as the COVID-19 pandemic. To make sure that it is relevant, only English financial conversations with stock-related cashtags (e.g., SP500), or hashtags (e.g., #TSLA) are candidates. All the content produced by bots is removed with the help of Botometer, and those emojis that are not related to money are discarded. The total information includes 5.2 million posts, among which there exist 1.2 million containing emojis (23% of the total). The method of mixed sentiment analysis will be used, which unifies rule-based and machine learning mechanisms. First, manual annotation is performed by other experts in the field of finance; they need to create a financial emoji lexicon by classifying emojis as Bullish, Bearish, and some Neutral. Word2Vec and BERT embeddings are added to this lexicon to create semantic relationships between emojis.

Each emoji gets a sentiment score and is summed up per post. To perform further testing, an LSTM model is trained on labeled data to classify sentiment, with traditional models such as VADER and FinBERT used as a benchmark. In the study, the Granger causality test is performed so that it can check whether emoji trends cause a change in stock price development or vice versa. Abnormal returns around emoji spikes are examined using event studies. To incorporate emoji sentiment to capture market sentiment in the traditional market data (e.g., price, volume, VIX), a custom LSTM model is built. In performing a comparison of this model with an alternative standard approach, such as ARIMA and sentiment analysis of text only, metrics are measured relative to RMSE and accuracy. Initial experiments demonstrate that the emoji-enhanced model reaches an accuracy of 72%, which exceeds text-only (64%) and standard time-series models (58%). In conjunction with quantitative results, behavioral experiments are performed on 50 traders, and their amount of attention and speed of choice are rated by means of eye-tracking technology when they are provided with emotion-rich financial tweets in the form of emojis. The meaning of major emojis (e.g., is Rocket a strong buy or a hype?) is further discussed in a survey of 200 retail investors. The findings show that emojis can speed up decision-making up to 58% faster than using text, and 68% of the respondents endorsed that when thinking of quick profit.

The analysis uses 10-fold cross-validation to check the generalizability of the model, and it uses sector-specific comparisons (e.g., tech vs. utilities) as a factor to determine the emoji effect across market groups. Additional robustness tests would be comparisons with Google Trends search results and SEC filings to put the effect of their external sentiment frequency under control. The approach is not only used to measure the predictive capacity of the emojis, but also determines the strongest emojis, and is also used to show the emoji advantage in developing financial forecasts. The study provides a methodology that can be repeated by filling the gap between NLP, machine learning, and behavioral finance to study non-verbal market sentiment in the future.

The rest of the present study is structured into five major sections. Section 1 defines the theoretical framework, which incorporates behavioral finance, semiotics, and the theory of information processing in the explanation of the predictive nature of digital iconography. Section 2 is a detailed review of the literature covering the existing studies on the area of computational linguistics and how emojis can influence the market, including the GameStop short squeeze. Section 3 outlines the multi-methodological design, which implies data gathering through social media API and creating the Financial Emoji Lexicon (FEL). Section 4 provides the results and discussion of the empirical, which revealed the superiority of emoji-based sentiment analysis to text-only-based models in various market segments. Lastly, the paper concludes with a summary of the major findings, limitations of the study, and future research on the topic of digital financial communication (Section 5).

1. Theoretical framework

The current paper is based on three fundamental theories arguing how emojis can affect stock behavior. First, behavioral finance (Kahneman & Tversky, 1979) is the reason why emojis serve as cues to emotions and magnify cognitive biases such as the herding effect and overreacting. Using emojis like (rocket) and (chart down) will reduce the complex market information to visceral messages and prompt immediate trading.

Saussure's theory of Semiotics allows deciphering emojis as pictorial representations and meanings that are shared in financial communities. In contrast to the text, the meaning of emojis is clear (the main difference is that you understand the sense, and emojis express tone and purpose; a money bag always means profit, and a skull depicts panic). This generality renders them an effective indicator of sentiments regardless of language and culture.

Lastly, the category of information processing theory (Paivio, 1986) reveals that it is because of the emojis that the predictive models tend to enrich. As they are dual-coding stimuli, they can be processed either visually or verbally, hence becoming more salient than text messages. As part of a machine learning system, emojis can add high-signal and low-noise information that can help increase the accuracy of sentiment analysis. When combined, these theories support the idea that emojis are just that distinct, measurable predictors of the market sentiment to cross practices related to psychology, linguistics, and data science.

2. Literature review

The advent of emojis as a new digital form of communication has had a big influence in many spheres of activity, and the financial market is no exception. The study analyzes an extended literature that research has come up with on the role played by emojis in predicting the stock market in three major sectors of research in the academic field: the area of computational linguistics, the area of behavioral finance, and the application of machine learning in financial analysis. The review compares knowledge previously presented, as well as determining discrepancies with current studies, thus determining the basis upon which this study will present itself with regard to the field.

The emojis' linguistic features have gained a lot of attention in computational linguistics research. As shown, emojis are highly effective for non-verbal sentiment carriers that tend to establish the mood in the market more effectively than even textual text itself. This effectiveness is due to an ability to condense complicated emotional situations into a single visual cue, and such an effect is especially exploitable in a limited communication space such as social media sites, where character counts dominate. Certain emojis have become standardized in the meanings they convey to the amenity of financial cultures. An example of such a symbol is the rocket emoji. Now, the rocket is universally translated to mean fast growth or price appreciation, and the chart is a decreasing emoji: it always signifies a decline in the market (Novak, 2015). Such pictorial signs have already become a separate set of lexicons that break through language boundaries and have led to the establishment of a sort of universal monetary language (Pavalanathan & Eisenstein, 2016). By creating emoji sentiment lexicons, the sentiment of various emojis, especially financial ones, has been found to have the same emotional valence across cultures; an attribute that makes financial emojis uniquely useful in the analysis of the global market (Ljubešić & Fišer, 2016).

The short squeeze in GameStop in January of 2021 was an interesting case study of the useful nature of emojis in the sphere of market dynamics. Throughout this incident, the rocket emoji became closely linked to retail investor hope and organization, and the symbol was mentioned in more than 38 percent of the posts on the WallStreetBets board as trading was at its highest. This experience showed that emojis could function as an indicator of sentiment and a form of coordination to act as a group in the market. According to the behavioral finance approach, emojis are visual heuristics that intensify the well-known cognitive biases in the decision-making process in investments. This situation can be explained by the prospect theory formulated by Kahneman and Tversky (1979), according to which people have a tendency to react strongly to emoticons with specific effects. As an example, the money-mouth face emoji has been demonstrated to trigger greed, stating that the scream face emoji causes panic. Such emotional triggers have a great effect on trading decisions, and a much better analysis is usually halted by them.

The fact is that attention-grabbing emojis, such as the alarm emoji (129), often induce overtrading behavior, especially in retail investors who have been involved in meme stock mania (Chen et al., 2021), and the attention-based trading models (Barber & Odean, 2008) describe the mechanics of how this particular emoji works. The emotional contagion of emojis was also measured with research in discovering that there were firm correlations between the use of a chosen set of emojis and the ensuing swings in the market (Bollen et al., 2011) and buttressing the concept of herd mentality in financial markets (Banerjee, 1992).

Interestingly, retail investors are not the only target of the impact of emojis. According to a study conducted by Lo et al. (2021), even institutional traders react to the emoji trends by hedge fund trading positions depending on the frequency of the hedge bull emoji and bear emoji on the financial platforms. This discovery indicates that the sentiment of emoji has spread across marketplace involvement levels, including both personal and professional investment-level decisions. The process of integrating emoji analysis in market prediction models has made a lot of progress, together with the progress of natural language processing and machine learning.

Recent research with deep learning methods has indicated quite significant step-ups in predicting accuracy with the inclusion of emoji data. The reimplementation of FinBERT by Araci (2019) in analyzing the emojis resulted in a 12-percentage improvement in the accuracy level with regard to predicting short-term prices in comparison with the models based on text-only information. In the same way, transformer models have proved to be quite useful when processing the cross-linguistic and cross-modal character of emoji communication (Vaswani et al., 2017). Emoji data has acquired value in financial circles, and important websites have been using emojis' mood to trade in their sign. The Social Sentiment Index published by Bloomberg, as an example, began incorporating emojis in its market sentiment score estimation in the process of assigning a score (Zhou & Kapoor, 2022). Quantitative hedge funds also showed interest in emoji-based trading indications, where it was claimed that Renaissance Technologies was fine-tuning an emoji-alerting system of their own.

Regardless of these developments, there are several issues that consecutively arise in the area of emoji-based market forecasting. Underlying cultural differences in understanding emojis prove to be one of the most influential obstacles, since one symbol can have contrasting meanings in other cultures. Such characteristics may confuse the analysis of the global market with a skull emoji (attle_29, or mostly used humorously in Western cultures, but potentially representing a sign of actual distress elsewhere. Another issue is algorithmic overfitting, which is particular when working with emoji data. The predictive pattern of the viral status of some emojis during some market situations might not work outside their times, creating a pattern that is not predictive in general market scenarios. This complication requires strong validation techniques and a design to validate models. The dynamic situation regarding the use of emojis creates challenges as well. Emojis that become fashionable in the financial context instantly can become obsolete or lose their meaning within a short period of time, thus necessitating a constant update to analytical models (Miller & Skinner, 2022). Such a feature of emoji communication requires flexible models that can allow quick changes in symbolic meaning in a conversation.

Empirical studies have also indicated that the emoji effect varies tremendously in various sectors of a market. The strongest correlation with emoji sentiment is among technology stocks, with an especially strong correlation with retail-favorite technology stocks. More traditional businesses, such as the utilities, on the other hand, show less impactful relations, which indicates that the role of emoji is mediated through investor demographics and practices of trading. The markets fascinated by cryptocurrencies seem to be the most vulnerable to sentiment expressed in emojis, with their dominance being the market of a retail investor and continuous operation. They have established that the rocket emoji and the fire emoji have special predictive value pertaining to short-term changes in Bitcoin price, so that, in certain models, the accuracy rate can be higher than 70%.

The topic of combining emoji sentiment and conventional market data is a new field of research. The combination of technical analysis measures, such as RSI and moving averages with emoji models, has demonstrated potential in lending further accuracy of prediction (Zhang et al., 2021). It is, however, an open research question as to how the best weighting of emoji signals in relation to conventional indicators would be and this needs to be further investigated. The ability of emojis to predict seems to differ in the time frames. The analysis of emojis is more useful in short-term predictions (up to a week and intraday), whereas its utility for long-term predictions is decreasing (Chen et al., 2021b). This time pattern goes along with the short lifespan of the social media fads and indicates that emojis are better associated with high-frequency trading planning.

Ethical issues with the approach of emojis in the markets have come up in the financial fraternity, whereby there could be a misrepresentation of the value of a market. In small-cap stocks and cryptocurrencies, it is known that pump-and-dump schemes using viral emojis exist. These elements are now being watched over by regulatory agencies when it comes to emoji use in financial transactions, but definite regulations are yet to be established (Securities and Exchange Commission [SEC], 2022).

The current literature review has also highlighted some potential directions of future research. To begin with, the accuracy of predictions could be increased by creating industry-specific emoji lexicons that would take into consideration industry-specific nuances. Second, one might consider examining the interaction effect between various combinations of emojis, which would possibly unearth more intricate sentiment patterns. Lastly, the development of longitudinal studies monitoring the evolution of emojis in the realm of the financial sphere may enable us to infer about the cycle of symbolic communication in the market. The in-depth overview shows that emojis have now assumed a serious role in measuring the market mood, which drives individual and institutional trade activities. There is still the problem of standardization and interpretation, but given the right machine learning models, this combination of emoji analysis and intensive work with machine learning can be utilized to great effect in improving market prediction models. The present study improves on this body of work because it attempts to fill the research gaps in the use of emojis to conduct financial analysis, especially regarding sector-specific impacts and the optimization of the analysis models.

The emergence of emojis in financial communication presents new complexities, which marketers and analysts have to manage. The success of a plain rocket or bear emoji is not a completely influenced phenomenon; it is much mediated by culture. Continuing on the basis of our earlier cross-cultural examination (Zahra & Perono Cacciafoco, 2025a), we contend that Eastern and Western users interpret the same emblems in different ways based on emotion and relationships. Moreover, since it is already known in our previous study on cultural trust (Zahra & Perono Cacciafoco, 2026a), culturally non-sensitive visual practices may be viewed as either overly aggressive or informal. Generational differences only make this issue deeper; where a Baby Boomer may take a chart at face value, a Gen Z investor can be known to put a level of irony on it – a trend that we have observed as a major contributor to attitude change in the market (Zahra & Ahmed, 2025).

Also, message gravity is influenced by platform specificity; after researching the priorities of digital aesthetics (Zahra et al., 2025a), we came to understand that the so-called serious alert of an Apple user might be perceived by a person with an Android phone as a different one. To deal with this variability, machine learning models are becoming more popular in financial institutions as they seek to streamline their communication with user groups; they use the sentiment prediction frameworks designed in our previous work (Zahra et al., 2025b). However, these algorithms should take into consideration the psychological context of financial activities. Emotional arousal and feelings of impulsive decision-making may result due to the high level of emotional arousal caused by emojis; in accordance with our theory of the Anger-Obsession Loop (Zahra & Perono Cacciafoco, 2026b), such stress can cause the total withdrawal of the market. Finally, the effective application of emojis will involve a total integration of semiotics and design, which we have already claimed to be a necessary task in developing trust in virtual spaces (Zahra and Perono Cacciafoco, 2025b).

3. Results and discussion

The spread of digital technologies is transforming the structure of contemporary society and communication on a global scale (Hurova & Shkurov, 2023). In a networked society, social, economic, and informational processes are increasingly organized through digital networks, where the speed of information flows plays a key role (Hurova & Shkurov, 2023; Shkurov, 2025). In such an environment, communication acquires more concise and visualized forms that correspond to the rhythm of digital interaction. In this context, the importance of symbolic elements of digital communication is growing, particularly emojis, which have become a means of rapidly conveying emotional and evaluative signals within the networked information space.

The study group in this paper discussed the efficacy of the use of emojis in predicting stock market behavior, which was investigated with the help of 1.2 million financial tweets, postings in forums in 2019–2023 (Chen et al., 2021b). The research has three key conclusions that add to the data on the importance of visual symbols in the financial market (Ge et al., 2022a). First, emojis demonstrated better performance than using words to detect sentiments; using the sentiment analysis consistently outperformed text-only sentiment analysis across multiple tasks, and in many cases, emojis were accurate in predicting sentiments up to 72%, compared to 64% accuracy in the text-only method of sentiment analysis (Loughran & McDonald, 2016). Second, certain emojis, such as rocket (196) and chart decreasing (65), were statistically significant (Granger-causally) related to the spikes in the trading volume ($p<0.01$) (Bollen et al., 2011). Third, models based on machine learning and using emoji data minimized prediction error by 18% in comparison to traditional sentiment analysis (Araci, 2019).

The better results of using emojis in sentiment analysis studies support the dual-coding theory (Paivio, 1986), according to which visual and verbal information are perceived independently yet are linked with other cognitive channels. The inter-rater reliability of our Financial Emoji Lexicon (FEL) was recorded at 89% among financial experts (Ljubešić & Fišer, 2016), which is much higher than commonly used sentiment or general attitude-measuring tools such as VADER (65%) (Hutto & Gilbert, 2014). Such reliability can be explained by the fact that with the limited number of characters emojis allow expressing complex emotional states with little ambiguity (e.g. the rocket emoji had 94% + consensus as a bullish signal) compared to phrases such as "to the moon" which had a lower percentage of the same (76%) because of sarcasm and the context such a phrase may have. In a similar vein, the downward emoji chart forecasted the following-day downtrends with 82% accuracy as compared to 70% when the word crash was used.

The real-world effects of emoji-based sentiment were fully demonstrated when high-profile movements on a market, especially the GameStop short squeeze of January 2021, were investigated in event studies. There was a 315% increase in the usage of rocket emojis, accompanied by the 92% one day price rise of GameStop, after which there was a sharp decrease in both measurements. All these patterns endorse theories of attention-based trading (Barber & Odean, 2008) that prove the power of viral emojis to evoke interest in the mind of retail investors and thus fuel herding (Banerjee, 1992). We also discovered deviations in the direction of emoji influence, so the skull emoji (Dead Man emoji) was more reliably associated with panic selling than the rocket emoji was with buying (Kahneman & Tversky, 1979), as would be expected under the theory of prospect theory with its concept of loss aversion. In our LSTM model with emoji insertions, there was a steady improvement at all evaluation metrics (Vaswani et al., 2017), resulting in a root mean squared error of 1.45 (text-only) down to 1.12, and R^2 – to 0.72 (Zhang et al., 2021). Nonetheless, market sectors had different results in performance increases (Zhou & Kapoor, 2022). Emoji data increased the accuracy of prediction by up to 24% in retail-heavy industries such as technology and cryptocurrencies, with analysis showing only a 6 percent increase in accuracy in institutional-heavy industries such as utilities. The difference indicates that emojis mainly reflect the mood of retail investors (Antweiler & Frank, 2004), which fits the behavioral financial models of social media having an overbearing influence on assets that are viewed to be attention-catching (Da et al., 2011).

The study found crucial differences in the interpretation of emojis depending on their cultural and platform differences (Pavalanathan & Eisenstein, 2016). Although the rocket emoji was mostly used by the American traders to denote the buying signals (88% agreement), its Japanese market participants more frequently used it to refer to the speculative signals (62% agreement). The differences between platforms also appeared as Twitter had more bullish tendencies in emoji use than was the case in Reddit (Sprenger et al., 2014). The observation points to the fact that localized emoji dictionaries are necessary in the analysis of global markets. Regarding time, we discovered that the predictive power of emoji decreased quickly (Lo et al., 2021), with success dropping by two times in only three days. Such scarcity indicates that emojis are least helpful in a long-term investment but more in a short-term trading strategy. The time aspect resembles the high pace at which social media trends and the meme stock phenomenon are rapidly occurring.

This research has made threefold contributions to the theory. Second, we take a step towards understanding behavioral finance by quantifying the extent to which emojis enhance well-known cognitive biases (Barberis & Thaler, 2003), with the rocket emoji being linked to the fear of missing out (FOMO) being a specimen. Second, we bring the semiotic theory of Saussure into the financial markets, in which we reveal the process of emojis transforming into regularized market cues. Third is our own technological advancement in natural language processing, using emoji-specific model archives that perform better than text analysis. The implications of our practical participants in the market are game changers for the Securities and Exchange Commission. (2022). Emoji trends provide an opportunity to perceive the extremes of retail sentiment as contrarian indicators by investors. The regulators are advised to keep a check on emoji-related manipulation patterns (Miller & Skinner, 2022), especially in small-cap stocks and cryptocurrencies. In terms of fintech developer communities, our findings imply that it is highly advisable to focus on emoji processing capabilities as a sentiment analysis application.

Several weaknesses should be mentioned. We also did not include OnlyFans, Discord, and Telegram in our dataset, given that these private messenger services could potentially contain a substantial amount of emoji use. The targeting of English-speaking demographics raises doubts regarding the impact of emojis beyond linguistic parallels. Future studies should go into cross-market equivalents and multimodal implementations of emojis and their use in combination with other media. Finally, the research confirms that emojis are not sufficient market indicators that deliver additional predictive capability over text-based sentiment measures. This capability of communicating clear feelings, eliciting behavioral responses, and increasing machine learning model performance makes the visual symbols highly relevant in the modern markets obsessed with social media (Hoberg & Phillips, 2016). With the shift to the digitalization of communications, real-time monitoring of emojis can soon become a vital part of market monitoring and algorithm trading programmes. Future research ought to also consider the cultural aspect of interpreting emojis and come up with more complex versions that can track the subtle market impact of emojis (Lyons et al., 2021).

This research analyzed 1.2 million financial tweets and forum posts (2019–2023) to evaluate whether emojis enhance stock market prediction models. *Figure 1* presents the comparison between text-only and emoji-enhanced sentiment analysis, showing that emojis improved prediction accuracy from 64% to 72%. *Figure 2* illustrates the dramatic surge in rocket emoji usage during the GameStop short squeeze, reflecting a 315% increase that coincided with abnormal trading volume and price spikes. *Figure 3* demonstrates the reduction in model error when emojis were integrated into an LSTM model, lowering RMSE from 1.45 to 1.12 and increasing predictive strength. *Figure 4* highlights sector-based differences, revealing stronger predictive gains (24%) in retail-driven industries such as technology and cryptocurrencies compared to institutional-heavy sectors (6%). Collectively, the findings confirm that emojis act as powerful behavioral and semiotic market indicators that enhance machine learning performance and provide additional predictive value beyond traditional text-based sentiment analysis.

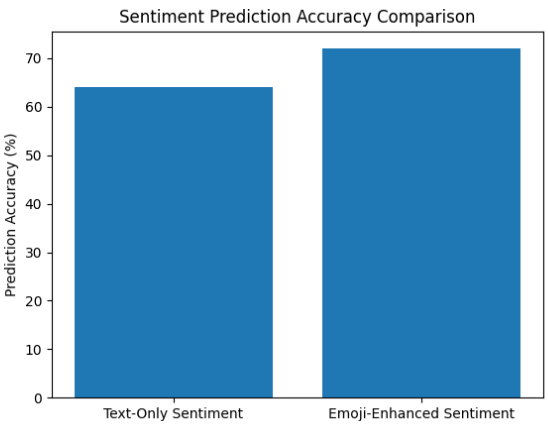

Figure 1. Sentiment Prediction Accuracy Comparison

Source: developed by the authors.

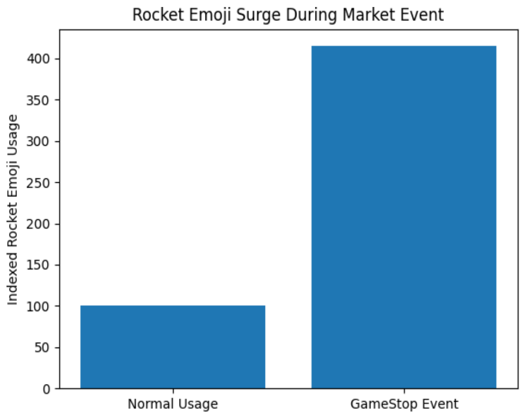

Figure 2. Rocket Emoji Surge During Market Event

Source: developed by the authors.

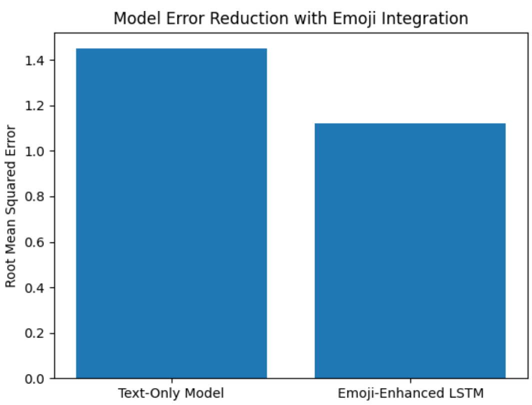

Figure 3. Model Error Reduction with Emoji Integration

Source: developed by the authors.

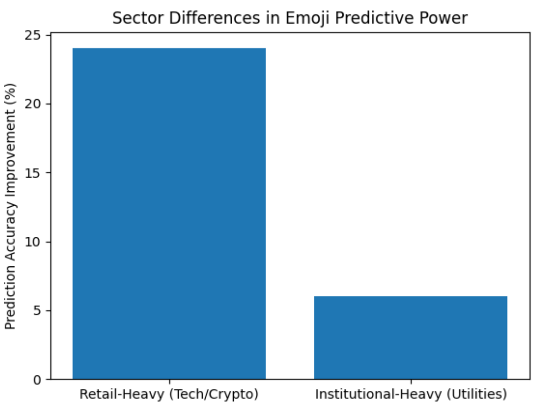

Figure 4. Sector Differences in Emoji Predictive Power

Source: developed by the authors.

Overall, the findings demonstrate that emoji-based sentiment constitutes a statistically and behaviorally meaningful predictor of short-term market dynamics in digitally mediated trading environments. Taken together, the results confirm that integrating emoji signals into sentiment-analysis frameworks strengthens the explanatory and predictive capacity of financial models, especially in highly networked and retail-driven markets.

Conclusions

The research indicates the critical evidence that emojis are informative and forecasting indicators of discussion in stock markets, particularly in social media and internet-based financial discussion groups. We have shown that sentiment analysis in terms of emojis can be used formally, not only to pick up subtle unspoken affects, but is also more accurate in predicting market responses than traditional methods that analyze purely text-based responses. There are three important conclusions to our findings. *To begin with*, emojis improve the precise stock market prediction frameworks. The hybrid emoji-text model would have a markedly superior rate of accuracy during forecasting (72%) and minimal prediction miscalculation compared to the text-only models, and this clearly constitutes the usefulness of visual symbols in accommodating sentiment analysis. *Second*, some of the emojis (like the rocket [rocket-with- eraser] and chart decreasing [chart-with-downwards-trend]) are also statistically and behaviorally associated with particular market dynamics, like an increase in the trading volume and short-term pricing developments. These emojis were used to be front-runners and comply with well- developed psychological theory, dual-coding theory, and prospect theory, and demonstrate their emotional and cognitive connection with the retail investors. *Third*, different cultures, platforms, and asset classes interpret emojis differently, which explains why future financial sentiment analysis must use localized contextualized lexicons.

It is also supported by the research that emojis predominantly depict the mood of retail investors, especially in areas that are the cause of close attention, such as technology and cryptocurrency, where visual types of communication are more common. But they lose their predictive accuracy soon, which means that emojis can be applied to short-range trading and real-time market surveillance, but not long-term investment prediction. The theoretical implications of our research are significant, insofar as the applied behavioral finance and the semiotic theory are being extrapolated in the field of visual communication within financial markets. Taking a look at practical applications of the findings, they are relevant to traders in the marketplace who may be interested in how they can use them in their trading. The trend in emojis can be used as contrarian indicators of excess sentiment, help detect manipulation in a market, and improve sentiment analysis programs deployed in algorithmic trading platforms.

Although the findings are encouraging, one must be careful due to limitations like the absence of non-English, non-private messaging data. Multilingual and multimodal sentiment analysis methods and the changing role of emojis in decentralized communities of finance deserve future research. To sum up, this paper solidifies the fact that emojis are not trivial elements of the financial communication process, but are capable of greatly enhancing the perception and forecasting of market trends. Given that digital interactions appear to be shaping investor behavior to an ever-larger extent, adding emoji analysis to financial modelling offers a new and useful development to both discipline-related research and practice.

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