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Article

Algorithm for predicting financial investor behavior based on biomechanical data and planning recognition

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Abstract: In complex and volatile financial markets, investor behavior is an important factor driving market volatility. Traditional studies have mostly relied on methods such as financial market data, questionnaires and psychological scales, but these methods have limitations such as data lag, subjectivity and difficulty in quantification. In recent years, with the development of biomechanics and neuroscience, researchers have begun to explore the use of biomechanical data to predict the behavioral trends of financial investors, which provides a new perspective and methodology for financial market research. This study aims to predict financing behavior in the stock market by constructing an investor sentiment index and combining it with a planning recognition model. Based on the close relationship between biomechanics and emotions, the biomechanical representations of different emotions of investors and their effects on behavior are dissected. Meanwhile, the partial least squares method is used to construct the investor sentiment index, and a planning identification model consisting of Markov chain, planning identification graph and expected utility function is introduced to predict the stock market trend and financing behavior, which is more accurate than the Markov model based on objective data only. In order to enrich the theoretical system of financial market prediction through this study, it provides more accurate market prediction and investment advice for financial institutions and investors. By introducing biomechanical data and planning recognition model, it provides new ideas and methods for understanding the intrinsic connection between investor sentiment and market volatility, and promotes the development of financing business in the domestic market as well as maintains the health and stability of the domestic stock market.

Keywords: investor sentiment; planning recognition; PLS; financing behavior

1. Introduction

In financial markets, investor behavior plays a key role in market volatility. Traditionally, Almeida and Gonçalves held that research on investor behavior mainly relies on methods such as financial market data, questionnaires, and psychological scales, but these methods have limitations such as data lag, subjectivity, and difficulty in quantification [1]. Since 2015, with the development of biomechanics and neuroscience, researchers have begun to explore the use of biomechanical data to predict the trend of financial investor behavior, which opens up new perspectives and methods for financial market research to open up new perspectives and methods.

The research by Kléber and Veras [2] shows that investor sentiment is significantly correlated with stock market fluctuations, which has been verified in numerous market fluctuations from 2010 to 2020. Optimistic investors drive the market up, while pessimistic investors may cause the market to fall, and this sentiment-driven market behavior affects both short-term volatility and may also play a role in long-term market trends. Therefore, Cheema and Fianto [3] argue that accurately identifying and predicting investor sentiment is of great significance for understanding market fluctuations and formulating investment strategies. Biomechanical data, such as body posture, movement mobility, and muscle tone, are important vectors of emotional expression. Van Oeveren et al. [4] argue that the biomechanical features of the human body vary significantly in different emotional states, for example, optimism is characterized by open and relaxed body posture, while pessimism is characterized by tense and stiff body. Lohr et al. [5] Scholars believe that from 2017 to 2023, sensor technology, artificial intelligence and big data technology developed rapidly, and the ability of acquisition and analysis of biomechanical data was significantly improved. Modern sensors can monitor the biomechanical properties of human beings in real time and automatically process and analyze them by algorithms, while artificial intelligence technology makes it possible to extract useful information from complex data [5]. Yuan et al [6]. and other scholars believe that these technological advances after 2022 provide strong support for using biomechanical data to predict the behavioral trends of financial investors.

Applying biomechanical data to financial investor behavior prediction research can help to deeply understand the intrinsic connection between investor sentiment and market volatility on the one hand, and provide financial institutions and investors with more accurate market predictions and investment advice on the other hand, as well as provide new ideas and methods for the regulation of the financial market to promote the healthy and stable development of the financial market.

2. Biomechanics and investor emotions

2.1. Interaction between biomechanics and emotion and regulatory mechanisms

Biomechanics is a discipline that applies the principles and methods of mechanics to study the mechanical phenomena within the organism and its interaction with the external environment. It integrates the knowledge of multiple disciplines, such as physics, engineering, biology and medicine, and aims to reveal the behavioral laws of organisms in a mechanical environment and their intrinsic connection with life activities through quantitative means [7]. Its research object is wide-ranging, covering the structure of living organisms at different levels from the macroscopic biological whole and organ systems to the microscopic cells and molecules [8]. Yeadon et al. argue that at the macroscopic level, biomechanics focuses on studying the laws of motion, postural control, and mechanical properties of the skeletal-muscular system of organisms. At the microscopic level, it delves into the mechanical properties of biomolecules and the mechanical behaviors of the cytoskeleton. By applying the principles and methods of mechanics, biomechanics can quantitatively describe the mechanical state of organisms, analyze the internal conditions of organisms and their interaction processes with the external environment, and provide new perspectives and tools for understanding life phenomena [9].

There is a close mutual influence relationship between biomechanics and emotion, by consciously adjusting the biomechanical state of the body, it is possible for people to improve their emotional state and enhance their mental health, and from the biomechanical point of view, physiological manifestations such as body posture, movement and muscle tension are deeply affected by the emotional state [10]. When a person is in a negative emotional state such as tension and anxiety, the body tends to show biomechanical features such as muscle tension and stiff posture, such as shoulder shrugs and tight back. These changes in the body not only reflect the internal emotional state, but also further alter the biomechanical state of the body, which may affect the body's blood circulation, respiratory efficiency, and other physiological functions [11]. Conversely, changes in biomechanics may also have a feedback effect on emotions. Maintaining good body posture and movement habits can promote blood circulation and smooth breathing in the body, which helps to relax the body muscles, which in turn positively affects mood and makes people feel calmer and more comfortable [12]. On the contrary, poor posture and movement habits may lead to physical discomfort and increase the feeling of stress in the body, thus further worsening the emotional state. In addition, some specific exercises and physical activities can effectively improve the emotional state by adjusting the biomechanical state of the body, such as enhancing body flexibility and coordination, and relaxing the muscles [13].

2.2. Research on the application of biomechanical data in the prediction of financial investor behavior

Although the application of biomechanical data in finance has not yet been directly studied, existing research has provided a solid theoretical foundation for its potential in the prediction of financial investor behavior [14]. Numerous studies have shown that there is a significant relationship between investor sentiment and financial investor behavior. Behavioral finance, as a discipline that studies the impact of investors' psychological factors on the market, has revealed how investor sentiment affects investment decisions, asset pricing, and overall market movements [15]. When optimism is prevalent in the market, investors may overchase the market, leading to market bubbles, while when pessimism is prevalent in the market, investors may overkill the market, triggering market panic [16]. These studies emphasize the importance of emotions in financial markets. Second, research in the field of biomechanics has shown that biomechanical features such as body posture, movement and muscle tension are affected by emotional states [17]. When a person is in a negative emotional state such as tension or anxiety, the body tends to experience muscle tension and stiff posture, and these biomechanical changes can be considered as external manifestations of the emotional state [18]. Conversely, biomechanical adjustments may also have a positive impact on mood, such as good body postures and movements that can promote relaxation and improve mood states [19].

The application of biomechanical data in finance is gradually gaining attention, and biomechanical data may indirectly predict the behavioral trends of financial investors through the mediating role of emotions [20]. This potential research direction has theoretical feasibility and potential for practical application. Through in-depth analysis of investors' biomechanical characteristics, it is possible to gain insights into their emotional states and thus predict their investment decisions and market behaviors.

1) Biomechanical expressions of optimism and financial investor behavior

When investors are in a state of optimism, their biomechanical expression may be reflected in an open and relaxed body posture, such as lifting the chest, head up and smiling. This positive body language not only reflects the investor's inner confidence and expectation, but may also be transmitted to other market participants through nonverbal means, which in turn affects the emotional climate of the whole market [21]. In the financing and securities financing business, optimistic investors may be more inclined to carry out financing and buying operations because they believe that the market will continue to rise, thus exacerbating the optimistic expectations and volatility of the market.

2) Biomechanical expression of calm emotions and financial investor behavior

Investors with calm emotions may be biomechanically expressed by a natural and stable body posture, with no apparent muscle tension or postural rigidity. They may be more rational and cautious in making investment decisions and less susceptible to market mood swings. In the financing and securities financing business, investors with calm emotions may pay more attention to risk control and avoid excessive financing or securities financing, thus contributing to the stability of the market [22].

3) Biomechanical expression of pessimism and financial investor behavior

Pessimistic investors may biomechanically exhibit tension and stiffness in body posture, such as shrugging shoulders, hunching back, and stony facial expressions. This negative body language may reflect the investor's concern and uneasiness about the market outlook. In the financing and securities financing business, pessimistic investors may be more inclined to engage in securities financing and selling operations because they anticipate that the market will fall, which may exacerbate pessimism and volatility in the market.

To ensure the accuracy and reproducibility of the study, the openness of the body posture was quantified by measuring the angles of the shoulder and hip joints; motion capture technology was used to record the trajectory of the movements during trading operations, and the smoothness and speed of the movements were calculated to quantify the fluidity of the movements. Surface electromyography (EMG) technology was utilized to monitor EMG signals from key muscles during trading, and muscle tension was assessed by signal strength and frequency.

Biomechanical data is collected through the following steps: (1) Use of wearable devices integrated with inertial measurement units, surface EMG sensors, to ensure that the investor's body posture, movement fluidity and muscle tension can be accurately recorded; (2) Recruit investors from financial institutions and trading platforms to ensure a diverse and representative sample; (3) In a real trading environment, investors were allowed to wear the devices to perform trading operations while their biomechanical data and trading behavior were recorded; (4) Cleaning and pre-processing the collected raw data to eliminate outliers and noise to ensure the accuracy and reliability of the data.The specific results are shown in **Table 1**.

Table 1. Characterization of biomechanical expression in different emotional states.

State of mind	Biomechanical expression	Element
Optimism	Posture	Chest up, smile, body relaxed, show confidence and openness.
	Smoothness of movement	Quick and fluid movements and decisive decisions in trading operations reflect inner positivity and certainty.
	Muscle tension	Quick and fluid movements and decisive decisions in trading operations reflect inner positivity and certainty.
Calm	Posture	Natural and comfortable, without excessive movement or expression, he appears calm and collected.
	Rhythm of Movement	Trading operations are robust and organized, not rushed, and the decision-making process is relatively rational.
	Physiological indicators	Smooth breathing and normal heart rate reflect inner peace and stability.
Pessimism	Posture	Shrugged shoulders and hunched back, stony facial expression, body appears tense and restless.
	Tardy	Shrugged shoulders and hunched back, stony facial expression, body appears tense and restless.
	Muscle tension	Muscle tension or stiffness, which may be accompanied by involuntary trembling or twitching, indicates that the investor is feeling nervous and anxious.

In order to more accurately assess the impact of financing and securities financing business on stock market volatility, researchers have proposed to construct an investor sentiment index and apply it to the prediction of stock market financing behavior by combining with planning identification methods. This method not only relies on objective market data, but also fully considers the subjective emotional factors of investors, especially through the introduction of biomechanical features as part of the sentiment index (Newall and Weiss-Cohen) [23]. Biomechanical features can reflect investors' emotional states, such as the relaxation and openness of the body when optimistic and the tension and stiffness when pessimistic, etc., and these emotional expressions directly affect investors' investment decisions and market behavior. Therefore, incorporating biomechanical features into the research framework of financing and securities financing business can help to understand the root causes and mechanisms of market volatility in a more in-depth way, and provide strong support for promoting the healthy development of financing business and maintaining the stability of the stock market.

3. Build investor sentiment based on PLS

3.1. The PLS principle

PLS is a mathematical optimization method that builds a function model by minimizing the data error sum of squares, which is especially suitable for the case of data scarcity and complex parameters. When constructing the investor sentiment index, PLS technique can effectively improve the accuracy of the model as follows:

Assuming that equity earnings are linearly associated with current sentiment, namely:

$$E(R_{t+1}) = a + \beta M_t \tag{1}$$

Among them, the variable $E(R_{t+1})_t$ represents the investors' forecast of the next stock earnings, and M_t represents the investors' sentiment index.

Based on this, the next phase of the stock earnings can be expressed as follows:

$$R_{t+1} = E(R_{t+1}) + \varepsilon_{t+1} = a + \beta M_t + \varepsilon_{t+1} \tag{2}$$

Where ε_{t+1} represents the error term.

Let x_t indicate that the sentiment index of individual investors at time *t* can be expressed as follows:

$$x_t = \eta_0 + \eta_1 M_t + \eta_2 E_t + e_t \tag{3}$$

Where η_1 and η_2 represent x_t respectively, the variation sensitivity coefficient for M_t and E_t; E_t represent the common error term between all investor sentiment index and stock market forecast returns; e_t represent related noise x_t.

To separate x_t from M_t of Equation (3) and eliminate the effects of E_t and e_t. The OLS regression method was used.

First, establish the regression equation:

$$x_{t-1} = \pi_0 + \pi_1 R_t + U_{t-1} \tag{4}$$

where R_t represents stock returns in period *t*, π_1 represents the sensitivity of x_{t-1} to M_{t-1} through realized R_t, reflecting the sensitivity of x_{t-1} to M_{t-1}, R_t consists of $E(R_t)$ with error, and the expected return is mainly related to M_{t-1}, and thus, $x_{t-1}$is determined by M_{t-1} within certain limits. For each period *t*, the following regression equation is constructed:

$$x_i = c + M^{PLS}\pi_1' + v_i \tag{5}$$

Among them, M^{PLS} represents the investor sentiment index estimated by PLS, which is derived from Equation (4) and serves as the explanatory variable, while M^{PLS} is the parameter to be measured. As can be seen from the above derivation process, PLS is using Equations (2) and (3) to introduce M^{PLS}. PLS achieves the effect of dimension reduction by using the stock return of *t* + 1 period, so as to extract those related to the expected return and eliminate the common approximation error and noise unrelated to the expected stock return.

From the above derivation, the PLS method is based on Equations (2) and (3) to achieve dimension reduction by using *t* + 1 stock return, aiming to extract information related to the expected return M_t and eliminate irrelevant common approximation error and noise. Finally, the investor sentiment index can be expressed in the form of a *T* 1 order vector:

$$M^{PLS} = XJ_N X' J_T R (R' J_T X J_N X' J_T R)^{-1} R' J_T R \tag{6}$$

Where *X* is the *TN* order matrix, representing the measurement result of individual investor sentiment, namely $X = (x_1', \cdots, x_T')$; *R* is the *T* 1 order vector, which represents the yield rate, namely $R = (R_2, \cdots, R_{T+1})$; matrix $J_T = I_T - \frac{1}{T} l_T l_T'$, I_T is the vector of *T* order unit matrix and the elements of l_T are all 1. According to the mathematical derivation of Equation (6), the PLS method finally builds 6 models such as:

$$M^{PLS} = \beta X \quad (7)$$

Among them, $X = (X_1, \cdots, X_N)$ represents a single investor sentiment index, while $\beta = (\beta_1, \cdots, \beta_N)$ represents the proportion of each sentiment index of M^{PLS}.

3.2. Relevant indicators

Previous studies show that the construction of investor sentiment index covers two categories of indicators: Subjective survey index and indirect survey index. Specifically, the subjective survey indicators include the China Consumer Confidence Index (CCI) and the China Securities Market Investor Confidence Index (SICI), while the indirect survey indicators include the turnover rate (TURN), the number of new investors (NIA), and the closed-end fund discount rate (CEFD). Through the comprehensive use of these two indicators, the investor sentiment index can be effectively constructed.

3.3. The Construction of the investor sentiment index

When constructing the investor sentiment index, Yi Zhigao deliberately included the lag period of these indicators because of the possible time lag of the relevant indicators. First, all indices were standardized and the processed indicators were replaced into Equation (6) to obtain partial least squares (PLS) for model building M^{PLS}. Subsequently, M^{PLS} analyzed the correlation with each index to determine the degree of association between them. By comparing the correlation coefficient of index M^{PLS} in the previous stage, the index with high correlation coefficient is selected as the basis for the final construction of index M^{PLS} investor sentiment index. The specific results of the correlation analysis are shown in **Table 2**.

Table 2. M^{PLS} correlation coefficients with the ten indicators.

Indicator	CCI_{t-1}	$SICI_{t-1}$	$TURN_{t-1}$	NIA_{t-1}	$CEFD_{t-1}$
Pearson	0.4121	0.6822	0.7674	0.7143	−0.3251
Pearson	0.4234	0.6916	0.8682	0.8569	−0.3357

According to the data in the above table, the indicators with high correlation coefficient with *M* are the previous China Consumer Confidence Index (CCI_t), China Securities Market Investor Confidence Index ($SICI_t$), turnover rate ($TURN_t$), number of new investors (NIA_t) and discount rate of closed-end funds ($CEFD_t$). This indicates that there is a strong correlation between these indicators and M. Subsequently, we replaced these five indicators into Equations (6) and (7) again, and used the partial least squares method (PLS) for algorithm processing, and conducted the correlation analysis. The specific results are shown in **Table 3**.

Table 3. The result of construction of 1 M^{PLS}.

Index	CCI_t	$SICI_t$	$TURN_t$	NIA_t	$CEFD_t$
Pearson	0.4121	0.6822	0.7674	0.7143	−0.3251
Pearson	0.4234	0.6916	0.8682	0.8569	−0.3357

Based on the Beta values in **Table 3**, the expression of investor sentiment index M is obtained:

$$M^{PLD} = 0.1461CCI_t + 0.7283SICI_t + 0.8683TURN_t + 0.8642NIA_t - 0.2871CEFD_t \quad (8)$$

Using this equation, the investor sentiment index M^{PLS} for the period from April 2016 to March 2024 was calculated and the results are presented in **Figure 1** below.

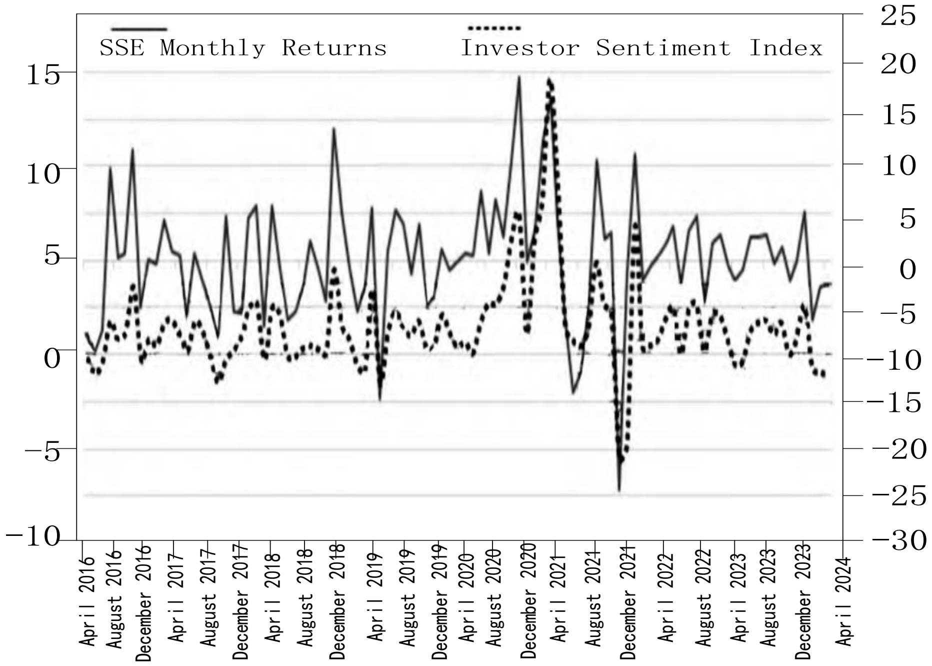

Figure 1. The relationship between the yield rate of the Shanghai Composite Index and the investor sentiment index.

The state of contrast M^{PLS} can be divided into three states: Optimistic, pessimistic and calm. When the investor sentiment index constructed based on the biomechanical data is between −0.5 and 0.5, the investor is in a calm state. At this time, the biomechanical expression may be natural and stable body posture, steady and orderly action rhythm, and physiological indicators such as stable breathing and normal heart rate. When the investor sentiment index is greater than or equal to 0.5, investors are in an optimistic state. The biomechanical expression is reflected in the open and relaxed body posture, such as chest-up, smiling, smooth and rapid action, decisive decision-making, moderate muscle tension and show a confident and open attitude. When the investor sentiment index is less than or equal to −0.5, the investor is in a pessimistic state, the body posture tension and stiff, such as hunched, facial expression dignified, slow movement, muscle tension or stiffness, may be accompanied by involuntary trembling or convulsions.

In order to verify the relationship between biomechanical indicators and investors' emotional state, correlation analysis and significance tests were performed. The results showed that there was a significant correlation ($r = 0.72$, $p < 0.01$) between shoulder and hip angles and investor mood state, and that open body posture was significantly associated with optimism, whereas tense body posture was significantly associated with pessimism. Smoothness and speed of movements also showed significant correlations with investor emotional states ($r = 0.68$, $p < 0.01$), with smooth movements correlated with optimism and sluggish movements correlated with pessimism. The intensity and frequency of EMG signals also showed a significant correlation with investor mood state ($r = 0.75$, $p < 0.01$), with tense muscles significantly correlated with pessimism and relaxed muscles correlated with optimism.

4. Planning recognition model

In the process of developing the planning identification model, a three-layer structure is designed: The first layer utilizes the Markov chain to forecast the future movements of the stock market in order to reveal potential changes in the stock market trend; the second layer calculates the final probability prediction by integrating the planning identification graph with the investor sentiment index in the second layer; and in the third layer, the utility function is applied to screen the optimal financing decision for the investor.

4.1. Layer 1: Markov modeling

Markov process, proposed by Russian mathematician Andrey Markov in 1907, is a model that describes stochastic phenomena. Its core property is that the future state of a system depends only on the current state, not on the past state, a property known as "no posteriority". In the field of stock market forecasting, investors rely on Markov models to make trend forecasts that are not based on historical trends, but rather focus on the current state of the stock market. Therefore, Markov models provide an effective method for stock market forecasting by utilizing the transfer probabilities of states to predict future stock market movements.

4.2. Layer 2: Planning recognition map

In 1986, Kautz and Allen first formalized the theory of planning recognition by constructing the Kautz planning recognition model based on minimal behavioral actions, which centers on solving the planning recognition by graph covering problem. After decades of development, Goldman, Geib and Miller et al. proposed a novel planning recognition model that focuses on the execution process and computes the corresponding probabilities at each execution stage to reason about the subsequent execution paths. Compared with the Kautz model, which relies on minimal behavioral actions, the new model makes the prediction results more reasonable and close to the actual behavior through probabilistic inference. The application of planning recognition to stock market trend prediction, combined with investor psychological analysis, can significantly improve the accuracy of prediction results and market fit, which is of great significance for optimizing investors' financing decisions and promoting the stable development of the stock market. The construction of the planning recognition graph follows the following steps:

1) Determine the initial state target of the stock market at time step 1;
2) Subdivide investor sentiment into optimistic, calm and pessimistic states;

3) Calculate the probability distribution of the stock market trend for each state of sentiment;
4) Determine the trend of the stock market in different emotional states based on these probabilities;
5) Synthesize the percentage of each state to arrive at a probabilistic prediction of the overall state of the stock market.

The investor sentiment state is represented by the symbols a_1, a_0, a_{-1}, respectively, optimistic, calm, pessimistic, corresponding to the probability of $P(a_1)$, $P(a_0)$, $P(a_{-1})$; the stock market trend state is represented by the symbols P_1, P_0, P_{-1}, respectively, rising, flat, falling, corresponding to the probability of $P(P_1)$, $P(P_0)$, $P(P_{-1})$, The new states and their share coefficients under different combinations of stock market trend and investor sentiment are shown in **Table 4**.

Table 4. Description of symbols.

State of Affairs	**Percentage share (*N*)**
$a_1\&\&P_{-1}$	η_1
$a_0\&\&P_{-1}$	η_2
$a_{-1}\&\&P_{-1}$	η_3
$a_1\&\&P_0$	η_4
$a_0\&\&P_0$	η_5
$a_{-1}\&\&P_0$	η_6
$a_1\&\&P_1$	η_7
$a_0\&\&P_1$	η_8
$a_1\&\&P_1$	η_9

These new states and ratio coefficients help to further analyze the relationship between biomechanical data and financial investor behavior, and can more accurately predict the behavioral trends of financial investors through the comprehensive consideration of investor emotional states and stock market trend states. For example, when investors are in an optimistic mood state, if the stock market shows an upward trend, their behavior may be more proactive and they may increase the amount of investment or conduct more risky investment behaviors; while when investors are in a pessimistic mood state and the stock market is trending downward, investors may take a more conservative investment strategy, such as reducing the investment or conducting risk aversion operations. By analyzing these states and ratio coefficients, we can gain insights into the behavioral changes of investors in different moods and market trends, and provide more valuable references for forecasting and investment decisions in the financial market.

Following the construction process of the planning identification diagram, **Figure 2**, a planning identification diagram incorporating probabilistic analysis, is finally generated. With the help of this diagram, it is possible to select the most appropriate decision-making program based on probabilistic assessment.

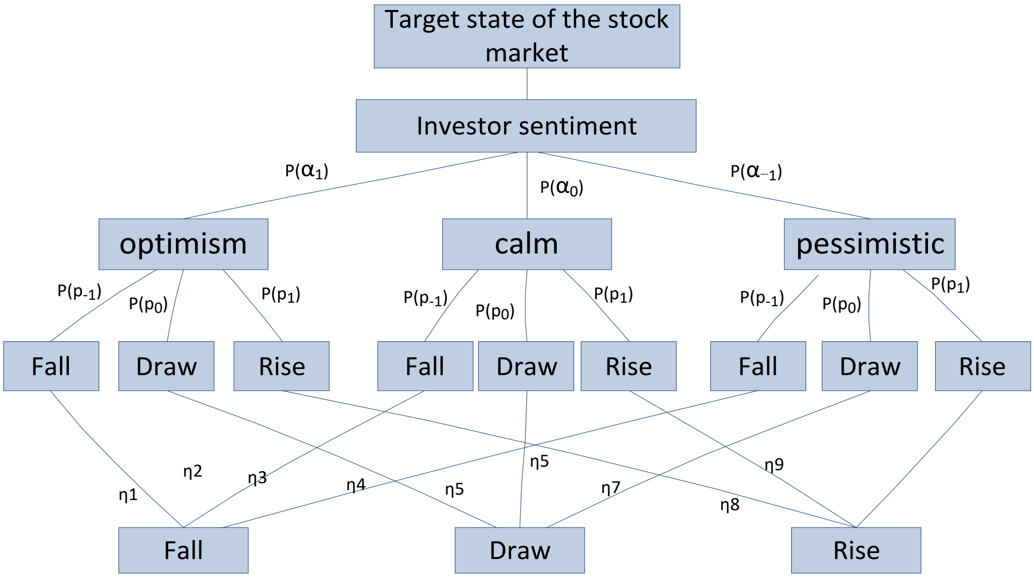

Figure 2. Planning Identification Fig.

Based on **Figure 2**, the calculation equation s for the probabilities of each state of the stock market in combination with investor sentiment can be summarized as follows:

1) Stock market decline state

$$P'(P_{-1}) = \delta_1[\eta_1 P(a_1)P(P_{-1}) + \eta_2 P(a_0)P(P_{-1}) + \eta_3 P(a_{-1})P(P_{-1})] \tag{9}$$

2) Stock market flat/stable state

$$P'(P_0) = \delta_2[\eta_4 P(a_1)P(P_0) + \eta_5 P(a_0)P(P_0) + \eta_6 P(a_{-1})P(P_0)] \tag{10}$$

3) Stock market rally state

$$P'(P_1) = \delta_3[\eta_7 P(a_1)P(P_1) + \eta_8 P(a_0)P(P_1) + \eta_9 P(a_{-1})P(P_1)] \tag{11}$$

Where: δ (i = 1, 2, 3) represents the normalization factor.

4.3. Third layer: Decision-making and reasoning layer

Given the differences in investors' expectations and risk tolerance, the expected utility function is introduced to guide investors in making rational decisions under specific conditions, thereby avoiding market fluctuations caused by blind investments and promoting the healthy development of the stock market.

In the third layer of the model, the expected utility function is integrated, with key parameters including:

1) Stock market states (representing stock market rally, flat P_1, P_0, P_{-1} stable, and decline, respectively)

$$\Omega = (P_{-1}, P_0, P_1) \tag{12}$$

2) Decision-making financing options (representing buying as ω_1, selling as ω_0, and holding as ω_{-1})

$$A = (\omega_1, \omega_0, \omega_{-1}) \tag{13}$$

3) Average loss rate and return rate of the stock market:

$$\begin{cases} \lambda_{-1} & \text{Average loss rate} \\ \lambda_0 & \lambda_0 = 0 \\ \lambda_1 & \text{Average rate of return} \end{cases} \tag{14}$$

Combining the weighted stock market trend probabilities derived from the planning recognition layer with the expected utility function, the expected income (Income) is calculated:

$$Income = \sum_{i \in (-1,0,1)} \lambda_1 P'(\beta_i) \tag{15}$$

Ultimately, the corresponding decision ω_1 will be made based on the value of the expected income (Income).

$$\begin{cases} \omega_{-1} & Income < 0 \\ \omega_0 & Income = 0 \\ \omega_1 & Income > 0 \end{cases} \tag{16}$$

If the expected income (Income) is positive, the decision is to buy; if it is negative, the decision is to sell; if Income is exactly zero, the strategy is to hold.The real-time update characteristics of the biomechanical data are fully considered in the implementation of the planning recognition model. The model goes through a pre-processing step by integrating a real-time data stream processing module to ensure the quality and consistency of the data.

5. Experimental results and discussion

5.1. Dataset

This study uses the monthly rise and fall data of the Shanghai Composite Index for a total of 96 months from April 2016 to March 2024, and based on this, an investor sentiment index is constructed as an observation and analysis object.

5.2. The first layer processing of planning recognition algorithm

The number of transitions between the various states of the stock market trend is counted and the results are presented in **Table 5**.

Table 5. Number of status shifts.

$P_i \to P_j$	P_{-1}	P_0	P_1
P_{-1}	22	1	21
P_0	1	0	1
P_1	21	1	27

According to the data in **Table 5**, $P_{ij} = \frac{n_{ij}}{n_i}$ can be calculated (where n_{ij} represents the frequency of the stock market state shifting from P_i to P_j, and n_i represents the i th row, that is, the total frequency of the stock market state P_i).

Based on the above data, the one-step transition probability matrix T_1 of the stock market's rise and fall is further derived.

$$T_1 = \begin{pmatrix} 0.5 & 0.023 & 0.477 \\ 0.5 & 0 & 0.5 \\ 0.429 & 0.02 & 0.551 \end{pmatrix} \tag{17}$$

Given the initial state vector is P [1, 0, 0], the probability distribution of each state of the subsequent stock market can be predicted. The specific results are shown in **Table 6**.

Table 6. Future state of the stock market.

	Probability		
Time	$\boldsymbol{P(P_{-1})}$	$\boldsymbol{P(P_0)}$	$\boldsymbol{P(P_1)}$
2024–04	0.5	0.023	0.477
2024–05	0.466	0.021	0.513
2024–06	0.464	0.021	0.515
2024–07	0.463	0.021	0.515
2024–08	0.463	0.021	0.515
2024–09	0.463	0.021	0.515

According to the probability measured by the first floor of the planning identification, the financing behavior planning is formulated, and the results are shown in **Table 7**.

Table 7. The Markov model prediction results.

Time	**Forecast of the stock market status**	**Planning of the financing activities**
2024–04	fall	offtake
2024–05	rise	buy in
2024–06	rise	buy in
2024–07	rise	buy in
2024–08	rise	buy in
2024–09	rise	buy in

The number of transitions between investor sentiment states is counted, and the results are summarized in **Table 8**.

Table 8. Number of state shifts in investor sentiment.

$\boldsymbol{a_i \rightarrow a_j}$	$\boldsymbol{a_{-1}}$	$\boldsymbol{a_0}$	$\boldsymbol{a_1}$
a_{-1}	19	7	13
a_0	9	1	7
a_1	11	9	19

From **Table 8**, we can calculate $P_{ij} = \frac{n_{ij}}{n_i}$ (where n_{ij} represents the frequency of investor sentiment state shifting from a_i to a_j, and n_i represents the total number of rows i, that is, the frequency of investor sentiment state a_i).

Then the one-step transition probability matrix 11 of investor sentiment state is obtained:

According to the data in **Table 8**, we can calculate the transition frequency $P_{ij} = \frac{n_{ij}}{n_i}$ between investor sentiment states (n_{ij} represents the number of times a_i shifts from state to state) and the total frequency of each row. Based on this, the one-step transition probability matrix a_j of investor sentiment state is further derived T_2:

$$T_1 = \begin{pmatrix} 0.487 & 0.18 & 0.333 \\ 0.529 & 0.059 & 0.412 \\ 0.282 & 0.231 & 0.487 \end{pmatrix} \tag{18}$$

Given the initial state vector P [1, 0, 0], the probability distribution of the subsequent investor sentiment state can be predicted (**Table 9**):

Table 9. Probabilities of the future state of investor sentiment.

	Probability		
Time	$\boldsymbol{P(a_{-1})}$	$\boldsymbol{P(a_0)}$	$\boldsymbol{P(a_1)}$
2024–04	0.487	0.18	0.333
2024–05	0.426	0.175	0.399
2024–06	0.412	0.178	0.41
2024–07	0.41	0.179	0.411
2024–08	0.41	0.179	0.411
2024–09	0.41	0.179	0.411

5.3. Second layer processing of row identification algorithm

Combined with the stock market rise and fall of the next few months predicted by the algorithm and the probability of investor sentiment state, the stock market planning identification map is constructed to integrate investor sentiment into the stock market trend analysis. The calculation, the probability of the stock market rise or fall in the next five months (**Table 10**).

Table 10. Final probability of the future state of the stock market.

	Probability		
Time	$\boldsymbol{P(a_{-1})}$	$\boldsymbol{P(a_0)}$	$\boldsymbol{P(a_1)}$
2024–04	0.498	0.05	0.442
2024–05	0.447	0.033	0.52
2024–06	0.477	0.033	0.49
2024–07	0.467	0.025	0.508
2024–08	0.467	0.025	0.508
2024–09	0.467	0.025	0.508

5.4. The third layer processing of the planning and recognition algorithm

Through the analysis of the stock market data, we conclude that the average yield of 96 trading months is λ_1 = 4.7%, and the average loss rate is λ_2 = −5.2%. Based on the probability of the stock market trend state of investor sentiment, the algorithm algorithm is used to calculate the Income of each state, and then the expected benefit value Income of the predicted result is obtained according to Equation (12), as shown in **Table 11**.

Table 11. Expected benefit values of the stock market.

Time	**Expect benefit value**
2024–04	−0.4624
2024–05	0.1643
2024–06	−0.1297
2024–07	0.0059
2024–08	0.0059
2024–09	0.0059

The investment behavior planned according to the expected benefit value Income (Equation (13)) is shown in **Table 12**.

Table 12. Financing behavior planning table.

Time	**Financing behavior**
2024–04	sell out
2024–05	buy in
2024–06	sell out
2024–07	buy in
2024–08	buy in
2024–09	buy in

5.5. Detection and comparison of the prediction results

First of all, by comparing the prediction results of the Markov model with the prediction results of the algorithm planning identification and the real situation of the stock market since April 2024, the advantages of the two algorithms can be obtained from the comparison results. The comparison results are as follows.

According to the data analysis in **Table 13**, it is found that compared with the Markov prediction model that only relies on objective data, the planning recognition algorithm integrating investors' subjective emotions shows a higher prediction accuracy. Especially when investors are optimistic, the algorithm can more accurately predict its financing and buying behavior by capturing its biomechanical features, such as posture, expression, and behavioral fluency. This method not only deepens our understanding of the relationship between investor behavior and market volatility, but also provides more accurate market forecast and investment advice for financial institutions and investors, which effectively promotes the steady development of the financial market.

Table 13. Test and comparison of the prediction results of both algorithms.

Time	Reality circumstances	Planning dentification Behavioral results	Accuracy level	Markov Forecast results	Accuracy level
2024–04	fall	sell out	accuracy	sell out	accuracy
2024–05	rise	buy in	accuracy	buy in	accuracy
2024–06	rise	sell out	accuracy	buy in	inaccurate
2024–07	rise	buy in	accuracy	buy in	accuracy
2024–08	fall	buy in	inaccurate	buy in	inaccurate
2024–09	fall	buy in	inaccurate	buy in	inaccurate

6. Conclusion

This study proposes a financial investor behavior prediction algorithm based on biomechanical data and planning recognition, which has significant practical value for financial institutions. Implementation of the system requires wearable devices with integrated inertial measurement units and surface EMG sensors to collect biomechanical data; construction of a professional data analysis platform to process the data and build a sentiment index and planning recognition model; and cooperation with scientific research institutes and vendors to ensure the reliability of the technology. Planning recognition is an interdisciplinary subject that belongs to psychology and artificial intelligence. This paper uses the method of planning recognition in the stock market to break through the tradition of stock market prediction only based on objective data, and adds the subjective emotional factors of investors. Considering the factors that affect the stock market prediction from subjective and objective data, the results obtained are more in line with the expectations of investors, which is conducive to investors' correct behavior of financing, buying and selling securities. The standardization of investors' behavior is conducive to the development of financing business in the domestic market and the health of the domestic stock market. However, the Markov model has the characteristics of no aftereffect, and the results after the fourth month of prediction are basically the same, with little reference. It can be seen that the Markov model is effective for the results in a certain period of time, and it is necessary to reconstruct the investor sentiment index to predict the next data. The workload is relatively large, and it is necessary to consider combining other algorithms to solve this problem.

Despite the great potential of biomechanical data in predicting financial investor behavior, there are challenges to its application. Individual differences in biomechanical expression exist across investors, and it may be difficult for generic metrics to accurately reflect the emotional state of all investors. In addition, collecting biomechanical data on a large scale in real market environments faces practical difficulties such as privacy protection, device wearing comfort, and data synchronization accuracy. Future research needs to explore ways to overcome these limitations in order to improve the validity and reliability of biomechanical data in predicting investor behavior.

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