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Article

Analysis of the Relationship between College Students' Mental Health Fluctuations and The Effect of the Civics Program Based on the ARFIMA Model

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Abstract: This study establishes a methodological framework for quantifying the dynamic relationship between fluctuations in college students' mental health and the effects of ideological and political education courses based on the Autoregressive Fractional Integrated Moving Average (ARFIMA) model. By integrating multi-source heterogeneous data and combining time series feature representation techniques (Fourier transform, piecewise aggregation approximation), the study systematically analyzes the long-term memory characteristics of mental health. Experiments on public datasets (StudentLife, WeiBo) demonstrate that the ARFIMA model significantly outperforms baseline models in mental health level prediction, achieving a weighted average F1 score of 50.56% (an improvement of 7.27% over the best baseline SOTA), with a maximum F1 score of 97.05% on the WeiBo dataset. To address the issue of overfitting in small samples, a low-rank adaptive (LoRA) optimization mechanism was introduced, reducing the validation set loss from 1.051 to 0.956 and enhancing the model's generalization capability. After LoRA optimization, the emotion recognition model demonstrated high discriminative power for positive emotions (97.77% accuracy) and sadness (91.79%), but neutral emotion recognition exhibited confusion (90.12% accuracy). Related analyses of the effectiveness of ideological and political education courses showed that course learning outcomes were most strongly correlated with positive psychological qualities ($r = 0.494$), particularly in the dimensions of cognition ($r = 0.481$) and self-control ($r = 0.479$). Regression analysis further indicates that course content ($\beta = 0.136$, $p < 0.05$) and diverse development ($\beta = 0.089$, $p < 0.05$) are core predictive factors for cognitive qualities. This study provides data-driven decision support for optimizing ideological and political education courses and confirms the effectiveness of time series modeling in mental health interventions.

Keywords: ARFIMA model; college students' mental health; ideological and political course effects; time series analysis; LoRA optimization

1. Introduction

Currently, the integration of ideological and political theory courses with mental health education in higher education institutions is an inevitable trend. The convergence of these two fields has driven their mutual development. On the one hand, focusing on mental health education for college students has enriched the content and methods of ideological and political education, thereby enhancing the educational impact of ideological and political theory courses [1]. On the other hand, the development of ideological and political education methods has significantly promoted the development of mental health education, particularly by seeking connections between traditional Chinese culture and modern mental health education, thereby avoiding the mere adoption of foreign theories [2-4]. Therefore, universities should continue to promote the deep integration of mental health education and ideological and political education content. Under the new ideological and political education perspective, the development of ideological and political education work should emphasize the formation of synergistic effects between various professional courses and ideological and political theory courses. Mental health education and ideological and political theory course development should naturally form such synergistic effects [5-7]. At the same time, the development of mental health education must not directly replicate Western psychological and mental health education models. China's mental health education requires localization and should be guided by the excellent traditions of Chinese culture [8-10]. Although mental health education and ideological and political education in higher education institutions differ in terms of educational content, methods, teacher-student relationships, and skill development, they can be integrated in terms of educational objectives, content, methods, and faculty resources to jointly fulfill their roles and functions in talent cultivation [11-13]. Therefore, strengthening the organic connection between ideological and political education and mental health education, advocating the integration of mental health education into ideological and political education, and promoting their close integration can effectively enhance educational outcomes while addressing students' mental health issues [14-15].

As the education sector develops, an increasing number of psychological issues among college students are emerging. The most common method in university mental health education is ideological and political education, which plays a crucial role in addressing college students' psychological issues. He, X., et al. point out that while the internet has provided college students with efficient learning methods and increased their interest in learning, the complex and diverse online information also impacts their mental health. Based on this, they analyzed the challenges and issues faced by ideological and political education and mental health education in the information age, providing valuable references for collaborative education in an information-driven environment [16]. Yao, W. emphasized that the integration of necessary mental health training with ideological and political education is essential, as it can effectively mitigate the impact of the current online environment and harmful information on college students' mental health, thereby creating a favorable educational and learning environment for them [17]. Li, X. et al. explored the therapeutic effects of collaborative intervention between ideological and political education and mental health education on college students' negative emotions, finding that this collaborative education model can effectively improve the current mental health education system for college students, and plays a positive guiding role in addressing negative emotions among college students [18]. Pan, C. and Yeh, J. L. studied the important paradigms of the synergistic development of ideological and political education and mental health education, proposing bidirectional long-term memory Bayesian optimization (BO-BLSTM) to identify different categories of political emotions, which helps consolidate students' spiritual foundation under synergistic education [19]. Abudoukeremu, D. demonstrated that establishing an integrated education system combining ideological and political education with mental health education can effectively improve educational quality and efficiency, while actively cultivating students' moral character and values, thereby promoting their comprehensive development [20]. Therefore, for the mental health and future development of college students, it is of great significance to simultaneously focus on ideological and political education and students' mental fluctuations during the university education process.

The article systematically outlines the foundational principles of key time series methods. First, data on college students' psychological states are inherently time series obtained through sequential observations over time. To effectively extract their key fluctuation characteristics and reduce data dimensions to meet modeling requirements, the paper delves into time series data feature representation methods, focusing on transform-based frequency domain feature representations (e.g., Fourier transform) and segment-based feature representations (e.g., segmented aggregation approximation PAA, segmented linear representation). Second, to model and predict the extracted features or the original sequence (after appropriate preprocessing), the focus is on stationary time series models, with detailed explanations of the core principles, mathematical forms, and applicability conditions of autoregressive models (AR), moving average models (MA), and their combined models (ARMA). Finally, considering that the evaluation of the effects of ideological and political education courses requires the integration of multi-dimensional student data, a comprehensive student data analysis system based on university ideological and political education courses is proposed. The core objective of this system is to efficiently integrate multi-source heterogeneous data such as learning behavior, psychological state, and interactive feedback, and to process and analyze them using machine learning and visualization technologies, thereby providing technical support for generating high-quality, structured input data streams suitable for time series modeling.

2. Time Series Based on ARFIMA and Its Application in the Analysis of the Effectiveness of Ideological and Political Courses

2.1. Feature Representation of Time Series Data

2.1.1. Frequency Domain Feature Representation Based on Transformation

Transform-based feature representation methods involve mapping and transforming time series data across different domains using various techniques. The most common transformations involve converting time series data between the time domain and the frequency domain. For different application scenarios, these methods primarily include the Fourier transform and the wavelet transform.

The Fourier transform converts a function from the time domain to the frequency domain to extract the frequency information contained in the data. The continuous Fourier transform of a periodic signal $x(t)$ is defined as:

$$F(k)=\int_{-\infty}^{+\infty} e^{-2\pi ikt}x(t)dt \tag{1}$$

Using Euler's formula, the Fourier transform can further decompose a function into sine and cosine waves, i.e., the sum of sine and cosine functions of different amplitudes and frequencies:

$$F(k)=\int_{-\infty}^{+\infty}(\cos(2kt)-i\sin\cos(2kt))x(t)dt \tag{2}$$

In practical applications, since time series data is often obtained as discrete values sampled at a specific frequency, the discrete Fourier transform is more commonly used in engineering. It is defined as:

$$f_k=\sum_{0}^{N-1}x_n e^{-\frac{2\pi ikn}{N}} \tag{3}$$

where x_n is an element of the original time series data, N is the length of the original time series data, and f_k is an element of the transformed discrete Fourier series. With the development of Fourier transform-related technologies, more computationally efficient fast Fourier transforms have been developed. The fast Fourier transform reduces the computational complexity from $O(n^2)$ for the discrete Fourier transform to $O(n\log n)$.

2.1.2. Segment-Based Feature Representation

One of the primary reasons for feature representation of time series data is to reduce the dimensionality of the original data. Therefore, the simplest method is to sample the original time series data. This method involves sampling the original time series data $P(p_1,\dots,p_m)$ with a length of m at a sampling rate of m/n, thereby compressing the original time series data into a sequence of length n. The sampling compression of time series data is illustrated in Figure 1. However, if the sampling rate is too low, the subsegment obtained after sampling may lose key features of the original time series data (e.g., shape, period, inflection points, etc.).

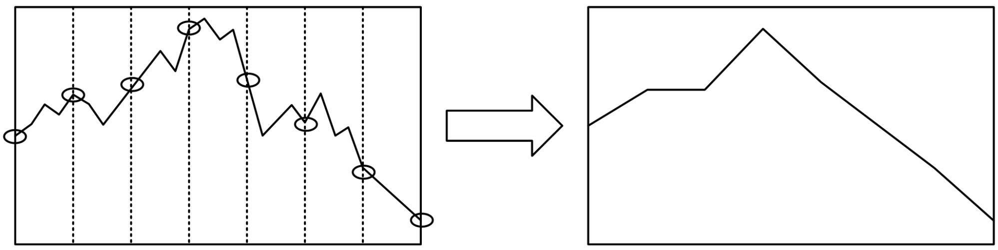

Figure 1. Sampling and compression of time series data.

This paper improves upon the sampling method by proposing a segmented mean representation method, which represents the corresponding data point set by calculating the average value of each segment. The segmented mean representation of time series data is shown in Figure 2. Specifically, for a time series data set $P(p_1,\dots,p_m)$ of length m, compression yields a subsequence $Q(q_1,\dots,q_n)$ of length n, defined as:

$$q_k = \frac{1}{e_k - s_k + 1}\sum_{i=s_k}^{e_k} p_i \tag{4}$$

Here, s_k and e_k denote the start and end points of the time series data P at the k th time interval, respectively. This method is also known as the segmented aggregation approximation representation. To adapt the segmented aggregation approximation representation method to different scenarios, many scholars have proposed improved versions, such as adaptive approximation representation and segmented variation.

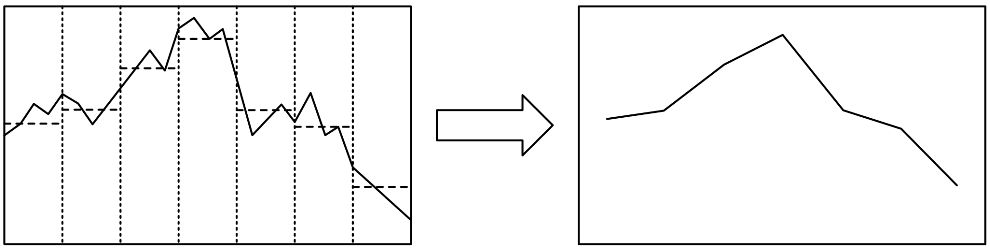

Figure 2. Piecewise mean representation of time series data.

In addition to the above-mentioned segmented feature representation based on aggregation, another method is to approximate time series data using straight lines. This method primarily encompasses two categories: linear regression and linear interpolation. Methods based on linear regression use the optimal fitting line to represent the original time series data. A commonly used method based on linear interpolation is segmented linear representation, which represents the subsequence $P(p_i,\dots,p_j)$ by connecting the data points p_i and p_j with a straight line. This method is a bottom-up algorithm that first treats every two data points as a segment and then iteratively merges these segments until the required number of segments is satisfied. Furthermore, the piecewise linear representation is extended to a hierarchical structure. The piecewise linear representation is improved by analyzing factors such as the weights of the sub-sequences.

2.2. ARFIMA Model for Stationary Time Series

The three types of models commonly used for analyzing and studying smooth time series are the autoregressive model (AR), the moving average model (MA), and the autoregressive moving average model (ARMA). Their specific forms are as follows:

2.2.1 Autoregressive Model AR

The $AR(p)$ model is also known as the p th-order autoregressive model:

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \varepsilon_t \tag{5}$$

In this context, $\{\varepsilon_t\}$ denotes a white noise sequence, p is the order of the autoregressive (AR) model, $\varphi_1, \varphi_2, \cdots, \varphi_p$ are the coefficients of the AR model, and $\varphi_p \neq 0$. When the roots of the polynomial (6) of the lag operator L are all greater than 1, the model is said to be stationary.

$$\varphi(L) = 1 - \varphi_1 L - \varphi_2 L^2 - \cdots - \varphi_p L^p \tag{6}$$

2.2.2. Moving Average Model MA

The $MA(q)$ model is also known as the q th order moving average model:

$$X_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \tag{7}$$

Among them, $\{\varepsilon_t\}$ represents the white noise sequence, q is the order of the moving average model MA, $\theta_1, \theta_2, \cdots, \theta_q$ are the coefficients of the moving average model MA, and $\theta_q \neq 0$. The roots of the polynomial (8) of the lag operator L are all greater than 1, which means that the model is stationary under any conditions.

$$\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - \cdots - \theta_q L^q \tag{8}$$

2.2.3. Autoregressive Moving Average Model (ARMA)

$ARMA(p,q)$ The model is also known as the autoregressive moving average model:

$$\begin{aligned} X_t &= \varphi_0 + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} \\ &+ \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \end{aligned} \tag{9}$$

Among these, $\{\varepsilon_t\}$ denotes a white noise sequence, p is the autoregressive order, q is the moving average order, $\varphi_1, \varphi_2, \cdots, \varphi_p$ and $\theta_1, \theta_2, \cdots, \theta_q$ are the coefficients of the autoregressive moving average model ARMA, and $\varphi_p \neq 0, \theta_q \neq 0$. Clearly, when

when $p = 0, q \neq 0$, the model is transformed into the $MA(q)$ model. When $p \neq 0, q = 0$, the model is transformed into the $AR(p)$ model. The order of the ARMA model can be determined by observing the trend characteristics of the autocorrelation function plot and the partial autocorrelation function plot of the research object. Generally, if the autocorrelation function plot shows obvious tailing characteristics, while the partial autocorrelation function plot shows obvious p -order truncation characteristics, then the $AR(p)$ model is selected for the prediction model. If the autocorrelation function exhibits a clear q th-order truncation feature, while the partial autocorrelation function exhibits a clear tailing feature, then the $MA(q)$ model is selected for the prediction model. If both the autocorrelation function and the partial autocorrelation function exhibit clear tailing features, then the $ARMA(p,q)$ model is selected.

2.3 Building a Comprehensive Student Data Analysis System Based on College Ideological and Political Courses

Classic stationary time series models such as AR, MA, and ARMA provide a fundamental framework for analyzing short-term dependencies. This section will explore the application of these models to assess the long-term impact of ideological and political education courses on mental health, efficiently and accurately obtaining and integrating multi-dimensional time series input data for modeling. A comprehensive student data analysis system integrated for the ideological and political education course context will be constructed. This system not only handles data collection, storage, and management but also performs the core task of using advanced data processing and analysis techniques to convert raw student activity data into high-quality structured time-series datasets directly usable by the aforementioned time-series models, providing the data foundation for revealing the dynamic associations between ideological and political education courses and fluctuations in mental health.

In higher education ideological and political practice courses, constructing a comprehensive student data analysis system is a critical step toward enabling digital profiling. The aim is to provide scientific and precise teaching decision support for ideological and political education by integrating and analyzing multi-dimensional data such as students' learning behaviors, psychological states, and interactive feedback. First, it is necessary to establish a platform for comprehensively collecting student data, including but not limited to records of students' online learning activities, classroom participation, homework and test scores, and social media interactions. This data will be updated in real time through advanced data collection technologies to ensure its timeliness and accuracy. The data analysis system must employ machine learning and artificial intelligence algorithms to process and analyze this large volume of data. Through algorithmic models, the system can identify patterns and trends in student learning, assess the impact of ideological and political education, and even predict changes in student behavior and mental health.

Additionally, the data analysis system should include a powerful visualization tool that can convert complex data into intuitive charts and reports, helping teachers and educational administrators better understand the information behind the data. For example, by generating heat maps of student engagement and learning outcomes, teachers can clearly see which parts of the course attract students' interest and which parts need improvement.

3. Evaluation Experiments and Optimization Based on the ARFIMA Time Series Model

Based on the theoretical framework and data system constructed in Chapter 2 using ARFIMA, this chapter empirically tests the effectiveness of the model in analyzing fluctuations in mental health using multi-source heterogeneous datasets, with a focus on verifying the capture of emotional fluctuations in college students' mental health and the prediction of such fluctuations through long-memory characteristics.

3.1. Cross-Dataset Experiments on Mental Health Prediction over Time

3.1.1. Dataset

To validate the feasibility and effectiveness of the proposed ARFIMA model for smooth time series, this paper conducted experiments on the publicly available StudentLife dataset and a dataset of posts about mental health status from students' Sina Weibo accounts. The StudentLife dataset comprises mobile sensor data from 60 students over a 10-week period.

This experiment utilized a subset of the StudentLife dataset, including three types of sensory data—accelerometer sensor data, microphone sensor data, and Wi-Fi data—as well as mental health status. Accelerometer sensor data reflects students' activities, including four states: stationary, walking, running, and unknown, collected every 2–3 seconds; microphone sensor data reflects the sound environment around students, including four states: quiet, speaking, noisy, and unknown, collected every 1–3 seconds; Wi-Fi data reflects students' location information, provided in the form of specific geographic locations. By integrating these three types of sensory data, students' behaviors can be effectively analyzed and characterized.

The mental health status in the dataset is measured using PAM scores, reflecting students' positive/negative emotional states, with values ranging from 1 to 16. To facilitate mental health prediction experiments, this paper maps PAM values to four levels, obtaining four levels of mental health status labels for students. The following are the mental health levels and their meanings corresponding to each PAM score: Mental Health Level 1 (PAM 1-4): Low arousal, negative valence; Mental Health Level 2 (PAM 5-8): High arousal, negative valence; Mental Health Level 3 (PAM 9-12): Low arousal, positive valence; Mental Health Level 4 (PAM 13-16): High arousal, positive valence.

Arousal and valence are two dimensions used in psychology to characterize emotions. Arousal refers to the current level of calmness or excitement, with arousal ranging from low to high, representing a continuous distribution from calm to excited; valence refers to the degree of positivity or negativity, with valence ranging from negative to positive, representing a continuous distribution from unhappy to happy. This paper combines the distribution of arousal and valence levels to describe students' positive and negative emotions and characterize their mental health levels.

The WeiBo dataset is a balanced dataset constructed based on the Sina Weibo platform for user-level depression detection, containing 1,000 college student Sina Weibo users. The basic annotation criterion is that if a user has more than five negative keywords such as “depression” at different times, they are labeled as a depressed user. Ultimately, 98 users at risk of depression were labeled, with a total of 18,723 user posts crawled, averaging 12 Chinese characters per post. For the selection criteria of the normal control group users, if a user had never posted any content containing depressive expressions and was not a public figure or organization, they were labeled as not at risk of depression.

3.1.2. Evaluation Indicators

This paper uses four metrics to evaluate model performance: accuracy (A), precision (P), recall (R), and the F1 score (F1), which is the harmonic mean of P and R.

A represents the proportion of correctly predicted samples out of the total number of samples. P focuses on evaluating the proportion of data with the true value of a certain psychological level among all data predicted to be of that level. R focuses on evaluating the proportion of students successfully predicted to be of a certain psychological level among all students with the true value of that level. Considering the imbalance in the distribution of psychological levels, this paper uses a weighted average method to combine the P and R metrics for the four psychological level categories. F1 is a comprehensive evaluation of P and R; the higher the F1 value, the better the overall performance of the model.

3.1.3. Comparison with Baseline Model

To validate the effectiveness of the SBTM-SABMHP algorithm proposed in this paper, the proposed method is compared with six other algorithms. The first two are classical machine learning algorithms, the third is a deep learning algorithm, the fourth is a classical time series neural network algorithm—the LSTM network, the fifth is the state-of-the-art (SOTA) method for the same task on the same dataset, and the sixth is a cutting-edge method in the field of campus behavior time series modeling, which is similar to the task in this paper. The six algorithms are described in detail below.

(1) Random Forest (RF): All short-term behavior representations of students are concatenated and input into RF for classification to predict their mental health status.

(2) Support Vector Machine (SVM): Similar to the RF algorithm, the concatenated short-term behavior representations of students are directly input into SVM for mental health status prediction.

(3) Deep Neural Network (DNN): Similar to the RF algorithm, the concatenated short-term behavioral representations of students are input into a two-layer deep neural network for prediction. The layers of this DNN are fully connected.

(4) LSTM: The short-term behavioral representations of students are input into the LSTM in sequence according to their temporal relationships, and the hidden layer state of the final step of the LSTM is used to predict the mental health status of students.

(5) SOTA: This is the state-of-the-art algorithm for the same task, which studies the use of heterogeneous information networks for student behavior representation in multi-data source scenarios. This method constructs a local-global heterogeneous behavior graph to predict students' mental health status.

(6) MFSTGCN: A multi-fragment semantic spatio-temporal graph convolutional network model that considers the temporal, spatial, and relational aspects of campus behavior. In comparative experiments, the heterogeneous information network graph constructed from daily behavioral fragments is input into the semantic spatio-temporal graph convolutional network, and FCL is used to predict mental health status.

Considering the training speed and accuracy of the model, after parameter comparison experiments, the optimization method and hyperparameter settings used for network training in this paper are as follows: the batch size used in training is set to 128, the learning rate is set to 1e-4, the model optimizer uses the adaptive momentum random optimization method Adam, and the number of times the learning algorithm works on the entire training dataset is set to 500.

3.1.4. Experimental Results of the StudentLife Dataset

The comparison results of this method with other models on the StudentLife dataset are shown below. Figure 3 shows the F1 values for each mental health level, and Figure 4 shows the weighted average of each indicator for each model on the StudentLife dataset.

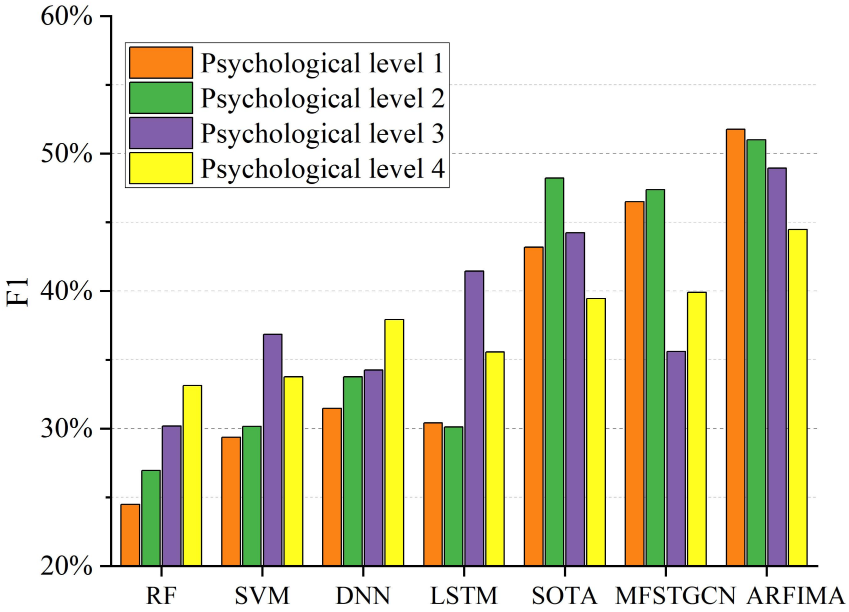

Figure 3. The F1 values under each mental health level.

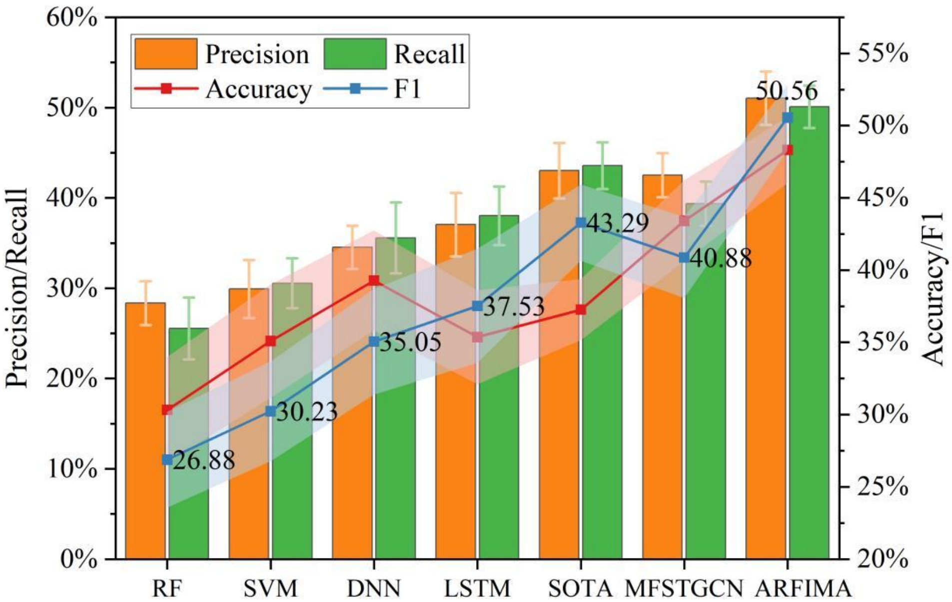

Figure 4. The various indicators of each model after weighted average.

It can be seen that ARFIMA is comprehensively superior, with the F1 scores of the ARFIMA model significantly higher than those of other models across all psychological levels, particularly showing the greatest advantage in low arousal negative valence (Level 1) and high arousal negative valence (Level 2) (F1 > 0.5). The weighted average F1 value of the model in this paper reaches 50.56%, which is 7.27 percentage points higher than the second-place SOTA model's 43.29%. Among these, traditional models (RF/SVM) perform the weakest: their F1 values are below 0.35, indicating limited ability to capture temporal mental health data. Deep learning models (DNN/LSTM) performed moderately, with LSTM performing well at Level 3 (low arousal positive valence) with an F1 score of 41.44%, but overall performance was highly variable. Graph neural networks (MFSTGCN) showed uneven performance, approaching SOTA at Levels 1-2 but significantly declining at Levels 3-4, possibly due to unstable associations between spatial features and mental states. All models perform best at Level 4 (high arousal positive valence) with F1 > 33, indicating that positive emotions are easier to identify. Level 1 (low arousal negative valence) is the most challenging to predict, with only ARFIMA exceeding 50% F1, reflecting the complexity of depressive tendencies and the need for long-term memory features.

3.1.5. Impact of the Number of Posts on the WeiBo Dataset on Model Performance

To further explore the impact of post quantity on model performance, this section conducts experiments at different sampling rates and proposes post sampling methods based on random sampling and retrieval-based sampling for each user. Table 1 shows the F1 performance of the model under different sampling rates and sampling strategies on the WeiBo dataset, and Figure 5 shows a line chart visualization.

Table 1. The F1 of the model under different sampling rates and sampling strategies.

Sampling rate	Random-based Sampling							Retrieval-based Sampling						
	RF	SVM	DNN	LSTM	SOTA	MFSTGCN	ARFIMA	RF	SVM	DNN	LSTM	SOTA	MFSTGCN	ARFIMA
0.1	58.31	60.09	62.35	69.30	69.34	71.18	76.57	62.01	63.29	66.65	74.20	75.94	73.38	82.07
0.2	61.75	58.23	64.66	70.82	75.36	66.03	81.47	64.45	65.03	70.36	75.12	79.76	71.53	84.17
0.3	63.67	59.74	65.56	71.05	81.52	76.27	83.06	66.07	65.84	71.06	73.85	83.82	81.27	86.96
0.4	64.49	63.47	71.66	71.14	81.83	73.77	89.75	69.79	67.47	73.96	77.44	85.33	77.67	91.95
0.5	66.41	63.44	70.36	74.16	79.89	76.56	89.50	70.71	68.04	73.96	79.76	84.99	83.36	93.80
0.6	65.45	65.93	72.55	73.80	85.12	80.08	90.20	72.45	69.43	76.05	80.00	87.42	86.38	93.80
0.7	71.51	69.54	73.26	72.33	81.99	85.41	91.46	74.31	71.64	79.76	78.13	84.29	89.51	96.36
0.8	71.54	71.85	76.15	76.12	77.78	82.37	92.78	75.24	74.55	79.65	82.32	82.78	85.57	95.08
0.9	68.58	70.09	78.52	81.72	81.18	79.12	92.97	75.48	75.59	82.32	84.52	87.18	82.32	95.77
1.0	74.58	75.31	77.30	79.30	83.75	78.99	92.15	78.48	77.91	82.90	84.40	89.85	84.99	97.05

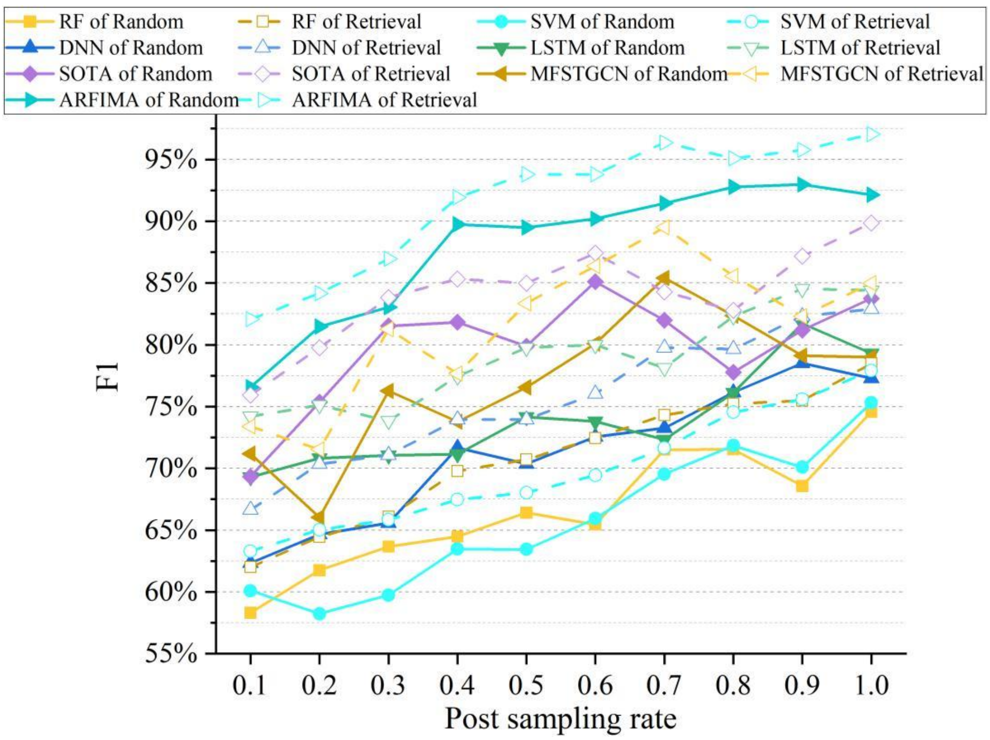

Figure 5. F1 of the model under different sampling rates and sampling strategies.

The ARFIMA model also demonstrates a clear advantage, with F1 scores significantly higher than other models across all sampling rates and strategies, reaching a maximum of 97.05%. Even when using only 10% of the data (sampling rate of 0.1), ARFIMA achieves F1 scores exceeding 76.57%/82.07% under random/retrieval sampling, validating its robustness with small samples. At low sampling rates (0.1–0.3), ARFIMA maintains an F1 score above 80, while other models (such as RF/SVM) generally fall below 70, highlighting its adaptability to sparse data. At high sampling rates (0.7–1.0), ARFIMA achieves an F1 score exceeding 95+ under retrieval sampling, approaching perfect prediction; other models (such as SOTA) reached a maximum of only 89.85. SOTA/MFSTGCN performed well at specific sampling rates (e.g., SOTA achieved 81.52 at 0.3 random sampling), but their overall stability was far inferior to ARFIMA; LSTM showed significant improvement under retrieval sampling, indicating that temporal models benefit from high-quality data.

It can be observed that after applying the retrieval-based sampling strategy, the performance of the proposed model in this paper is significantly improved, indicating that sampling user posts is necessary. Through retrieval-based sampling, the model can focus more on learning depression-related knowledge, effectively reducing the impact of noisy data on the model while lowering computational overhead. At the same time, it can also be observed that after applying the retrieval-based sampling strategy, the performance of each model becomes more stable as the sampling rate increases. However, after applying the random sampling strategy, the performance of the model exhibits significant fluctuations. This may be because the retrieval-based sampling strategy selects posts related to depression during each sampling process. In contrast, the random sampling strategy can only select users' posts through random screening, so it cannot guarantee that the selected posts are all related to depression.

3.2. Research on Sentiment Analysis Technology Based on LoRA and Word Embedding Fine-Tuning

Although ARFIMA performs excellently in mental health prediction, there is still a risk of overfitting in small sample scenarios. To address this issue, this section introduces the LoRA optimization mechanism to improve the model's generalization ability through low-rank adaptive technology.

3.2.1. LoRA Optimization Settings and Dataset Description

As can be seen from the experimental results in Section 3.1, the StudentLife dataset has a limited amount of data and is not sufficiently large, leading to overfitting issues. Additionally, both SOTA and MFSTGCN, as well as the ARFIMA model proposed in this paper, exhibit slow training speeds. To address this issue, LoRA was employed to optimize the model.

In scenarios with limited data, models are prone to learning noise and overly specific patterns from the training data, leading to overfitting. LoRA reduces the number of free parameters by introducing low-rank matrices, thereby lowering model complexity and helping to mitigate overfitting. Additionally, LoRA's regularization effect encourages the model to learn broader, more general language features rather than merely fitting specific training samples, thereby enhancing the model's generalization ability on unseen data. Since LoRA only requires updating a small number of parameters (i.e., low-rank matrices), the training process is more efficient compared to fully fine-tuning all parameters of ARFIMA, which is particularly important in scenarios with limited data, enabling better training results in a shorter time. By focusing on adaptive adjustments to the model's critical components, LoRA helps the model better capture the features of the minority class in imbalanced datasets, potentially improving the model's ability to handle imbalanced data.

In summary, LoRA provides an effective solution for using ARFIMA for college students' mental health sentiment analysis in scenarios with limited and imbalanced data, improving model performance and generalization capabilities by reducing model complexity and increasing training efficiency.

In this section's experiments, the SMP2022EWECT dataset was selected, with the original data sourced from Sina Weibo and provided by the Weihot Big Data Research Institute. The Weibo content related to college students' mental health covers a wide range of topics. It is categorized into six emotional categories: fear, positivity, neutrality, anger, surprise, and sadness. The dataset is divided into three parts: training set, test set, and validation set. The training set consists of 14,724 entries, including 783 entries of fear (5.32%), positive (6,231, accounting for 42.32%), neutral (2,632, accounting for 17.88%), anger (2,382, accounting for 16.18%), surprise (894, accounting for 6.07%), and sadness (1,802, accounting for 12.24%).

3.2.2. Comparison of Loss Function Curves

To validate the effectiveness of LoRA, particularly its performance in alleviating overfitting and reducing model complexity, two models were used for comparative training with LoRA: the MFSTGCN model based on semantic spatio-temporal graph convolutional networks and the ARFIMA model based on stationary time series proposed in this paper. The experiments were conducted using the SMP2022 general-purpose dataset, and their loss function curves are shown in Figure 6, which visually demonstrate the impact of LoRA.

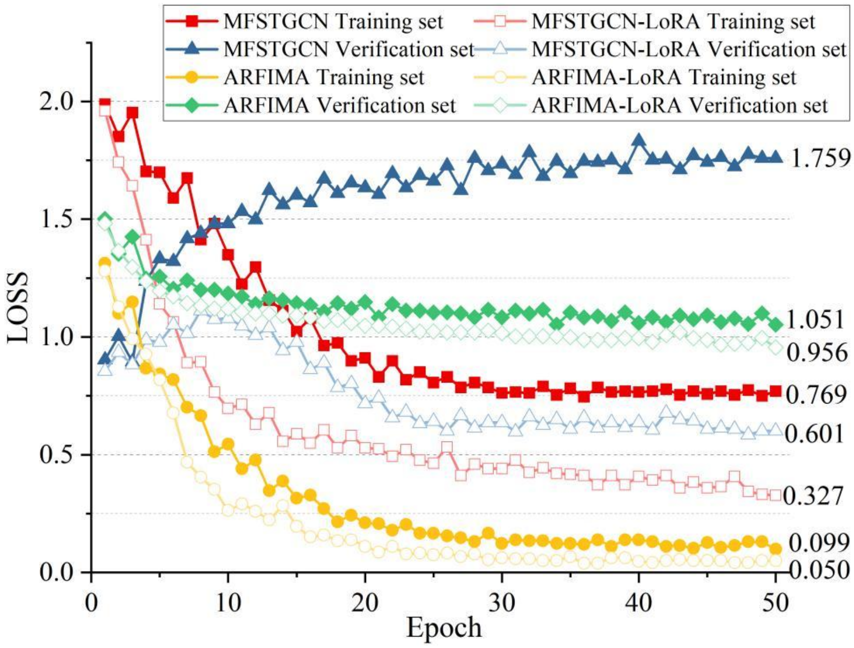

Figure 6. The loss function curves before and after LoRA optimization.

As shown in Figure 6, for the ARFIMA model of the stationary time series in this paper, when the model remains unchanged without optimization using LoRA, it is observed that the loss function on the training set gradually decreases and approaches 0 as training progresses. This indicates that the model achieves increasingly higher fitting accuracy on the training data, demonstrating strong learning capabilities and effectively capturing the features of the training data. At 50 training iterations, the loss eventually stabilizes at 0.099; however, the loss function on the validation set of the MFSTGCN model exhibits the opposite trend, increasing as training progresses and ultimately reaching 1.759. This is a classic manifestation of overfitting, indicating that the model is overly complex and has “memorized” noise and details in the training data rather than learning generalizable patterns applicable to unseen data. This suggests that the model's training is not progressing in the correct direction. After training with LoRA, the situation improved significantly. By introducing a low-rank structure into the model and reducing the amount of parameter updates, the model's complexity is effectively controlled, thereby enhancing its generalization ability. Ultimately, the training loss of the MFSTGCN model decreased to 0.601.

The Dropout in the LoRA configuration resulted in the lowest loss function value on the training set not being as low as that of the original model, which is a positive sign indicating that the model avoided overfitting to the training data. More importantly, on the validation set, the loss function of the model using LoRA is significantly lower than that of the original model, and as training progresses, the loss function tends to stabilize and converge. This indicates that LoRA helps the model maintain good generalization capabilities while learning from the data, making its performance on unseen data more stable and reliable. The final loss of the ARFIMA model optimized with LoRA on the validation set is 0.956 (1.051 before optimization).

In the experiments, the introduction of LoRA effectively alleviated the overfitting problem and promoted model convergence on both the training and validation sets. This is crucial for building robust machine learning models, especially when dealing with limited training data or datasets with significant noise. By reducing the number of trainable parameters in the model, LoRA mitigates the model's excessive sensitivity to training data details, driving the model toward more efficient information extraction and processing.

3.2.3. Confusion Matrix for Model Emotion Recognition

The confusion matrix for six-class sentiment recognition using the LoRA-optimized ARFIMA model on the SMP2022EWECT dataset is shown in Figure 7.

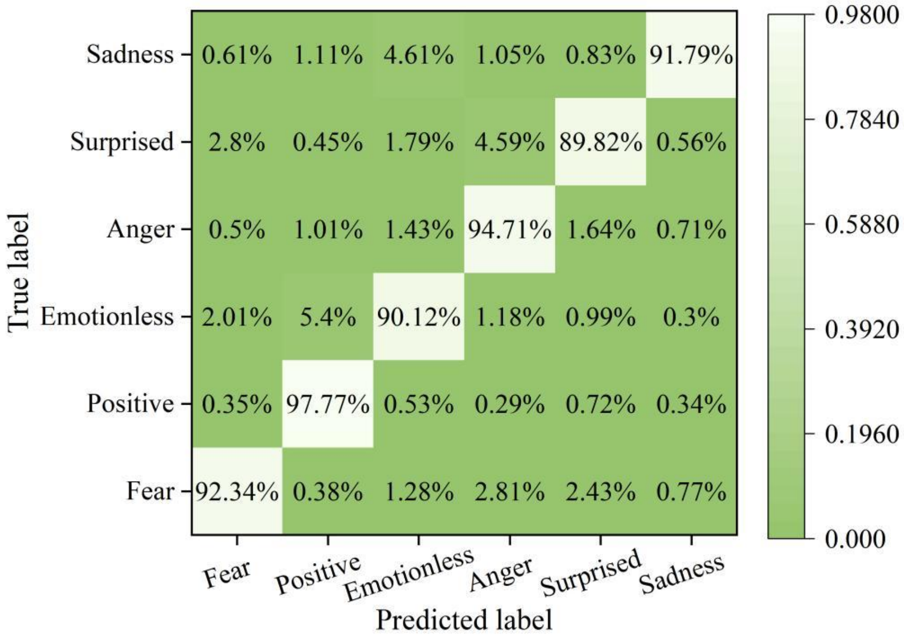

Figure 7. Six types of emotion recognition confusion matrices.

The ARFIMA model optimized with LoRA demonstrated significant differences in the sentiment classification task on the SMP2022EWECT dataset. The model demonstrated the strongest recognition capabilities for positive emotions (97.77% accuracy) and sad emotions (91.79%). Among positive emotion samples (6,231 instances), misclassifications primarily occurred in the "no emotion" category (142 cases, accounting for 5.40%); for sad emotion samples (1,802 instances), only 6.5% were misclassified (primarily as "no emotion").

Extreme emotion recognition exhibits specific patterns: misclassifications of fear (783 instances) were concentrated in "no emotion" (53 cases) and 'surprise' (25 cases); misclassifications of surprise (894 instances) primarily flowed toward "fear" (19 cases). The emotionless category (2,632 samples) was the most challenging to identify (90.12% accuracy rate), with 4.61% of misclassified samples flowing into the sadness category (83 cases), indicating confusion between neutral emotions and mildly negative emotions. The 94.71% high accuracy rate for anger emotions (2,382 samples) confirmed the model's ability to capture strong negative emotions.

4. Research on the Impact of Ideological and Political Courses on Mental Health

To analyze the effects of ideological and political courses in colleges and universities, this experiment examined the impact of such courses on students' mental health. A questionnaire survey was conducted on 1,062 college students using the College Students' Positive Psychological Quality Scale and the Ideological and Political Course Evaluation Questionnaire to analyze the factors influencing ideological and political courses.

4.1. Research Subjects and Research Tools

This study employed a questionnaire survey method to conduct a random sample of students from various grades and majors at a certain university, distributing 1,223 questionnaires and receiving 1,062 valid responses, resulting in a response rate of 86.84%.

College Students' Positive Psychological Quality Scale: This scale includes six subscales, 12 positive psychological qualities, and a total of 50 questions. The cognitive subscale includes creativity, curiosity, thinking, and insight; the emotional subscale includes sincerity and perseverance; the interpersonal subscale includes love and kindness; the fairness subscale includes leadership and cooperation; the self-control subscale includes tolerance, humility, and restraint; and the transcendence subscale includes spiritual insight, humor, belief, and hope. The questionnaire uses a 5-point rating scale, where 1 indicates “very much disagree” and 5 indicates “very much agree.” The scales demonstrate good reliability and validity, with a Cronbach's α coefficient of 0.943 in this study.

The Ideological and Political Education Course Evaluation Questionnaire is divided into seven dimensions: course content, teaching methods, teacher competence, classroom atmosphere, learning outcomes, diverse development, and value transformation. The scale consists of 25 items and uses a 4-point rating scale. Higher scores indicate more effective ideological and political education course content and higher student satisfaction with the course. The scale has good reliability and validity, with a Cronbach's α coefficient of 0.921 in this study.

4.2. Research on Positive Psychological Qualities of College Students and Factors Affecting Ideological and Political Education Courses

4.2.1. Correlation Analysis between Ideological and Political Courses and Positive Psychological Qualities

Independent sample t-tests were conducted to examine the relationship between various dimensions of ideological and political courses and positive psychological qualities. The correlation analysis between ideological and political courses and positive psychological qualities is shown in Table 2.

Table 2. Analysis of the Correlation of Political Courses and Psychological Qualities.

	Course content	Teaching methods	Teacher's quality	Classroom atmosphere	Learning effect	Diverse development	Value transformation
Cognition	0.348**	0.246**	0.296**	0.104**	0.481**	0.253**	0.227**
Emotion	0.313**	0.327**	0.309**	0.169**	0.431**	0.226**	0.387**
Interpersonal relationship	0.326**	0.231**	0.387**	0.241**	0.419**	0.208**	0.215**
Justice	0.342**	0.213**	0.247**	0.134**	0.442**	0.265**	0.317**
Temperance	0.352**	0.238**	0.203**	0.104**	0.479**	0.308**	0.234**
Beyond	0.363**	0.206**	0.179**	0.096	0.309**	0.284**	0.368**
Positive psychology	0.395**	0.307**	0.308**	0.168**	0.494**	0.316**	0.326**

Table 2 shows the Pearson correlation coefficients between the seven dimensions of ideological and political courses and six types of positive psychological qualities (all passed significance tests, $p<0.01$). The data show that learning outcomes are most strongly correlated with psychological qualities ($r=0.494$), with a particularly significant impact on cognitive ($r=0.481$), self-control ($r=0.479$), and fairness ($r=0.442$) qualities. The promotional effect of course content on transcendence is the most prominent ($r = 0.363$), but it has the lowest dependence on classroom atmosphere ($r = 0.096$, not significant). Value transformation (the internalization of ideological and political knowledge into behavior) was highly correlated with emotional qualities ($r = 0.387$), indicating that emotional cultivation should be combined with practical transformation. It can be seen that all course dimensions were significantly positively correlated with positive psychological qualities ($r = 0.168–0.494$), validating the multidimensional enhancement of mental health by ideological and political courses.

4.2.2. Regression Analysis of Factors Influencing Positive Psychological Qualities among College Students

Using the six dimensions of positive psychological qualities among college students (cognitive, emotional, interpersonal, fairness, self-control, and transcendence) as dependent variables, and seven dimensions including course content, teaching methods, teacher competence, classroom atmosphere, learning outcomes, diverse development, and value transformation as independent variables, a multiple linear regression analysis was conducted using the Stepwise method (αin = 0.07, αout = 0.09). The results of the multiple linear regression analysis of the factors influencing positive psychological qualities are shown in Table 3. The findings indicate that the independent variables of ideological and political courses have a certain explanatory power for the various dimensions of positive psychological qualities among college students, with an overall R^2 of 0.263.

Table 3. Multiple linear regression analysis of positive psychological qualities.

Dependent variable	Factor	b	b'	sb	t	P	R^2	F
Cognition	Constant	2.834		0.522	5.096	0.000	0.264	1.923
	Course content	0.136	0.117	0.135	1.747	0.041		
	Teaching methods	0.112	0.172	0.273	2.378	0.019		
	Teacher's quality	0.216	0.140	0.091	1.685	0.047		
	Classroom atmosphere	0.202	0.101	0.213	2.217	0.022		
	Learning effect	0.109	0.174	0.068	2.040	0.033		
	Diverse development	0.245	0.089	0.073	2.063	0.019		
	Value transformation	0.213	0.248	0.155	1.786	0.031		
Emotion	Constant	2.568		0.508	4.694	0.002	0.239	1.638
	Course content	0.171	0.118	0.275	1.621	0.048		
	Teaching methods	0.292	0.107	0.289	2.343	0.016		
	Teacher's quality	0.134	0.194	0.227	1.955	0.032		
	Classroom atmosphere	0.178	0.225	0.015	1.928	0.035		
	Learning effect	0.126	0.191	0.178	2.039	0.011		
	Diverse development	0.111	0.187	0.209	1.679	0.041		
	Value transformation	0.164	0.108	0.245	1.744	0.039		
Interpersonal relationship	Constant	2.387		0.488	4.924	0.001	0.211	1.384
	Course content	0.231	0.218	0.183	2.127	0.017		
	Teaching methods	0.207	0.234	0.076	2.082	0.023		
	Teacher's quality	0.242	0.217	0.117	2.056	0.022		
	Classroom atmosphere	0.243	0.055	0.102	2.352	0.016		
	Learning effect	0.129	0.119	0.154	2.375	0.015		
	Diverse development	0.199	0.128	0.193	2.307	0.009		
	Value transformation	0.257	0.282	0.176	1.569	0.045		
Justice	Constant	2.471		0.576	5.706	0.000	0.244	1.283
	Course content	0.281	0.194	0.356	1.742	0.037		
	Teaching methods	0.195	0.122	0.206	2.346	0.013		
	Teacher's quality	0.114	0.167	0.274	1.844	0.034		
	Classroom atmosphere	0.120	0.109	0.273	2.329	0.008		
	Learning effect	0.146	0.166	0.133	2.389	0.008		
	Diverse	0.237	0.190	0.235	2.112	0.010		

	development							
	Value transformation	0.162	0.243	0.194	1.972	0.033		
Temperance	Constant	1.976		0.515	4.587	0.000	0.189	1.568
	Course content	0.182	0.095	0.347	1.750	0.048		
	Teaching methods	0.159	0.187	0.308	2.302	0.011		
	Teacher's quality	0.156	0.135	0.284	2.070	0.017		
	Classroom atmosphere	0.144	0.264	0.240	1.679	0.051		
	Learning effect	0.128	0.245	0.180	2.161	0.021		
	Diverse development	0.133	0.123	0.176	1.669	0.046		
	Value transformation	0.178	0.222	0.161	1.897	0.043		

Based on multiple linear regression (stepwise method), Table 3 reveals that cognitive quality is primarily driven by learning outcomes ($\beta = 0.174$, $p = 0.033$) and diverse development ($\beta = 0.089$, $p = 0.019$); the core predictive factors for emotional quality are teaching methods ($\beta = 0.107$, p = 0.016) and classroom atmosphere ($\beta = 0.225$, $p = 0.035$); the predictive power for self-control quality is relatively weak ($R^2 = 0.189$), primarily dependent on value transformation ($\beta = 0.222$, $p = 0.043$).

The regression model for cognitive quality had the highest explanatory power ($R^2 = 0.264$), while interpersonal quality had the lowest ($R^2 = 0.211$), indicating that non-curricular factors (such as individual differences) have a greater impact on interpersonal skills. Teacher competence had the highest standardized coefficient for interpersonal quality ($\beta = 0.217$, $p = 0.022$), highlighting the importance of the teacher's role in fostering social skills.

5. Conclusion

This study established a dynamic analytical framework for the fluctuations in college students' mental health and the effects of ideological and political courses based on the ARFIMA model, utilizing multi-source data fusion and time series modeling.

The ARFIMA model significantly outperforms traditional methods in capturing the long-term memory characteristics of mental health. On the StudentLife dataset, its weighted average F1 score reached 50.56%, an improvement of 7.27% over the best baseline SOTA. Notably, the F1 score exceeded 50% in predicting low arousal negative valence (Level 1), validating the necessity of long-term memory in analyzing depressive tendencies. On the WeiBo dataset, the ARFIMA model achieved an F1 score of up to 97.05% (at a sampling rate of 1.0+retrieval sampling), and maintained an F1 score of over 82% even when using only 10% of the data, highlighting its robustness to sparse data.

After introducing LoRA technology, the validation set loss of ARFIMA decreased from 1.051 to 0.956, effectively alleviating overfitting. In the emotion recognition task, the accuracy rate for positive emotions reached 97.77%, and for sad emotions reached 91.79%, but there was confusion in the recognition of neutral emotions (accuracy rate of 90.12%).

Correlation analysis indicated that all dimensions of ideological and political education courses were significantly positively correlated with positive psychological qualities ($r = 0.168–0.494$, $p < 0.01$), with the strongest correlation observed in learning outcomes ($r = 0.494$), particularly in enhancing cognitive qualities ($r = 0.481$) and self-control qualities ($r = 0.479$). Regression analysis further revealed that course content ($\beta = 0.136–0.281$, $p < 0.05$) and diverse development ($\beta = 0.089–0.308$, $p < 0.05$) are core predictors of cognitive and self-control qualities; teacher competence contributes most to interpersonal qualities ($\beta = 0.217$, $p = 0.022$); and value transformation (knowledge internalization) has a prominent predictive power for emotional qualities ($\beta = 0.387$, $p < 0.01$).

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