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Differences in emotional expression among college students: a study on integrating psychometric methods and algorithm optimization

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Abstract

Background College students are in an important stage of life development, and their emotional expression ability has a profound impact on their mental health, interpersonal relationships, and academic performance. There are significant differences in emotional expression among individuals, which are influenced by various factors such as gender, cultural background, and personality traits. However, traditional research on emotional expression often relies on a single measurement method, which has problems such as single data dimensions, limited analysis methods, and lack of real-time dynamism and personalization. To overcome these limitations, this study conducted a comprehensive analysis using psychometric methods and algorithm optimization techniques.

Methods The Emotional Intelligence Scale (EQ-i) and the depression-anxiety-stress-21 (DASS-21) were used to quantitatively evaluate the emotional state of college students, and their facial expressions and speech emotion data were collected. In order to improve the precision of data analysis, random forests, support vector machines, and neural network machine learning algorithms were applied, and the variance analysis was used to calculate and compare the emotional differences of different genders and academic backgrounds in different grades.

Results The research results showed that gender, major, and grade differences significantly affected the emotional expression of college students. The F-values for the total EQ-i score of different genders were 7.00, and the F-values for depression, anxiety, and stress scores between different grades were 22.45, 12.48, and 9.14. Male engineering students scored higher in emotional intelligence than female liberal arts students, but liberal arts students showed more significant improvement in later academic years, reflecting the differing impacts of disciplinary environments on emotional development. Female students generally exhibited higher levels of anxiety and stress, particularly those in liberal arts, while female engineering students faced additional psychological burdens due to gender imbalance and biases. Anxiety and stress levels increased across all students as they advanced in their studies, correlating with academic and graduation pressures.

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Conclusion This article was based on the integration of psychometric methods and algorithm optimization techniques, exploring the differences in emotional expression among college students, providing new ideas for personalized mental health interventions for college students, enriching the theoretical basis of emotional expression research, and providing important references for education and mental health practice.

Keywords Emotional intelligence scale, Variance analysis, Differences in emotional expression, Psychometric methods, Algorithm optimization

Introduction

University is an important stage of personal growth, during which students may encounter various challenges and opportunities, and emotional expression ability has a significant impact on their mental health, interpersonal relationships, and academic performance. During this period, college students are experiencing significant changes in self-awareness [1], identity exploration, and interpersonal relationships, in which the way and effectiveness of emotional expression [يلÑ2] play a crucial role. It should be pointed out that there are significant differences in emotional expression among college students, which may be influenced by various factors, including gender, cultural background, personality traits, and personal experiences. Some college students tend to internalize emotions [3], expressing emotions through introspection and reflection. However, others tend to externalize emotions [4], conveying their emotions through language, behavior, or facial expressions [5]. Therefore, understanding the differences in emotional expression among college students and the factors behind them is of great significance for promoting their mental health [6] and adaptability [7], as well as enhancing their interpersonal relationships [8] and academic performance.

Previous studies on emotional expression among college students mostly rely on a single measurement method [9], such as questionnaire surveys [10] or communication observation. Although these methods help people understand the characteristics and patterns of emotional expression to a certain extent, their limitations have become increasingly apparent. Firstly, emotional expression is a complex and ever-changing process, and relying solely on questionnaire surveys or communication observations [11] often only captures static and one-sided emotional expression data, making it difficult to comprehensively present the diversity of individual emotional expression [12] and dynamic changes [13]. Secondly, the data dimensions collected by these methods [14] are relatively limited and often cannot cover all the features and details of emotional expression. This limitation affects the accuracy [15] and reliability [16] of research results, and many subtle but important emotional expression features may be overlooked as a result. In addition, the analysis methods of traditional methods are relatively single, mostly relying on subjective judgment [17] or simple statistical analysis [18], making it difficult to fully explore and utilize the potential patterns and information in the data. To address these issues, researchers need to explore and adopt more diverse and comprehensive research methods in order to capture the emotional expression of college students more comprehensively and dynamically.

Scholars have conducted relevant discussions on the differences in emotional expression among college students. Professor Mangaroska proposed a research method using multidimensional and multimodal data [19], attempting to collect gaze data, facial expression data, and EEG activity data from students through eye tracking devices, electroencephalogram (EEG), and cameras, in order to comprehensively evaluate the emotional expression of college students. However, this method faces many challenges in practical operation, not only dealing with the complexity of data collection, but also solving the technical difficulties of data processing and model construction, thereby increasing the difficulty of data collection and analysis [20]. In addition, some studies, although simplifying complex and diverse data to a certain extent, ignore the correlation and interaction between different data [21], resulting in insufficient exploration of information and patterns in the data. Looking at the literature, most studies on the differences in emotional expression among college students are still at the theoretical level, lacking sufficient practical basis and actual data support.

In this context, this study combines psychometric methods [22] and algorithm optimization techniques to conduct a comprehensive and in-depth study on the differences in emotional expression among college students. The study uses the Emotional Intelligence Scale (EQ-i) [23] and the depression-anxiety-stress-21 (DASS-21) [24] for quantitative evaluation, combined with facial and speech emotion data [25]. Machine learning algorithms such as Random Forest [26], Support Vector Machine, and Neural Network [27] are used to construct and optimize the predictive model for emotional expression [28]. Through these methods, this research can reveal the diversity and dynamic changes of emotional expression among college students, providing personalized recommendations for mental health interventions. This not only enriches the theoretical foundation of emotional expression research, but also provides important support for practical applications, helping to better understand and respond to the emotional needs of college students.

This study aims to explore the differences in emotional expression among college students by integrating psychometric methods and algorithm optimization techniques [29]. The Emotional Intelligence Scale (EQ-i) and the depression-anxiety-stress-21 (DASS-21) are used to quantitatively evaluate respondents and collect their facial expressions and speech emotion data. Next, machine learning algorithms such as random forest, support vector machine [30], and neural network were used to construct an emotion expression prediction model, and its performance was optimized. In the research process, the differences in emotional scores among different genders and academic backgrounds in different grades are compared through analysis of variance. The experimental steps include subject recruitment, data collection and processing [31], model construction and optimization [32], as well as data analysis and result interpretation. Through these methods, it is hoped to gain a deeper understanding of the emotional expression characteristics of college students, providing new perspectives and methods for theoretical research and practical applications.

Methods and materials

Data collection

The target group of this study is college students, and it is expected to recruit 500 college students from different grades, majors, and genders to ensure sufficient statistical power, model training needs, and sample diversity and representativeness. The recruitment notice is posted on the bulletin board of the university campus, explaining the research purpose, participation conditions, process, as well as the rights and privacy protection measures of the respondents. The school's official social media platform is used, such as WeChat official account, microblog, etc., to release recruitment information and expand the scope of publicity. Moreover, in the relevant courses, the research project is briefly introduced, and interested students are invited to participate. Among the recruited students, only those who meet the conditions of stable mental health and no history of major mental illness can participate in the experiment. In recruiting qualified interviewees, the purpose, process, and data usage of the research are detailed, and the written informed consent of the interviewees is obtained. Table 1 shows the number of respondents by grade, gender, and major.

Table 1 Number of respondents by grade, gender, and major

Classification	Project	Number of people
Gender	Male	254
	Female	246
Grade	First grade	120
	Second grade	119
	Third grade	134
	Fourth grade	127
Major	Engineering	254
	Liberal arts	246

In this study, the sampled population primarily consists of two major academic groups: science and engineering students and humanities students. The science group includes students from disciplines such as engineering, computer science, physics, and chemistry, while the humanities group encompasses students from fields such as literature, history, philosophy, sociology, and law. To ensure the representativeness of the sample, students from different grades and genders were recruited from each academic group. All participants met the criteria of stable mental health and no history of major mental illnesses. The study specifically focused on the emotional expression differences between science and humanities students, aiming to provide theoretical support for personalized mental health interventions by analyzing the emotional characteristics of students from different academic backgrounds.

For this study, the EQ-i and the DASS-21 are first used to test the emotions of the respondents. The EQ-i is used to assess the emotional intelligence level of respondents in emotional recognition, emotional management, and emotional expression, and the DASS-21 is used to assess their levels of depression, anxiety, and stress. The questionnaire star online survey platform is used to create test links, which not only facilitates respondents to fill out, but also ensures the anonymity of respondents when answering questions and improves the authenticity of data. After completing the EQ-i and DASS-21 tests, a centralized test is conducted on the respondents, organizing them to watch emotional movie clips, recall emotional events, participate in emotional discussions, etc., in a laboratory environment to induce authentic emotional responses from the respondents. By using high-resolution cameras, high-quality microphones, and recording devices, the facial expressions and voice data of the interviewees are recorded, ensuring that each task can be recorded clearly and completely. Afterwards, using automatic annotation tools, the video data is annotated based on the Facial Action Coding System (FACS), and facial action units (AUs) are identified and recorded. The speech data based on speech emotional features is annotated to recognize and record emotional changes. Then, the annotator performs calibration and confirmation. Finally, in the process of data collection and storage, numbers are used to replace the personal information of respondents, ensuring data anonymity, and all collected data are encrypted and stored to prevent unauthorized access. Through statistical analysis, the Cronbach's α coefficients for the EQ-i and DASS-21 scales were found to be 0.85 and 0.92, respectively. The conclusion is that both scales have good internal consistency and are suitable for emotional analysis research.

The data collection in this study combines facial expression recognition technology and speech emotion analysis technology. First, facial expression recognition captures the subjects' facial images in real time using cameras, and algorithms are applied to analyze changes in facial features to identify the emotional state of the subjects. Specifically, the Facial Action Coding System (FACS) is used to capture and recognize the facial muscle movements of the subjects in real time, analyze their emotional changes, and reduce human intervention through the software's automatic analysis function. In addition, the 300 Face in Wild face detection dataset is used for testing.

For speech emotion analysis, Praat software is used to visually analyze the pitch, speech rate, volume, and other feature information of the subjects' voices to determine whether their emotional state is happy, sad, angry, surprised, disgusted, or neutral. Based on the fact that angry speech usually has a higher fundamental frequency (F0), while sad speech has a lower and less fluctuating F0, the F0 value of the speech signal is extracted and analyzed to assess the emotional changes of the subject. The F0 value can be calculated using Formula (1), where T represents the duration of one speech cycle.

$$F_0 = \frac{1}{T} \tag{1}$$

At the same time, volume is also an important parameter for emotion analysis, typically measured by the amplitude of the signal. The volume of the same person may vary under different emotional states. Angry speech typically has a higher volume, while sad speech has a lower volume. Speech rate refers to the number of words or syllables spoken per unit of time. Analyzing speech rate can reflect the subject's tense, excited, or relaxed state. When anxious or excited, speech is usually faster, while when depressed or sad, speech is relatively slower. Finally, prosodic features, including patterns of changes in pitch, volume, and speech rate, are important aspects of emotional expression. By analyzing the prosodic features of speech, the emotional state of the subject can be more accurately identified. The specific process of speech emotion analysis is shown in Fig. 1.

Model construction

In this study, the Random Forest, Support Vector Machine (SVM), and Neural Network models each played a key role in emotional analysis, working in synergy to achieve the emotional classification task. The specific workflow is as follows:

First, in the data collection phase, emotional data were gathered through facial expressions and speech features. Facial expression features were captured and analyzed using the Facial Action Coding System (FACS), while speech features, such as tone, volume, and speech rate, were extracted using Praat software. These data were then prepared as inputs for the machine learning models for analysis.

In the Random Forest model workflow, the facial expression and speech feature data were first input into decision trees. The Random Forest model generates multiple decision trees and uses the output from each tree to vote, determining the final emotional classification result. Each decision tree makes judgments based on different features, and the model overcomes the overfitting problem of a single model by integrating the results from multiple trees. This integration also enhances the model's robustness against noisy data.

Next, the Support Vector Machine (SVM) was applied to handle the high-dimensional features of the data. The main task of the SVM is to construct a separating

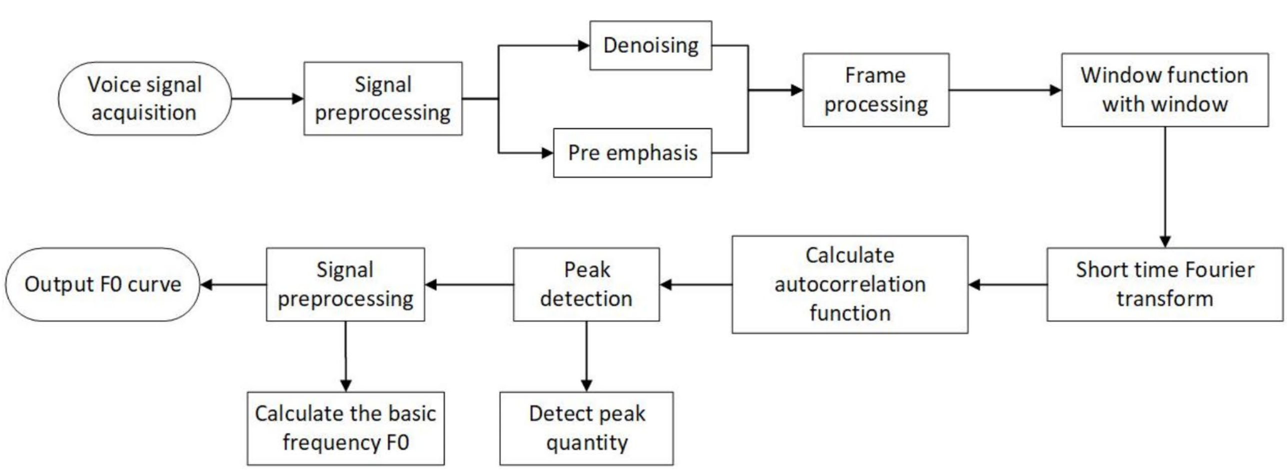

Fig. 1 Speech emotional analysis flowchart

hyperplane to distinguish samples of different emotional categories. During the emotional classification process, SVM constructs a hyperplane in a high-dimensional space based on facial expression and speech data, correctly classifying the emotional samples. By maximizing the margin, SVM improves classification accuracy and is capable of handling complex nonlinear problems, particularly in cases of complex emotional data. It avoids overfitting and maintains strong generalization capability.

Finally, the Neural Network was used for multimodal emotional analysis. The neural network consists of an input layer, a hidden layer, and an output layer. The input layer receives facial expression and speech feature data, which is processed by multiple neurons in the hidden layer and ultimately results in emotional classification at the output layer. Through multiple layers of nonlinear processing, the neural network extracts deep features and adapts to the complex patterns in the data. During training, the neural network automatically adjusts parameters using backpropagation, optimizing itself to improve the accuracy of emotional classification.

By combining these three models, this study was able to conduct a multi-dimensional analysis of college students' emotions, accurately identifying different emotional states based on both facial expressions and speech features. Figure 2 shows a simple neural network structure diagram.

The first step in data preprocessing is data cleaning. Firstly, for records with significant missing key variables, they are deleted. For small missing values, the mean filling method is used for interpolation. Afterwards, the outliers are identified and processed using the

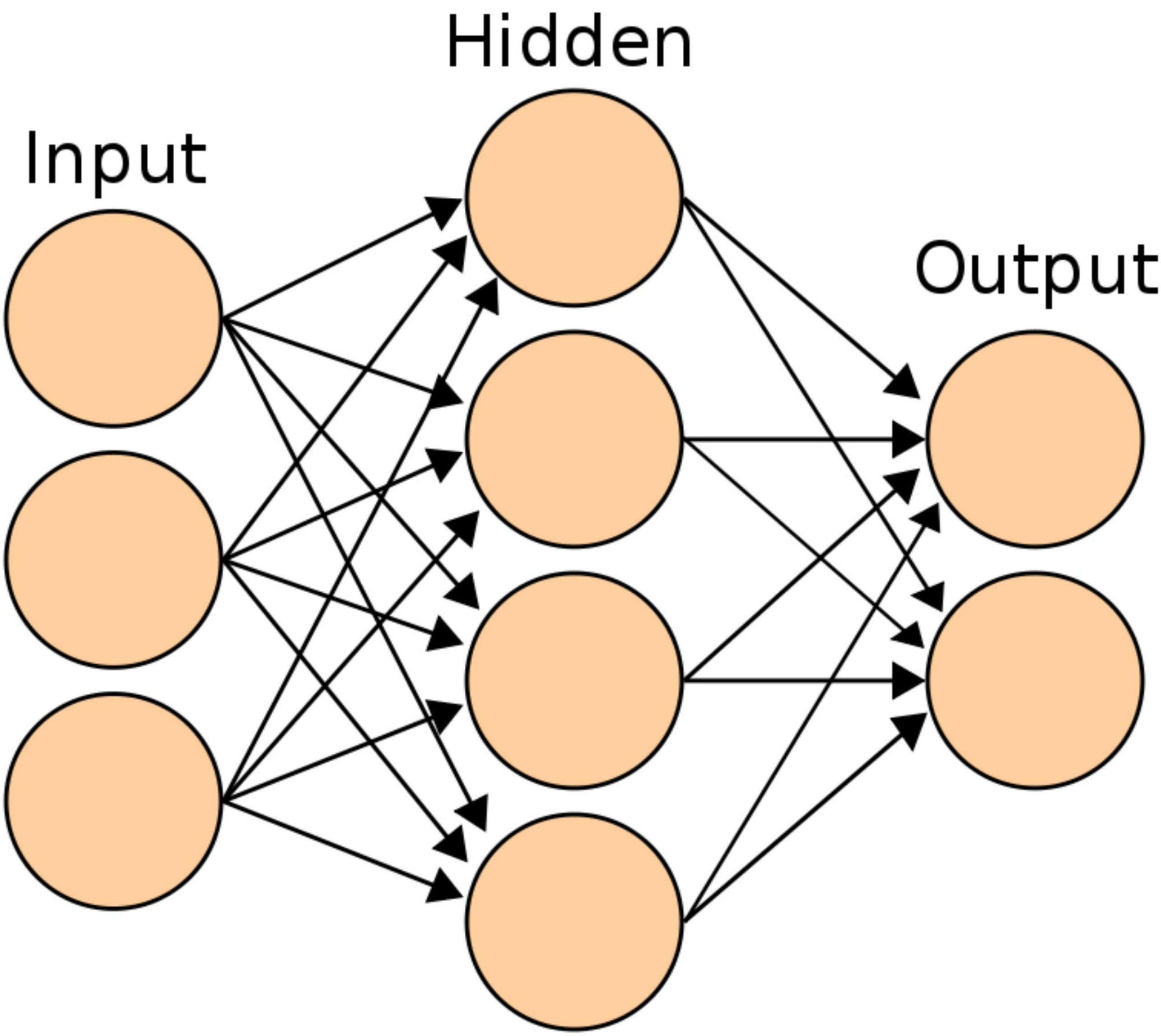

Fig. 2 Simple neural network structure diagram

Table 2 AU data values of respondents

Respondents	AU1	AU2	AU3	AU4	AU5	AU6	AU7	AU8
First grade engineering male	3.5	4	2.8	3.1	4.5	3.7	2.7	3.1
First grade engineering female	3.6	4.3	2.9	3.2	4.6	4	2.8	3.5
First grade liberal arts male	3.7	4.2	3	3.4	4.6	3.8	2.9	3.3
First grade liberal arts female	3.8	4.5	3.2	3.6	4.7	4.2	3.2	3.6
Second grade engineering male	3.6	4.1	2.9	3.3	4.4	3.8	2.6	3.2
Second grade engineering female	3.7	4.4	2.9	3.5	4.5	4.1	2.7	3.7
Second grade liberal arts male	3.6	4.2	3.1	3.6	4.7	4	2.8	3.4
Second grade liberal arts female	3.9	4.5	3.2	3.8	4.8	4.3	2.9	3.8
Third grade engineering male	3.7	4.1	3	3.5	4.5	4.1	2.8	3.3
Third grade engineering female	3.9	4.4	3.2	3.8	4.6	4.2	3	3.6
Third grade liberal arts male	3.8	4.3	3.1	3.6	4.6	4.2	3.2	3.5
Third grade liberal arts female	3.9	4.4	3.2	3.8	4.7	4.3	3.6	3.7
Fourth grade engineering male	3.4	4.1	2.8	3.3	4.4	3.9	2.7	3.4
Fourth grade engineering female	3.8	4.2	2.9	3.5	4.5	4.1	2.8	3.6
Fourth grade liberal arts male	3.6	4.4	3.2	3.7	4.5	4.2	3.2	3.5
Fourth grade liberal arts female	3.7	4.5	3.3	3.8	4.7	4.4	3.4	3.8

Table 3 Voice emotional analysis data of respondents

Respondents	Pitch	Volume	Speech Rate	F0	Formant
First grade engineering male	110 Hz	75 dB	150 wpm	120 Hz	500 Hz
First grade engineering female	210 Hz	70 dB	160 wpm	200 Hz	550 Hz
First grade liberal arts male	115 Hz	72 dB	155 wpm	125 Hz	520 Hz
First grade liberal arts female	205 Hz	68 dB	165 wpm	195 Hz	560 Hz
Second grade engineering male	112 Hz	74 dB	152 wpm	122 Hz	510 Hz
Second grade engineering female	208 Hz	69 dB	158 wpm	198 Hz	545 Hz
Second grade liberal arts male	117 Hz	71 dB	153 wpm	127 Hz	515 Hz
Second grade liberal arts female	202 Hz	67 dB	162 wpm	190 Hz	555 Hz
Third grade engineering male	114 Hz	73 dB	151 wpm	124 Hz	505 Hz
Third grade engineering female	211 Hz	71 dB	159 wpm	202 Hz	540 Hz
Third grade liberal arts male	116 Hz	72 dB	154 wpm	126 Hz	512 Hz
Third grade liberal arts female	203 Hz	69 dB	164 wpm	192 Hz	552 Hz
Fourth grade engineering male	113 Hz	75 dB	153 wpm	123 Hz	507 Hz
Fourth grade engineering female	207 Hz	70 dB	161 wpm	197 Hz	543 Hz
Fourth grade liberal arts male	119 Hz	74 dB	156 wpm	129 Hz	518 Hz
Fourth grade liberal arts female	204 Hz	68 dB	160 wpm	193 Hz	550 Hz

box plot method, and for the determined outliers, they are selected and adjusted to a reasonable range. Finally, duplicate records are detected and deleted to ensure that each data record is unique. In order to ensure that all features are on the same scale and avoid unfair effects of certain features on the model due to dimensional issues, it is necessary to standardize the data. The normalization method is shown in Formula (2) for minimum-maximum normalization.

$$\mathrm{X}' = \frac{\mathrm{X} - \mathrm{X}_{\min}}{\mathrm{X}_{\max} - \mathrm{X}_{\min}} \tag{2}$$

The second step is to use facial recognition algorithms to extract features such as facial key points and expression action units, forming high-dimensional feature vectors. Table 2 shows the average facial recognition data obtained from respondents of different grades, majors, and genders. From the data in Table 2 and the range of values combined with AU (0–5), it can be seen that the following AU values are within a reasonable range.

The third step is to use audio processing tools to extract the time domain and frequency domain features of speech signals. Table 3 shows the average values of speech emotional analysis data from respondents of different grades, majors, and genders. By collecting data on the pitch, volume, speaking speed, basic frequency, and formant of the respondents, their emotional states during the experiment are analyzed.

Comparing Table 3 with Table 4, it is found that the data in Table 3 is within the range of Table 4, indicating that the data in Table 3 is reasonable and effective.

Finally, the processed dataset is evaluated for model performance. Based on model-based feature selection,

Table 4 Range of data for pitch, volume, speaking speed, fundamental frequency, and formant

Features	Male	Female
Pitch	85–180 Hz	165–255 Hz
Volume	60 dB – 70 dB (General Conversation) 75 dB – 85 dB (Excited or loud talking)	60 dB – 70 dB (General Conversation) 75 dB – 85 dB (Excited or loud talking)
Speaking speed	150–180 wpm	150–180 wpm
F0	85–180 Hz	165–255 Hz
Formant	200–1000 Hz	200–1000 Hz

decision tree models are used to calculate the importance of features, and features with higher importance are selected. The process is shown in Formula (3). Among them, $\mathrm{P_k}$ is the probability of category k, and K is the total number of categories. The importance of features is represented by the mean reduction in impurity of all trees.

$$\mathrm{Gini}\left(\mathrm{D}\right)=1-\sum\nolimits_{\mathrm{k}-1}^{\mathrm{K}}\left(\mathrm{P_k}\right)^2 \quad (3)$$

After data preprocessing and feature fusion are completed, the next step is to construct and train machine learning models to predict and analyze differences in emotional expression among college students. In order to make the experiment rigorous and effective, this article applies random forest, support vector machine, and neural network algorithms. Firstly, random forest is an ensemble learning method based on decision trees, which has advantages such as strong resistance to overfitting. The calculation formula is shown in Formula (4), Among them, $\widehat{\mathrm{y}}$ is the prediction result; N is the number of decision trees; $\mathrm{T_i}\left(\mathrm{x}\right)$ is the prediction result of the i-th decision tree. Secondly, Support Vector Machine (SVM) is a supervised learning model used for classification and regression, which has the advantages of efficient processing of high-dimensional data. The calculation formula is shown in Formula (5), Among them, w and b are hyperplane parameters; C is the regularization parameter; $\mathrm{y_i}$ is the label; $\mathrm{x_i}$ is the feature vector. Neural networks are computational models that mimic the structure of the human brain and possess strong expressive power, making them suitable for processing large amounts of data. The calculation formula is shown in Formula (6). Among them, W_1 and W_2 are weight matrices; b_1 and b_2 are bias vectors; σ is the activation function.

$$\widehat{y}=\frac{1}{N}\sum\nolimits_{i-1}^{N}T_i\left(x\right) \quad (4)$$

$$Min_{w,b}\frac{1}{2}\left|\left|W\right|\right|^2+C\sum\nolimits_{i-1}^{n}max\left(0{,}1-y_i\left(w\cdot x_i+b\right)\right) \quad (5)$$

Table 5 Gender and grade distribution data

Grade	Male engineering	Male liberal arts	Female engineering	Female liberal arts
First grade	52	13	10	45
Second grade	46	15	12	46
Third grade	49	16	18	51
Fourth grade	51	12	16	48

$$\widehat{y}=\sigma\ \left(W_2\sigma\ \left(W_1+b_1\right)+b_2\right) \quad (6)$$

Model training includes data preparation, model initialization, loss function definition, optimization algorithm selection, and training process control. Firstly, the dataset is divided to ensure that samples of each category are evenly distributed across different datasets. Afterwards, the number of trees in the random forest, the kernel function type of SVM, the number of layers in the neural network, and the number of neurons is initialized as model parameters. Then, the cross-entropy loss function is selected to measure the difference between the model's predicted value and the true value, as shown in Formula (7). Finally, the random gradient descent algorithm is chosen to update the model parameters and minimize the loss function.

$$\mathrm{L}\left(\widehat{\mathrm{y}},\mathrm{y}\right)=-\frac{1}{\mathrm{n}}\sum\nolimits_{\mathrm{i}-1}^{\mathrm{n}}\left[\mathrm{y_i}\log\left(\widehat{\mathrm{y}}_\mathrm{i}\right)+\left(1-\mathrm{y_i}\right)\log\left(1-\widehat{\mathrm{y}}_\mathrm{i}\right)\right] \quad (7)$$

The performance of the model is evaluated based on metrics such as accuracy, precision, recall, and F1 score obtained from the validation and test sets used for the model. The calculation formulas are shown in Formulas (8), (9), (10), and (11). Among them, TP is true positive; TN is true negative; FP is false positive; FN is false negative.

$$\mathrm{Accuracy}=\frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \quad (8)$$

$$\mathrm{Precision}=\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \quad (9)$$

$$\mathrm{Recall}=\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \quad (10)$$

$$\mathrm{F1Score}=\frac{2\times\ \mathrm{Precision}\times\ \mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}} \quad (11)$$

Results

This article organizes and analyzes the collected data.

The data in Table 5 records the number of male and female liberal arts and engineering subjects among the respondents in different grades. From Table 5, it can be seen that the majority of people are from male engineering and female liberal arts, while the number of people from male liberal arts and female engineering is relatively small.

According to the data in Table 6 on the EQ-i values of male and female liberal arts and engineering students in each grade, the EQ-i value of male engineering students in the fourth grade is the highest, and that of female liberal arts students in the first grade is the lowest. From the distribution of data, it can be seen that the EQ-i value of male engineering is generally higher than that of female liberal arts, and that of female engineering is higher than that of female liberal arts. Moreover, as grades increase, the EQ-i values of both males and females in liberal arts and engineering show varying degrees of improvement. After calculation, the average EQ-i for males is 71.5 and for females it is 69.

From the bar chart of anxiety score distribution in Fig. 3, it can be seen that as the grade level increases, both males and females, as well as those in liberal arts and engineering, have their anxiety scores increasing. From the cylindrical distribution, it can be seen that female students majoring in liberal arts have higher anxiety scores than female students majoring in engineering, while male students majoring in liberal arts have lower anxiety scores than male students majoring in engineering. According to the classification of anxiety levels from 0 to 7 as normal, from 8 to 9 as mild, from 10 to 14 as moderate, from 15 to 19 as severe, and from 20 to above as extremely severe, fourth grade liberal arts females have moderate anxiety. Fourth grade engineering male and female students, as well as third grade engineering female and liberal arts female students, have all experienced mild anxiety.

According to the bar chart of stress score distribution in Fig. 4, it can be seen that the stress of college students increases with the increase of grade level. The stress

Table 6 EQ-i values for male and female Liberal arts and engineering subjects in each grade

Grade	Male engineering	Male liberal arts	Female engineering	Female liberal arts
First grade	70	68	68	66
Second grade	72	70	69	68
Third grade	73	72	70	69
Fourth grade	74	73	72	70

score of fourth grade engineering females is the highest, while the stress score of first grade liberal arts males is the lowest. In addition, the stress score of engineering females is higher than that of engineering males, and the stress score of liberal arts females is also higher than that of liberal arts males. According to the classification of stress levels from 0 to 14 points as normal, from 15 to 18 points as mild, from 19 to 25 points as moderate, from 26 to 33 points as severe, and from 34 points and above as extremely severe, fourth grade engineering females have a moderate level of stress; the second grade engineering female, third grade engineering female, engineering male, and liberal arts female, and fourth grade engineering male, liberal arts male, and liberal arts female all experience mild stress.

It can be clearly seen from the bar distribution in Fig. 5 that college students have relatively low depression scores in their first year of college, but their depression scores also increase to varying degrees with the increase of grade. According to the data in Fig. 5, it can be concluded that the depression scores of first grade engineering males and liberal arts males are the lowest, while fourth grade engineering females have the highest depression scores. From the cylindrical distribution, it can be seen that the depression scores of liberal arts students are lower or the same as those of engineering students, while the depression scores

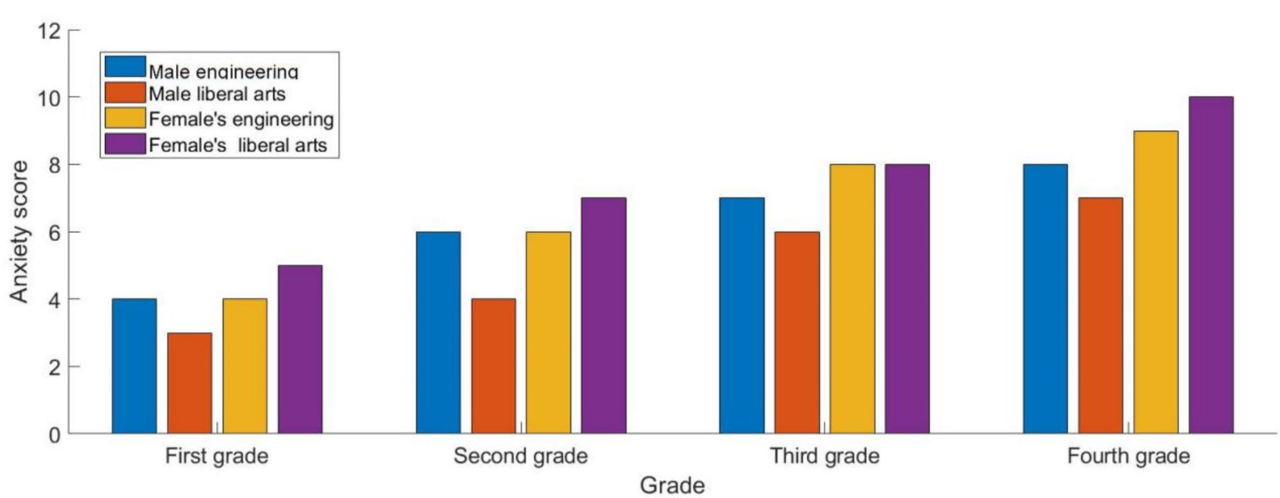

Fig. 3 Anxiety score distribution bar chart

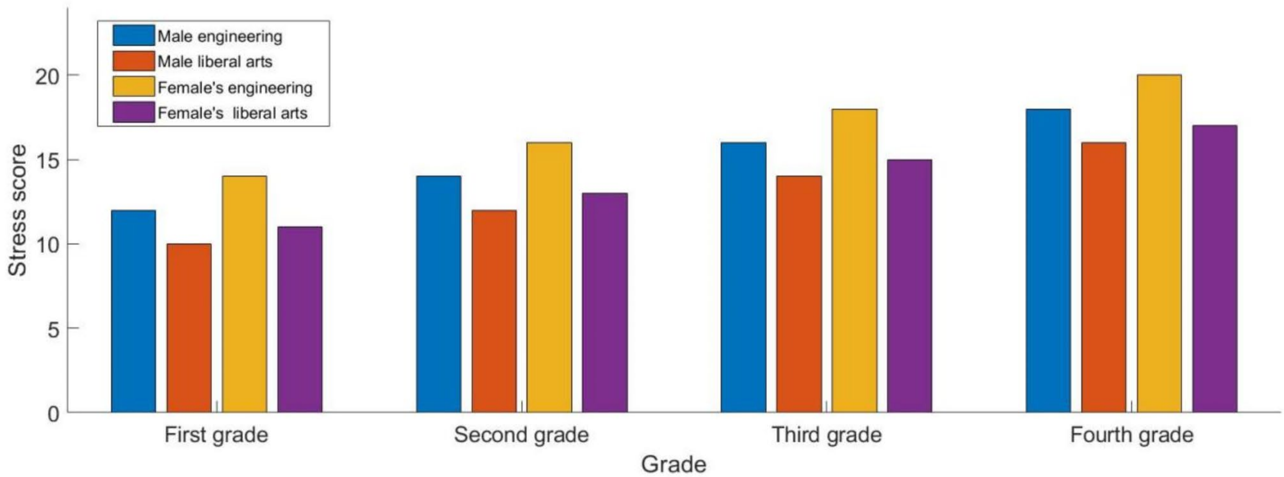

Fig. 4 Stress score distribution bar chart

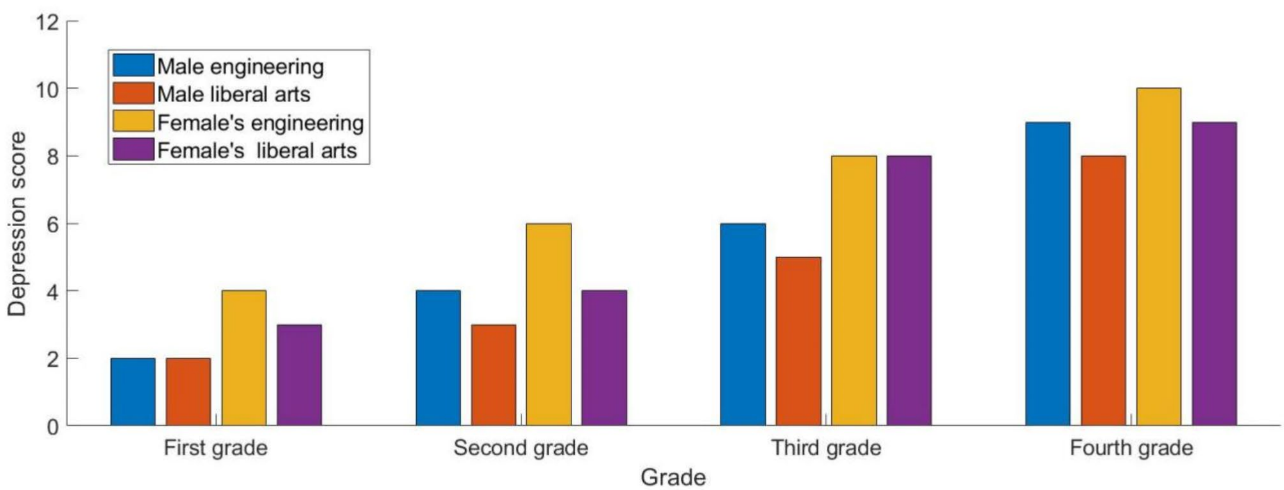

Fig. 5 Depression score distribution bar chart

of males are lower or the same as those of females. According to the classification of depression levels from 0 to 9 as normal, from 10 to 13 as mild, from 14 to 20 as moderate, from 21 to 27 as severe, and from 28 to above as extremely severe, fourth grade female engineering students may experience mild depression.

Through the statistical technique of cluster analysis, this paper delves into the complex patterns of emotional expression among engineering students. The cluster analysis groups the collected emotional data (such as scores for anxiety, stress, depression, etc.) according to students' gender, grade, and disciplinary background, thereby revealing the characteristics of emotional expression among different groups. The results of the cluster analysis show that while there are certain differences in emotional states between engineering and liberal arts students, the individual differences in emotional expression within the same disciplinary group are also significant. By analyzing the clustering results of emotional data, it can be observed that students in certain grades (such as seniors) exhibit a noticeable increase in scores for emotions like anxiety and stress, while emotional fluctuations are relatively smaller in other grades. Furthermore, the cluster analysis also reveals differences in emotional expression patterns between male and female students within the engineering cohort, as shown in Table 7.

Through analysis of variance, the emotional differences between different genders and academic backgrounds in different grades are calculated and compared. The calculation steps for analysis of variance are as follows. Among them, $\bar{X}$ is the total mean, and $\bar{X}_i$ is the mean of the i-th group. SSB represents the sum of squared deviations between the mean of each group and the total mean; SSW represents the sum of squared deviations between the observed values within the group and the group mean; SST is the sum of SSB and SSW; dfB is the degree of freedom between groups; dfW is the degree

Table 7 Clustering analysis results

Grade	Gender	Anxiety Score (Mean)	Stress Score (Mean)	Depression Score (Mean)	Cluster Group
First	Male	7.4	10.2	5.3	A
First	Female	8.1	11.4	5.6	A
Second	Male	8.5	11.8	6.1	B
Second	Female	9.2	12.6	6.4	B
Third	Male	9.1	12.3	7	C
Third	Female	9.6	13.2	7.5	C
Fourth	Male	9.8	13.7	7.9	D
Fourth	Female	10.4	14.5	8.2	D

Table 8 Analysis of variance calculation results for EQ-i total score, depression score, anxiety score, and stress score

Emotional score type	F-value between genders	Interdisciplinary F-value	F-value between grades
EQ-i total score	7.00	1.91	4.45
Depression score	1.53	0.41	22.45
Anxiety score	2.48	0.06	12.48
Stress score	1.19	3.89	9.14

of freedom within the group; MSB is the mean square between groups; MBW is the mean square within the group; F is a test statistic used to test whether there is a significant difference in the mean between groups. The total score of EQ-i, depression score, anxiety score, and stress score are calculated using analysis of variance, and the results are shown in Table 8.

$$\bar{X}=\frac{\sum_{i=1}^{k}\sum_{j=1}^{n_i}X_{ij}}{N} \tag{12}$$

$$\bar{X}_i=\frac{\sum_{j=1}^{n_i}X_{ij}}{n_i} \tag{13}$$

$$SSB=\sum_{i=1}^{k}n_i\left(\bar{X}_i-\bar{X}\right)^2 \tag{14}$$

$$SWW=\sum_{i=1}^{k}\sum_{j=1}^{n_i}\left(X_{ij}-\bar{X}_i\right)^2 \tag{15}$$

$$SST=SSB+SSW \tag{16}$$

$$dfB=k-1\ \ ;\ \ dfW=N-k \tag{17}$$

$$MSB=\frac{SSB}{dfB}\ \ ;\ \ MSW=\frac{SSW}{dfW} \tag{18}$$

$$\mathrm{F}=\frac{\mathrm{MSB}}{\mathrm{MSW}} \tag{19}$$

From the F-values in Table 8, it can be seen that there are significant differences between genders in the total EQ-i score. There are significant differences between grades in depression score, anxiety score, and stress score, while the differences between disciplines in stress score are the smallest.

Data analysis and discussion

The findings of this study reveal significant differences in emotional expression among college students, influenced by gender, academic discipline, and grade level. These results not only align with existing literature but also highlight several knowledge gaps and offer practical implications for intervention strategies.

Gender and emotional intelligence

Our results indicate that male engineering students scored higher in emotional intelligence (EQ-i) compared to female liberal arts students. This finding aligns with previous research suggesting that engineering disciplines, which emphasize logical thinking and systematic problem-solving, may enhance emotional recognition and management skills [5]. However, this advantage is not absolute. As students progress through their academic years, liberal arts students show a greater increase in emotional intelligence. This suggests that the rich social interactions and emotional experiences embedded in liberal arts environments may have a more profound impact on emotional development over time [2]. This trend underscores the importance of considering both initial emotional intelligence and its development over time when designing interventions.

Anxiety, stress, and depression across grades

The clustering analysis indicates that anxiety, stress, and depression scores generally increase with grade level. Both male and female fourth-year students show higher emotional scores, reflecting significant academic and graduation-related pressures. This finding is consistent with previous studies that have identified senior year as a critical period for mental health challenges due to the culmination of academic demands, career uncertainties, and evolving interpersonal relationships [6]. Female engineering students, in particular, exhibit higher emotional scores compared to their male counterparts, which may be attributed to gender differences and societal role expectations. This dual burden of academic challenges and gender stereotypes can lead to increased psychological stress and isolation [3].

Disciplinary differences in emotional health

In terms of emotional health indicators, female students, especially those in liberal arts, exhibit higher levels of anxiety and stress. This is linked to the nature of liberal arts curricula and teaching methods, which often emphasize emotional resonance, personal expression, and social sensitivity. These elements may lead female liberal arts students to experience more intense emotions when confronting complex feelings [7]. On the other hand, female engineering students show higher scores in stress and depression, which might stem from the gender imbalance and potential biases in engineering fields. These students face the dual pressure of academic challenges and gender role expectations, such as proving their competence academically while also countering stereotypes suggesting that "women are less capable in engineering." This dual burden may leave them feeling isolated and exhausted, further compounding their psychological stress [1].

Intervention strategies

A. Based on these findings, several intervention strategies can be proposed to address the emotional challenges faced by college students:
B. Personalized Mental Health Support for Senior Students: Given the heightened levels of anxiety, stress, and depression among senior students, universities should offer more systematic mental health support. This could include personalized counseling, emotional management workshops, and group support activities. These interventions can help alleviate psychological stress and enhance emotional coping skills [24].
C. Gender-Specific Support Programs: Female students, particularly those in engineering, may benefit from gender-specific support programs. These programs could address the unique challenges faced by women in male-dominated fields, providing mentorship, networking opportunities, and stress management resources. Additionally, workshops on combating gender stereotypes and building resilience could be beneficial [30].
D. Curriculum Adjustments: Universities should consider adjusting course schedules and academic workloads based on students' actual conditions and psychological states. Offering more psychological counseling and stress management courses can help alleviate academic pressure. Integrating emotional intelligence training into the curriculum, especially in engineering programs, could also promote better emotional regulation and interpersonal skills [26].
E. Real-Time Emotion Monitoring Systems: The study identified unique linguistic and facial changes in students under psychological stress. With the support of artificial intelligence and machine learning, real-time emotion monitoring systems could be developed to track students' emotional states by collecting data on speech, facial expressions, and other physiological signals. Such systems would enable educators to identify psychological issues promptly and offer personalized emotional regulation advice, preventing further deterioration of mental health problems [15].

Conclusions

This study explores the differences in emotional expression among college students by integrating psychometric methods and algorithmic optimization techniques. The research finds that grade level, major, and gender have significant impacts on emotional expression. Upperclassmen demonstrate better emotional intelligence, but their scores for depression, anxiety, and stress also increase notably, especially among engineering students. Female students generally score higher in depression, anxiety, and stress than their male counterparts, particularly in the upper grades. Therefore, it is recommended that universities provide more mental health support and counseling during the upperclassmen years to help students effectively manage stress and emotions, avoiding the negative impacts of emotional issues on academic and personal life. Additionally, course schedules and academic workloads should be appropriately adjusted based on students' actual conditions and psychological states, offering more psychological counseling and stress management courses to alleviate academic pressure.

This study reveals the significant impact of grade level, gender, and major on college students' emotional expression, but it still has some limitations and does not fully account for other potential influencing factors. Although the study found that female students generally score higher than males in depression, anxiety, and stress, it did not adequately consider additional psychological pressures that women may face, such as interpersonal violence, which could exacerbate emotional distress. Furthermore, while emotional issues are more prominent among upper-year students, the study did not deeply analyze the underlying social factors behind emotional variations across gender and academic disciplines, such as gender bias and academic burden. Future research should incorporate more influencing factors and explore more diverse methods of emotional monitoring and intervention to more accurately reveal the complexity of emotional expression and mental health.

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Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

All procedures involving human participants in this study were conducted in accordance with the Declaration of Helsinki (as revised in 2013). The study received approval from the Ethics Committee of School of Civil Engineering and Architecture, Anhui University of Science and Technology, Huainan, Anhui, China. All participants provided written informed consent. All procedures were conducted in accordance with the relevant guidelines and regulations outlined in the Declaration of Helsinki.

Consent for publication

Not applicable.

Clinical trial number

Not applicable.

Competing interests

The authors declare no competing interests.

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