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AI-enabled Investor Sentiment Analysis and Stock Market Prediction

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Abstract: The efficient market hypothesis assumes that investors have complete rationality, while traditional theories advocate that stock prices are determined by the fundamentals of the enterprise. Previous studies have often used lagged trading indic ators such as turnover rate and fund discount rate to measure investor sentiment. However, these methods have insufficient accuracy and poor timeliness, and cannot capture retail public opinion in real time, explain frequent stock price fluctuations and var ious market anomalies in the stock market. With the continuous development of natural language processing and big model technology, relying on artificial intelligence text quantification methods to analyze investor emotions contained in financial informatio n, stock bar comments, and social platform public opinion has become a popular research direction in the fields of behavioral finance and intelligent finance. However, there are still many shortcomings in existing related research. Most existing literature separately explores one direction, namely AI text technology, investor sentiment transmission mechanism, and stock market prediction model, and has not yet systematically integrated the relationship between the three. Most studies have not comprehensively sorted out the new market risks caused by false information and emotional interference, and the overall resea rch framework is relatively scattered. Based on this, this article provides a systematic review of the application of artificial intelligence in investor sentiment monitoring and stock market prediction, focusing on three issues: how AI technology can compensate for the shortcomings of traditional sentiment measurement methods; The transmission channel of investor sentiment on short-term stock market fluctuations; The research gap, new risks, and response strategies left by generative AI for market sentiment analysis. I hope to clarify the internal logic of artificial intelligence empowering investor sentiment analysis by sorting out the above research context, making up for the fragmented shortcomings of the existing research system, and providing reference ideas for subsequent empirical research and stock market risk prevention and control.

Keywords: Investor sentiment, artificial intelligence, Stock market prediction, Behavioral Finance.

1. Introduction

1.1. Macro Research Background

According to conventional financial theory, the fluctuations in stock prices are mainly determined by the overall economic environment and the company's own operating conditions. In theory, those who participate in stock trading will make rational choices. However, there are many ordinary individual investors in the stock market, and it is easy for them to follow the trend and make irrational trading behaviors due to the influence of online news. Traditional financial data cannot explain the short-term fluctuations of the stock market well. So investors' emotions gradually become a key factor affecting the short-term direction of the stock market.

In the past, researchers generally used trading data such as closed-end fund discounts and market trading activity to roughly judge people's investment sentiment. This type of data has obvious latency and can only calculate market sentiment based on the results of transactions that have already occurred. It is difficult to capture the emotional changes brought by various online news in a timely manner and cannot distinguish between media opinions and the inner thoughts of ordinary investors. Nowadays, Internet finance is becoming more and more popular. Financial information, forum posts, and messages on social platforms generate a large number of text messages, bringing rich data to emotion related research. With the help of artificial intelligence technology for capturing and analyzing text, we can address the shortcomings of traditional research methods, real-time grasp market sentiment trends, explore the relationship between emotions and stock price fluctuations, and open up new research avenues.

1.2. Research Ideas and Research Questions

Based on this, this article uses literature research method to systematically sort out relevant research results at home and abroad, clarify the technical context of artificial intelligence in identifying investor emotions, summarize the research progress of emotion transmission laws and stock market prediction, identify the shortcomings of existing research, and look forward to future research directions, in order to enrich the cross research system of intelligent finance and behavioral finance.

2. How Can the Limitations of Traditional Emotion Measurement Methods Be Compensated for by AI Technology

2.1. Traditional Methods for Measuring Investor Sentiment and Their Inherent Shortcomings

Traditional behavioral finance research has long focused on measuring investor sentiment through transactional proxy indicators, relying on secondary market trading results such as closed-end fund discount rates, market turnover rates, IPO first day returns, and margin trading balances to infer overall

market sentiment. [1] Such indicators were formed at the research stage when the public opinion information dissemination channel was single and unstructured text data was difficult to process. They can only indirectly depict the overall level of emotion through the completed transaction data, gradually exposing multiple inherent defects in the current Internet financial environment. They can only complete emotion statistics after the completion of the transaction, and cannot capture the public opinion signals fermenting in stock bar comments, financial news, and social platform discussions in real time; [2] At the same time, indicators can only reflect the overall market sentiment and cannot separate the emotional differences of different entities, making it difficult to distinguish the hierarchical transmission characteristics of professional media public opinion and ordinary retail investor sentiment.

At the same time, Li Xinhua proposed that early scholars mainly relied on questionnaire surveys and market proxy variables to measure investor sentiment. [3] Before 2000, the measurement of investor sentiment was mainly indirect, with questionnaire surveys as the core method. The "CCTV Watch" program in China has constructed the CCTV Watch Index BSI by inquiring and analyzing the views of 100 domestic securities investors on the future market, which has been widely used in early behavioral finance empirical research. However, the long-term practice of "CCTV viewing" has also exposed the inherent shortcomings of questionnaire based emotion measurement that are difficult to overcome.

(1) There is a selection bias in the sample, with institutional analysts being the main research subjects in the early stages and insufficient coverage of individual investors, making it difficult to fully reflect the true emotions of a large number of individual investors in A-shares;

(2) There is a significant lag in the questionnaire survey, and there is a time difference in the collection, statistics, and release of opinions, which makes it impossible to track the rapid changes in market sentiment in real time;

(3) The survey options are simple to set, only distinguishing between ups and downs, and cannot capture refined characteristics such as emotional strength and differentiation, let alone distinguish the differences between media emotions and individual investor emotions.

Overall, the traditional sentiment measurement methods mentioned above are unable to accurately observe investor sentiment indicators.

2.2. Systematic Compensation of Traditional Measurement Deficiencies by Artificial Intelligence Technology

Since 2010, breakthroughs have been made in machine learning and big model technology, giving rise to a new paradigm of emotion analysis. Unstructured texts such as news reports, social media posts, company reports, and various research reports have become carriers for directly measuring emotions. An increasing number of empirical studies have found that textual emotions can affect investor sentiment, which in turn affects the stock market. With the development of natural language processing and artificial intelligence technology, researchers have begun to parse text on a large scale. Artificial intelligence technologies represented by natural language processing and text mining are the core tools for processing unstructured text.

This research paradigm can be traced back to Tetlock's classic study [4], which for the first time incorporated financial news texts into the emotion measurement system, proving that media text emotions can predict stock market fluctuations, breaking away from the traditional research framework of relying solely on trading data. With the iteration of machine learning algorithms, Bollen et al. further included public texts on social platforms in their analysis scope [5], and used AI emotion classification models to extract public opinion tendencies. Empirical results showed that text-based emotion indicators had better predictive performance than traditional trading indicators. Different from lagging transaction data, AI can perform real-time semantic analysis on daily news, posts, and comments, transforming scattered and fragmented public opinion into analyzable emotional signals, solving the core problem of insufficient timeliness of traditional indicators. The integration of AI technology precisely addresses the shortcomings of traditional sentiment measurement methods mentioned above, forming a systematic compensation and becoming a new research paradigm for investor sentiment observation.

At the same time, the development of generative artificial intelligence has further expanded the boundaries of emotion research. National Research Network pointed out that generative AI can identify false public opinion and hype information generated by algorithms, filter out the interference of noisy public opinion on emotion measurement, and further improve the accuracy of emotion indicators [6].

2.3. Technological Evolution Brings About a Paradigm Shift in Research

Overall, traditional transactional sentiment indicators are constrained by data format and measurement logic, and have shortcomings such as time lag, single dimensions, and inability to utilize textual public opinion; Artificial intelligence technology, with its advantages of massive text processing, real-time emotion analysis, and multi-layer emotion decomposition, systematically compensates for the core shortcomings of traditional measurement methods, and promotes the shift of investor sentiment research from "transaction result backtracking" to "pre observation of public opinion signals". It is also an important development direction in the intersection of behavioral finance and intelligent finance.

3. The Transmission Path of Investor Sentiment Affecting Short-Term Fluctuations in the Stock Market

Investor sentiment significantly influences short-term fluctuations in the stock market. The efficient market hypothesis posits that stock prices are determined by fundamental corporate information, which struggles to explain the frequent and intense short-term fluctuations observed in the capital market. Behavioral finance theory incorporates investor sentiment into the asset pricing analysis framework. Numerous studies have confirmed that sentiment does not directly affect stock prices. Instead, it relies on information dissemination, individual trading, and herd contagion to form a multi-layered transmission chain, ultimately amplifying short-term fluctuations in the stock market. Based on existing research, investor sentiment primarily impacts the market through three pathways: layered transmission of sentiment via media, noise trading, and a positive feedback loop of herding behavior. These three

pathways exhibit a clear progressive logic: information shapes sentiment (pathway one) → sentiment is transformed into individual trading behavior (pathway two) → individual behaviors aggregate and amplify, forming positive feedback fluctuations at the market level (pathway three). These pathways cascade from the information end to the trading end, collectively forming a complete closed loop of sentiment shocks.

3.1. Hierarchical Information Transmission Path from Media Sentiment to Retail Sentiment

The first path involves the hierarchical transmission of information from media sentiment to retail sentiment. In classic theoretical literature, Mullainathan & Shleifer proposed that the media is not an objective and neutral information carrier, but rather can exhibit selective narratives and biased viewpoints, laying a theoretical foundation for the transmission of media sentiment [7]. Tetlock was the first to empirically confirm that media sentiment embedded in financial news texts can significantly predict short-term market fluctuations. As the source of public information dissemination, financial media are the first to generate biased media sentiment. After relevant information flows through online platforms, it is received by ordinary individual investors, thereby shaping retail sentiment [4].

Recent empirical research: Liu Wenjuan further distinguished between media sentiment and retail sentiment, pointing out that there are significant conduction time lags and effect differences between the two [2]. Media sentiment can spread through news reports, social media, and other channels, affecting investors' emotional states. Media views first flow into social platforms and stock forums, gradually influencing the cognition of ordinary retail investors. The two types of sentiment do not change synchronously, and traditional sentiment measurement indicators cannot identify this hierarchical structure. Li Xinhua proposed based on text big data research that with the acceleration of information diffusion in the Internet era due to massive unstructured text, sentiment spreads rapidly through online media, laying the foundation for short-term market fluctuations. This is also the core reason why analyzing text sentiment with natural language processing technology has short-term market prediction value [3]. He Yong confirmed based on A-share short videos and stock forum text data that the hierarchical conduction effect of media sentiment to retail sentiment is stronger in the A-share market where retail investors account for a higher proportion [8].

From the perspective of empirical evidence strength, the evidence level of this path is relatively high. It has both mature theoretical models and a large number of time series empirical studies based on news, stock forums, and social media texts, which have been repeatedly verified in both domestic and foreign markets. The limitation lies in the fact that this path only completes the generation and diffusion of emotions, bringing only expected changes at the level of expectations. It does not directly cause stock price fluctuations and requires subsequent trading channels to be implemented.

3.2. Micro-fluctuation Path Driven by Noise Trading

The second path is the noise trading channel, which is also the micro-core of how sentiment translates into price fluctuations. Classical theoretical literature: De Long et al. (1990) constructed the DSSW noise trader theoretical model, pointing out that there are a large number of noise traders in the market who do not make decisions based on fundamentals. Their irrational beliefs can directly cause asset prices to deviate from intrinsic value, laying the theoretical foundation for noise trading-asset volatility [9]; Black (1986) proposed the concept of noise trading, distinguishing between rational information traders and noise traders, and arguing that noise can induce short-term price disturbances [10].

Recent empirical research indicates that a significant number of retail investors in the market are noise traders, relying on emotions, public opinion, and gossip for their trading decisions, rather than fundamental corporate data. When optimistic sentiment spreads, noise traders tend to buy in a concentrated manner, driving stock prices away from their intrinsic value; when pessimistic sentiment prevails, there is a concentrated selling behavior. Bollen demonstrated through research based on social text sentiment that noise trading driven by emotions can lead to short-term excess volatility [11]. Li Xuefeng conducted an empirical study on the A-share market, showing that noise trading is an important source of short-term volatility in the stock market, and its activity significantly increases during periods of high market sentiment [12]. Shen Kunrong and Fang Wenquan extended the DSSW model, proving that in China's market environment with a high proportion of retail investors, noise trading further enhances the short-term price impact effect [13]. Under traditional measurement methods, it is difficult for scholars to capture the noise trading tendencies of retail investors on a large scale. However, artificial intelligence text mining can continuously monitor changes in retail investor sentiment, identify the rise and decline of noise trading, and effectively explain the impact mechanism of emotional fluctuations on short-term stock prices.

Empirical evidence strength: This path has a high level of evidence, with a comprehensive behavioral finance foundation model. A large number of domestic empirical studies have been tested based on A-share trading data and stock forum texts. This path follows the market sentiment output from the previous path, transforming public sentiment and psychological emotions into real individual trading orders. It serves as the micro-execution carrier of the entire transmission chain. Without the actual orders placed by noise traders, the sentiment diffused by the media will only remain at the cognitive level and will not lead to price changes.

3.3. Positive Feedback Loop Fluctuation Path Triggered by Herd Effect

The third path is the dynamic positive feedback loop driven by herd behavior. Classical theoretical literature: Bikhchandani proposed the information cascade theory to explain the logic behind herd behavior. Investors, under conditions of information uncertainty, abandon private signals and imitate group behavior, forming consistent trading decisions [14]; Banerjee constructed a basic theoretical model of herd behavior, demonstrating how individual imitative behaviors converge into a market-level force of same-direction trading [15].

Recent empirical research indicates that a significant number of retail investors rely on general large models for investment advice, weakening their ability to think independently and contributing to consistent trading behaviors. Li Bingyu proposed in his research on herding

behavior and generative AI that generative AI serves as an information intermediary to unify market narratives, and social networks accelerate emotional convergence, which can easily lead to consistent, directional trading and amplify short-term market volatility [16]. Uliari proposed the algorithm imitation effect, stating that when a large number of investors use similar large models to obtain investment views, market narratives tend to become homogenized, significantly increasing the probability of herding behavior [17]. Financial views generated by AI spread rapidly through stock forums and social media, accelerating the contagion of market sentiment and thus amplifying short-term fluctuations in the stock market. Once the sentiment is fully released, stock prices usually return to fundamentals, resulting in the common phenomenon of short-term spikes and rapid corrections in the stock market.

Empirical evidence strength: The evidence for traditional herding behavior in this pathway is high; however, the amplification of herding effects by generative AI is an emerging direction with moderate empirical evidence. The existing research mainly focuses on panel regression and behavioral experiments, and large-sample long-term time series evidence still needs to be supplemented. This pathway is an amplification stage based on the previous two steps: after the media completes emotional rendering and noise traders complete their first transactions, the positive feedback loop of herding further amplifies the transaction scale, transforming local individual irrational transactions into short-term severe fluctuations at the market-wide level.

3.4. Coordination Mechanism of the Three Conduction Paths

Overall, the three transmission paths are intertwined and work synergistically to form a complete progressive transmission loop of "information rendering - individual trading - group amplification".

(1) The layered transmission of media sentiment is responsible for the initial shaping and diffusion of market sentiment, laying the foundation for the overall market expectation tone. This stage belongs to the information input phase, outputting an overall optimistic or pessimistic sentiment atmosphere in the market, but it does not directly cause price fluctuations.

(2) Noise trading serves as a micro-trading medium for emotional expression, converting public sentiment into tangible buying and selling actions. Following the media's amplifying of market sentiment, noise traders are the first to transform psychological expectations into actual orders, triggering the initial round of price fluctuations. They act as an intermediary bridge connecting emotional perception and market prices.

(3) The herd effect amplifies the intensity of emotional shocks through a positive feedback mechanism, exacerbating short-term stock price deviations. When noise trading brings about initial price movements, fueled by social media and generative AI narratives, more investors follow suit, and the same-direction trading behavior continuously reinforces itself, amplifying the magnitude of fluctuations. When emotional energy is exhausted, prices return to fundamentals, completing a complete round of short-term market volatility.

4. The Research Gap, New Risks, And Response Paths Brought by Generative Artificial Intelligence to The Emotion Analysis Market

Relying on natural language processing to achieve text mining and construct investor sentiment indicators is a long-term research direction in the field of behavioral finance. As mentioned earlier, traditional emotional measurement methods such as questionnaire surveys have limitations in sample size and weak timeliness, while artificial intelligence text mining technology can capture massive amounts of unstructured text such as stock bars and financial news, effectively filling the gaps of traditional measurement methods [1, 4]. However, early research was mostly based on basic machine learning and shallow pre trained language models, with research materials limited to financial texts created by humans, and did not fully discuss the new issues arising from the intervention of generative large models in capital market information dissemination. With the rapid implementation of generative artificial intelligence, existing research on investor sentiment is gradually showing a clear gap, while giving rise to a series of new market risks.

4.1. Current Research Gaps in the Field

From the perspective of emotional transmission mechanisms, firstly, most literature has severed the interactive relationship between media emotions, individual investor emotions, and information generated by artificial intelligence. Previous studies have mainly focused on human generated financial texts, with default information sources being news media and retail communities, and a lack of analysis on the emotional transmission mechanism of AI generated texts [3]. How financial information and investment perspectives generated by large-scale models can participate in hierarchical information transmission, and whether AI led emotional narratives will change the efficiency of transmitting media emotions to retail investor emotions, are also prominent research gaps in the current literature system. Some studies have begun to focus on the impact of AI generated text on financial markets, "Social Finance in the Age of AI: Evidence from Machine-Generated Content" It is pointed out that machine generated content is reshaping the information ecology of the capital market, but a hierarchical transmission analysis framework for investor sentiment has not yet been constructed [18].

Secondly, existing research lacks a systematic discussion on the emotional resonance caused by algorithm homogenization. The research on herd behavior and generative AI by Guoyan Network suggests that the popularization of generative AI can easily lead to algorithm level herd behavior [6]. However, most existing theories on investor sentiment are based on the irrational behavior of human investors, and have not yet established an analysis framework for herd behavior in the context of AI participation in information dissemination, making it difficult to fully explain the emotional evolution laws of human-machine participation in market information interaction.

4.2. New Market Risks Derived from Generative Artificial Intelligence

At the same time, generative artificial intelligence also brings new risks that traditional emotion research cannot cover.

(1) Risk of financial information pollution. Market entities use generative artificial intelligence to generate false and biased financial texts in batches at low cost, deliberately guiding the market to form irrational emotions. Massive amounts of forged information are mixed into online public opinion data sources, misleading retail investors to make irrational trading decisions and exacerbating abnormal stock price fluctuations; On the other hand, it interferes with the measurement of investor sentiment based on text mining, causing systematic bias in sentiment indicators and reducing the effectiveness of sentiment analysis results. For example, some illegal individuals use AI to fabricate "major positive/explosive announcements for enterprises" in batches, which spread on major financial forums, quickly driving optimism or panic among retail investors, and taking the opportunity to manipulate stock prices.

(2) Algorithm convergence risk. A large number of institutions using similar large-scale models for sentiment analysis can lead to highly homogeneous sentiment signals for market participants, triggering synchronous trading behavior and amplifying short-term stock market volatility.

(3) Big model black box risk. The "black box" nature of large models leads to insufficient interpretability of emotional signals. Once erroneous market expectations are formed based on AI emotion analysis, the speed of risk propagation will far exceed traditional information channels. Market entities may use the "black box" model to implement selective architecture design, and even abuse their market dominance for data exploitation [19].

4.3. Governance Response Path for Related Risks

Overall, generative artificial intelligence has expanded the boundaries of investor sentiment observation, but existing theoretical frameworks and empirical paradigms are lagging behind, requiring governance measures to be implemented from multiple perspectives including market entities, technology, and regulation.

(1) Promote the construction of diversified institutional models and avoid model homogenization. Encourage financial institutions to use differentiated large models and different dimensions of public opinion datasets for sentiment analysis, to prevent market entities from using highly unified analysis tools and to avoid synchronous trading behavior amplifying stock market volatility.

(2) Improve the theoretical and empirical research system. Future research needs to incorporate AI generated content into a complete emotional transmission system, improve new risk identification pathways, and construct an investor sentiment analysis framework that is adapted to the human-machine coexistence market environment.

(3) Establish a sound industry regulatory system. Accelerate the implementation of regulatory rules related to generative AI financial applications, clarify the legal responsibilities for using AI to create false financial information and manipulate the market; Establish an access, testing, and normalized regulatory system for financial models, and build a risk defense line at the institutional level.

5. Conclusion

In summary, investor sentiment is an important irrational factor driving short-term fluctuations in the stock market, effectively compensating for the deficiencies of the traditional efficient market hypothesis in explaining abnormal market fluctuations. Investor sentiment primarily affects the short-term performance of A-shares through three progressive paths: hierarchical transmission of media sentiment, noise trading drive, and positive feedback loop of herding effect, forming a complete transmission loop from information diffusion, individual trading, to group resonance. Compared to traditional questionnaire surveys and proxy indicator measurement methods, text sentiment mining based on natural language processing can hierarchically identify media sentiment and retail sentiment, significantly improving the timeliness and accuracy of sentiment measurement. However, in the new scenario where generative artificial intelligence is fully integrated into financial information dissemination and investment decision-making, the traditional sentiment transmission mechanism and research paradigm show significant inadequacy in adaptability.

This paper presents two core research insights. Firstly, the impact of investor sentiment on stock market volatility is not a single sentiment shock, but a systematic transmission process that is layered, progressive, and closed-loop. The media shapes expectations, noise trading manifests prices, and herd behavior amplifies volatility, which together constitute the core logic of short-term market fluctuations. Secondly, generative AI does not simply optimize traditional sentiment research tools, but reshapes the way sentiment is generated and transmitted in financial markets. Algorithmic homogenization narratives, AI-generated fake information in bulk, and intelligent herd trading have given rise to new types of stock market volatility risks that traditional theories cannot cover.

Based on the deficiencies in this study and the existing research gaps, future research can be deepened from three aspects. Firstly, a multi-level emotional interaction analysis framework under the scenario of human-machine symbiosis can be constructed, incorporating media, retail investors, and AI narrative subjects, to clarify the variation mechanism of emotional transmission paths under AI intervention. Secondly, an interpretable and noise-resistant AI financial sentiment recognition model can be developed to filter AI false information pollution and enhance the stability of sentiment analysis in extreme market environments. Thirdly, an emotional risk tracing and early warning mechanism can be established for algorithmic herding effects, and a new market fluctuation supervision system can be constructed based on the homogenization characteristics of algorithms. While leveraging the advantages of intelligent text analysis technology, it can achieve the standardized and intelligent upgrading of capital market sentiment governance.

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