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Advanced artificial intelligence (AI)-based affective computing in online learning

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Advanced artificial intelligence (AI)-based affective computing in online learning

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Research on the Relationship Between College Students' Participation in Sports Activities and Self-Harmony Assessment Based on the Moderating and Mediating Effects of Mental Toughness

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College students are the future of the motherland, the hope of the nation, and the reserve force to realize the great rejuvenation of the Chinese nation. The period of college students is an important period for the formation of ideals, beliefs, and world views. However, due to the contradictions between physiological maturity and psychological maturity and the contradictions between independent consciousness and cognitive ability in the growth process of college students, it is easy to cause internal psychological problems of inconsistency and disharmony. Correct sports lifestyle is conducive to promoting individual self-harmony. In the daily life and learning process of college students, the role of self-harmony is often ignored and not paid enough attention to. This indicates that it is necessary to further study the effect of physical activity on adolescents' self-harmony. Mental toughness is one of the important factors affecting self-harmony. Therefore, the variable of mental toughness is introduced to analyze the correlation between physical activity and self-harmony. This study investigate the relationship between physical activity, mental toughness, and self-harmony in college students. Also this study can promote the re-recognition of college students of sports activities, explore the relationship between physical activity and self-harmony. Its purpose is to directly or indirectly promotes the college students' mental health, and further enriches health psychology, exercise psychology, and development psychology-related theory and method. By analyzing the correlation among sports activities, mental toughness, and self-harmony, this study provides a theoretical reference for improving and enhancing the self-harmony degree of college students and providing beneficial suggestions for relevant management departments when making plans.

Keywords: college students, sports activities, self-harmony assessment, mental toughness, moderating and mediating effects

INTRODUCTION

Mental toughness is embodied in different aspects, such as social adaptability, academic development, emotional adaptation, and so on. In addition, the effect of mental toughness in different fields is not the same. For example, college students show higher mental toughness in academic studies but lower mental toughness in social adaptability. A correct understanding of the connotation of college students' mental toughness is conducive to a comprehensive understanding of the impact of college students' mental toughness. The correlation between sports activities and mental health has been confirmed by more and more researchers. In the analysis of sports activities and mental health, many scholars say that sports activities can alleviate individual negative emotions, and sports activities can enhance individual self-confidence, optimism, tenacity, and other positive psychological qualities (Estrella et al., 2013; Stamp et al., 2017). Sports activities also have a promotion effect on the physiological level of the individual, specifically, they can improve the individual's physical health and physical state and promote dopamine hormone secretion and other positive changes to promote the overall mental health level of the individual (Madrigal et al., 2013). Previous studies have also confirmed that sports activities have a positive role in promoting individual mental health, but relevant departments, schools, and society have not received corresponding attention, resulting in the neglect of physical education and individual mental health education in the process of physical education (Safian, 2020). Therefore, the interaction between sports activities and mental health should be emphasized in future educational practice (Gucciardi and Jones, 2012). At present, the psychological problems of college students are considered by researchers in various fields. Many college students commit suicide, feel weary, lack a yearning for life, and face other psychological problems frequently (Driska et al., 2012). This study mainly discusses the relationship among college students' sports activities, mental toughness, and self-harmony. The purpose of studying the relationship among the three is to attract the attention of schools and parents and encourage college students to establish correct sports activities and establish correct lifelong sports awareness, which plays an irreplaceable role in improving college students' mental health.

CONCEPT INTRODUCTION

Sports Activity Participation

Research on sports activities has been interpreted differently by researchers in each field, and Michael (2012) defined that the concept of sports activities as the key to physical activity lies in physical means, improvement of physical and mental health, enrichment of material and cultural life, and other factors. Based on the combination of nature and hygiene, physical means are used to improve health and physique, develop physical quality, and regulate mental state. An activity aimed at enriching people's cultural life and controlling their leisure time. Fen et al. (2015) believed that sports activities refer to planned, regular, and repeated sports activities under the interaction of their own conditions and external environment with the main purpose of enhancing physical fitness and improving physical and mental health. In this study, sports activities refer to all kinds of sports activities conducted by college students in accordance with their own needs and interests at school or outside school, as well as all sports activities arranged by the school curriculum, interclass exercise, and extracurricular activities. This study mainly investigates the sports activity items, sports activity time, sports activity frequency, and sports activity intensity of college students, so as to analyze the correlation among sports activity, mental toughness, and self-harmony.

Self-Harmony

Bodroža (2011) argued that true self-harmony means that the self can freely follow the heart and choose what it wants to do, and the realization of true self-harmony must harmonize the real, realistic, and rational self in order to bring them into harmony and unity. According to Park et al. (2018), self-harmony refers to the ability of an individual to reconcile various contradictions and conflicts. If the ideal self or social self is far from the real self, it will lead to self-disharmony, inner conflict and tension, and psychological disorders. Fan et al. (2011) suggested that self-harmony refers to the consistency or closeness between self-knowledge and actual performance. In addition, good individual mentality, positive cognition, healthy psychology, optimistic spirit, and self-harmony promote each other. Guo (2013) believed that self-harmony means that the basic needs of self and external behavior can promote the personalized and social development of people and keep pace with the times to promote the construction of a harmonious society. In addition, the realization of self-harmony is of great significance to humans, nature, and society and is an important basis for promoting interpersonal, natural, and social harmony. This study adopts the definition of self-harmony given by Xiao (2013) and holds that the essence of self-harmony lies in self-satisfaction with the current life state or external environment, and being able to accept the cognition of internal and external environments of the body. Even if the individual's own internal needs, self-set goals, and ideal results are not realized, or even the self-performance in all aspects is poor and difficult to surpass others, as long as the individual can accept the true self, without psychological obstacles and troubles, then he/she has achieved self-harmony.

Mental Toughness

Mental toughness, also known as resilience, refers to an individual's effective response and good adaptation to life pressure and setbacks (Mengmen and Suo, 2019). It belongs to the category of positive psychology, is a kind of positive psychological quality, and is a kind of ability that people can actively deal with difficulties and setbacks. Mental toughness is a bad resource, which can resist individual psychological disorders and behavioral problems. And the mental toughness has a positive impact on individual happiness. The improvement of college students' mental toughness can not only help individuals improve their ability to overcome difficulties but also improve their life satisfaction and happiness levels and promote their mental health (Yasar and Turut, 2020). With the diversified development of society, people have higher and higher expectations and requirements of contemporary college students, which makes them bear great pressure in study and life, resulting in a series of psychological problems such as anxiety and depression. Life satisfaction is one of the important indicators to measure the mental health level of college students, and the improvement of life satisfaction is conducive to improving the mental health level. The increase of psychological resilience can effectively predict the increase of positive emotions and overall wellbeing (Gucciardi, 2011), and life satisfaction is one of the important dimensions of overall happiness, so psychological resilience may play an important role in the relationship between nostalgia and life satisfaction.

RESEARCH OBJECT AND METHODS

Research Objects

The survey began in March 2021, and the research subjects were college students. Questionnaires were distributed to college students in the form of online electronic questionnaires, and 124 valid questionnaires were collected. Among them, there are 58 male students, accounting for 46.77%, and 66 female students, accounting for 53.23%. The basic information of the research object is shown in **Table 1**.

Research Methods

Sports Activity Participation Measurements

According to Liang (1994), the Physical Activity Compile Physical Activity Rating Scale (PARS-3) measures the amount of exercise from three aspects, which are sports activity time, sports activity frequency, and sports activity intensity. Each item has five different levels of options from low to high. The specific calculation formula is as follows:

$$\text{Exercise Score} = \text{Intensity} \times (\text{time}-1) \times \text{Frequency}$$

Self-Harmony Measurement

According to the Self-harmony Rating Scale compiled by Wang and Cui (2007), the scale includes three subscales: "the disharmony between self and experience," "the self-flexibility," and "the self-rigidity." There are a total of 35 items on the scale, and each item is divided into five grades and recorded as 1–5 points, respectively. The total score of self-harmony can be calculated. Specifically, "the self-flexibility" is scored in reverse and then added to the scores of the other two subscales.

TABLE 1 | Basic information of the research subject.

Statistical variables of the sample		Number of the sample	Proportion (%)
Grade	Freshman	39	31.45
	Sophomore	41	33.06
	Junior year	21	16.94
	Senior year	23	18.55
Gender	Male	58	46.77
	Female	66	53.23
Origin of student	City	36	29.03
	Villages and towns	56	45.16
	Rural	32	25.81

Mental Toughness Measurement

Mental toughness is compiled by Dagnall (mental toughness questionnaire-10, MTQ-10). The scale has a total of 10 items, which are optimized by the author and selected as follows: objective focus, emotion control, positive cognition, family support, and interpersonal assistance were measured from 1 (strongly disagree) to 5 (strongly agree). The higher the score, the better the individual's psychological resilience (Driska et al., 2012). MTQ-10 was used in this study, and Cronbach's α coefficient of consistency reliability of the scale was 0.72, greater than 0.7, indicating good reliability and reliable measurement results.

Research Hypothesis

Jackman et al. (2017) pointed out that for college students to have a better understanding of themselves, they must face some setbacks in the process of engaging in sports activities, find themselves from setbacks, better play their potential, and better adapt to setbacks, pressure, and negative emotions in a better and faster manner. This study preliminarily analyzes the research results on the relationship among sports activities, mental toughness, and self-harmony of college students and proposed the following five research hypotheses:

> Hypothesis 1: There are significant differences in demographic variables among sports activities, mental toughness, and self-harmony among college students.
> Hypothesis 2: There is a significant positive correlation between sports activities and mental toughness of college students.
> Hypothesis 3: There is a significant negative correlation between sports activities and self-harmony of college students.
> Hypothesis 4: There is a significant negative correlation between college students' mental toughness and their self-harmony.
> Hypothesis 5: Mental toughness plays a mediating role in the correlation between sports activities and self-harmony.

Statistical Method

SPSS 22.0 software was used to analyze the data, including descriptive statistics, one-way variance, independent sample *t*-test, internal consistency test, multiple linear regression analysis, and path analysis.

RESULTS

Demographic Results

To better understand the relationship among college students' sports activities, mental toughness, and self-harmony. Descriptive statistics were made on the relationship among sports activities, mental toughness, and self-harmony among college students. Demographic results are shown in **Table 2**.

Difference Between Sports Activity Participation and Mental Toughness and Self-Harmony

One-way ANOVA was conducted for the mental toughness, factors, and self-harmony of college students with different sports activities. The results show that there are significant differences between college students and college students' mental toughness. There is a significant correlation between sports activity time and objective focus, emotion control, positive cognition, and interpersonal assistance, with a correlation coefficient <0.05. There is no significant correlation between sports activity time and family support. Therefore, there is a significant positive correlation between sports activity time and objective focus, emotion control, positive cognition, and interpersonal assistance.

The sports activity frequency of college students is significantly correlated with objective focus, emotion control, positive cognition, and family support, with the correlation coefficient reaching <0.05. There is no significant correlation between sports activity frequency and interpersonal assistance ($P > 0.05$). Therefore, there is a significant positive correlation among sports activity frequency and objective focus, emotion control, positive cognition, and family support, exercise intensity, exercise time, and exercise frequency, and there are significant differences between college students and college students' mental toughness. The difference between sports activities participation and mental toughness and self-harmony is shown in **Table 3**.

Correlation Matrix Between Sports Activity Participation and Mental Toughness and Self-Harmony

There is a significant correlation between college students' sports activity intensity and objective focus, emotion control, and positive cognition, with a correlation coefficient of <0.05. There is no significant correlation between sports activity intensity and family support and interpersonal assistance ($P > 0.05$). Therefore, there is a significant positive correlation between sports activity intensity and objective focus, emotion control, and positive cognition.

There is a significant correlation between sports activity time and objective focus, emotion control, positive cognition, and interpersonal assistance, with a correlation coefficient of <0.05. There is no significant correlation between sports activity time and family support. Therefore, there is a significant positive correlation between sports activity time and objective focus, emotion control, positive cognition, and interpersonal assistance.

The sports activity frequency of college students is significantly correlated with objective focus, emotion control, positive cognition, and family support, with the correlation coefficient reaching <0.05. There is no significant correlation between sports activity frequency and interpersonal assistance ($P > 0.05$). Therefore, there is a significant positive correlation between sports activity frequency and objective focus, emotion control, positive cognition, and family support. The correlation matrix between sports activity participation and mental toughness and self-harmony is shown in **Table 4**.

There is no significant correlation between college students' sports activity intensity and disharmony between self and experience and self-rigidity ($P > 0.05$). There is a significant correlation between sports activity intensity and self-flexibility of college students, and the correlation coefficient is <0.05. There is a significant correlation between sports activity

TABLE 2 | Demographic results.

First-level indicator	Second-level indicator	Average	Standard deviation
Sports activities participation	Sports activity intensity	12.32	5.45
	Sports activity time	23.15	1.76
	Sports activity frequency	23.29	1.85
Self-harmony	Disharmony between self and experience	23.75	1.59
	Self-flexibility	22.82	13.26
	Self-rigidity	53.21	8.05
Mental toughness	Objective focus	95.15	9.68
	Emotion control	46.25	13.26
	Positive cognition	28.18	9.66
	Family support	19.73	7.28
	Interpersonal assistance	52.01	13.18

TABLE 3 | Difference between sports activity participation and mental toughness and self-harmony.

Factor	Sports activity intensity	Sports activity time	Sports activity frequency	*F*
Objective focus	17.25 ± 3.51	18.81 ± 3.50	18.77 ± 3.52	2.180
Emotion control	18.55 ± 4.50	20.24 ± 4.55	20.19 ± 5.04	2.446
Positive cognition	14.79 ± 2.72	16.08 ± 2.68	16.28 ± 3.01	1.135
Family support	20.70 ± 4.96	21.33 ± 2.96	22.17 ± 4.46	1.128
Interpersonal assistance	19.24 ± 5.18	20.20 ± 5.49	20.24 ± 5.28	0.769
Disharmony between self and experience	45.65 ± 8.36	44.53 ± 9.35	44.58 ± 9.70	1.308
Self-flexibility	44.28 ± 5.48	45.73 ± 5.64	45.52 ± 6.23	1.147
Self-rigidity	18.59 ± 4.17	18.09 ± 3.89	18.27 ± 4.39	0.947

TABLE 4 | Correlation matrix between sports activity participation and mental toughness and self-harmony.

Factor	Objective focus	Emotion control	Positive cognition	Family support	Interpersonal assistance
Sports activity intensity	0.136	0.128	0.068	0.028	0.026
Sports activity time	0.223	0.165	0.071	0.036	0.082
Sports activity frequency	0.169	0.132	0.114	0.068	0.046

TABLE 5 | Correlation matrix between college students' sports activity participation and self-harmony.

Factor	Disharmony between self and experience	Self-flexibility	Self-rigidity
Sports activity intensity	−0.028	0.065	−0.029
Sports activity time	−0.112	0.121	0.023
Sports activity frequency	−0.071	0.120	0.015

TABLE 6 | Correlation matrix between college students' mental toughness and self-harmony.

Factor	Objective focus	Emotion control	Positive cognition	Family support	Interpersonal assistance
Disharmony between self and experience	−0.234	−0.536	−0.078	−0.271	−0.465
Self-flexibility	0.432	0.208	0.369	0.215	0.246
Self-rigidity	−0.118	−0.204	−0.123	−0.175	−0.317

TABLE 7 | Regression analysis of sports activity participation on mental toughness.

Factor	Standard regression coefficient	*t*	*R*	R^2	Adjusted R^2	*F*
Sports activity time	0.135	3.854				
Sports activity frequency	0.104	2.713	0.206	0.043	0.047	22.563

time and disharmony between self and experience and self-flexibility, and the correlation coefficient is <0.05. There is no significant correlation between sports activity time and self-rigidity ($P > 0.05$). There is a significant correlation between the sports activity frequency of college students and disharmony between self and experience and self-flexibility, and the correlation coefficient is <0.05. There is no significant correlation between sports activity frequency and self-rigidity ($P > 0.05$). Therefore, there is a significant negative correlation between the sports activity frequency and the disharmony between self and experience and a positive correlation between the sports activity frequency and the self-flexibility. The correlation matrix between college students' sports activities participation and self-harmony is shown in **Table 5**.

There is a significant correlation between college students' mental toughness and disharmony between self and experience, self-flexibility, and self-rigidity, with the correlation coefficient <0.05. Moreover, there is a significant negative correlation between mental toughness and disharmony and between self and experience, self-rigidity, and positive correlation with self-flexibility, that is, the higher the score of mental toughness, the lower the score of disharmony between self and experience and self-rigidity, and the higher the score of self-flexibility. In other words, college students with a high level of mental toughness have a lower degree of disharmony between self and experience, a lower degree of self-rigidity, a higher degree of self-flexibility, and a higher degree of self-harmony. The correlation matrix between college students' mental toughness and self-harmony is shown in **Table 6**.

Regression Analysis of Sports Activity Participation and Mental Toughness and Self-Harmony

Regression Analysis of Sports Activity Participation on Mental Toughness

Sports activity intensity, time, and frequency are the independent variables, mental toughness total score is the dependent variable, regression equation model is established, the selection of mental toughness of most prediction model is analyzed, stepwise regression method is used for analysis, and *F*-test is used to screen whether variables are included in the regression equation. $P < 0.05$ is included in the regression equation, and $P > 0.1$ is excluded from the regression equation. As shown in **Table 7**, only the time and frequency of sports activity enter the regression equation, and a model is established with a coefficient of determination of 0.206. The explanation of physical activity for mental toughness is 4.3%, and the variance test also reaches the significance level. The regression analysis of sports activity participation on mental toughness is shown in **Table 7**.

Regression Analysis of Sports Activity Participation on Self-Harmony

With the total score of sports activities and each factor as an independent variable and self-harmony as a dependent variable, the step regression method is used for analysis, *F*-test is used as the criterion to screen whether variables are included in the regression equation, $P < 0.05$ is included in the regression equation, and $P > 0.1$ is removed from the regression equation. The results are shown in **Table 8**. Physical activity intensity is entered into the regression equation, and a model is established. The determination coefficient of the model is 0.113, the amount of physical activity explaining self-harmony is 1.7%, and the variance test reaches the significance level. The regression analysis of sports activity participation on self-harmony is shown in **Table 8**.

Regression Analysis of Mental Toughness to Self-Harmony

Mental toughness total score and each factor score are independent variables, the self-harmony total score is the dependent variable, which is analyzed with the method of stepwise regression analysis, and the *F*-test is used as a standard of whether screening of variables into the regression equation, $P < 0.05$ is into the regression equation, $P > 0.1$ is in eliminating regression equation, and the selection of self-harmony of the

TABLE 8 | Regression analysis of sports activity participation on self-harmony.

Factor	Standard regression coefficient	*t*	*R*	R^2	Adjusted R^2	*F*
Sports activity intensity	−0.105	−3.414	0.113	0.017	0.013	12.063

TABLE 9 | Regression analysis of mental toughness to self-harmony.

Factor	Standard regression coefficient	t	R	R^2	Adjusted R^2	F
Objective focus	0.062	2.312				
Positive cognition	0.069	2.563				
Family support	−0.812	−18.926	0.563	0.456	0.423	203.328

TABLE 10 | Fitting index of each model index.

Model indexes	Model fitting index before modification	Model fitting index after modification	Critical value
CMIN	341.208	63.158	
CMIN/DF	8.506	2.084	
IFI	0.845	0.936	>0.90
CFI	0.847	0.925	>0.90
NFI	0.836	0.928	>0.90
GFI	0.925	0.974	>0.90
RFI	0.752	0.936	>0.90
AGFI	0.896	0.964	>0.90
PNFI	0.602	0.534	>0.50
PGFI	0.557	0.436	>0.50
RMSEA	0.086	0.037	<0.05

most prediction model are studied. The results are shown in **Table 9**. Objective focus, positive cognition, and family support enter the regression equation, and a model is established. The coefficient of determination of the model is 0.563, and the amount of explanation of resilience to self-harmony is 45.6%. The regression analysis of mental toughness to self-harmony is shown in **Table 9**.

Mediating Effect Test

Analysis of Various Model Indicators

The indicators all meet the critical value, indicating that the research model has a good degree of fit. From the model analysis, the CMIN is equal to 63.158, and the P-value is equal to 0.000 ($P < 0.005$), indicating that there is a significant difference between the variance matrix derived from path analysis and the variance matrix derived from the hypothetical model; and the overall fitting index of the model meets the basic requirements, so the model established in this study conforms to the path analysis, and the model is accepted. The fitting index of each model index is shown in **Table 10**.

Path Factor Analysis

The fitting degree of each model index in this study is good, so the path coefficients among physical activity level, mental toughness, and self-harmony are all meaningful. Amos was used to calculate the standardized path coefficients between each path (Parkes and Mallett, 2011). Results from the path output showed that the factor load P-value is less than 0.001, except for the physical activity on the self-harmony between the path factor P-value is greater than 0.05. The standardized path coefficient of sports activities to mental toughness is 0.26, the standardized path coefficient of sports activities to self-harmony is 0.08, and the standardized path coefficient of mental toughness to self-harmony is −0.78. Path analysis of intermediate variables is shown in **Figure 1**.

Mediating Effect Analysis

The Amos test equation model is used to output the results. To analyze whether mental toughness is a partial intermediary or a complete intermediary in the impact of sports activities on self-harmony in this study, Amos was used to conduct path analysis, Bootstrap is used to calculate standardized estimates and standard deviations, and the results are analyzed according to the output results of the path (Mahoney et al., 2014).

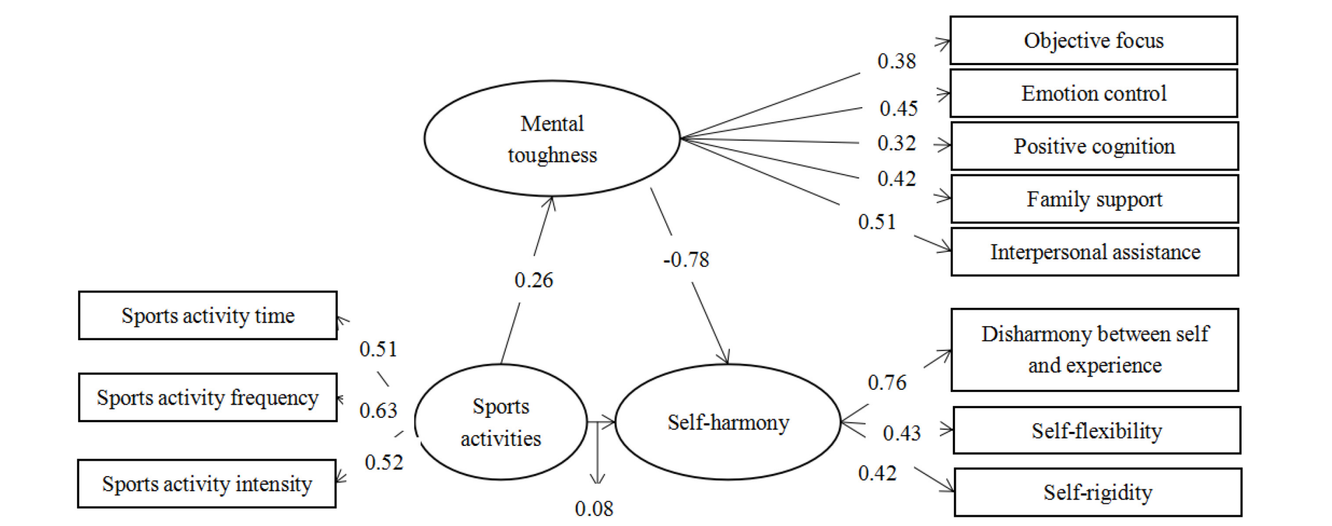

FIGURE 1 | Path analysis of intermediate variables.

TABLE 11 | Mediating effect analysis results.

Coefficient name	Normalized path coefficients	Standard error	Significant or not
a	0.265	0.048	Yes
b	−0.816	0.049	Yes
C	−0.153	0.067	Yes
c'	0.054	0.039	No

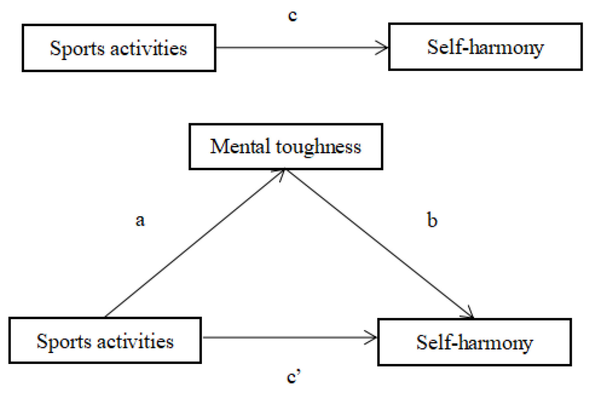

FIGURE 2 | Mediation equation model.

TABLE 12 | Path analysis results.

Path name	Normalized path coefficient	Ratio of total effect (%)	Upper limit	Lower limit	Significant or not
Direct effect	0.049	36.52	0.129	−0.025	No
Indirect effect	−0.209	63.15	−0.130	−0.286	Yes
Total effect	−0.152	–	−0.059	−0.234	Yes

Therefore, mental toughness plays a complete mediating role in the relationship between sports activities and self-harmony. Mediating effect analysis results are shown in **Table 11**.

The mediation equation model is shown in **Figure 2**.

The total effect value of physical activity on self-harmony is −0.152, which is also the sum of the direct effect value and the indirect effect value. The direct effect value is 0.049, and the indirect effect value is −0.209. The direct path of physical activity to self-harmony is not significant, while the indirect path of sports activities to self-harmony is significant through mental toughness. According to the bootstrap mediation test method, there are two confidence intervals in the path analysis result report, namely, the bias-corrected percentile method and the percentile method. The bias correction confidence interval is used to observe the influence of physical activity on self-harmony. In this study, the lower and upper limits of total effect and indirect effect do not contain 0, while the confidence interval of direct effect contains 0. The total effect and indirect effect of sports activities on self-harmony are significant, while the direct effect of sports activities on self-harmony is insignificant. It also confirms that mental toughness played a completely mediating role in the relationship between sports activities and self-harmony. The indirect effect accounted for 63.15% of the total effect. The path analysis results are shown in **Table 12**.

RESEARCH CONCLUSION

University is a relatively complex small society, and the ability of college students to adapt to this small society depends on their mental toughness to a certain extent. Mental toughness is a buffer for college students to face setbacks and failures, and it is a kind of resilience ability in life pressure and frustration. College students with high mental toughness can better overcome adversity and setbacks and pursue positive self-realization. College students who regularly participate in sports activities have a higher level of mental toughness than those who do not participate in sports activities. Meanwhile, sports activities can directly affect the level of the mental toughness of college students, and sports activities can also indirectly affect the level of mental toughness by affecting other psychological variables. The conclusions of this study include the following:

(1) At present, most of the physical activities of college students belong to a small amount of exercise. The amount of physical activity of college students has a significant difference in gender, grade, and origin. In terms of scores, freshmen and sophomores are higher than juniors and seniors, and cities are higher than towns and villages.
(2) The degree of college students' mental toughness is above average, and there is a significant difference in the origin of college students' mental toughness. In terms of scores, cities are higher than towns and villages. The degree of self-harmony of college students is medium and high, and there are significant differences in the grade and origin of students. The degree of self-harmony of college students in cities is higher than that in towns and villages.
(3) Sports activities have a direct impact on college students' mental toughness. There are significant differences in exercise intensity, exercise time, exercise frequency, and exercise quantity, and there is a significant positive correlation between sports activities and mental toughness.
(4) There is a positive influence between sports activities and college students' self-harmony. There are significant differences in the time and frequency of exercise among college students, but no significant differences in the intensity and amount of exercise. There is a significant correlation between intensity, time, frequency, physical activity, and self-harmony.
(5) The direct path of sports activities on college students' self-harmony is not significant, but the indirect path of sports activities on college students' self-harmony is significant through enhancing the level of mental toughness. Therefore, mental toughness is a complete mediator between sports activities and self-harmony, and the indirect effect is 63.15% of the total effect.

The innovation of this study include: by investigating college students' sports activities, the relationship between mental toughness and self-harmony promotes the re-recognition of college students of sports activities; this study further explores the relationship between physical activity and self-harmony, and finds that sports activities can directly or indirectly promotes the college students' mental health. Furthermore, our study have found that sports activities can greatly enrich the relevant theories and methods of health psychology, sports psychology, and developmental psychology. However, due to the constraints of time and funds in the process of research and investigation, the number of questionnaires issued is relatively small. In effective questionnaires, the sample size is relatively small, and 124 valid questionnaires were collected. But there are certain limitations in the area of investigation, which may not represent the overall situation of college students in China. In related research in the future, it is better to conduct a survey on the sports activities of national college students, so that the results of this study can be more representative. Further attention of relevant departments must be aroused to better strengthen the mental health education of college students.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

HX contributed to wiring, data collection, and methodology.

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Discourse Moves and Emotion in Knowledge Building Discourse and Metadiscourse

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This paper explores the possibility that knowledge building metadiscourse-discourse about knowledge building-can produce a positive feedback loop, with positive emotional state and knowledge advancement serving to increase each other. Grades 2 and 3 students' utterances over several months were analyzed as a unit of study, starting with identification of each discourse move and corresponding emotion, defined as a state. These states were then analyzed over time, with a focus on metadiscourse sessions in which students reflected on earlier discourse to identify questions and ideas to be pursued in greater depth. Each discourse move-emotional state was analyzed to determine frequency, transition from one state to another, and spread of each state such as "reflection and positive" and "proposing new directions for inquiry and curiosity." These two states were among the most frequently occurring in the metadiscourse sessions and virtually absent in other discourse sessions. Transition rates indicated that reflection tended to trigger more reflection, and proposing a new direction led to more proposals for new directions. Sequential pattern analysis suggested sub-sequences specific to metadiscourse sessions. Overall, results indicate that engaging in metadiscourse contributes to students' productive KB and positive emotions.

Keywords: Knowledge Building, discourse, metadiscourse, emotion, idea improvement, discourse move, young students

INTRODUCTION

Emotions and cognitive decision making are central to human response to the dynamic environments they face (Afraimovich et al., 2011), forming interconnections (Oatley et al., 2014) involving participation and coordination of overlapping brain centers (Afraimovich et al., 2011). Cognitive judgment influences emotional responses with emotional appraisals forming the base for coordinated responses (Feldman Barrett et al., 2019). To better understand how emotions are framed and contextualized within learning activities and environments, researchers increasingly study emotion and cognition as unified and interconnected actions (e.g., Chevrier et al., 2019; Hod and Katz, 2020; Isohätälä et al., 2020a,b; Vogl et al., 2020).

Productive collaborative learning requires students to be aware of and coordinate their cognitive, emotional, and metacognitive resources and processes (Hadwin et al., 2018; Järvelä et al., 2019). Knowledge Building (KB), emphasizes students' collective social and cognitive responsibility to advance community knowledge (Scardamalia and Bereiter, 2014). Such endeavors involve students' engagement in knowledge building metadiscourse, discourse about knowledge building, in which they make decisions, form goals, identify and remedy understanding gaps, and discuss future inquiry directions (Zhang et al., 2015). Engaging in high-level cognitive and metacognitive work requires a broad and reflective view of their discourse, treating discourse as an object for formative assessment, inquiry, and refinement (Resendes et al., 2015). Metadiscourse allows students to work on ideas they think are important and valued and take greater control over learning than they usually do. The control-value theory (CVT; Pekrun, 2006; Pekrun and Perry, 2014) suggests students may experience more positive emotions in metadiscourse sessions. CVT assumes that subjective controls (i.e., the extent to which a student perceives causal influence over actions and outcomes) and values (i.e., how important and attractive they think the actions and outcomes are) influence students' emotions during learning tasks. This framework for understanding the generation and influencing factors of emotions in learning settings guides researchers to design environments to support students' positive emotions. For instance, this study did so by engaging students in KB metadiscourse sessions that were likely to enhance students' control of learning and the value of their collaborative inquiry.

Students who participate in collaborative learning, including KB, experience cognitive and emotional interactions (Isohätälä et al., 2020a,b). Previous studies suggest that engaging in metadiscourse will help sustain and deepen KB (e.g., Resendes et al., 2015; Yang et al., 2016; Tao and Zhang, 2018; Zhang et al., 2018). What remains unknown are the effects of engaging in metadiscourse on students' emotions. Furthermore, studies indicate that metacognitive processes usually mediate the effects of emotions on learning outcomes (e.g., D'Mello et al., 2014; Mega et al., 2014; Obergriesser and Stoeger, 2020). KB discourse and metadiscourse unfold over time, and it is important to study the temporal dimension of students' learning process (Chen et al., 2017; Zhu et al., 2019b). Therefore, this study considered students' emotions and KB discourse moves together to understand when students' control over learning was supported at different levels in discourse and metadiscourse, how their discourse moves and emotion states differed, and the transitions and sequences of the states. Considering the discourse move and corresponding emotion of each utterance as a paired unit allowed us to generate insights of how cognition reflected in a discourse move and emotion co-occur, and change over time, which was not possible in previous analyses which studied cognition and emotion separately or examined relationships (e.g., Chevrier et al., 2019; Buono et al., 2020). Research into the co-occurrence of cognitive-emotional states is needed to further our understanding of emotions that promote or impede learning with implications for designing more positive socioemotional environments for collaborative inquiry learning. This study has theoretical and methodological novelty. Theoretically, it addresses the research gap concerning limited understanding of students' discourse moves and emotions in discourse and metadiscourse sessions. Methodologically, this study considers the discourse move and emotion coding of an utterance as a whole (i.e., state) and investigates frequency, transition, and spread.

LITERATURE REVIEW

Knowledge Building and Discourse Moves

Knowledge Building advocates for students' collaborative responsibility to advance community knowledge (Scardamalia and Bereiter, 2014), to better prepare them to engage with a society wherein knowledge is continuously refined, and new knowledge quickly emerges. Advancing community knowledge involves pursuing more coherent explanations that encompass more new facts and a deepening understanding of why theories work (Scardamalia, 2002; Thagard, 2007). When an experimental idea is published in natural science, like biology, scholars worldwide can test and build on it. Similarly, in KB, students' ideas and theories are seen to have a public life: they are open to testing, questioning, criticizing, putting up alternatives, and improving (Popper, 1972; Bereiter, 1994; Scardamalia et al., 1994; Philip, 2009).

Ideas are improved through progressive KB discourse and metadiscourse in offline KB talks and online platforms such as *Knowledge Forum* (KF). Usually, a class of students and teachers form a KB community. As shown in **Figure 1**, in KB talks (Reeve et al., 2008), students and teachers sit in a circle to discuss community norms, questions, ideas, and theories that they think are important to share, discuss, and research. The community may also decide what ideas to focus on and what experiments, field trips, and other investigative activities to pursue. KB discourse can also occur online in KF—the technology built specifically to support knowledge-creating interactions (Scardamalia, 2004). In KF, Students are encouraged to record the important ideas, resources, or examples they have discussed in KB talks to deepen their understanding of these issues. Within KF (see **Figure 2**), students can post ideas as notes onto a public space called a "view." They can co-author, revise, read, reference, build on, and annotate notes as ways of building community knowledge. When writing notes, students can use scaffolds such as "my theory," "I need to understand," "a better theory," and "constructive uses of authoritative sources." These scaffolds can be co-constructed by the teacher and students to facilitate student thinking and writing.

Different measures have been developed to study students' KB discourse and metadiscourse. For example, Zhang et al. (2009) used the "epistemic complexity" and the "scientific sophistication" measures to code students' scientific understanding. The epistemic complexity of ideas indicates students' efforts to produce theoretical explanations and elaborations on community ideas. Measures of scientific sophistication assess the extent to which students move from

FIGURE 1 | An example of Knowledge Building talk.

an intuitive to a scientific understanding. Yang et al. (2016) classified students' notes into three categories: question, idea, and community. The question category is further distinguished into fact-seeking, explanation-seeking, and metacognitive questions. The idea category includes simple claim, elaboration, explanation, and metacognitive statement. The community category includes negotiating a fit and synthesizing note. Hmelo-Silver and Barrows (2008) categorized the statements generated in medical students' KB discourse into collaboration and complexity. The collaboration category consists of new ideas, modifications, agreement, disagreement, and "meta," while complexity includes the simple, causally elaborated, and elaborated levels. This study integrated and adapted these coding schemes to analyze students' discourse moves in their discourse and metadiscourse sessions.

Furthermore, it is critical to study the transitions and temporal sequences of discourse moves of collaborative learning, especially for KB which emphasizes students' idea improvement. Knowledge construction, collaborative problem solving, and idea improvement occur over time (Reimann, 2009; Knight et al., 2017). An idea (e.g., a question, a piece of information, or an explanation) needs to be understood in its context (i.e., previous ideas) to evaluate how it contributes to idea improvement. Using lag-sequential analysis and frequent sequence mining, Chen et al. (2017) analyzed the sequential patterns among students' contribution types (i.e., discourse moves) in KB. They found that productive threads were characterized by more transitions among notes coded as questioning, obtaining information, working with information, and theorizing. In contrast, merely opinion-giving did not contribute much to idea improvement. In a collaborative inquiry learning context, Zhu et al. (2019b), indicated that when groups successfully solved their problems, their discourse was characterized by a higher probability of transitions from proposition generation to orientation, from interpretation and conclusion to experimentation, and from proposition generation

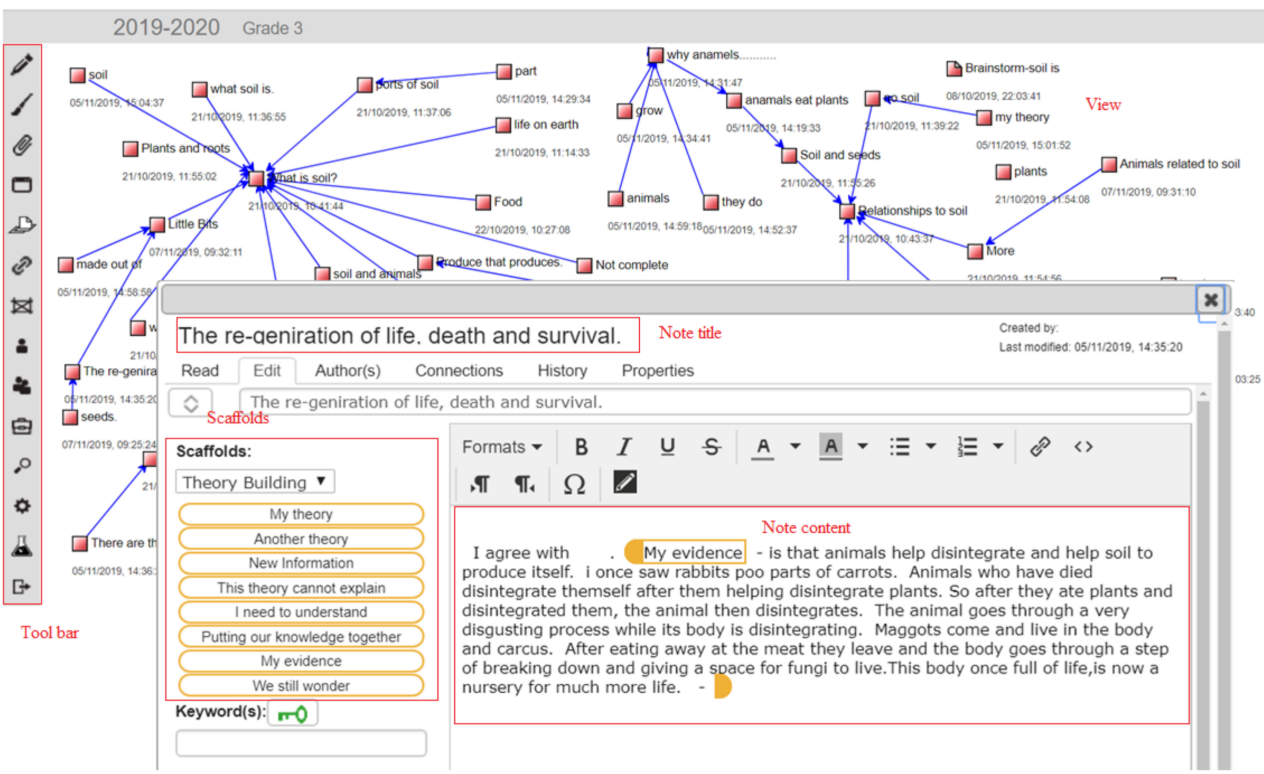

FIGURE 2 | Grade 3 Knowledge Forum view showing a note open for editing (student misspelling was not corrected).

to sustaining mutual understanding. These results suggest that students in groups who solved problems successfully tended to ensure that everyone in their group had a shared understanding of the relationship between the variables. However, existing studies (e.g., Chen et al., 2017; Zhu et al., 2019b), have been focused on analyzing online discourse, leading to a limited understanding of how offline discourse may unfold over time.

Emotion and Emotion Transitions in Learning

Emotions emerge as part of a stimulus-appraisal process (Fiedler and Beier, 2014), wherein an individual engages with an object (e.g., environment, person, memory) and passes a judgment on it. This series of judgments can happen on a conscious or unconscious level and are affected by various personal factors and dynamic processes of collaborative inquiry (Bakhtiar et al., 2017). The social nature of that interaction precipitates an emotional response that can then be analyzed based on the circumstances surrounding the individuals and the response/judgment they bring to that set of circumstances. It is important to note that emotions, especially in performance-based learning environments, do not simply emerge without cause. Cognitive psychology describes how the appraisal process ties together the causal reasoning, deliberation, goal appraisal, and planning processes that surround emotions, which are mediated through the experience of emotions (D'Mello and Graesser, 2012). The cognitive mechanisms in our mind help transform the appraisals and actions surrounding a situation into emotions that can be externally expressed (Shuman and Scherer, 2014) in the form of a physical indicator (e.g., an action, reaction, physical gestures, movement).

Various theories have emerged to describe how individuals emotionally respond to their environments. These theories include emotion regulation in achievement settings (ERAS; Harley et al., 2019), the component process model (CMP; Scherer, 2009), and the CVT (Pekrun, 2006; Pekrun and Perry, 2014). These models share similarities in how they situate emotions to the time and place where an individual makes a judgment regarding a stimulus or environment, which then results in an emotional expression. These emotion theories, especially the CVT and ERAS, allow researchers to describe how emotions emerge in a host of achievement-oriented environments (Loderer et al., 2020), and describe the emergence of emotions as an appraisal of two components: (1) control and (2) value. Subjective control refers to a student's perceived causal influence over actions or outcomes (e.g., expectations that persistence at studying can be enacted and can lead to success, Skinner, 1996). Subjective value denotes the student's perceived valence of actions and outcomes (e.g., the perceived importance of success). As described above, in the KB context, students' authentic ideas and epistemic agency are emphasized, conveying value and control. By enabling students to reflect on their community discourse status, identify understanding gaps, and make inquiry plans, metadiscourse further provides them with opportunities to work on ideas they think are of importance and value and take greater control through reflecting on earlier work. As such, we argue that KB contributes to students' positive emotions, and metadiscourse sessions are more likely to foster positive emotions than the first-pass discourse sessions.

Thornton and Tamir's (2020) three-dimensional mental state model, which frames humans' experiences of thoughts and feelings, helps explain the transitions of mental dynamics. The researchers synthesized and verified that a mental state could be represented with three dimensions: (1) rationality, (2) social impact, and (3) valence. Rationality is about the degree of cognition (e.g., agency, competence, reasoning) involved in a state. Social impact describes the intensity and sociality of a state, for example, how impactful a state is on social relationships. Valence indicates the positive or negative extents of a state. Thornton and Tamir (2020) suggested that a mental state is more likely to transit to a near state in the mental space. The emotional transitions that individual learners make while engaging in KB change their appraisal of their ideas and environments, therefore necessitating the need to understand how emotions co-develop with ideas.

Metadiscourse

Metadiscourse engages students in metacognitive conversations about their ongoing collaborative inquiry. In metadiscourse, students take collective responsibility for high-level cognitive work such as making decisions, forming goals, identifying and remedying understanding gaps, and discussing future inquiry directions (Zhang et al., 2015). Several studies have shown the positive impact of metadiscourse on students' community knowledge advancement (e.g., Resendes et al., 2015; Lei and Chan, 2018; Zhang et al., 2018). However, metadiscourse is rarely observed in inquiry-based learning without intentional support (Scardamalia, 2002; van Aalst, 2009). Researchers have been studying how to support metadiscourse or reflective assessment with pedagogical and technical designs. For instance, Hewitt and Woodruff (2010) integrated a wiki page that held a permanent and group-authorable summary of the discourse in KF to help students maintain a meta-level collective understanding of the progress. Chen et al. (2015) designed a *Promising Ideas Tool* that helps students select, aggregate, and display the ideas that they think can lead in the most productive directions. Resendes et al. (2015) investigated grade 2 students' ability to engage in productive discussions of their community knowledge status with the support of two group-level feedback tools: a tool that displays the overlapping and different words used in students' notes and authoritative sources, and a tool that shows the frequency of KF scaffolds used in notes. Yang et al. (2016) used two questions to guide the reflection of 20 grade 11 students on their community knowledge: *Are we a community that collaborates*? and *Are we putting our knowledge together*? Tao and Zhang (2018) and Zhang et al. (2018) examined how Idea Thread Mapper (ITM), a time-based inquiry-structuring tool (Chen et al., 2013), helped teachers and students to monitor their community status and decide which threads to focus on. In Lei and Chan's (2018) study, the students wrote group e-portfolios as their KB unfolded as a way of engaging in collaborative reflective assessment. These designs have informed the metadiscourse design of the current study.

Self-regulation and metacognition are two constructs very relevant to metadiscourse. Three mechanisms describe the process of self-regulated learning: (1) assessing the effectiveness of strategies that students employ to help them meet their learning goals, (2) modifying plans, and the effort they exert to meet those modified plans, and (3) engaging in effective and meaningful self-reflection and having a sufficient mechanism by which to do this (Azevedo and Aleven, 2013). Socially shared regulation learning that encourages students to negotiate and achieve shared goals, plans, and strategies as a group (Järvelä and Hadwin, 2013) is more relevant to this study context—students taking collective responsibility to build knowledge. Metacognition is the thinking process about one's thoughts (Clarebout et al., 2013). This process is driven by the interaction of metacognitive knowledge, experiences, and strategies, which help the learner to be able to objectively think about and monitor their abilities and goals, and in turn can inform other processes critical to learning, such as self-regulation.

These self-regulated and metacognitive processes mediate the effects of emotions on learning outcomes and reinforce positive processes that can help learners achieve success. For instance, Buono et al. (2020) study with 150 6- to 9-year-old students indicated that students' planning fully mediates the effect of frustration on their narrative storytelling scores, and frustration is significantly related to fewer planning behaviors. Mega et al. (2014) showed that positive emotions only foster undergraduate students' learning when mediated by self-regulated learning and motivation. D'Mello et al. (2014) found that confusion can contribute to learning when appropriately induced, regulated, and resolved. Järvenoja et al. (2019) explored which challengers triggered students' socially shared emotional regulation during collaborative learning and which emotional regulation strategies emerged. They found that socially shared emotional regulation is an established part of regulation when collaborative learning is challenged. Obergriesser and Stoeger (2020) conducted a temporal analysis to investigate how elementary students' enjoyment and boredom predict their effective use of learning strategies and vice versa. They found that students' self-reported enjoyment positively predicted their effective use of learning strategies, while boredom did not; in turn, learning strategies neither predicted enjoyment nor boredom. However, these studies were mainly conducted at the individual learning level. Few studies have investigated how metacognition may influence emotions and cognition at the collaborative level.

Conceptual Framework and Research Questions

Previous research suggests the interconnection of cognition and emotion, the importance of studying the sequential patterns of discourse move and emotions in the KB context, and the impact of metadiscourse and relevant self-regulation and metacognition on cognition and emotions. Furthermore, the three-dimensional mental state model suggests a state tends to transit to similar states, suggesting discourse move-emotion states would spread in KB communities in which students take collective responsibility to advance their knowledge and engage in various cognitive and emotional interactions. KB, as suggested by its principles (including real ideas, authentic problems, and epistemic agency), emphasizes students working on ideas they care about and driving their inquiry by engaging in high-level cognitive work such as negotiating shared goals and making plans. Although this high-level cognitive work may occur at all levels, KB metadiscourse sessions provide students with more opportunities to discuss the ideas and problems they care about and how to work on these issues by reflecting on their current KB discourse, identifying understanding gaps, proposing future inquiry directions, and making plans to further advance their community knowledge. This may help students to perceive the relevance and value of learning and take more control over their learning. According to the CVT, students would feel increased positive emotions and decreased negative emotions in metadiscourse sessions.

We conjecture that students' discourse moves-emotion states in KB discourse and metadiscourse sessions differ, as do the transitions of these states. As shown in **Figure 3**, a conceptual framework of discourse move-emotion states in KB discourse and metadiscourse sessions was developed to guide this study. This study aimed to investigate the following three questions:

1. What are the frequently occurring discourse move-emotion states in discourse and metadiscourse sessions?
2. What are the transition patterns of students' discourse move-emotion states in KB discourse and metadiscourse sessions?
3. How do discourse move-emotion states spread in KB discourse and metadiscourse sessions?

METHODS

Participants and Research Context

Twenty-two 7- to 9-year-old students participated in this study, starting in January 2019, and ending in December 2019. The participants were from one private school in a large metropolitan city. Two of the students left the class at the end of grade 2, and two new students joined in grade 3. In grade 2, there were eleven girls and eleven boys; in grade 3, 12 girls and 10 boys. The school had a well-established inquiry program with ethnic and cultural diversity of the city represented in the student population. The students engaged in KB talks when they were in Junior Kindergarten and began using KF at the end of grade 1. Therefore, most of the students were familiar with KB talks and KF.

The following descriptions of the grade 2 and 3 teachers, Emily and George, were based on email responses to questions regarding when they started teaching, when they adopted Knowledge Building, and how they understood and practiced KB. Both teachers had been engaged in KB, although their work in the current study represented their first attempt to implement it in grade 2 and grade 3 classrooms. Their initial introduction to KB was in their previous roles as Teacher Librarian, Technology Integrator, and Physical Education teacher. Emily is a female teacher who started teaching in 2013 after receiving a master's

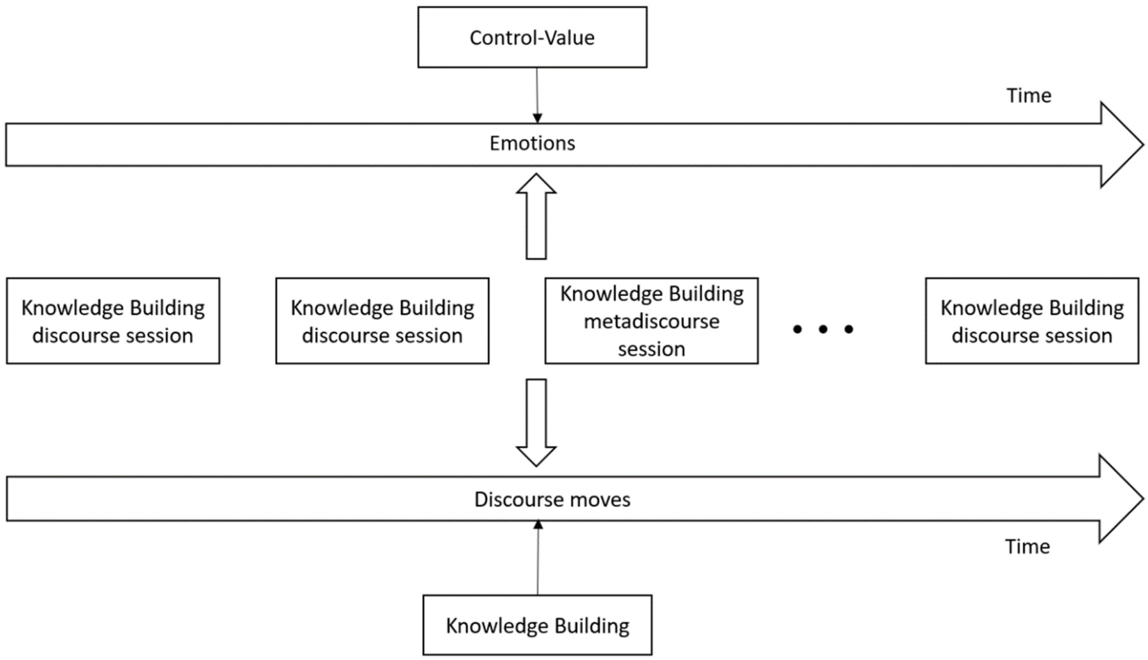

FIGURE 3 | A conceptual framework of discourse move-emotion states in Knowledge Building discourse and metadiscourse sessions over time.

degree in Child Study and Education. She had been teaching for 6 years when the study started in 2019. Emily became familiar with KB as a teacher candidate. Her role as a Teacher Librarian and Technology Integrator engaged her in the world of KB as part of her job chairing meetings between teachers and KB researchers. She came to learn about the KB principles and how to apply them in multiple ways in a classroom setting. She adapted what she learned from others into her teaching in the library before she became a grade 2 teacher. As Emily reflected, she believed that KB could occur in many capacities and across many curricular areas. In her class, children were constantly asking questions and she was to help children ask rich, deep questions—moving beyond surface-level ideas that could be easily answered, to questions that required investigation. She and the children gathered as a community to respond to experiences they had or to unpack a question that was posted by a member of the community. As they engaged in their learning together, they often paused and reflected on what they had learned thus far and discussed what they would like to learn next, what they might still be wondering about, and how they could further gather information. Children moved from constantly saying, "I know" to then saying, "maybe" when they were sharing an idea. This showed their growth in understanding that there were many possible answers and their idea was one of many.

George is a male teacher who started teaching in 2010. He developed his understanding of KB in different teaching roles in the school. For example, when George started as a Physical Education teacher, he thought of Physical Education as exclusively teacher-directed, requiring an 'expert' to impart knowledge to students to ensure things are done correctly and safely. However, through observing and reflecting, he shifted the Physical Education program to include greater student voice and agency to make the learning more meaningful for students. It was George's first year of teaching grade 3 when the study was conducted. He believed everyone in the KB community had things to offer and could bring diverse ideas, and KB made learning about the process, not just producing a product. By placing ideas at the center of learning, the community openly discussed their theories, questions, and goals, becoming metacognitive about the learning journey itself. He thought KB allows them to explicitly think about the process of learning in ways he had never thought of before joining the school.

Discussions on which this research is based lasted for about 4 months in grade 2 starting in January 2019, and two-and-a-half months in grade 3 starting in October 2019. In grade 2, the students mainly worked on Growth and Changes in Animals and related topics, and in grade 3, they studied Soils in the Environment. The outbreak of COVID-19 in the city in March 2020 forced an end to the KB in grade 3 although the students and teachers were planning to conduct their soil and seed experiments in the spring. Therefore, the relatively shorter KB period does not indicate students' disengagement.

Curriculum and Pedagogical Design

The KB talks were labeled discourse and metadiscourse sessions based on their focus. Discourse sessions represent classroom talks such as working with information, constructing theories, discussing observations and readings. Metadiscourse sessions were talks specially designed to reflect on earlier discourse and assess their overall state of understanding, feelings, and future inquiry directions. Of course, discourse and metadiscourse are interrelated and may happen simultaneously. However, we designed monthly metadiscourse sessions in which the students intensively reflected on their previous discourse sessions and planned their following discourse. The reason for doing so was because metadiscourse may not take place naturally given students' slowly developing metacognitive skills and challenges in regulating collaborative knowledge construction (Järvelä et al., 2016). KB principles such as collective responsibility, embedded and transformative assessment, epistemic agency, and rise above were especially highlighted and guided the design of metadiscourse sessions (Scardamalia, 2002). Next, we elaborate on the design of discourse and metadiscourse sessions.

Discourse Sessions

In both grades 2 and 3, the students engaged in face-to-face KB discourse (see **Figure 1**), in which they discussed questions that they cared about with the facilitation of their teachers. In grade 2, the students were curious about what kind of living environment salmon need, how to create a diagram of the life cycle of Atlantic salmon, the difference between ideal and current salmon habitats, what they could do to protect the environment, etc. The grade 3 students focused on researching what soil is, how soil develops different colors, how plants and animals relate to soil, and how and why different soils are made.

Various learning opportunities supported the students in researching questions and sustaining interest. In the beginning, some anchors were used to explore students' interests and curiosity. For instance, in grade 2, a salmon tank was set up in the classroom to hatch salmon eggs (see **Figure 4**), which enabled students to observe the growth and change of salmon. In grade 3, the students collected soil samples around the school and their neighborhoods (see **Figure 5**). In grade 2, creating a new diagram to display the life cycle of Atlantic Salmon drew the students' interest when they noticed the discrepancies between different resources. Another main research strand was building ideal and current salmon habitats. In grade 3, the students studied the soil samples to check their components, colors, hardness, and other properties. They also did experiments with the soil samples, for instance, shifting the soil samples and putting the soil samples into water. The classes went on field trips or invited knowledgeable people to their classrooms. For instance, the grade 2 cohort invited educational staff from the World Wildlife Fund, Toronto Zoo, Toronto and Region Conservation Authority, and the School of the Environment at the University of Toronto to discuss salmon, animals, waste, water contamination, and microplastics with the students. The grade 3 students visited the Humber Arboretum to learn, observe, and experiment with soils. The students read relevant books, watched videos, and annotated information for evidence, which also inspired new questions. In both grades, the students wrote, read, and built ideas in KF to record, sustain and improve their discourse.

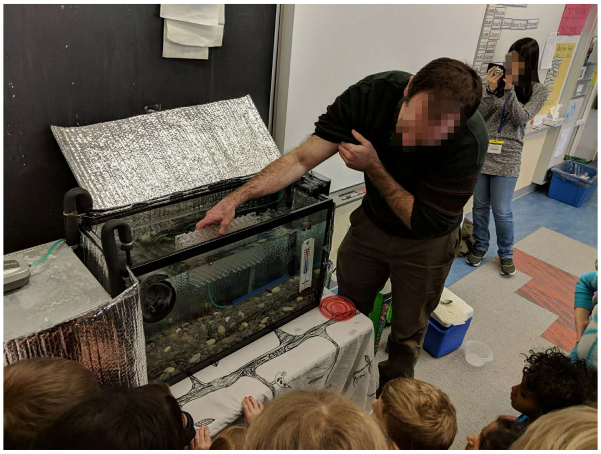

FIGURE 4 | Setting up Salmon tank in grade 2 classroom.

FIGURE 5 | A grade 3 student collecting a soil sample.

Metadiscourse Sessions

In grades 2 and 3, the students engaged in metadiscourse about once every month. The students mainly discussed, reflected upon, and summarized what they had learned, what they still wondered about, and how they could improve ideas and build a more supportive and positive socio-emotional environment. We used several methods to support metadiscourse sessions.

In grade 2, questions such as "What have you learned about salmon? How have your ideas about salmon changed? What do you still wonder about salmon? How did you feel during this work?" guided students' metadiscourse. Furthermore, we used the Time Machine Tool embedded in the KF to support students' discourse. This tool can replay the development of KF views and help the students to recall their idea building. As the following excerpt from a grade 2 metadiscourse session shows, the students built on each other's ideas regarding future inquiry directions after discussing how their understanding had changed (student name information was unavailable for this session). The students not only referred to previous discussions proposing new directions for inquiry but also suggested alternatives. Eventually, they decided to first design salmon habitats in the KF or using paper, and then build ideal and current salmon habitats using materials.

> "Adding onto Tom and Will, I think half the class can make an ideal habitat. And the other half can make what exists right now."
> "I was thinking, basically like Emma's, we could make it on the computer and then we could try and make it in reality."
> "I like Emma's idea, but I don't wanna do it on the computer cause it's hard."
> "I think it would be cool if the red group did something, like let's say the bad, like what we shouldn't do, and then the blue group did what we should do."

In the middle of grade 3, the students reflected on the discourse move distribution chart of their community in grade 2 (see **Figure 6**) and discussed what stood out to them in the bar graph. They noticed they had a lot of information but less "putting our knowledge together" and discussed why and what to do next:

> Sophia: But I notice that putting our knowledge together has the least and information has the biggest.

> Noah: Information is the stuff we know. If we try to put knowledge together, it's hard to do that. Harder than just writing down information.

Later, the students individually reflected on and wrote about things that made them frustrated. Their writing was collected, and the data was compiled using a bar graph. Then, the students reflected on the graph, which represented collective elements that made the class frustrated. The students were asked to choose one of the things that they could work on to make the community more friendly. They were also asked not to monitor others to avoid bullying possibilities.

Data Sources

The data included in this study were video recordings of 32 discourse sessions (about 5 h in grade 2 and 8.5 h in grade 3) and 8 metadiscourse sessions (about 1.3 h in grade 2 and 1.4 h in grade 3) in grades 2 and 3. All the videos were first transcribed verbatim. All the metadiscourse sessions conducted in grades 2 and 3 were included for analysis as well as all of the discourses sessions if the video was not shorter than 14 student utterances in each video transcript. **Figure 7** shows the number of students who spoke at least once in the discourse and metadiscourse sessions, indicating 8–19 students participated in each session. In 75% of the sessions, at least half of the students participated. The frequency of the fourth bar is zero because the students' name information was unavailable in the grade 2 teacher's notes when the first author was absent that day. We checked the utterances and removed the ones that did not carry ideas, but simply comments such as "yes," "yeah," "no," "I know." The utterance of each speaking turn was considered as a unit. Finally, we included 2,409 student utterances in 32 discourse sessions and 513 student utterances in 8 metadiscourse sessions in this study.

Data Analysis

Figure 8 shows the study protocol for this research. The same discourse move coding scheme was employed to analyze each utterance in the discourse and metadiscourse sessions. It

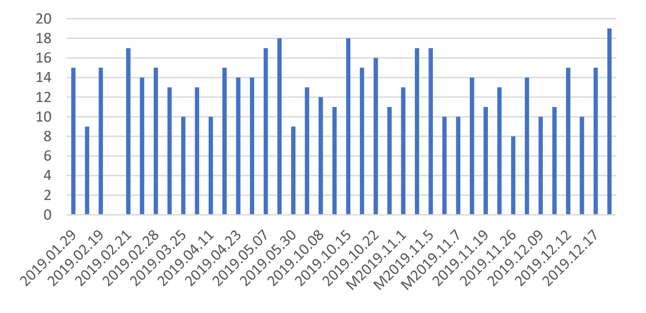

FIGURE 7 | Number of students participating in discourse and metadiscourse sessions.

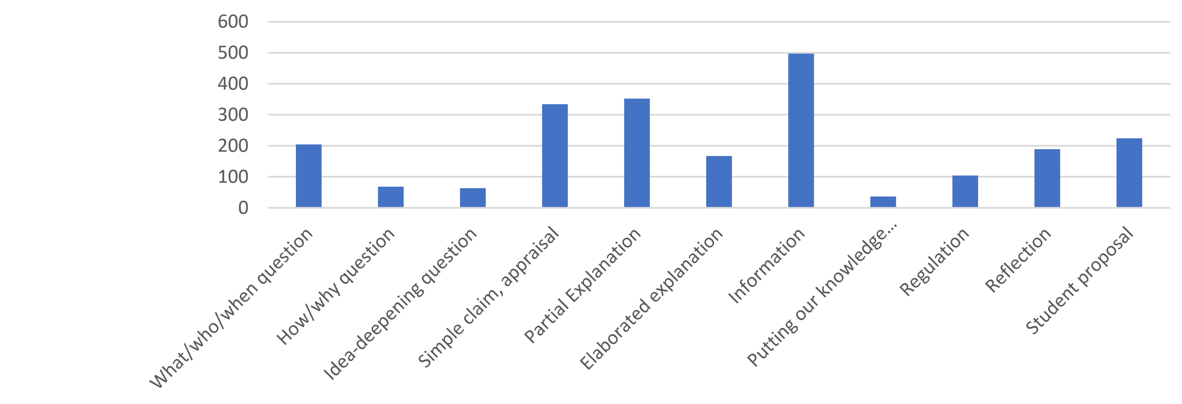

FIGURE 6 | The distribution of students' discourse moves in grade 2 that grade 3 reflected on.

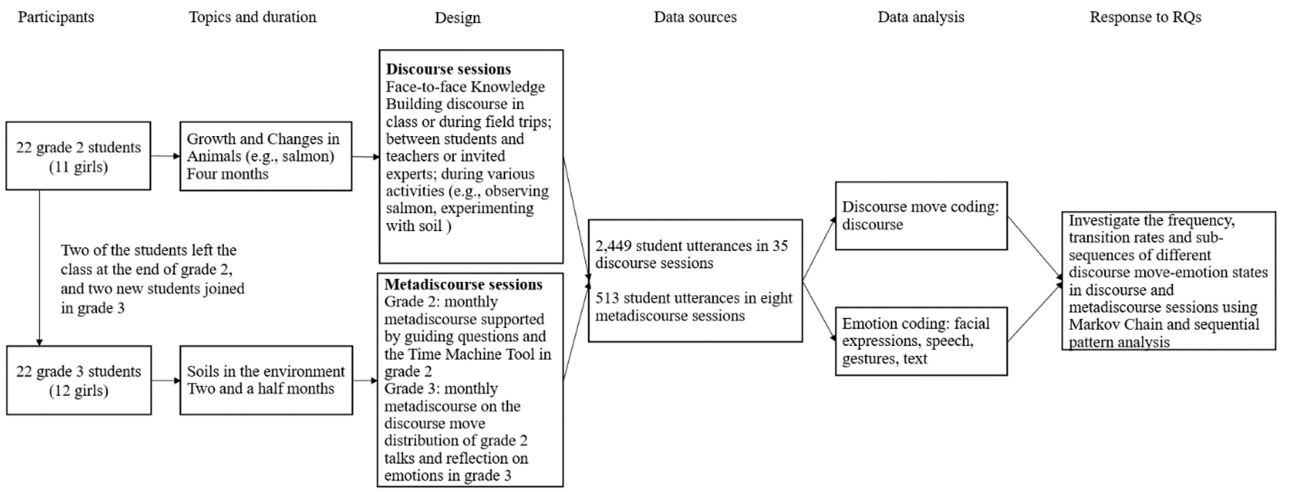

FIGURE 8 | Diagram of the study protocol.

should be noted that because KB emphasizes idea improvement and emotions are also influenced by previous utterances, we coded each utterance in context rather than as an independent speaking turn. For instance, we coded questions that extended previous discourse by seeking deeper explanations or more specific information as "idea-deepening/elaborating question(s)." Similarly, paraphrasing previous explanations were not considered "elaborated explanation(s)." We did not separate discourse and metadiscourse coding schemes but considered all the indicators as discourse moves. The discourse move scheme was adapted from our previous studies (Zhu et al., 2019b,a). **Table 1** shows the discourse moves and descriptions. There are seven discourse moves: question, simple claim/appraisal or information, partial explanation or integration, elaborated explanation or integration, proposing new directions for inquiry, reflection, and regulation. Proposing new directions for inquiry and reflection are indicators of metadiscourse but can also happen in the discourse sessions.

Similarly, the same emotion coding scheme (see **Table 2**) was applied to each utterance clip in the discourse and metadiscourse sessions. Individuals' spoken words, gestures, facial expressions, voice, or punctuation were considered when coding the emotions. The multi-faceted coding approach for analyzing emotions was adapted from our previous studies (Zhu et al., 2019b,a). As shown in **Table 2**, there are five emotional states: positive, negative, curiosity, surprise, and unidentifiable.

Regarding grade 2 data, two researchers coded 432 units, accounting for 21.90% of grade 2 records. The agreement was 77.78% for discourse move coding, and 86.34% for emotion coding. The disagreements between the two researchers were discussed and resolved. Because in the large project to which this current study belongs, two researchers coded grade one students' utterances in terms of discourse moves and emotions and reached agreements of 85.60 and 91.44%, respectively. We considered the researchers might have reached their best practice in terms of shared understanding and coding validity. Therefore, the first author coded the remaining data.

We considered the discourse move and emotion coding of each utterance as a pair. There were 32 discourse move-emotion states in total, as there was no occurrence of "reflection and surprise," "partial explanation or integration and surprise," or "proposing new directions for inquiry and surprise." To answer the first question on the frequently occurring discourse move-emotion states, we ranked the 10 most frequently occurring discourse move-emotion states in the discourse and metadiscourse sessions. Then for each discourse move-emotion state that ranked top 10 in both the discourse and metadiscourse sessions, we conducted a Chi-square test to examine whether there is significant difference in the percentage of the state between the two different kinds of sessions.

Concerning the second research question, we conducted a Markov Chain analysis using the TraMineR package (Gabadinho et al., 2011) to investigate the transitions of the 10 most frequently occurring discourse move-emotion states in discourse and metadiscourse sessions separately.

The transition-rate analysis can produce information about the changes in states that occurred most frequently among the discourse and metadiscourse sessions (Yang et al., 2018; Zhu et al., 2019b). For instance, given two states ("student proposal and positive" and "partial explanation or integration and positive") represented as (s_i, s_j), the transition-rate analysis calculates the probability of a change from "student proposal and positive" to "partial explanation or integration and positive" at a given position. We can define $n_t(s_i)$ as the number of sequences that end with "student proposal and positive" (s_i) at position t, and $n_t^{t+1}\left(s_i, sj\right)$ as the number of sequences with "student proposal and positive" (s_i) at position t and "partial explanation or integration and positive" (s_j) at position t+1. M is the maximum sequence length of different KB sessions. Then, the transition rate $p(s_j| \, s_i)$ between "student proposal and

TABLE 1 | The categories and descriptions of discourse move coding scheme.

Discourse move categories	Descriptions
Questions	Different kinds of questions that seek facts, evidence, explanations, or more specific details.
Simple claim/appraisal or information	Discourse moves that do not require lots of cognitive efforts such as providing opinions without any elaboration or justification, restating previous ideas or mentioning of personal experiences or other sources.
Partial explanation or integration	Producing an explanation, adding details to ideas or previous ideas but may contain some scientific flaws; connecting or comparing ideas contributed by students without explanations.
Elaborated explanation or integration	Elaborating the reasons, relationships/comparison, processes, or mechanisms of how things work; connecting or comparing ideas with judgments/examples/details and reasoning.
Proposing new directions for inquiry	Suggesting how to conduct their inquiry or what they should research.
Reflection	Evaluating their work or interactions, sharing their learning experiences, challenges, feelings, etc.
Regulation	Managing time, deciding speaking turns, discussing community norms, and other issues that are directly related to idea building.

TABLE 2 | The categories and descriptions of emotion coding scheme.

Emotion categories	Description
Positive	An indication of happiness, excitement, or satisfaction talking about ideas fluently, with increasing volume or expressing disagreement explicitly.
Negative	An indication of unhappiness, not understanding, tiredness, or disinterest.
Curiosity	An indication of willingness and interest to explore ideas or express requests.
Surprise	An indication of feeling surprised because of unexpected ideas or phenomena.
Unidentifiable	There are not enough clues to identify the emotion.

positive" (s_i) and "partial explanation or integration and positive" (s_j) is:

$$p(s_j|s_i) = \frac{\sum_{t=1}^{M-1} n_t^{t+1}(s_i, s_j)}{\sum_{t=1}^{M-1} n_t(s_i)}$$

Furthermore, we compared the transition difference to examine what discourse move-emotion states characterize students' metadiscourse sessions in KB communities.

Concerning the third question about the spread of discourse move-emotion states, we conducted sequential pattern mining of the states in the discourse and metadiscourse sessions. Sequential pattern mining identifies a set of sub-sequences that occur above a set frequency threshold, namely, confidence (Zhu et al., 2019b). We used the ArulesSequences Package for R, which implements the SPADE algorithm, to identify the frequent sub-sequence (Zaki, 2001). The length of a sub-sequence can be one or more. Confidence is computed as the possibility of sub-sequences appearing in the input database. We use the sequences in **Table 3** to illustrate the process of sequential pattern mining. In this study, the results of the sequential pattern mining are a series of sub-sequences consisting of different discourse move-emotion states. For instance, the sequence {SP} is a sub-sequence of SID 1, 2, 3, and 4, and its confidence, namely, the probability of occurrence, is 1 (4 out of 4). The sequence {SP}, {PEU} is only a sub-sequence of SID 3 and 4, and its confidence is 0.50. If we set 0.80 as the threshold, {SP} will be picked up as a sub-sequence of the four sequences in **Table 3**, but {SP}, {PEU} will not. This study set 0.80 as the confidence value to identify sub-sequences that occurred in most sessions. We compared the difference between the sequential states in the discourse and metadiscourse sessions. Finally, we selected representative students' utterances to illustrate the sequential patterns.

TABLE 3 | An example sequence dataset.

Sequence ID (SID)	Sequence
1	<{SP}, {SU}, {QC}, {PEU}>
2	<{SP}, {SP}, {PEP}, {PEU}>
3	<{SP}, {PEU}, {QC}>
4	<{SP}, {SP}, {PEU}, {QC}, {QC}>

RESULTS

Most Occurring Discourse Move-Emotion States in Discourse and Metadiscourse Sessions

Table 4 shows the 10 most occurring discourse move-emotion states in grades 2 and 3 discourse sessions, accounting for 85.97% of utterances. **Table 5** shows the 10 most frequently occurring discourse move-emotion states in the metadiscourse sessions of grades 2 and 3, accounting for about 78.17% of all states. In the discourse sessions, the percentage of simple claim/appraisal or information and unidentifiable (21.92%) is significantly higher than that in the metadiscourse sessions (10.53%) [χ^2 (df = 1, N = 2,922) = 4.00, $p < 0.05$], suggesting students' relatively lower cognitive efforts in the discourse sessions. Furthermore, "proposing new directions for inquiry and positive," "proposing new directions for inquiry and unidentifiable," and "proposing new directions for inquiry and curiosity" are among the most occurring states in the metadiscourse sessions, indicating

TABLE 4 | The descriptive data of the 10 most occurring discourse move-emotion states of discourse sessions.

Discourse move-emotion pair	Frequency	Percentage	Cumulative percentage
Simple claim/appraisal or information and unidentifiable	528	21.92	21.92
Simple claim/appraisal or information and positive	477	19.80	41.72
Question and curiosity	305	12.66	54.38
Partial explanation or integration and positive	222	9.22	63.60
Partial explanation or integration and unidentifiable	152	6.31	69.91
Elaborated explanation or integration and positive	135	5.60	75.51
Proposing new directions for inquiry and positive	78	3.24	78.75
Regulation and curiosity	67	2.78	81.53
Regulation and unidentifiable	59	2.45	83.98
Regulation and positive	48	1.99	85.97

TABLE 5 | The descriptive data of the 10 most occurring discourse move-emotion states in metadiscourse sessions.

Discourse move-emotion pair	Frequency	Percentage	Cumulative percentage
Simple claim/appraisal or information and positive	71	13.84	13.84
Reflection and positive	70	13.65	27.49
Simple claim/appraisal or information and unidentifiable	54	10.53	38.01
Question and curiosity	46	8.97	46.98
Partial explanation or integration and positive	34	6.63	53.61
Proposing new directions for inquiry and positive	31	6.04	59.65
Proposing new directions for inquiry and unidentifiable	27	5.26	64.91
Elaborated explanation or integration and positive	23	4.48	69.40
Partial explanation or integration and unidentifiable	23	4.48	73.88
Proposing new directions for inquiry and curiosity	22	4.29	78.17

students' high level of cognitive work and epistemic agency in the metadiscourse sessions. Overall, students had significantly higher percentage of proposing new directions for inquiry in the metadiscourse sessions than in the discourse sessions [χ^2 (df = 1, N = 2,922) = 8.1, $p < 0.005$]. When students were proposing ideas, they tended to express positive or curious emotional clues. Similarly, the students reflected on their learning more frequently (i.e., reflection and positive, 13.65%) in the metadiscourse sessions, while reflection and positive was not even among the 10 most-occurring discourse move-emotion states in the discourse sessions. In contrast, the students regulated more in the discourse sessions (i.e., regulation and curiosity, regulation and unidentifiable, regulation and positive, in total 7.22%), whereas non-regulation relevant states ranked top 10 in the metadiscourse sessions. These results suggest that in the metadiscourse sessions, students tended to discuss what their thinking was, what they learned, and what they should research in the future. In contrast, in the discourse sessions, the students were likely to manage time, decide speaking turns, and discuss community norms and other issues that were not directly related to idea building.

The Transition Rate of Discourse Move-Emotion States in Discourse and Metadiscourse Sessions

Figure 9 shows the transition rates among the 10 most occurring states in the discourse and metadiscourse sessions. Only transition rates above 0.15 are displayed to make the diagram more readable (see **Tables 6**, **7** for the complete matrices). In the discourse sessions, "simple claim/appraisal or information and positive" and "simple claim/appraisal or information and unidentifiable" have more central roles in the transition visualization, indicating most states had a higher chance of being led or followed by these two states. In contrast, in the metadiscourse sessions, several states, such as "partial explanation or integration and positive," "partial explanation or integration and unidentifiable," and "simple claim/appraisal or information and positive," have more influential roles in the transition network. This difference suggests that, compared to the discourse sessions, in the metadiscourse sessions, more states tended to lead to or follow students' more advanced cognitive contributions (i.e., partial explanation or integration).

Furthermore, in the metadiscourse sessions, if the current state is "reflection and positive," there is a 0.53 chance for the next state to be "reflection and positive," suggesting that a student's reflection tended to trigger subsequent reflection. When students reflected on their learning, they were likely to have positive feelings. Similarly, if the current state is "proposing new directions for inquiry and curiosity," there is a 0.73 possibility for the next state to be "proposing new directions for inquiry and curiosity." If the current state is "proposing new directions for inquiry and positive," there is a 0.29 possibility for the next state to be "proposing new directions for inquiry and positive." The chance for "proposing new directions for inquiry

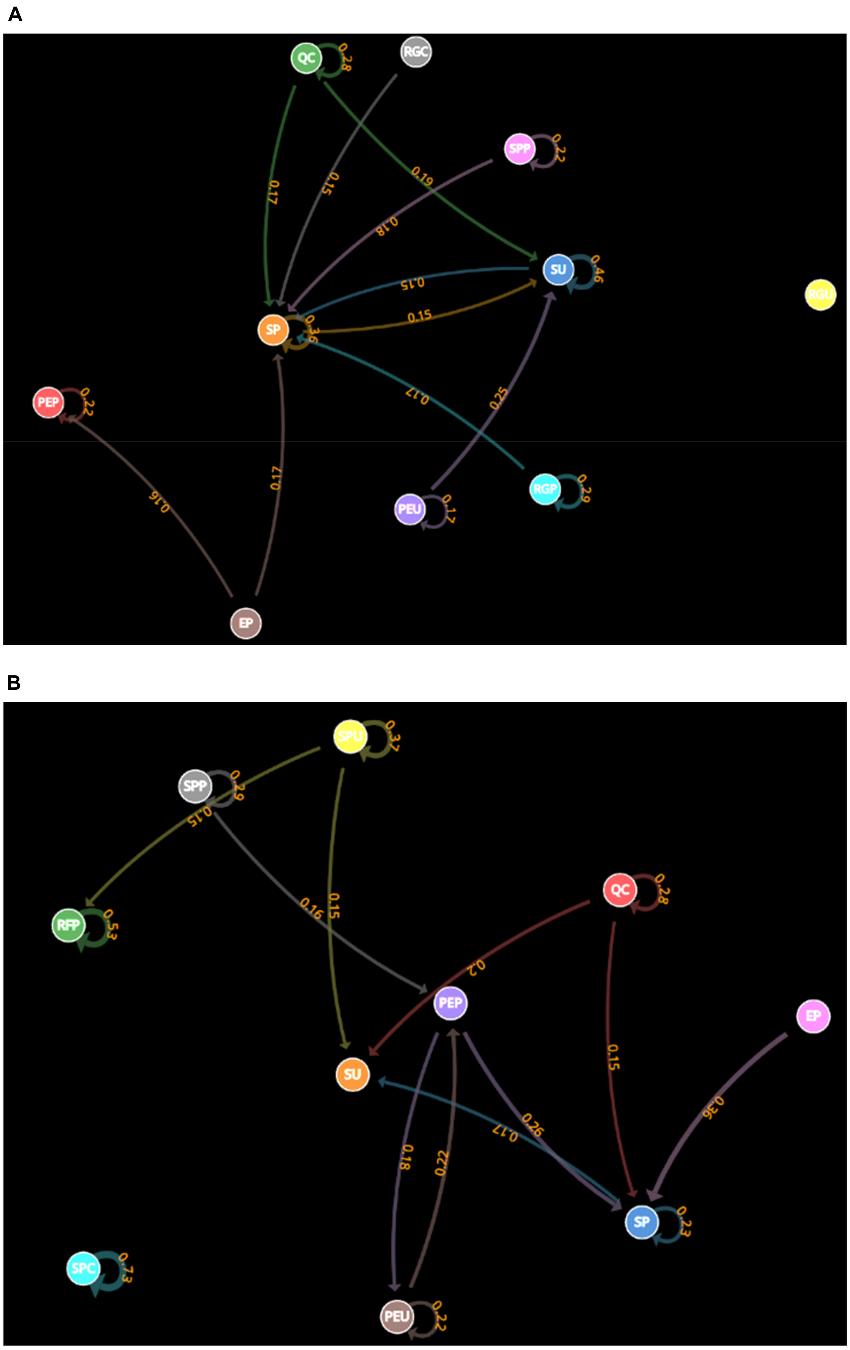

FIGURE 9 | Markov Chain analysis results of the 10 most occurring states. **(A)** Discourse sessions. **(B)** Metadiscourse sessions. SP, simple claim/appraisal or information and positive; SU, simple claim/appraisal or information and unidentifiable; RFP, reflection and positive; QU, question and curiosity; PEP, partial explanation or integration and positive; PEU, partial explanation or integration and unidentifiable; EP, elaborated explanation or integration and positive; SPP, student proposal and positive; SPU, student proposal and unidentifiable; SPC, student proposal and curiosity; RGC, regulation and curiosity; RGU, regulation and unidentifiable; RGP, regulation and positive.

and unidentifiable" to transit to itself is 0.37. These results suggest that in the metadiscourse sessions, the students tended to consecutively propose new directions for their inquiry, which indicates different students might have offered various ideas regarding their future collaborative inquiry.

The following excerpt illustrates how students (the name information was unavailable because of data collection issues) proposed ideas, discussed what they wanted to work on, and built on each other's ideas with generally positive emotions. Finally, they agreed to make ideal and

TABLE 6 | The transition matrix of the 10 most occurring states in discourse sessions.

	SU	SP	QC	PEP	PEU	EP	SPP	RGC	RGU	RGP
SU	0.46	0.15	0.08	0.05	0.07	0.03	0.01	0.02	0.02	0.01
SP	0.15	0.36	0.12	0.10	0.02	0.03	0.04	0.02	0.02	0.02
QC	0.19	0.17	0.28	0.04	0.04	0.04	0.03	0.03	0.02	0.01
PEP	0.12	0.11	0.10	0.22	0.09	0.12	0.01	0.01	0.00	0.02
PEU	0.25	0.08	0.13	0.13	0.17	0.10	0.01	0.01	0.01	0.01
EP	0.12	0.17	0.07	0.16	0.14	0.10	0.01	0.02	0.05	0.01
SPP	0.06	0.18	0.09	0.09	0.01	0.01	0.22	0.03	0.03	0.00
RGC	0.13	0.15	0.12	0.01	0.03	0.07	0.03	0.06	0.12	0.03
RGU	0.06	0.09	0.12	0.14	0.08	0.11	0.00	0.06	0.14	0.02
RGP	0.02	0.17	0.10	0.04	0.06	0.08	0.00	0.04	0.06	0.29

SU, simple claim/appraisal or information and unidentifiable; SP, simple claim/appraisal or information and positive; PEP, partial explanation or integration and positive; PEU, partial explanation or integration and unidentifiable; EP, elaborated explanation or integration and positive; QC, question and curiosity; SPP, proposing new directions for inquiry and positive; RGC, regulation and curiosity; RGU, regulation and unidentifiable; RGP, regulation and positive.

TABLE 7 | The transition matrix of the 10 most occurring states in metadiscourse sessions.

	SP	SU	RFP	QC	PEP	PEU	EP	SPP	SPU	SPC
SP	0.23	0.17	0.03	0.08	0.11	0.01	0.11	0.04	0.03	0.01
SU	0.13	0.09	0.04	0.07	0.07	0.02	0.04	0.11	0.07	0.00
RFP	0.07	0.06	0.53	0.04	0.07	0.00	0.00	0.01	0.01	0.00
QC	0.15	0.20	0.07	0.28	0.00	0.04	0.02	0.02	0.04	0.00
PEP	0.26	0.06	0.00	0.03	0.06	0.18	0.12	0.06	0.06	0.00
PEU	0.13	0.04	0.04	0.09	0.22	0.22	0.00	0.04	0.04	0.00
EP	0.36	0.05	0.09	0.05	0.14	0.00	0.09	0.09	0.00	0.00
SPP	0.10	0.13	0.03	0.03	0.16	0.10	0.00	0.29	0.06	0.00
SPU	0.00	0.15	0.15	0.04	0.00	0.11	0.00	0.04	0.37	0.07
SPC	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.05	0.05	0.73

SP, simple claim/appraisal or information and positive; SU, simple claim/appraisal or information and unidentifiable; RFP, reflection and positive; QC, question and curiosity; PEP, partial explanation or integration and positive; PEU, partial explanation or integration and unidentifiable; EP, elaborated explanation or integration and positive; SPP, proposing new directions for inquiry and positive; SPU, proposing new directions for inquiry and unidentifiable; SPC, proposing new directions for inquiry and curiosity.

current salmon habitats and create a book about animals in salmon habitats.

We should make a book about all the predators because they probably have a lot of predators. There are probably a few of them, and we could all draw one.

> I also like Daniel's idea, and I want to know how the first ocean became?
> Adding onto Tom and Will, I think half the class can make an ideal habitat. And the other half can make what exists right now.
> I was thinking, basically like Emma's, we could make it on the computer, and then we could try and make it in reality.
> My idea is the same as Sophia's, to make a book about all the different things. I also want to learn about, I want to make a book, and it's all about different types of fish that are like salmon and have the same predators. Maybe they may get lampreys.
> What more can we do to protect the salmon? Like where the birds don't know.
> Another idea? I had an idea that we take the map, and I thought it would be interesting if we could see which parts are the best for Atlantic salmon.
> So, looking at the waterway using Google earth?

In **Figure 9**, there are no transition links from other states to the "elaborated explanation or integration and positive" state because the possibilities are smaller than 0.15. However, as shown in **Table 6** , in the discourse sessions, "elaborated explanation or integration and positive" had a higher chance to follow states such as "partial explanation or integration and positive" (0.12), "partial explanation or integration and unidentifiable" (0.10), "elaborated explanation or integration and positive" (0.10), and "regulation and unidentifiable" (0.11). These results suggest that "elaborated explanation or integration" is usually built upon itself or "partial explanation or integration," which conveys a notion of progressive KB discourse. As shown in **Table 7**, in the metadiscourse sessions, "simple claim/appraisal or information and positive" and "partial explanation or integration and positive" were more likely to lead to "elaborated explanation or integration and positive," with transition rates of 0.11 and 0.12, respectively. Furthermore, there is a 0.09 possibility for an "elaborated explanation or integration and positive" to lead to another "elaborated explanation or integration and positive." These results not only indicate progressive KB discourse, but also suggest that positive emotions tend to lead to positive emotions within KB communities.

The Spread of Discourse Moves and Associated Emotions in Discourse and Metadiscourse Sessions

The sequential pattern analysis shows that when the threshold was set as 0.8, 333 state sequences were identified in the discourse sessions, while 274 state sequences were discovered in the metadiscourse sessions. To investigate their difference, we filtered the state sequences that only occurred in the discourse sessions and metadiscourse sessions, respectively. As a result, 223 state sequences were specific to discourse sessions, while 166 state sequences were unique to metadiscourse sessions. Given the frequent occurrence of "simple claim/appraisal or information and positive," "simple claim/appraisal or information and unidentifiable," and "question and curiosity" and their combinations in discourse and metadiscourse sessions, we further examined the state sequences that include at least another type of state. In the metadiscourse sessions, we found 84 state sequences that include other states such as "proposing new directions for inquiry and unidentifiable," "partial explanation or integration and unidentifiable," "partial explanation or integration and positive," and "reflection and unidentifiable." **Table 8** shows some examples of these specific sequences. However, in the discourse sessions, none of the sequences include other states.

Overall, the specific sequences of metadiscourse sessions suggest progressive KB discourse and the spread of similar emotions, with "simple claim/appraisal or information and positive," "simple claim/appraisal or information and unidentifiable," and "question and curiosity" leading to more advanced cognitive contributions (i.e., "partial explanation or integration and unidentifiable," "partial explanation or integration and positive") or metacognitive contributions (i.e., "proposing new directions for inquiry and unidentifiable," "reflection and unidentifiable"). For instance, the longest specific sequence in metadiscourse sessions is <{SP}, {SP}, {PEP}, {PEU}, {QC}> ⇒ <{QC}>, indicating students' idea improvement from simple claims to partial explanations to continuous questions and the spread of positive emotions and curiosity within the thread.

TABLE 8 | Examples of specific discourse move-emotion sequences in metadiscourse sessions.

Sequence ID	Specific sequences	Confidence
1	<{SP},{SU},{SU}> ⇒ <{SPU}>	0.88
2	<{SP}> ⇒ <{RFU}>	0.88
3	<{SP},{SU}> ⇒ <{PEU}>	0.88
4	<{SP},{SU},{QC}> ⇒ <{PEU}>	0.88
5	<{SP},{SP},{PEP}> ⇒ <{PEU}>	0.88
6	<{SP},{PEU}> ⇒ <{QC}>	0.88
7	<{SP},{SP},{PEU},{QC}> ⇒ <{QC}>	0.88
8	<{SP},{PEP},{PEU},{QC}> ⇒ <{QC}>	0.88
9	<{SP},{SP},{PEP},{PEU},{QC}> ⇒ <{QC}>	0.88

SP, simple claim/appraisal or information and positive; SU, simple claim/appraisal or information and unidentifiable; SPU, proposing new directions for inquiry and unidentifiable; PEP, partial explanation or integration and positive; PEU, partial explanation or integration and unidentifiable; QC, question and curiosity; RFU, reflection and unidentifiable.

The following quotes illustrate an example of sub-sequence <{SP}, {SU}, {SU}> ⇒ <{SPU}>. When the grade 2 students talked about when might be the best time for the class to go to the river to see the salmon that were hatched in their classroom but later released, Amy, Emma, and Lucas provided information based on their observations or experiences or made simple claims. Then, Mia proposed that the class should visit at the end of the school year because it is closer to summer. Their emotions were mainly positive and unidentifiable.

> Amy: The summer. Because usually when I was there for a walk, I saw a huge salmon.
> Emma: Fall.
> Lucas: Because they migrate upstream.
> Emma: To lay their eggs.
> Mia: Maybe at the end of the school year because it is closer to the summer.

The sequence <{SP}> ⇒ <{RFU}> also occurred frequently in the metadiscourse sessions. For instance, when the grade 3 students discussed what makes them upset, they reflected:

> Lucas: wait! There is one thing I notice.
> Amy: People don't like being tapped. If you're talking to each other, that just interrupts you. You feel like you are ignored, and nobody wants to listen to you.

The sub-sequences <{SP}, {SU}> ⇒ <{PEU}>, <{SP}, {SU}, {QC}> ⇒ <{PEU}>, and <{SP}, {SP}, {PEP}> ⇒ <{PEU}> show how various turns of "simple claim/appraisal or information and positive" may lead to "partial explanation or integration and unidentifiable." When the grade 2 students talked about what would happen if they touched a salmon egg, and how salmon take their eggs, Noah talked about his wondering and simple claim and Rose responded with a partial explanation, as shown in the following quotes:

> Noah: I wondered if the eggs were squishy.
> Noah: It would be like flat.
> Rose: Imagine, imagine, imagine a ball like bubble gum. And imagine a salmon egg taking the form of bubble gum.
> Rose: Um, how a salmon will take an egg, take an egg, um…

The sub-sequences <{SP},{PEU}> ⇒ <{QC}>, <{SP},{SP},{PEU},{QC}> ⇒ <{QC}>, <{SP},{PEP},{PEU},{QC}> ⇒ <{QC}>, and <{SP},{SP},{PEP},{PEU},{QC}> ⇒ <{QC}> are about how "simple claim/ appraisal or information and positive" led to one or more "partial explanation or integration" and was then followed by continuous questions. For instance, when the grade 3 students tried to classify and integrate their questions regarding soil after observing their collected soil samples, Emma, Jackson, and Tom provided different integration ideas, which were followed by Misha's further questions.

> Emma: Because it's kind of, it's kind of in both categories.
> Jackson: But both categories don't fit together.
> Tom: And "how did the first seed come to life," you forgot to attach them.

Emma: I think "what is soil" and "how do soil make trees grow" should go to [. . .]
Emma: It's kind of on that topic. Wait, wait.
Misha: I have a question. Why did you say soil is earth, if we don't have soil [. . .]? I don't get it.

DISCUSSION

This study examined how students' discourse move-emotion states develop over time in discourse and metadiscourse sessions. Researchers considered the discourse move and emotion coding of each utterance as a pair and compared the 10 most frequently occurring states in discourse and metadiscourse sessions. In addition, transitions from the most occurring states to subsequent states in the discourse and metadiscourse sessions were computed. The results indicate that students' reflections and proposing new directions for inquiry occurred more in the metadiscourse sessions; students usually felt positive when reflecting on their learning or proposing future inquiry directions. Furthermore, a student's reflection tended to trigger subsequent reflections. Proposing new directions for inquiry led to more proposals of future inquiry directions. This study represents one of the first to consider both students' cognition and emotion in KB discourse and metadiscourse sessions in which students reflected on their collaborative inquiry and future inquiry directions. Several findings are worth discussing.

This study suggests that when students were given the chance to take a wide and reflective view of their learning and engage in metadiscourse, they could reflect on what they had learned, how their thinking had changed, and how they hoped to deepen their inquiry. When students proposed ideas about future inquiry, they tended to show positive expressions, be curious about whether they could do certain things or work in the ways they proposed. In some cases, their emotions were not identifiable, but overall, enjoyment was significantly related to students' cognitive use of learning strategies at the intraindividual level (Obergriesser and Stoeger, 2020). Students' positive and curious emotions during the metadiscourse sessions may be related to their control over learning and the value they perceived in it (Pekrun et al., 2017). This interpretation aligns with Chevrier et al.'s (2019) study, which suggests that students tend to be more curious, and less surprised or bored if they have more constructivist beliefs and a mature understanding of the nature of science.

Students' discourse moves, such as proposing ideas and reflecting on learning, tended to be contagious amongst the community members. Proposing new directions for inquiry or reflections may be triggered by teachers' questions or a student proposal, with other students then building on with their various ideas. Thornton and Tamir (2020) found there is a higher chance for a mental state to transit to a similar state. These results suggest the importance of supporting students' metadiscourse because, unlike other states that might occur more naturally in discourse, metadiscourse might need to be facilitated as people's metacognitive skills develop slowly (Pressley and Ghatala, 1990) and they need support to regulate their collaborative knowledge construction or KB (Järvelä et al., 2016).

Similarly, the high transition rates between similar emotions suggest that positive emotions tended to be contagious in learning communities in which students felt safe and comfortable expressing their ideas. This may be explained by the emotional contagion theory (Hatfield et al., 1993), which posits that emotions may be amplified when they are expressed and used to coordinate group performance. As previously discussed, students' enjoyment is related to how competently and effectively they employ learning strategies (Pekrun, 2006; Obergriesser and Stoeger, 2020). Positive feelings can motivate students to continue and deeply engage in ongoing activities and deeply process information (Fredrickson, 2001). Positive emotions function as internal signals to continue or approach and have long-lasting consequences on individual growth and social connection (Fredrickson, 2001). Further research can build on this study and further examine the effects of positive emotions in a learning community.

The findings of this study show the differences in students' discourse move-emotional states, transition rates, and sequential patterns between discourse and metadiscourse sessions, and highlight the importance of intentionally and purposefully engaging students in metadiscourse sessions. Students' metacognitive contributions (e.g., proposing new directions for inquiry, reflection), which play important roles between learning and emotion, usually do not naturally occur and need to be intentionally scaffolded in metadiscourse sessions. Metacognition may help students manipulate cognitive resources that can be taken up by high arousal emotions. Some studies (D'Mello et al., 2014; Buono et al., 2020; Obergriesser and Stoeger, 2020) have shown that students' metacognition (i.e., self-regulated learning) mediates the relationships between learning and emotions. Negative emotions, in particular (e.g., confusion, boredom, frustration), can be regulated to play different roles in learning. However, in the literature, students usually learn at the individual level rather than the collaborative level, and therefore, they mainly need to plan, monitor, control, and reflect on individual learning (Pintrich, 2000). Future research should extend this direction by studying how to support students to collaboratively regulate the negative emotions in their KB communities.

LIMITATIONS AND FUTURE DIRECTIONS

This study has several limitations. First, we considered the data collected in grades 2 and 3 together and equally because our purpose is to investigate the discourse move-emotion state patterns in discourse and metadiscourse sessions rather than comparing grades 2 and 3. However, students' cognitive development should not be ignored. Second, in this study, we only analyzed students' discourse. However, in classrooms, teachers' discourse mediates students' discourse and influences the sequential patterns. Further research may include teachers' discourse in analyses. Third, although the nuanced discourse move-emotion states enable us to examine the subtle difference between states, similar states also distribute and hide some transition patterns. For instance, if only considering discourse moves but ignoring emotions, in the discourse sessions there is a transition chain from question to simple claim/appraisal or information (transition possibility 0.36), to partial explanation or integration (0.24) and elaborated explanation or integration (0.22). However, when including emotions in the analysis, different types of emotions distribute the transition rates and make the progressive KB discourse less visible. Finally, we did not investigate less-occurring emotions such as surprise and negative. Based on several recent studies on self-regulated learning and emotions (e.g., D'Mello et al., 2014; Buono et al., 2020; Obergriesser and Stoeger, 2020), negative emotions need more attention and regulation. Further research may qualitatively examine these emotions to examine their roles in KB discourse.

CONCLUSION

Knowledge Building process can trigger students' various emotions as they experience cognitive equilibrium, disequilibrium, and conflict when negotiating ideas and advancing community knowledge (Yang et al., 2022). The importance of emotion in its own right and in relation to learning has been increasingly recognized over the past two decades (Polo et al., 2016). However, emotion has been rarely investigated in the KB context, and in relation to students' cognition, especially discourse moves. The CVT indicates the benefits of supporting students' subjective control and value on their positive emotions, which suggests students might experience more positive emotions in KB metadiscourse sessions that provide students opportunities to discuss what ideas they think are valuable and to take greater control over learning than in earlier KB discourse sessions. Drawing these gaps and literature support, this study integrated KB, metadiscourse, emotions, and students' subjective control and value appraisals. We found that when providing the participants (as young as grade 2) with chances to engage in metadiscourse, they could take the opportunities to engage in high-level cognitive work. Positive emotions and knowledge work spread, lifting not only individuals but also the community. Therefore, teachers should facilitate students to engage in metacognitive activities to support their positive emotions and productive KB.

AUTHOR'S NOTE

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DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available because these data will be made available to other researchers on a case-by-case basis. Requests to access the datasets should be directed to GZ, gaoxia.zhu@nie.edu.sg.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the University of Toronto (U of T) Research Ethics Boards (REBs). Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

GZ designed and implemented the study, collected and analyzed the data, and drafted the manuscript. MS supervised and co-designed the study, and provided guidelines through the process. MMo helped write part of the study and provided the constructive feedback. MMa and RN co-designed and implemented the study in their classrooms. ZL assisted the data analysis. All authors contributed to the article and approved the submitted version.

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Extraction of PE Online Teaching Resources With Positive Psychology Based on Advanced Intelligence Algorithm

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Physical education (PE) teaching resources occupy a very important position in the teaching of PE theory. Especially in the context of the Internet era, how to effectively extract PE teaching resources from the Internet is very important for PE teachers. However, the quality of PE teaching resources on the Internet is uneven, if not correctly identified, it will bring harm to students' values. Therefore, it is very necessary to correctly identify the teaching resources of positive psychology. In the era of artificial intelligence, advanced intelligent algorithms provide a solution for the realization of this purpose. In this study, a text sentiment analysis model multi-layer-attention convolutional neural network (ACNN)-CNN based on hierarchical CNN is proposed, which combines the advantages of convolutional neural networks and the attention mechanism. In multi-layer-ACNN-CNN, position encoding information is added to the embedding layer to improve the accuracy of text sentiment classification. In order to verify the performance of the model, online PE teaching resources are extracted by a crawler system and the proposed model is used to classify the positive psychology of the teaching resources. By comparison, the proposed model obtained a better positive psychology classification effect in the experiment, which verifies that the model can extract text features more accurately, and is more suitable for emotion classification of long texts.

Keywords: PE online teaching resources, positive psychology, psychology classification, advanced intelligence algorithm, information extraction

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INTRODUCTION

The Ministry of Education of the People's Republic of China released the "Education Informatization 2.0 Action Plan" on April 13, 2018 (He, 2021; Yan and Yang, 2021). This action plan is an inevitable choice for the development of education in the era of intelligence, and it is a specific plan to promote "Internet + Education." In addition, in recent years, China has also issued a series of policy documents, which put forward new requirements for the construction of high-level teaching staff in the Internet era. College PE students and PE normal students are the typical teaching execution groups in the field of PE, and they are the reserve talents of teachers in China. However, at present, the single teaching method of PE and the outdated traditional learning forms are still the problems that need to be solved urgently in the training process. In the "Internet +" era, the "Education Informatization 2.0 Action Plan" is an effective way to accelerate the modernization of education. That is to say, using modern Internet information technology, building and upgrading online education platforms, optimizing online PE teaching resources, innovating and improving education and teaching methods to improve students' learning efficiency and reduce the cost of acquiring knowledge and information, will definitely make a huge contribution to the construction of a high-level PE teaching group. In 2020, COVID-19 broke out around the world, and it still has a huge negative impact on people's life and learning. It is also a test for teachers (Lu, 2020). Teachers need to better master new media technology and the ability to operate teaching software. Before teaching, teachers should collect a lot of information from the Internet, take the essence and get rid of the dross, and then process it into a lesson plan in the course. PE teachers need to establish fascinating teaching situations and provide students with multi-sensory comprehensive stimulation, which can improve students' learning enthusiasm and fully arouse students' interest in learning (Li, 2009). The network environment also provides students with learning resources with a large amount of information, vivid forms, rich contents and interactive functions. Students can obtain learning resources from various channels according to the needs of the discussion topics, which is more in line with the development law of students' cognitive structure. With its rich resources, the Internet provides a good platform for our education and teaching reform. Therefore, we should make full use of network teaching resources, strengthen the main body of students' learning, and guide students to conduct independent inquiry learning as the focus of physical education.

Different scholars have different views on the definition of PE teaching resources. Some scholars believe that PE teaching resources refer to all the materials, manpower and information which are useful for PE (Elliot et al., 2013). According to the scope of use, PE teaching resources are divided into six types, namely human resources, sports facilities resources, sports project resources, media resources, extracurricular and extracurricular resources, and natural resources. Environmental resources. In addition, some scholars believe that PE teaching resources are a concept with a wide range of content, which is the sum of all resources that are exposed in the process of PE, including social, school and family resources, as well as the geographical location and environments (Yang, 2021). Therefore, it is a general term for all resources that serve PE. In theory teaching of PE, text resources occupy the dominant position of all resources. The positive emotions contained in text resources of PE have an important influence on the formation of students' values. Don Hellison, a professor at the University of Illinois, believes that personality training and civic responsibility education are the development goals of PE (Hellison, 2010). Under the background of the increasingly serious personality crisis behavior of students, the moral learning involved in theory courses of PE has also received more and more attention. From current studies, we think that the purpose of PE teaching resources is to provide a kind of information service for teachers and students. This service integrates PE teaching mode, knowledge utilization, teacher-student relationship and so on, and then is embedded in the Internet platform as the carrier of the service.

Therefore, in this study, we take the text resources in PE theory teaching as the research object, and use advanced artificial intelligence methods to analyze the emotion of text resources (Xian, 2010; Yang et al., 2020; Wang, 2021; YanRu, 2021). The quality of PE teaching resources on the Internet is uneven, if not correctly identified, it will bring harm to students' values. Therefore, it is very necessary to correctly identify the teaching resources of positive emotions. In the era of artificial intelligence, advanced intelligent algorithms provide a solution for the realization of this purpose. Text emotion analysis refers to the use of natural language processing, text analysis and statistical learning to mine and identify the views and opinions contained in raw data (Chaffar and Inkpen, 2011; Ran et al., 2018). Text emotion classification is the core of emotion analysis. In this study, the main contributions can be summarized as: (1) a text emotion analysis model multi-layer-ACNN-CNN based on hierarchical CNN is proposed, which combines the advantages of convolutional neural networks and the attention mechanism. (2) In multi-layer-ACNN-CNN, position encoding information is added to the embedding layer to improve the accuracy of text emotion classification. The following sections are organized as follows. In "Positive Psychology Classification of PE Teaching Resources," we present our method regarding positive psychology classification of PE teaching resources. In "Experimental Studies on Extraction of PE Online Teaching Resources With Positive Psychology," we report our experimental results on extraction of PE online teaching resources with positive psychology. In the last section, we conclude the whole study.

POSITIVE PSYCHOLOGY CLASSIFICATION OF PE TEACHING RESOURCES

To achieve the text emotion classification task of online teaching resources of PE, in this study, based on convolutional neural networks (CNN; Chauhan et al., 2018), a hierarchical long text emotion classification model multi-layer-ACNN-CNN based on the combination of the attention mechanism and CNN is proposed. Multi-layer-ACNN-CNN consists of an embedding layer, an ACNN layer and a CNN layer, where the embedding layer is a word embedding layer with position information, the ACNN layer is composed of CNN based on the attention mechanism, and the last CNN layer is composed of CNN based on the text layer. The structure of multi-layer-ACNN-CNN is shown in **Figure 1**.

PE online teaching resources usually contain strong emotional tendencies, and there is a causal relationship in expression, so constructing sentence pairs can extract key information. Therefore, in PE teaching resources, the two

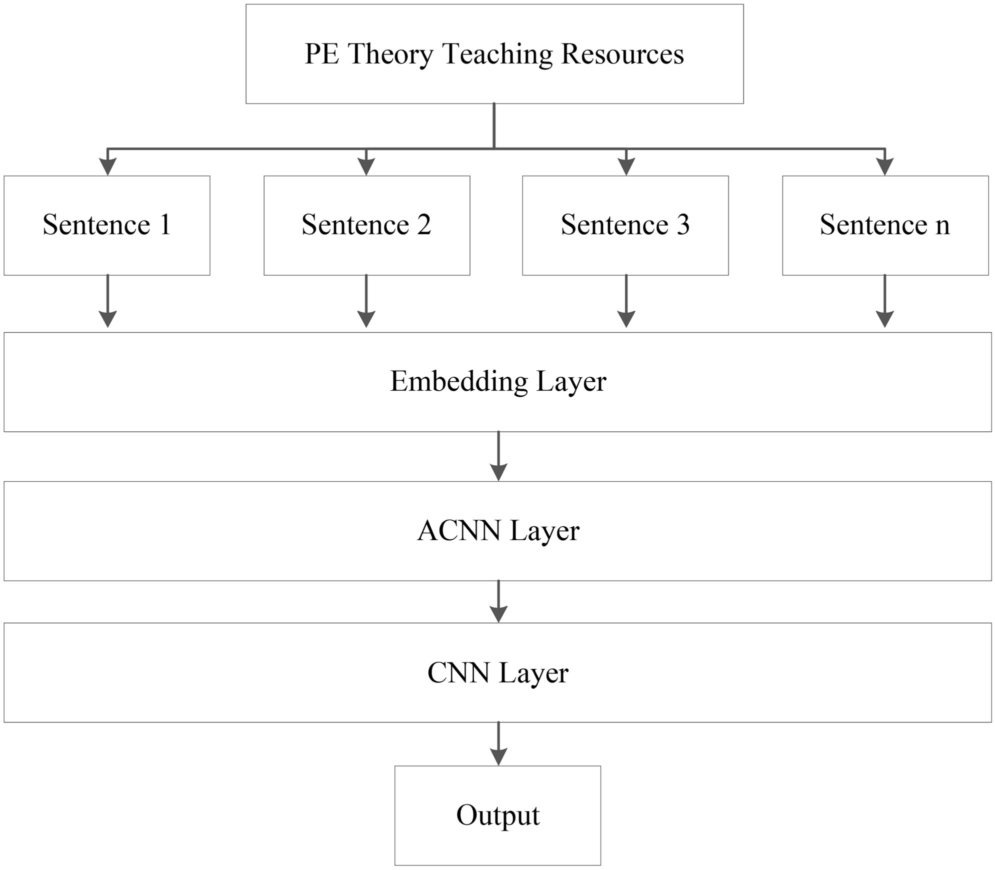

FIGURE 1 | Structure of multi-layer-ACNN-CNN.

sentences before and after are formed into a sentence pair. For each sentence, the word vector representation is first obtained through Word2vec (word to vector), and the position encoding information is added according to the word position. ACNN is used to extract the feature information between sentence pairs, and then the feature information of all sentence pairs is input into CNN, and the global features of the entire text are extracted through CNN. Based on the global features, the final emotion classification results can be obtained.

Word Embedding

There are many ways to represent word vectors, the most commonly used in the past is the bag-of-words model. However, the bag-of-words model does not consider the contextual relationship between words in a sentence, but only considers the weight of the word itself, which is only related to the frequency of the word appearing in the text. On the other hand, the bag-of-words model will have problems such as sparse distribution and high dimension, which is not easy to calculate and requires a lot of computation. In this study, Word2vec is used to obtain the word vector representation (Church, 2017). Word2vec is an open-source tool from Google which combines artificial neural networks and probabilistic models to improve neural language models. Word2vec includes two training models, CBOW and Skip-gram. In this study, we use the CBOW (continuous Bag of Words) model to obtain word vectors as the input of the ACNN layer (Liu, 2020). In this study, we take words as the unit. For a sentence, the sentence vector can be expressed as the result of splicing word vectors.

Since the proposed model is based on CNN, the ability to preserve sentence sequence information is not strong (Cheng et al., 2020). The sequence information represents the global structure and is particularly important. Therefore, in order to make full use of the order of the sentence itself, in this study, we added the relative position encoding information of the word in the sentence in each word. There are various ways to construct the position-encoding information function, here we use the sine and cosine functions (Chauhan et al., 2018). This method can be applied to the case where the sentence length in the test set is longer than that in the training set. The structure of the embedding layer with position information is shown in **Figure 2**. As shown in **Figure 2**, position information can be computed by the following three equations,

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{\frac{2i}{d}}}\right) \tag{1}$$

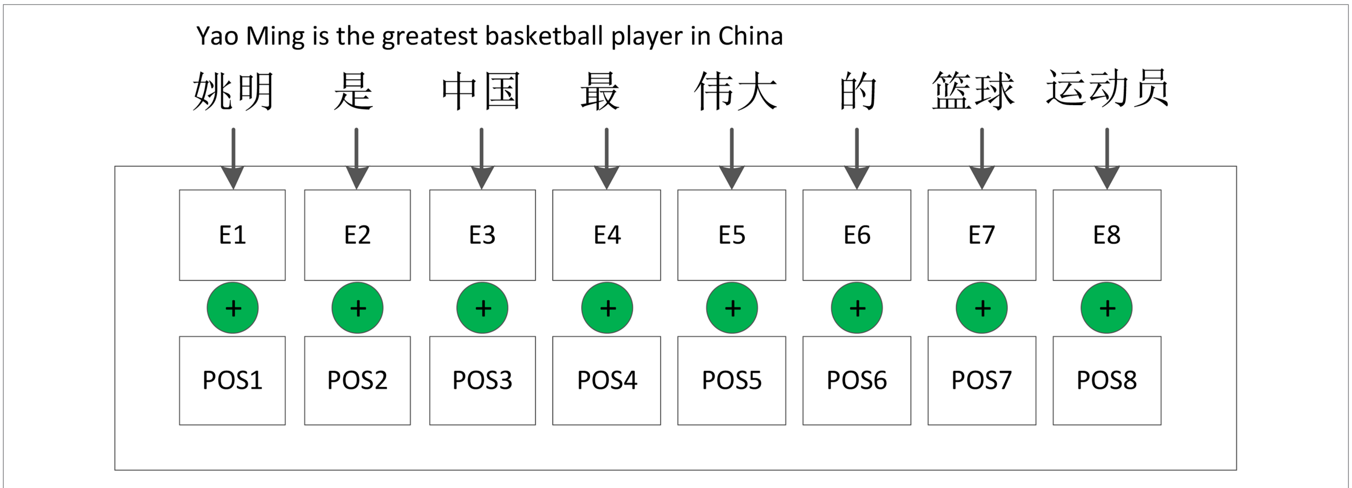

FIGURE 2 | Structure of embedding with position information.

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{\frac{2i}{d}}}\right) \quad (2)$$

$$POS = PE_{(pos,2i)} \oplus PE_{(pos,2i+1)} \quad (3)$$

where POS represents the position-encoding information vector of the word, pos is the position of the word in the sentence, d represents the dimension of the word vector, i represents the i-th element in the word vector, and $\oplus$ is the splicing operator. The encoding information has the same dimension as the word embedding vector matrix, which can be directly superimposed and summed for the following computation.

Attention Convolutional Neural Network

Below the embedding layer, a convolutional neural network model based on the attention mechanism (Fukui et al., 2019; Yan et al., 2019) termed as Attention Convolutional Neural Network (ACNN) is proposed, as shown in **Figure 3**. ACNN mainly consists of an input layer, a wide convolutional layer, an attention-based pooling layer, and a pooling layer. The input layer receives the output of the embedding layer, that is, the word vector feature matrix of each word in the sentence pair. The wide convolution uses its own characteristics to perform the convolution operation on the basic unit of the input layer to extract features. The attention mechanism is added to the pooling layer to extract the sentiment polarity between different words. Finally, the feature information of the two sentences is fused through the merge layer to obtain the feature representation vector of the sentence pair.

Wide Convolution

Suppose we have a convolution kernel of size k and a sentence of length n. $L_i \in R^d$ is the d-dimensional vector representation of the i-th word in the sentence, $L \in R^n \times d$ represents the input sentence, and the vector $m \in R^k \times d$ represents the convolution kernel used in the convolution operation. For the j-th position in the sentence, a window vector matrix of the same size can be obtained according to the size of the convolution kernel. It consists of k consecutive word vectors that can be computed by

$$w_j = \left[L_j, L_{j+1}, \ldots, L_{j+k-1}\right] \quad (4)$$

The convolution kernel m convolves the window vector (k-gram) at each position. The idea behind the one-dimensional convolution is to multiply the elements of the matrix by the convolution kernel m and each k-gram in the sentence L to obtain the feature map c_j as

$$c_j = f\left(m^T w_j + b\right) \quad (5)$$

where b is the bias term, $f(x)$ is a nonlinear transformation function, *sigmoid*, *tanh*, *reLU*, etc. In this study, *ReLU* is adopted as the activation function.

When using the traditional convolution kernel to perform convolution operations, it is often impossible to operate on the data at the edge. To solve this problem, in this study, zero-padding is used to construct a wide convolution. Suppose we have n input nodes, from L_1 to L_n, the size of the convolution kernel m is k. Through classical convolution operation, the number of input nodes is reduced to n-k+1. Note that There is no corresponding convolution operation for (k-1)/2 nodes at the edge, so relevant information about these two nodes will be lost. In this study, we use the zero-padding method, that is first to add (k-1)/2 nodes on the edge of the matrix, and then perform the convolution operation to get (n+k-1) nodes, even larger than the original matrix. We perform a wide convolution operation after the input layer to preserve all the information in the sentence as much as possible to improve the accuracy of the final classification.

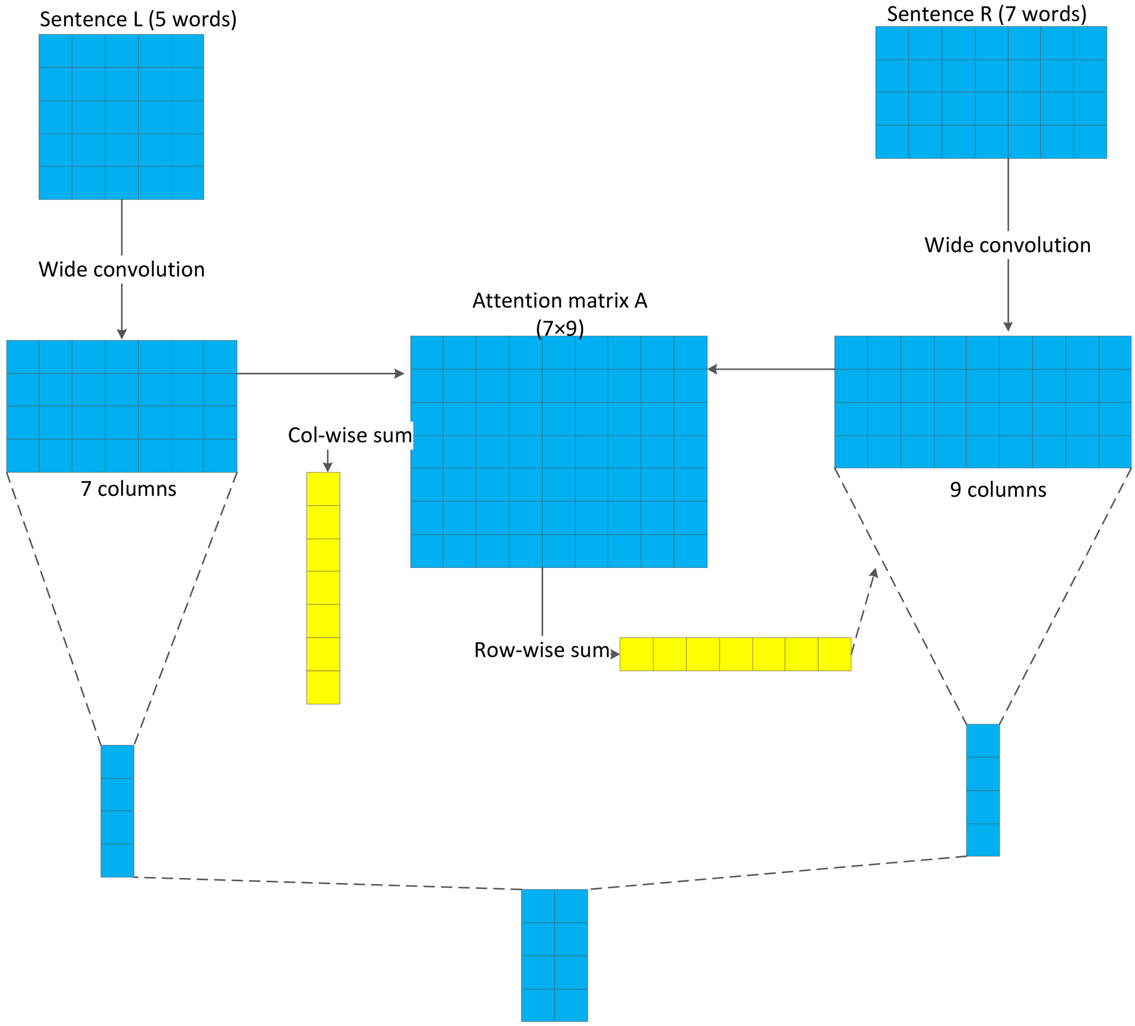

FIGURE 3 | Structure of ACNN.

Pooling Layer Based on Attention Mechanism

In order to make the model distinguish important information during training, in this study, we add an attention mechanism in the pooling layer to make the model pay high attention to this information. In the convolutional layer, we perform a wide convolution operation on two consecutive sentences to obtain two different output vectors, named C_L and C_R. Based on these two vectors, the attention weight vector matrix A can be obtained by

$$A_{i,j} = MatchScore\left(C_L[:,i], C_R[:,j]\right) \tag{6}$$

where $A_{i,j}$ represents the distance metric between the i-th column vector of C_L and the j-th column vector of C_R. It can be defined as $1/(1+|C_L\text{-}C_R|)$, $|C_L\text{-}C_R|$ represents the distance measure of the left and right vectors. There are many methods to compute the distance, such as Euclidean distance, cosine similarity, and Manhattan distance. In this study, Euclidean distance is used.

After obtaining the attention weight vector matrix A, we need to calculate the convolution vector weight, and assign a weight to each convolution layer. The attention weight $a_{L,j}$ corresponding to each unit of the left vector is the sum of the column vectors in the weight vector matrix A, which can be computed by

$$a_{L,j} = \sum A[j,:] \tag{7}$$

Similarity, $a_{R,j}$ can be computed by

$$a_{R,j} = \sum A[:,j] \tag{8}$$

When pooling, we multiply and sum the output feature matrix after convolution, associating with the weight value of attention, to extract important feature information, and then connect them into a vector to finally obtain the output of the pooling layer.

TABLE 1 | Example of PE online teaching resources.

Text	Emotion label
中国代表团在东京奥运会上获得38枚金牌，32枚银牌，18枚铜牌，4次打破世界记录 (The Chinese delegation won 38 gold medals, 32 silver medals, 18 bronze medals at the Tokyo Olympics, breaking world records 4 times).	Positive
苏炳添在东京奥运会田径男子100米半决赛中跑出9秒83的亚洲最好成绩 (Bingtian Su clocked an Asian best time of 9.83 s in the men's 100 m semi-finals at the Tokyo Olympics).	Positive
2013年，孙杨在杭州体育馆路口与一辆公交车发生了刮蹭，虽然是公交车负全责，但孙杨也被查出了无证驾驶，被国家游泳队处罚 (In 2013, Sun was caught driving without a license and was punished by the national swimming team, although the bus was fully responsible for his collision at the intersection of Hangzhou Stadium).	Negative

TABLE 2 | Four comparison models.

Models	Descriptions
CNN	Classical convolutional neural network
CNN-CNN	Two-layer classical convolutional neural network
ACNN	Convolutional neural network with attention mechanism
Position-ACNN	Convolutional neural network with attention mechanism and position information

CNN Layer

With ACNN, finally, the information features of sentence pairs can be obtained based on attention mechanism convolutional neural network. Suppose we have a certain text with s sentences to be classified, the two sentences before and after are organized into a sentence pair, so finally we have s-1 sentence pairs. Therefore, through the ACNN layer, we finally obtain s-1 feature vectors. The text vector can be represented as

$$F = P_1 \oplus P_2 \oplus P_3 \ldots \oplus P_{s-1} \tag{9}$$

The text feature vector F is used as the input of the CNN model. The entire CNN model consists of the following 4 parts. The first part is the input layer, which is expressed by F. The second layer is convolution layer. In this layer, different convolution kernels are used to extract features from F. The third layer is the pooling layer, in which max-pooling is used to get the optimal features. The last layer is the full connection layer which is used to compute the possibility distribution corresponding to the input features. *Softmax* is commonly is used to compute the possibility distribution.

TABLE 3 | Model parameter settings.

Parameters	Descriptions	Values
m	Kernel size	3, 4, 5
n	Number of kernels	128
p	Dropout rate	0.5
b	Batch size	64

EXPERIMENTAL STUDIES ON EXTRACTION OF PE ONLINE TEACHING RESOURCES WITH POSITIVE PSYCHOLOGY

PE Online Teaching Resources

We use a crawler system to extract PE online teaching resources from data fountain[1] and finally we obtain 4,000 text documents. A 20 PE teachers are employed to organized these text documents into 28,400 short texts. In addition, there 20 PE teachers are also invited to manually label 60% of these short texts with positive emotion and negative emotion. **Table 1** illustrates a toy example of the labeled short texts, where positive emotion refers the refers to the positive and objective content contained in the corpus. Negative emotion is those in which the corpus contains discouraging or deliberately false information. Among the 60% labeled short texts, 80% of them is used as the training set and 20% of them is used as the validation set.

Experimental Settings

To highlight the proposed multi-layer-ACNN-CNN, five external models are introduced for comparison studies, as shown in **Table 2**.

During the training process, Adam is used to optimize the model, and the activation function of the convolutional layer is ReLU. Other settings of specific parameters are shown in **Table 3**.

We also introduce Precision (P), Recall (R) and Accuracy as evaluation criteria to evaluate the performance of all models. P, R and Accuracy are defined as follows,

$$P = \frac{TP}{TP + FP} \tag{10}$$

$$R = \frac{TP}{TP + FN} \tag{11}$$

$$Accuracy = \frac{2 \times P \times \mathrm{R}}{P + R} \tag{12}$$

where TP is the number of samples whose real category is positive and predicted to be positive; FN is the number of samples with positive real category and negative predicted category; FP refers to that the number of samples with negative real

[1] https://www.datafountain.cn/datasets

TABLE 4 | Emotion classification results in term of Accuracy, P and R.

Models	Accuracy		Precision		Recall	
	Short text	**Long text**	**Short text**	**Long text**	**Short text**	**Long text**
CNN	0.8298	0.8312	0.8096	0.8111	0.8098	0.8231
CNN-CNN	0.8456	0.8678	0.8197	0.8200	0.8301	0.8378
ACNN	0.8765	0.8987	0.8398	0.8403	0.8487	0.8544
Position-ACNN	0.8982	**0.9021**	0.8611	0.8599	0.8642	0.8721
Multi-layer-ACNN-CNN	**0.9283**	0.8899	**0.8732**	**0.8811**	**0.8785**	**0.8890**

Bold values mean the best performance.

FIGURE 4 | Emotion classification comparison in term of Accuracy, P and R. **(A)** Short text and **(B)** long text.

category and positive predicted category; *TN* is the number of samples with negative real category and negative predicted category.

All experiments are conducted on a PC with i7-11800H CPU, GTX-2080 Ti 12G GPU, and 64G memory.

Experimental Result Analysis

As can be seen from **Table 4** that the overall deep learning-based model has achieved good classification results on PE teaching resources, and the Multi-layer-ACNN-CN model proposed in this study has the best performance in terms of Accuracy, P and R (**Figure 4**).

Comparing with the CNN and ACNN models, it can be seen that the performance of ACNN is far better than that of CNN. This is because the attention mechanism compares and analyzes the importance of each word in the text, so it can better grasp the impact of key words in the text on the text's emotional tendency, thereby improving the accuracy of sentiment classification. Comparing with the CNN and CNN-CNN models, it can be seen that the performance of the multi-layer model is better, indicating that the complex model has more advantages in the face of a large amount of data. Multi-layer models can better extract feature information from long texts. Comparing the three models of ACNN, position-ACNN and Multi-layer-ACNN-CNN, it can be seen that position-ACNN has slightly improved performance compared with ACNN, because Multi-layer-ACNN-CNN adds position coding information and retains words' location information, so its accuracy is higher. What is more, Multi-layer-ACNN-CNN adds a layer of CNN on the basis of pos-ACNN, which can better apply to complex data sets.

On the other hand, comparing the performance of all models on short and long texts, it is clear that the single-layer model performs better on short texts, but not on long texts. The performance of Multi-layer-ACNN-CNN proposed in this study on long texts is basically the same as that on short texts in terms of precision and accuracy, while the recall rate is 0.0093 higher, which verifies that position-applicability of the ACNN-CNN model on long texts. On the one hand, the complex hierarchical model is more suitable for feature extraction of long texts, and on the other hand, the application of attention mechanism and the combination of location information make the extracted features more accurate and more able to reflect the emotional tendencies of the text.

CONCLUSION

In this study, a text emotion classification model based on hierarchical CNN is proposed, which combines the model advantages of convolutional neural networks, and captures the important features of text through the attention mechanism, and at the same time adds position encoding information to the embedding layer, thereby improving the accuracy of text classification. In order to verify the performance of the model, it is tested on PE teaching resources, and multiple sets of comparative experiments are designed. The model obtained a better classification effect in the experiment, which verified that the model can extract text features more accurately, and is more suitable for emotion classification of long texts.

In the future work, the hierarchical attention mechanism will be considered, and the ordinary text emotion classification will be split into the classification from the sentence layer and the classification from the text layer, and combined with sequence information models such as LSTM to explore various combinations.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found at: https://www.datafountain.cn/datasets.

ETHICS STATEMENT

The studies were reviewed and approved by the Ethics Committee of Nanjing University of Finance and Economics and Nanjing Sport Institute. The participants provided their written informed consent to participate in this study. Written informed consent was not required for this study in accordance with the national legislation and the institutional.

AUTHOR CONTRIBUTIONS

WW contributed to writing and data collection. JH contributed to data preprocessing. All authors contributed to the article and approved the submitted version.

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Using sentiment analysis to study the relationship between subjective expression in financial reports and company performance

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In recent years, with the development and progress of text information research, the disclosure of non-financial and qualitative information has often be found to have an incremental function. Financial reports, including financial statements and other relevant information, provide important insights on an enterprise's financial status, operating results, and cash flow. Faced with a large number of financial reports, readers often do not know where to start, and as financial statements are prepared based on past transactions, they cannot fully reflect the past, present, and future economic conditions of the company. Information asymmetry and uncertainty make the text mining of financial reports of great significance to enterprise stakeholders. Accordingly, this paper takes financial reports as the research object and builds a research framework on the relationship between subjective expression in financial reports and company performance. Through natural language processing, sentiment analysis, and other text-mining technologies, the paper quantifies the subjective expression in financial reports and introduces intermediaries. Variables, moderating variables, and control variables are used to construct a multiple regression model. The empirical results show that the underlying emotional tendencies in subjective expressions substantially impact on the future development of listed companies. This paper enriches understanding of the multi-dimensional relationship between financial report text and company performance, and provides ideas for further exploring this relationship. It is of great practical significance to help them make rational decisions and ensure the normal operation of the company and the preservation and appreciation of capital.

KEYWORDS

financial reporting, subjective expression, company performance, sentiment analysis, multi-dimensional relationship

Introduction

The financial report is like a comprehensive business card, providing accounting information on the issuing company that reflects its financial status, operating results, and cash flow. Primarily, the financial statements objectively and fairly reflect the company's economic activities and transactions. By contrast, other parts of the financial report, such as off-balance sheet notes, are prepared using a series of estimates, judgments, and models that capture uncertainties. Providing performance information that may be short- or long-term, financial or non-financial, internal or external, and from different stakeholder perspectives, these parts of the report help users make economic decisions. Among prior studies of financial reports and corporate performance, Henry's (2006) empirical research revealed that the emotion in earnings news releases had a certain impact on investor behavior (Henry, 2006). Tetlock (2008) found that descriptions with negative affective words are related to negative company performance (Tetlock et al., 2008), while Li (2010) reported that partial sentiment in management discussion and analysis (MD&A) can mitigate the mispricing of accruals. This means that when managers price accruals with a "warning" emotion, their pricing tends to be fair (Li, 2010). Bollen and Huina (2011), Loughran and McDonald (2011), Samuel et al. (2011), and Chang et al. (2012) and others found that positive text sentiment is significantly positively correlated with the company's future performance. McKay Price et al. (2012) proposed that the language tone of conference calls is an important predictor of abnormal returns and transaction volume (McKay Price et al., 2012). This shows the need to continue in-depth research on text information. Hajek et al. (2013) combined sentiment indicators from financial reports with financial data indicators to improve the accuracy of stock price prediction models (Hajek et al., 2013). Meanwhile, Kearney and Liu (2014) extracted text information from various sources, studied the differences between content and methods, and found the impact of text sentiment on the individual, corporate behavior, and market levels (Kearney and Liu, 2014).

Emotional characteristics are a unique value of text information. The author's opinions and attitudes and other emotional information can be expressed through the words, grammar, and rhetoric of the text. This information is hidden in the text and the author may not even be consciously aware of it, meaning such information has special value (Qiujun and Chaoqun, 2011). Although financial reports are somewhat formulaic and standardized, there is still information in how meaning is expressed in the text. Loughran and McDonald (2011) developed a financial sentiment dictionary (hereafter, "L&M dictionary"), which is suitable for English-language research and can reduce the misclassification caused by the domain problem of text in sentiment analysis (Loughran and Mcdonald, 2011). In a study of British companies' annual reports, Yekini et al. (2015) used the frequency of positive words as defined in the L&M dictionary to measure the emotional tone and verified the market's reaction to the positivity of financial report narratives (Yekini, 2016). Similarly Hajek (2017) used the L&M dictionary to conduct a collocation analysis of positive words combined with negative words in the annual reports of American companies, and measured the ratio of various emotional words to the total number of emotional words. They found that after incorporating sentiment features, the abnormal stock returns could be much more accurately predicted (Hajek, 2017). In a study of the sentiment trend of Chinese companies' annual reports, Song et al. (2018) annotated sentences of reports in different industries and used the support vector machine method for sentiment classification (Song et al., 2018). Bakarich et al. (2019) studied the relationship between the tone of annual reports and the life cycle of enterprises; they found that the tone of annual reports was more positive, while the tone of enterprises in recession was the opposite (Bai et al., 2019; Beretta et al., 2019; Bian et al., 2019; De Souza et al., 2019; Campbell et al., 2020).

As technology continues to advance, scholars are experimenting with different techniques and models for analyzing the relationship between financial reporting and corporate performance. Due to information asymmetry, capital markets pose the risk of adverse selection and moral hazard. Ordinary shareholders and even corporate shareholders often know little about a company's real business status. When existing or potential investors read a large number of corporate financial reports, it is often difficult to discover the underlying performance information. Falsification of financial reports is the best illustration. No matter how brilliant the financial data might appear, the underlying performance information reflects the company's real financial situation. For this reason, applying sentiment analysis technology to financial reports and establishing a set of methods to effectively identify a company's real performance has important practical significance for both management and investors.

Sentiment analysis methods

Natural language processing

After obtaining text information from a company's financial report, it is necessary to further process and quantify the text using text-mining technology. As an extension of data mining, text mining is the extraction of implicit and imperceptible information with potential commercial value from semi-structured or even unstructured mass text information. Text mining is an extension of data mining, that is, data mining from the text information. After first segmenting the unstructured text, the text feature information is then extracted and stored in a structure similar to a relational database. Next comes the process of learning and knowledge pattern extraction, whereby data mining techniques (e.g., classification, clustering) are used to obtain valuable and important information. A basic text mining model is depicted in **Figure 1**.

The text of financial reports is processed using stuttering word segmentation, an excellent component based on Python. There are currently three word-segmentation modes, which can be adapted to different needs. The main algorithm implementation principle of stuttering word segmentation is based on the word search tree structure. It is a kind of hash tree that can realize efficient vocabulary scanning, find possible words in all text in the sentence, use these words to form a directed acyclic graph, then find the path with the largest word probability in the sentence and calculate the optimal segmentation combination according to word frequency. For unregistered words, the hidden Markov model is used for identification and the Viterbi algorithm is used. Stuttering word segmentation mainly adopts dictionary-based technology. There are three supported word-segmentation modes: (a) The precise mode, which divides the sentence into the most accurate word-segmentation process, which is suitable for text analysis; (b) the full mode, in which all possible words in the sentence are segmented and the segmentation rate is very high, but words cannot be accurately segmented according to the context and the ambiguity problem cannot be overcome; and (c) the search engine mode, which builds on the precise mode by segmenting some words again to improve the word-segmentation recall rate. Importantly, stuttering word segmentation supports traditional Chinese text segmentation and also supports custom dictionaries as needed. The stutter participle currently has Python, JAVA, C++, and Node.js versions. This paper uses the programming language R to segment financial reports. After first installing the stuttering word segmentation developer toolkit in in the R operating environment, we next performed word-segmentation processing, then cleaned the word segmentation results, and finally generated word frequency statistics.

Measure of subjective expression

Using natural language processing technology, we extracted subjective sentences from financial reports and marked the overall emotional tendency of each sentence. Because a sentence may describe more than a single aspect of the situation and express more than one emotion, the object of subjective expression is extracted by extracting and description. On average, each subjective sentence contains two sets of "object-description" subjective expressions. The expression of subjective emotions is complex, often affirming one aspect and criticizing others at the same time, but the emotional tendency of the whole sentence can be discerned. As the emotional expression in part of a sentence may not be consistent with the emotional tendency of the whole sentence, we marked emotional tendencies of not only whole sentences but also each "object-description" set, as shown in **Table 1**.

Focused on subjective expression in financial reports, this paper uses a dictionary-based method for evaluating sentiment words. The classification of sentiment words is mainly determined by the selected dictionary. At present, there are mainly two suitable dictionaries for use with Chinese text: the National Taiwan University Semantic Dictionary (hereafter "NTU dictionary") and the HowNet Sentiment Dictionary (hereafter "HowNet dictionary"). The NTU dictionary comprises 2,812 praise words and 8,276 derogatory words, whereas the HowNet dictionary includes two categories of praise and criticism, including 9,193 text evaluation words and 9,142 English evaluation words. It provides not only positive and negative sentiment words but also positive and negative evaluation words and degree adverbs. We therefore selected the HowNet dictionary to sort, classify, and count the sentiment words extracted from financial reports. The text data sorting process is shown in **Figure 2**.

After completing the download statistics of the data analysis samples of financial reports, we classified and sorted the word segmentation according to the HowNet dictionary. As the negative value phenomenon in the rooted part (where there are more negative emotional words than positive emotional words) causes missing or wrong values in the measurement formula, we avoid this by adding the absolute value and improving the measurement, as shown in formula (1):

$$JQG = \sqrt{\left|\frac{ZMQG - FMQG}{ZMQG + FMQG}\right|} \tag{1}$$

where JQG measures the net emotion; $ZMQG$ measures the proportion of all sentiment words that are positive in the text of the t-th financial report; and $FMQG$ measures the proportion of all sentiment words that are negative in the text of the t-th financial report. If the positive emotion proportion is greater than the negative emotion proportion, the value of JQG will be larger, indicating that the net emotion of the text tends to be optimistic; conversely, if the negative emotion proportion is greater than the positive emotion proportion, the value of JQG will be smaller, indicating that the net emotion of the description text tends to be pessimistic.

Regression analysis

A purely statistical test of subjective expression in financial reports can only reveal that events have a certain impact on

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FIGURE 1
Basic text mining model.

TABLE 1 Examples of subjective expression recognition in financial reports.

Sentence emotion	Sentence	Object	Describe	Describe the emotion
Negative	Mainly attributable to the significant year-on-year decline in the prices of chemical products and the year-on-year decline in the performance of the chemical sector.	Product price	Decline	Negative
Negative	These may have a greater impact on the company's production, operation, and benefits.	Production and operating and efficiency	Greater impact	Negative
Negative	Affected by changes in the market situation, the company's active adjustment of product structure, and the voluntary shutdown of some old models, the company's production and sales scale declined during the reporting period.	Production and sales scale	Slip	Negative
Positive	The company's stable management style, prudent financial management, and good credit accumulation have been recognized by international investors.	Business style	Steady	Positive
		Financial management	Careful	Positive
		Credit accumulation	Good	Positive
Positive	Facing the complex external environment and increasingly fierce industry competition, the company insists on "quality growth," with steady growth in scale and continuous improvement in operating efficiency.	External environment	Complex	Negative
		Industry competition	Increasingly intense	Negative
		Scale	Steady growth	Positive
		Operational efficiency	Constantly improving	Positive

corporate performance, and cannot accurately measure the magnitude of the impact. For the latter purpose, it is necessary to carry out a regression analysis. This paper establishes a regression model to investigate the relationship between the emotions expressed in a company's financial report and that company's future performance (measured by return on equity). The specific research framework is shown in Figure 3.

Sentiment analysis model design

Hypotheses development

Subjective expression in financial reports may influence the company's future performance via its reference value for investors. For most investors, confidence in a company will be boosted by text information in financial reports conveying positive emotions and predicting much room for improvement in future performance. In turn, investors' greater confidence affects their decision-making, leading to a rise in the company's stock price and a positive impact on the company's future performance. By contrast, the expression of negative emotion regarding a company's financial status likely leads investors to doubt the company's ability to develop in the future; such weakened confidence in the company's prospects likely increases investors' inclination to withdraw their investment from the company, thereby negatively impacting on the company's future performance. Based on these considerations, this paper proposes the following research hypothesis:

H1: The net sentiment expressed subjectively in financial reports affects investor confidence and, in turn, the company's future performance, so investor confidence plays an mediating role.

Earnings per share is generally an important indicator to measure company profitability. It shows that earnings per share is positively correlated with company performance, and people are more sensitive to the negative tone. Although written sentiment in financial reports is relatively neutral, negative sentiments are expressed implicitly and have been shown to be negatively correlated with the company's future performance. Therefore, it is preliminarily inferred that earnings per share

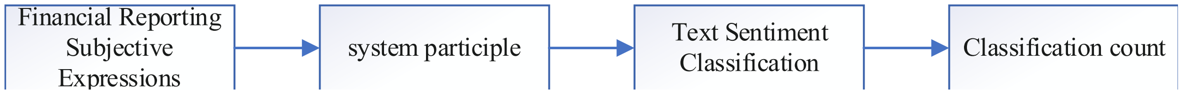

FIGURE 2
Text data sorting process.

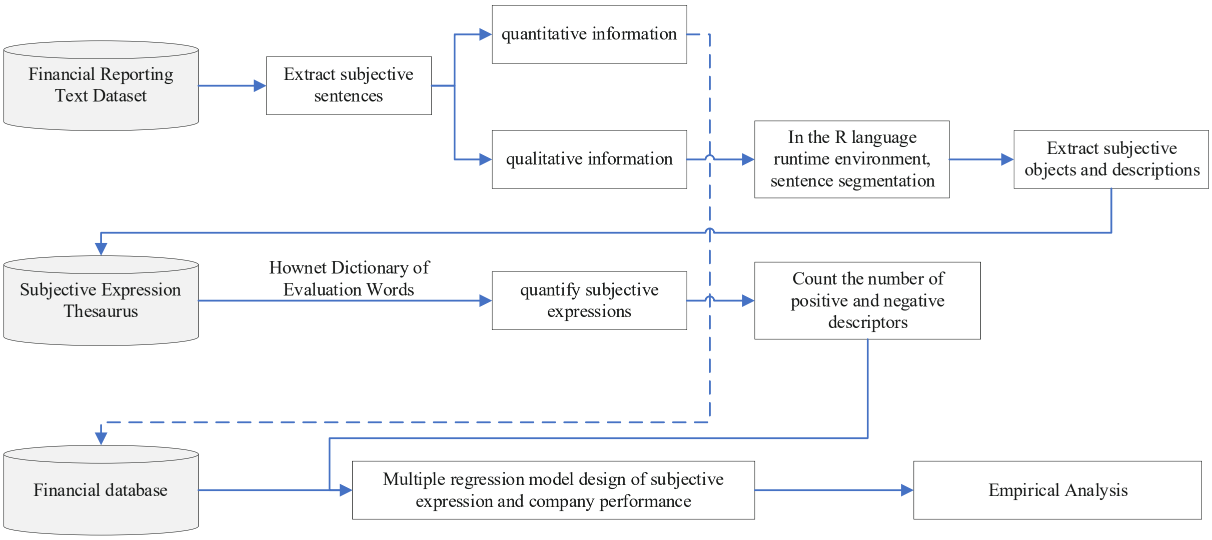

FIGURE 3
Research framework for exploring the relationship between subjective expression in financial reports and company performance.

weakens the negative correlation between the net sentiment of the text and the company's future performance. The following research hypothesis is thus proposed:

H2: Earnings per share plays a moderating role between the net sentiment of the text and the company's future performance by weakening their negative correlation.

Variables

We downloaded from company websites the financial reports of representative companies with a medium-to-high market value, such as Oriental Fortune and Snowball. After selecting a sample of over 920 companies, we used the word-segmentation system to segment the sentences. Then, according to the HowNet dictionary, we extracted positive and negative sentiment words. Table 2 describes the classification method of the HowNet dictionary. This paper will classify sentiment words in financial report texts according to this classification method. All data to analyze financial performance were downloaded from the databases of Guotai Junan and Ruisi.

The variables used in this paper are defined in Table 3.

Regression model design

Referring to the models of Xie and Lin (Deren and Le, 2014, 2015, 2016), this paper establishes four models: Models 1, 2, and 3 mainly test H1, while Model 4 mainly tests H2.

Models 1, 2, and 3 are proposed as formulas (2)–(4):

$$ROE_{iT+1} = \mu_0 + \mu_1 JQG + \mu_2 MB + \mu_3 YRET + \mu_4 LNSIZE + \mu_5 AGE + \xi_{iT} \tag{2}$$

$$ROE_{iT+1} = \alpha_0 + \alpha_1 IC + \alpha_2 MB + \alpha_3 YRET + \alpha_4 LNSIZE + \alpha_5 AGE + \xi_{iT} \tag{3}$$

$$ROE_{iT+1} = \beta_0 + \beta_1 JQG + \beta_2 IC + \beta_3 MB + \beta_4 YRET + \beta_5 LNSIZE + \beta_6 AGE + \xi_{iT} \tag{4}$$

TABLE 2 Summary of subjective expression in financial reports.

Emotion of words	Total number	Word description
Positive	854	Good, steadily improving, improving
Negative	1,423	Downward, slight, down

TABLE 3 Variable definitions.

Type	Description	Name	Definition and calculation formula
Dependent	Company's future performance	ROE_{iT+1}	Return on equity
Explanatory	Text positive emotion	*ZMQG*	Number of positive emotional words in the total number of emotional words
	Text net emotion	*JQG*	$JQG = \sqrt{\left\lvert \frac{ZMQG - FMQG}{ZMQG + FMQG} \right\rvert}$
Mediator	Investor confidence	*IC*	$IC = 0.7604 * Growth + 0.7182 * YrPB + 0.6163 * INST$ where *Growth* represents the growth rate of main business revenue, *YrPB* represents the price-to-book ratio, and *INST* represents the proportion of institutional investors
Moderator	Earnings per share	*EPS*	
Control	Scale	$SIZE_T$	Natural logarithm of total assets
	Listing period	*AGE*	
	Growth	*MB*	Net profit growth rate
	Market return	*YRET*	Return on invested capital

Model 1 includes *JQG* as the explanatory variable, rather than *ZMQG*. It should be noted that since this paper does not propose any hypotheses on how the negative sentiment of text may influence the company's future performance, it is mainly because the text of the financial report is after sorting out the text information, the negative emotional words in it will inevitably be weakened. In addition, emotional expression in the text is more subtle, which will inevitably affect research on the direct correlation between negative emotions and the company's future performance. However, as people are highly sensitive to negative emotions, this paper takes account of their impact when studying the relationship between net sentiment and company performance.

For H1 to be supported empirically, the verification Model 1 *JQG* is negative and significant, the verification *IC* is positive and significant, and the verification Model 3 after adding *IC*, *JQG* is not obvious, and *IC* is significant.

To test H2's prediction on the moderating role of earnings per share between the net sentiment of the text and the company's future performance, we include the interaction term of *JQG* and earnings per share (*EPS*) in Model 4:

$$ROE_{iT+1} = \theta_0 + \theta_1 JQG + \theta_2 JQG \times EPS + \theta_3 MB + \theta_4 YRET + \theta_5 LNSIZE + \theta_6 AGE + \xi_{iT} \quad (5)$$

Sample selection and data sources

Sample selection

The text information data are taken from the sample companies' 2019 financial reports. The two explanatory variables, positive sentiment (*ZMQG*) and net sentiment (*JQG*), are both measured using these data. As we are interested in how sentiment affects future performance, the dependent variable is measured using the return on equity in 2020 (ROE_{iT+1}). Many companies pay more attention to earnings per share as an indicator of profitability or performance, but if the growth rate of shareholders' earnings is higher than that of after-tax profit, then net profit (return on assets) of falling. ROE measures the efficiency of investment output, and so is considered suitable to measure company performance in this study.

However, earnings per share undeniably reflects the company's profitability to some extent. We therefore include it as a moderating variable in H2 and empirically test whether it can correlate with the net sentiment between words and the company's future performance. Adjust between them.

The intermediary variable investor confidence (*IC*) is calculated using the formula in Table 3. Since a company's annual report is a relatively authoritative information

TABLE 4 Descriptive statistics of variables.

Variable	Mean	Median	Maximum	Minimum	*SD*	Number of observations
ROE_{iT+1}	0.3372	−0.0159	11.5162	−23.1938	4.3706	908
ZMQG	0.7524	0.7857	0.9500	0.0000	0.1285	908
JQG	0.9672	0.7559	0.9486	0.0000	0.1981	891
IC	16.1719	11.0086	62.6143	−6.9037	3.8377	877
EPS	0.2664	0.20000	4.15	−4.4800	0.5234	908
LNSIZE	21.7363	21.6154	28.4133	14.9416	0.5862	908
AGE	9.8369	7.0000	25.0000	0.0000	6.7883	926
MB	−17.7670	12.4678	45.4048	−10.0587	3.5227	908
YRET	6.5855	6.1556	64.4569	−16.0109	1.0638	908

source, the sentiment of its text is particularly important for investors who lack information. Consequently, this sentiment affects investors' future expectations of the company, in turn influencing their investment decisions and, ultimately, the company's future performance. On this basis, investor confidence is included as an intermediary variable.

To account for factors likely to influence company performance, the following control variables were selected: the logarithm of the company's total assets in 2019 (*LNSIZE*); the growth rate of the company (*MB*), measured by the growth rate of the company's net profit in 2019; listing age (*AGE*) in 2019, measured from the year when the company went public; and market return (*YRET*), measured by the company's return on invested capital in 2019.

Data sources

The text information mainly comes from the financial reports of companies such as Oriental Fortune.com and Xueqiu.com. After screening, the text information of over 920 companies was included in the analysis. Subjective expressions were quantified, and collating counts were performed. It should be noted that owing to continuous data screening in the process of measuring different models, the number of observations is not the same for each variable; nonetheless, text data for at least 800 enterprises were empirically analyzed. Data for the dependent, mediator, moderator, and control variables were sourced from the databases of Guotai Junan and Ruisi. We mainly used EViews 7.2 for regression analysis.

Empirical analysis

Descriptive statistics

Table 4 shows the descriptive statistics of all variables, including the mean, median, maximum, minimum, standard deviation, and number of observations.

The mean of the dependent variable ROE_{iT+1} is 0.3372 but its median is −0.0159, indicating that it has both positive and negative values. Among the explanatory variables, the mean of *ZMQG* is 0.7524, the median is 0.7857, and the maximum is 0.9500. These values show that positive emotion accounts for a large proportion of text information, and the mean and median values are relatively average. *JQG* has a mean of 0.9672, a median of 0.7559, a maximum of 0.9486, and a minimum of 0.0000. The mediator variable *IC* has a mean of 16.1719 and a median of 11.0086. Meanwhile, the moderator variable *EPS* has a mean of 0.2664, a maximum of 4.1500, and a minimum of −4.4800, indicating that earnings per share varies greatly among the sample companies. For the control variables, the mean of *LNSIZE* is 21.7363, its median is 21.6154, its maximum is 28.4133, and its minimum is 14.9416; *AGE* has a mean of 9.8369, a median of 7.0000, and a maximum of 25.0000; the mean of *MB* is −17.7670 but its median is 12.4678, indicating that a large number of companies have a poor net profit growth rate;

TABLE 5 Correlation analysis results.

	ROE	*ZMQG*	*JQG*	*IC*	*EPS*	*MB*	*AGE*	*LNSIZE*	*TRET*
ROE	1								
ZMQG	−0.082*	1							
	0.014								
JQG	−0.015*	0.639**	1						
	0.656	0.000							
IC	−0.049	0.037	0.030	1					
	0.144	0.273	0.375						
EPS	0.001*	−0.013	−0.022	0.077*	1				
	0.770	0.685	0.508	0.022					
MB	−0.001	−0.016	−0.017	0.052	0.126**	1			
	0.782	0.637	0.602	0.123	0.000				
AGE	0.046	0.031	0.035	−0.104**	−0.168**	−0.048	1		
	0.165	0.351	0.289	0.002	0.000	0.150			
LNSIZE	−0.052	−0.0089**	0.062	−0.152**	0.100**	−0.032	0.386**	1	
	0.118	0.007	0.063	0.000	0.003	0.331	0.000		
TRET	−0.052	−0.031	−0.056	−0.050	0.590**	0.092**	−0.122**	0.077	1
	0.116	0.350	0.094	0.136	0.000	0.006	0.000	0.021	

*Significantly correlated at the 0.05 level (two-sided).
**Significantly correlated at the 0.01 level (two-sided).

TABLE 6 Regression results of the mediating effect of investor confidence.

	Dependent variable: ROE_{iT+1}		
Variable	**Model 1**	**Model 2**	**Model 3**
ZMQG			
JQG	−17.6787**		−18.3518**
	(−2.3574)		(−2.3826)
IC		−0.0662	−0.0661
		(−1.673)	(−1.6544)
MB	0.6561	0.8171	0.0001
	(0.1575)	(0.1945)	(0.2411)
YRET	−0.1588	−0.1616	−0.1287
	(−1.1308)	(−1.1312)	(−0.8880)
LNSIZE	−2.6936*	−3.4032**	−3.1846**
	(−1.8930)	(−2.3009)	(−2.1102)
AGE	0.4597*	0.4687*	0.4757*
	(1.9350)	(1.9319)	(1.9335)
N	891	877	860
F	2.7563	2.2706	2.803

*Indicates a significant correlation at the 0.05 level (two-sided); **indicates a significant correlation at the 0.01 level (two-sided).

TABLE 7 Regression results of the moderating effect of earnings per share.

	Dependent variable: ROE_{iT+1}
Variable	**Model 4**
ZMQG	
JQG	−19.2506**
	(−2.5585)
IC	
*JQG*EPS*	9.5262**
	(2.06100)
MB	0.4110
	(0.0099)
YRET	−0.2858*
	(−1.7768)
LNSIZE	−3.1515
	(−2.1922)**
AGE	0.5327
	(2.2216)
N	891
F	3.0133

*Indicates a significant correlation at the 0.05 level (two-sided); **indicates a significant correlation at the 0.01 level (two-sided).

YRET has a mean of 6.5855, a median of 6.1556, a maximum of 64.4569, and a minimum of −16.0109.

Correlation analysis

We tested the correlations between all variables. The results are shown in Table 5.

As shown in Table 5, the dependent variable ROE_{iT+1}, the explanatory variables *ZMQG* and *JQG*, the mediator variable *IC*, and the moderator variable *EPS* are basically unrelated. Therefore, the regression model in this paper is not greatly affected by multicollinearity.

Regression results

Analysis of the Subjective Expression of Financial Reports and the Results of Multiple Regression of Corporate Performance.

Mediating effect of investor confidence

This group of experiments uses CASIA data to compare the four models. To prove the ability of the attention mechanism to identify time series features, the CNN-LSTM model proposed in the literature Peng et al., 2022 is used for the first set of comparisons. The second set of comparisons uses the AC-BiLSTM model Dong et al., 2020, and the third set of comparisons uses the Self-Attention-BiGRU model Qiu et al., 2020 to ensure accuracy and stability.

Table 2 shows the comparison of sentiment classification parameters of the CNN-LSTM, AC-BiLSTM, Self-Attention-BiGRU, and DAtt-CBLSTM models with the CASIA data.

In the empirical results reported in Table 6, the coefficient on *JQG* in Model 1 is −17.6787, significant at the 5% level;

TABLE 8 Relationship between earnings per share and company performance.

.	Dependent variable: ROE_{iT+1}
Variable	**Model**
EPS	5.6935**
	−2.2406
MB	−0.1491
	(−0.2916)
YRET	−0.3125
	(−1.6418)
LNSIZE	−3.2304
	(−1.4197)
AGE	0.5187
	−1.3272
N	908
F	2.2141

**Indicates a significant correlation at the 0.01 level (two-sided).

the coefficient on *IC* in Model 2 is −0.0662 but not significant; in Model 3, the coefficient on *JQG* is −18.3518, significant at the 5% level, and the coefficient on *IC* is −0.0661 but not significant.

Research hypothesis H1: Untested, indicating that the mediating effect of investor confidence between text net sentiment and the company's future performance is not significant. Investor confidence can affect a company's future performance in part through its impact on the company's stock price. Deren and Le (2014) found that investors were obedient and have a significant positive response to positive emotion based on the annual performance briefing. Significantly negative reactions to negative emotions. However, they did not study whether investor reactions are related to the company's future performance. Bochkay (2019) found that in a calm and stable stock market, investor sentiment has little effect on stock price; however, in a period of stock market turbulence, investor sentiment is difficult to rationally control because of uncertainty about future prospects, so investment behavior at this time is mainly affected by investor sentiment, which has a greater impact on the stock price.

We find no significant correlation between investor confidence and the company's future performance. This may be because our models do not take into account the impact of the stock market environment and related financial management, such as earnings management, which are both known to affect company's performance.

Moderating effect of earnings per share

Model 4 tests H2, namely whether earnings per share plays a moderating role between the net sentiment of the text and the company's future performance.

As can be seen from the empirical results in **Table 7**, The coefficient on *JQG* is −19.2506, significant at the 5% level, while the coefficient on the interaction between *JQG* and *EPS* is 9.5262, also significant at the 5% level. These findings show that EPS somewhat weakens the negative relationship between *JQG* and ROE_{iT+1}, supporting H2. As shown in **Table 8**, earnings per share is positively correlated with company performance with a coefficient of 5.6935, significant at the 1% level.

Conclusion

The subjective expression conveyed in the text of financial reports provides valuable incremental information that can somewhat predict the company's future performance, thereby affecting investors' views on company prospects and meeting the decision-making needs of investors and business managers. This paper used text-mining technologies such as natural language processing and sentiment analysis to extract and analyze text sentiment from financial reports, and ran a multiple regression analysis to investigate its association with future performance. While investor confidence did not significantly mediate between text net sentiment and future performance, the negative relationship between them was somewhat weakened by earnings per share.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Ethics statement

The Ethics Committee of Shandong Land Development Group Co., Ltd. reviewed and approved the study.

Author contributions

NZ contributed to coding and writing the manuscript. JR contributed to data preprocessing. Both authors contributed to the article and approved the submitted version.

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Conflict of interest

NZ was employed by Shandong Tudi Development Group Co., Ltd. JR was employed by company China Construction Bank Shandong Branch.

Publisher's note

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Psychological support for public-funded normal students engaged in teaching profession

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Among primary and secondary school teachers in China, 70% of teachers believe that they are facing greater occupational pressure. 63.8% of teachers clearly stated that occupational pressure has caused a great or great impact on themselves. And this has had negative effects on them such as mental, physical and personal development. This article studies the group of public-funded normal students from the perspective of psychological support. This article uses the SCL-90 form to investigate the professional psychology of teachers for the psychological support of public-funded normal students engaged in the teaching profession. And it conducts a survey on the curriculum setting and satisfaction of the public-funded normal students during their study stage. The experimental results of this article show that only 11.9% of public-funded normal students are very willing to take root and serve township education. Moreover, the psychological pressure of teachers at different educational stages is quite different.

KEYWORDS
public-funded normal students, teaching profession, psychological support, investigation and analysis, professional psychology

Introduction

Education is the foundation. Teacher are the base of education plan. The rapid development of society and economy has aroused great concern and diverse needs for education. The teaching profession is becoming more and more complex, and the requirements for teachers are becoming more and more strict. While undertaking the task of imparting cultural knowledge to students, teachers should also take into account the moral education of cultivating students' good character and shaping good behavior and habits for students. The progress of society has made the burden on teachers' shoulders a little heavier. The pressures, setbacks, and challenges that teachers face follow. Teachers should adapt to challenges and cope with pressure in the context of today's high standards, high expectations, and high demands. This has a great impact on the overall development of education and the personal growth of teachers. In particular, the vigorous enrollment of public-funded normal students coupled with the development of education today. Therefore, it is urgent to explore the influencing factors of teachers' psychological resilience development and take effective measures to improve teachers' psychological resilience.

This article mainly has the following two innovations in the research on psychological support for the teaching profession: (1) The research subject of this article is public-funded normal students, which is rarely involved in other literatures. However, as the expansion of public-funded normal students has become more and more accepted, the proportion of public-funded normal students in education is increasing. Therefore, it is necessary to take public-funded normal students as the research object. (2) For the study of psychological support, this article not only analyses the psychological status of the teaching profession, but also conducts a questionnaire survey on public-funded normal students in school. Such a comprehensive investigation before and after the event is very beneficial to the research of the entire public-funded normal students engaged in the teaching profession group.

Related work

Research on teacher resilience began in the 1980s. It has become an important topic of teacher research in the new century. However, most of the research on teachers' psychological resilience comes from abroad, and there are relatively few researches on teachers' psychological resilience in China. The use of both languages is explored by Ganina et al. (2019). They consider cross-cultural differences in the initial educational training of students in the preparatory departments of finance of the Russian government, and how to improve their adaptation to the particularities of Russian university training. They discussed the characteristics of teaching mathematics to foreign students with English as the language of international communication and Russian as the host language (Ganina et al., 2019). He and Luo (2021) believe that in today's music classroom teaching, self-playing and singing is one of the core teaching skills of music teachers. Cultivating the independent performance and singing skills of students majoring in music education in colleges and universities can not only improve students' comprehensive music literacy, but also increase the practicability of students' music learning. This will play a huge role in the future work of music education (He and Luo, 2021). Renard (2017) conducted research on teacher education in Thailand. They argue that Ayutthaya and similar centers are inherently multiracial, literate "civilized" elites. From a social perspective, Thais have a negative impact on the newly defined "others" in forestry, citizenship, and other fields (Renard, 2017). The research by Moleyar (2019) aims to sensitize researchers to some of the ethical and public relations issues involved in decision-making in the field of education. They shed light on the dilemma faced by school management at Vidyalaya schools in the Indian state of Karnataka in response to a notice from the state government to pay huge compensation and re-absorb a teacher who was physically disabled as a result of an accident in the school building (Moleyar, 2019). Swai (2019) considers the local economy and proposes to take the bank as the research object. He did research on the psychology of teacher vocational education. His experimental results confirmed the reliability of the problem (Swai, 2019). Dickson et al. (2019) found that in Abu Dhabi, the capital of the United Arab Emirates, teachers of English teaching subjects in government schools were recruited from overseas with extensive years of teaching experience. They surveyed 249 foreign English-teaching teachers to explore how their teaching years varied with their classroom practice, teaching beliefs and confidence levels. Experienced teachers are more likely to show confidence in their abilities (self-efficacy). They found that the classroom practices of teachers with between 5 and 10 years of experience were most consistent with the inquiry-based and student-centered learning methods applied in Abu Dhabi classrooms (Dickson et al., 2019). Throughout the related research, most of them are decision-making research for education, and curriculum research for students. The research on public-funded normal students is in the minority, and there is no related research on the psychological support of public-funded normal students.

Publicly funded normal students and psychological support

Publicly funded normal students

The main object of the research on the training of public-funded normal students is the training of public-funded normal students in six subordinate normal universities. There are few studies on the training of public-funded normal students in local colleges and universities. There are very few researches specifically targeting public-funded normal students in disciplines (Kim, 2017; Manoilova, 2021). To sum up, this article will be based on a deep grasp and reflection on the actual needs and policy orientation. Based on the specific situation of college training, it studies the problem of training teachers with "one specialization and multiple abilities" for history major public-funded normal students. The characteristics of public-funded normal students are shown in **Figure 1**.

By 2007, six normal colleges and universities under the Ministry began to implement free education for normal students. Judging from the overall development context, the education of public-funded normal students has only lasted for more than 10 years. This obviously has problems such as lack of training experience and lack of summary and reflection (Hidalga and Gallego, 2017; Gill and Zeeshan, 2021). However, the training of history teachers with "one specialization and multiple abilities" in Shandong Province has been less than 4 years since the public-funded normal student education was launched in 2016. Therefore, the obstacles and problems in the

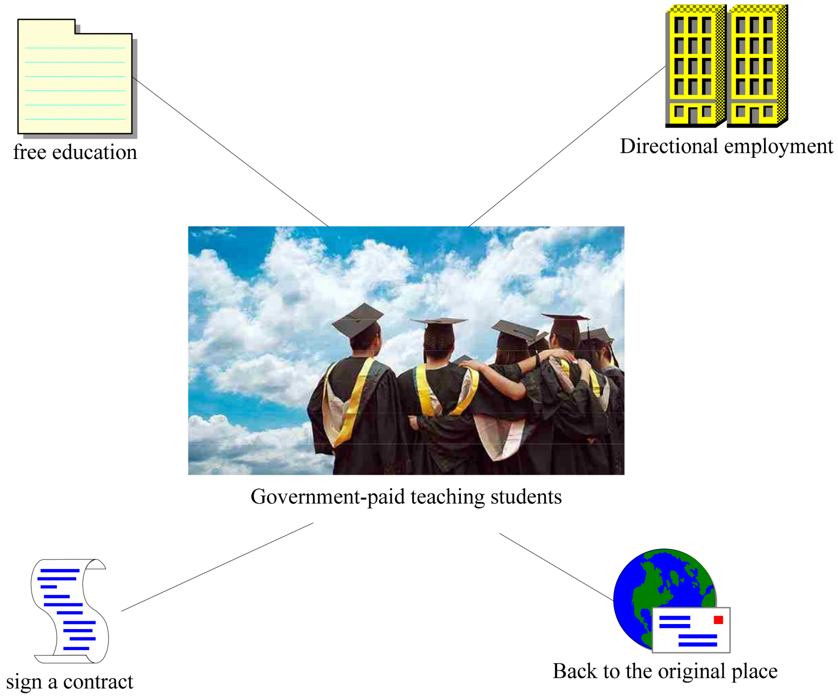

FIGURE 1
Characteristics of public-funded normal students.

training process are more prominent and concentrated, and we need to think and examine them comprehensively. This in turn finds a more effective training path, and continuously adjusts and optimizes the training of history teachers with "one specialization and multiple abilities." This can also provide reference and reference for the training work of other provinces and cities, especially in poverty-stricken areas (Ulrich and Frey, 2018; Rowicka, 2020).

Professional psychological support for teachers

Mental toughness

Mental resilience (Srman et al., 2019) was first used in the West when the word "resiliency" was used, which means "bounce," "recovery." Then Western scholars evolved it into a psychological condition and ability. The expression of the term mental toughness has also changed accordingly. It has changed from "resiliency" to "resilience," which means "resilience" and "resilience." Scholars believe that the latter concept is more appropriate for the concept of mental toughness. After decades of development, "resilience" has also attracted the attention of researchers in China. Domestic research on "resilience" is increasing. But the translation of this word is not uniform. Some scholars believe that the meaning of this word is similar to the word "psychological resilience" of "resilience" in physics, and should be translated as "psychological resilience." Some scholars believe that this is a kind of ability that can come from adversity, so it is translated as "resistance." Other scholars believe that the meaning of the word is to describe the ability to recover from adversity or difficulty, so it is translated as "resilience." Since there is no unified definition of the concept of "resilience" in the academic world, there are different opinions on the Chinese translation (Dar, 2019; Kiran and Daspurkayastha, 2020). The mental toughness diagram is shown in **Figure 2**.

Social support

Support from the outside world is an important resource for personal and professional development. In the 1970s, social support was first introduced in the psychiatric literature as an object of scientific research and as a professional concept. Since then, research on social support has been carried out in various fields. Generally speaking, social support as a general concept is often seen as care and help from family, friends and people around. However, as a scientific research object and a professional concept, its connotation has not been unified for a long time. It is shown in **Figure 3**.

Social support is a relatively complex concept with multiple structures. It includes not only environmental factors, but also the individual's internal self-cognition of environmental factors. It is an interaction, which mainly between individuals and others.

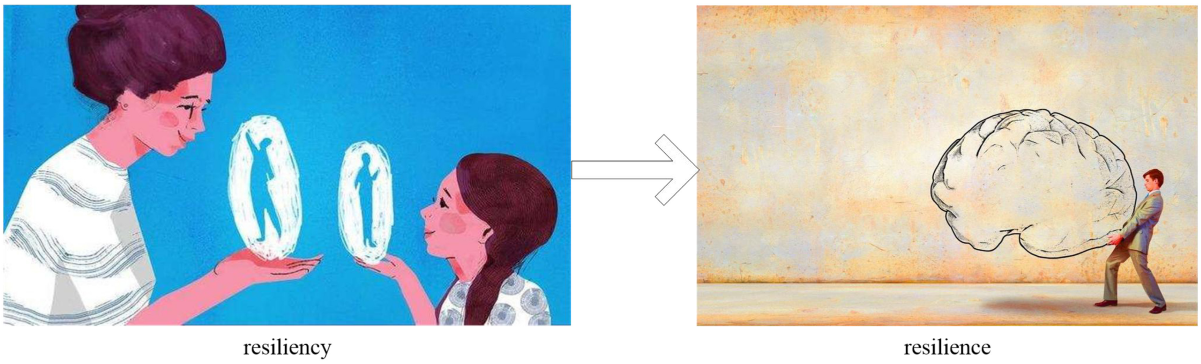

FIGURE 2
Mental toughness.

FIGURE 3
Social support.

Psychological evaluation criteria

At present, the methods commonly used to determine weights include fuzzy comprehensive evaluation method and gray theory method. However, these methods cannot solve the comprehensive evaluation problem of multi-person decision-making. It does not reflect the individual subjective preferences of review participants. The cloud model can describe qualitative concepts in natural language, and can establish a transformation model of uncertainty between values. And the aggregation algorithm of cloud model can solve the comprehensive evaluation problem of multi-person decision-making. Therefore, this article intends to construct an indicator weight model based on the cloud model-analytic hierarchy process (CM-AHP) method (Green et al., 2019; Jeawkok, 2021).

Judgment matrix based on cloud model scale

Assuming that there is a universe of discourse, the numerical features of the cloud $U = \{x\}, x = 1, 2, \ldots, 9$ are represented by expectation E_x, entropy E_x and super entropy E_n, then there is $A = (E_x, E_n, H_e)$. It uses the Nine Clouds Model $A_0, A_1, \ldots, A_8$ to establish the importance decision scale: The expected value is the none value from 1 to 9 corresponding to $E_{x_0}, E_{x_1}, \ldots, E_{x_8}$, and the larger the value, the more important the evaluation index is. The numerical features of its importance scale are shown in Table 1. According to the principle of the golden section, it calculates $A_0, A_1, \ldots, A_8$, $E_{x_0}, E_{x_1}, \ldots, E_{x_8}$, and $H_{e_0}, H_{e_1}, \ldots, H_{e_8}$, respectively. The calculation results are as follows:

$$\begin{aligned} E_{n_0} &= E_{n_2} = E_{n_4} = E_{n_6} = E_{n_8} \\ &= 0.382\alpha(x_{\max} - x_{\min})/6 = 0.437 \end{aligned} \tag{1}$$

$$E_{n_1} = E_{n_3} = E_{n_5} = E_{n_7} = E_{n_0}/0.618 = 0.707 \tag{2}$$

$$\begin{aligned} H_{e_0} &= H_{e_2} = H_{e_4} = H_{e_6} = H_{e_8} \\ &= 0.382\alpha(x_{\max} - x_{\min})/36 = 0.073 \end{aligned} \tag{3}$$

$$H_{e_1} = H_{e_3} = H_{e_5} = H_{e_7} = H_{e_0}/0.618 = 0.118 \tag{4}$$

TABLE 1 Importance scale.

Degree of importance	Definition
$A_0 = (E_{x_0}, E_{n_0}, H_{e_0}), E_{x_0} = 1$	u_i is as important as u_j
$A_2 = (E_{x_2}, E_{n_2}, H_{e_0}), E_{x_2} = 3$	u_i slightly more important than u_j
$A_4 = (E_{x_4}, E_{n_4}, H_{e_4}), E_{x_4} = 5$	u_i be more important than u_j
$A_6 = (E_{x_6}, E_{n_6}, H_{e_6}), E_{x_6} = 7$	u_i compared with u_j is very important
$A_8 = (E_{x_8}, E_{n_8}, H_{e_8}), E_{x_8} = 9$	u_i compared with u_j is extremely important
$E_{x_1} = 2, E_{x_3} = 4, E_{x_5} = 6, E_{x_7} = 8$	The degree of importance is in the middle of the above

In the formula: $x_{\max} = 9$; $x_{\min} = 1$; α is the adjustment coefficient, and the general value is 0.858.

Among them, u_i and u_j are the importance elements. The calculated nine cloud models are (1, 0.437, 0.073), (2, 0.707, 0.118), (3, 0.437, 0.073), (4, 0.707, 0.118), (5, 0.437, 0.073), (6, 0.707, 0.118), (7, 0.437, 0.073), (8, 0.707, 0.118), and (9, 0.437, 0.073). It then judges the importance of the evaluation indicators in pairs, and finally determines the weights of the evaluation indicators according to the aggregation method of floating clouds.

When there are only two base clouds, the calculation method is as follows: Assuming that A_1 and A_2 are two base clouds in the universe of discourse U, then a floating cloud A can be generated between A_1 and A_2 to represent the blank language value of the qualitative concept between them. When A moves from A_1 to A_2, the influence of A_1 on A will gradually decrease, while the influence of A_2 on A will gradually increase.

$$E_x = \beta_1 E_{x_1} + \beta_2 E_{x_2} \tag{5}$$

$$E_n = \frac{E_{n_1}(E_{x_2} - E_x) + E_{n_2}(E_x - E_{x_1})}{E_{x_2} - E_{x_1}} \tag{6}$$

$$H_e = \frac{H_{e_1}(E_{x_2} - E_x) + H_{e_2}(E_x - E_{x_1})}{E_{x_2} - E_{x_1}} \tag{7}$$

In the formula, β is the adjustment coefficient, which is determined by experts according to the specific situation. This lets $\beta_1 = \frac{k_1}{k_1+k_2}$, $\beta_2 = \frac{k_2}{k_1+k_2}$, and $k_i (i = 1, 2)$ be the aggregation times of the i-th cloud model. If the expert believes that no intervention in the assembly is required, then $\beta_1 = \beta_2 = 0.5$.

If there are m base clouds $A_1 = (E_{x_1}, E_{n_1}, H_{e_1})$, $A_2 = (E_{x_2}, E_{n_2}, H_{e_2}) \cdots A_m = (E_{x_m}, E_{n_m}, H_{e_m})$, the floating cloud $A_1 = (E_x, E_n, H_e)$ will be affected by the combined effect of $A_1, A_2, \ldots, A_m$. The way it is assembled is as follows:

$$E_x = \alpha_1 E_{x_1} + \alpha_2 E_{x_2} + \cdots + \alpha_m E_{x_m} \tag{8}$$

$$E_n = \frac{\alpha_1(E_{x_1} E_{n_1}) + \alpha_2(E_{x_2} E_{n_2}) + \cdots \alpha_m(E_{x_m} E_{n_m})}{\alpha_1 E_{x_1} + \alpha_2 E_{x_2} + \cdots \alpha_m E_{x_m}} \tag{9}$$

$$H_e = \sqrt{H_{e_1}^2 + H_{e_2}^2 + \cdots + H_{e_m}^2} \tag{10}$$

In the formula, $\alpha_1, \alpha_2, \ldots, \alpha_m$ is the adjustable criterion weight value.

One-level cloud model based on scale judgment matrix

According to the aforementioned method, it first establishes a judgment matrix for the pairwise importance comparison of a certain layer of evaluation indicators relative to other indicators. Its form is as follows:

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{bmatrix} \tag{11}$$

The cloud model on the diagonal line is $A_{ii} = (1, 0, 0)$. When comparing the pairwise importance of evaluation indicators, if the latter is more important than the former, there will be $a_{ij} = \frac{1}{a_{ji}}$. Its calculation process is as follows:

$$a_{ji} = A_{ji} = \frac{1}{a_{ij}} = \frac{1}{A_{ij}} = \left(\frac{1}{E_x}, \frac{E_n}{(E_x)^2}, \frac{E_e}{(E_x)^2}\right) \tag{12}$$

It then uses the square root method to calculate the element's expectation, ambiguity and relative weight, which is $W_i^{(0)}(E_{x_i}^{(0)}, E_{n_i}^{(0)}, H_{e_i}^{(0)})$. This involves multiplication of cloud models. The operation result: if there are n clouds $A_1, A_2, \ldots, A_n$ in the universe of discourse, then $A_1 = (E_x, E_n, H_e)$ is the calculation result, there are:

$$E_x = E_{x_1} E_{x_2} \cdots E_{x_n} \tag{13}$$

$$E_n = |E_{x_1} E_{x_2} \cdots E_{x_n}| \sqrt{\left(\frac{E_{n_1}}{E_{x_1}}\right)^2 + \left(\frac{E_{n_2}}{E_{x_2}}\right)^2 + \cdots + \left(\frac{E_{n_n}}{E_{x_n}}\right)^2} \tag{14}$$

$$H_e = |E_{x_1} E_{x_2} \cdots E_{x_n}| \sqrt{\left(\frac{H_{e_1}}{E_{x_1}}\right)^2 + \left(\frac{H_{e_2}}{E_{x_2}}\right)^2 + \cdots + \left(\frac{H_{e_n}}{E_{x_n}}\right)^2} \tag{15}$$

Then the elements in $W_i^{(0)}(E_{x_i}^{(0)}, E_{n_i}^{(0)}, H_{e_i}^{(0)})$ are:

$$E_{x_i}^{(0)} = \frac{E_{x_i}}{\sum E_{x_i}} = \frac{\left(\prod_{j=1}^{n} E_{x_{ij}}\right)^{\frac{1}{n}}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} E_{x_{ij}}\right)^{\frac{1}{n}}} \tag{16}$$

$$E_{n_i}^{(0)} = \frac{E_{n_i}}{\sum E_{n_i}} = \frac{\left(\left(\prod_{j=1}^{n} E_{x_{ij}}\right)\sqrt{\sum_{j=1}^{n}\left(\frac{E_{n_{ij}}}{E_{x_{ij}}}\right)^2}\right)^{\frac{1}{n}}}{\sum_{i=1}^{n}\left(\left(\prod_{j=1}^{n} E_{x_{ij}}\right)\sqrt{\sum_{j=1}^{n}\left(\frac{E_{n_{ij}}}{E_{x_{ij}}}\right)^2}\right)^{\frac{1}{n}}} \tag{17}$$

$$H_{e_i}^{(0)} = \frac{H_{e_i}}{\sum H_{e_i}} = \frac{\left(\left(\prod_{j=1}^{n} E_{x_{ij}}\right)\sqrt{\sum_{j=1}^{n}\left(\frac{E_{e_{ij}}}{E_{x_{ij}}}\right)^2}\right)^{\frac{1}{n}}}{\sum_{i=1}^{n}\left(\left(\prod_{j=1}^{n} E_{x_{ij}}\right)\sqrt{\sum_{j=1}^{n}\left(\frac{E_{e_{ij}}}{E_{x_{ij}}}\right)^2}\right)^{\frac{1}{n}}} \tag{18}$$

Finally, the consistency of the judgment matrix needs to be checked, where $C = (\lambda_{\max} - n)/(n-1)$, and $\lambda_{\max} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\sum_{j=1}^{n} E_{x_{ij}} W_{i1}}{W_{1j}}\right)$. R is the average value of the consistency index of the random judgment matrix of the same price. It needs to satisfy $I = C/R < 0.1$.

Psychological support for public-funded normal students

External support systems

The external support system includes the support and synergy provided by society, government, community, school, family, etc., to teachers' psychology. It mainly includes three levels: macro, meso, and micro. The macro level refers to national systems and policies. It includes six types: positive policy orientation, positive salary and benefits, positive teacher-respecting atmosphere, positive evaluation system, positive social environment, and positive prevention and control mechanism. The meso level mainly refers to schools. It includes a positive work environment, a positive school culture, a positive institutional mechanism, a positive interpersonal relationship, a positive family atmosphere, and a positive psychological service mechanism. Microsystems refer to families, including membership (Imran et al., 2021; Kuniyil, 2021).

As shown in **Figure 4**, the positive policy orientation is mainly reflected in the state's emphasis on and investment in education and teachers. It establishes the strategic position of priority development of education through legislation and policies. It establishes the higher economic and social status of the teaching profession. It realizes the professionalization of the teaching profession, the institutionalization of teacher rewards, the scientific evaluation of teachers, the lifelong teaching of teachers, and the respect of teachers' status.

Positive compensation benefits

It is mainly reflected in the form of legislation passed by the state. It guarantees that the salary and welfare of teachers is always above the medium level in various occupational divisions of the society. This includes the legislative provisions on teachers' salaries, the implementation effects of teachers' benefits, and the comprehensive evaluation of teachers' material benefits.

Positive teacher atmosphere

It is mainly reflected in the general respect of the teaching profession by the society. It has high attractiveness and has become a profession sought after by the society. Teachers have a sense of identity with their professional identity, and the teaching profession brings teachers dignity and happiness.

Positive working conditions

It is mainly reflected in the work, study and living environment. Schools and society create a good working and living environment for teachers, so that teachers can feel a close psychological bond. Teachers have a sense of identity, belonging, and responsibility to the work environment.

FIGURE 4
Psychological external support system.

Positive school culture

It mainly means that the school has established a teacher-oriented management concept, a united and harmonious working atmosphere, a scientific and fair assessment mechanism, a decision-making mechanism for democratic participation, a development environment of appreciation and encouragement, a warm and harmonious home atmosphere, and an inclusive fault-tolerant mechanism.

Positive relationships

It includes the relationship between teachers and families, the harmonious relationship between teachers and school leaders, colleagues and students, and the harmonious relationship between teachers and outside school. In addition to this, a positive family atmosphere and mental health services are also important.

Positive family atmosphere

It includes the health of family members, the convergence of value orientation and pursuit, and the understanding and care among members.

Active psychological services and prevention and control mechanisms

The mental health service mechanism includes institutions and places where society and schools have set up teachers' mental health services, prevention, diagnosis, intervention, and feedback. It staffs mental health services and conducts mental health prevention, diagnosis, intervention and service activities. School configuration can carry out the measurement and investigation of teachers' mental health. It evaluates the mental health status and finds out the problems existing in the teacher's mind in time. It can be diagnosed in a timely manner, and appropriate interventions can be taken according to the specific situation. For general psychological problems, school mental health teachers can use team counseling, encourage communication and other methods to relieve pressure and clear the knot for teachers. For problems that cannot be solved, psychological counselors can guide and help to seek help outside the school (Cox and Ward, 2019). The school establishes teachers' psychological files to track teachers' psychological changes. It also provides feedback with school administrators in a timely manner to ensure the mental health of teachers.

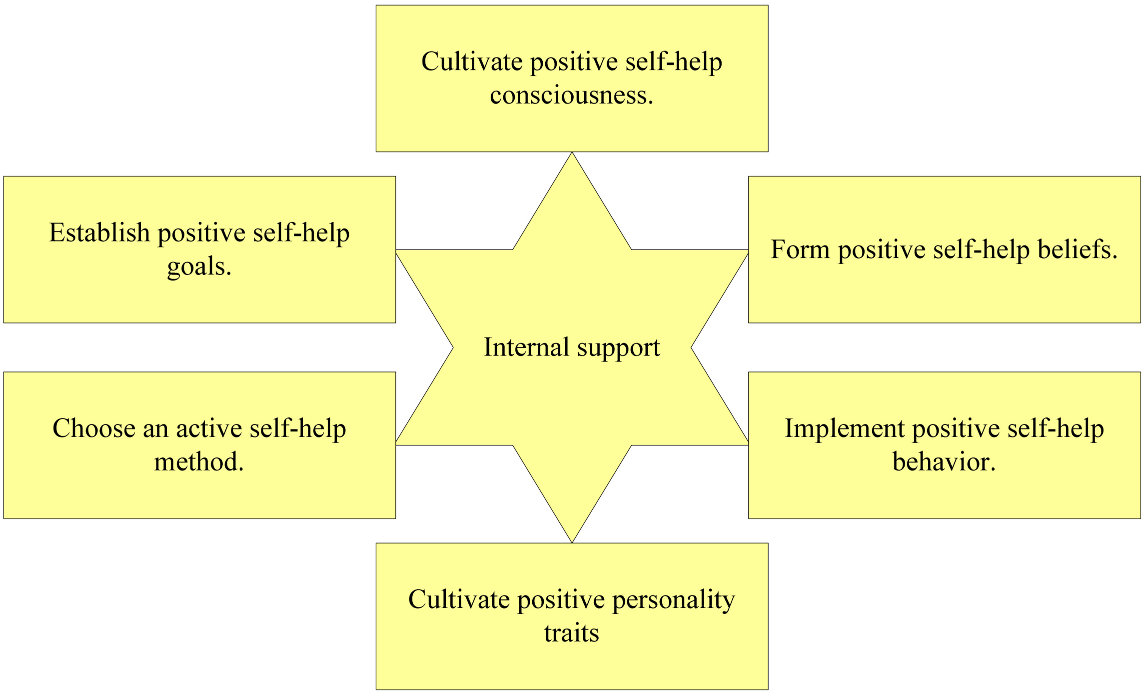

FIGURE 5
Psychological internal support system.

Internal support system

The internal support system is the individual's psychological self-help system. The psychological self-help system is under the control of self-consciousness, and consists of self-help consciousness, self-help goals, self-help environment, self-help methods, and self-help activities to form an individual's psychological activity process. Self-awareness is the soul and commander of the self-help system. When an individual has psychological problems, self-consciousness sends out self-help signals and determines self-help goals. It chooses the self-help method and evaluates the self-help effect. The construction of a teacher's psychological self-help system should be considered from the following aspects, as shown in Figure 5.

Positive self-help awareness needs to be developed. Self-awareness includes different levels of self-knowledge, self-experience, and self-control. The interaction between the three is the main mechanism of self-awareness. Self-knowledge is an individual's general awareness and evaluation of his physical and mental characteristics, as well as his relationship with others and the surrounding environment. It includes self-perception, self-concept, self-observation, self-analysis, and self-evaluation. This is the premise and foundation of self-awareness. Self-cognition of teacher's role mainly refers to teachers' knowledge and understanding of the nature, status, meaning, value, responsibilities and other aspects of their occupation. Self-experience is an emotional experience based on self-knowledge and evaluation. It is an attitude of the subjective self toward the objective self, such as self-confidence, inferiority complex, self-esteem, complacency, guilt, shame, etc. High self-esteem can make people experience more positive emotions. Self-control plays the role of supervision, guidance and maintenance, so that one's own behavior and thoughts and words conform to certain normative requirements. Since the economic and social status of teachers still needs to be further improved at this stage, the teaching profession has not yet become a popular profession sought after by people. Teachers' self-awareness of their roles will inevitably lead to differentiation and contradictions, which will inevitably affect teachers' self-experience. A positive consciousness system needs to be constructed, premised on teachers' positive understanding of the nature, status, meaning and value of the profession. It is necessary to establish a positive self-image with a sense of professional identity as the core. The goal is to develop high self-esteem emotional experiences of joy, serenity, interest, hope, pride, motivation, admiration, and love. And through the self-control system, we can timely discover and actively change negative emotional experience and self-awareness, and eliminate psychological barriers. This promotes the mutual adjustment between teachers and the environment, and promotes the psychological growth and development of teachers.

Positive self-help beliefs need to be formed. There is a close relationship between people's mental health and belief system. Teachers need to be helped to establish a positive belief system so that teachers fully realize the importance of mental health. This equips teachers with ways to improve mental health and reinforce positive beliefs. It needs the construction of school mental health mechanism, as well as the popularization, education and training of mental health knowledge. This makes teachers have a positive attitude toward psychological self-help and firmly believe that the goal of mental health can be achieved through their own efforts. When teachers have positive beliefs, they can translate beliefs into behavior. This in turn reinforces a positive view of life, work and self-worth.

Active self-help goals need to be established. It refers to the purpose and direction that an individual strives to achieve. That is to say, individuals resolve psychological contradictions and conflicts through their own efforts, so as to restore their psychology to a normal and harmonious state. Psychological research shows that people can only find true happiness and happiness by pursuing positive life goals, improving the essence of the lives with a positive attitude, and taking the continuous pursuit of positive life goals as the greatest joy in life. Helping teachers establish a positive target system should be carried out according to the origin of psychological problems and the characteristics and laws of psychological development. The goal of teachers' mental health can be divided into ultimate goal, stage goal, and specific goal. The ultimate goal of teachers is to achieve mental health. However, the situation of individual psychological problems is different, and the stage goals and specific goals are also different. For example, some reduce anxiety, and some change bad cognition. The stage goals and specific goals are achieved step by step, and finally the ultimate goal of mental health is achieved.

Active self-help approaches need to be chosen. This refers to the targeted use of self-regulation methods and techniques by teachers to promote individual mental health. These methods include stress coping, emotional regulation, and self-esteem maintenance. Positive psychology conducts psychological adjustment from two aspects: reducing negative emotions and increasing positive emotions.

Positive self-help behaviors are required. Positive psychology emphasizes that individuals construct a happy life through active progress and pursuit. It includes the improvement of ability in the pursuit of goals, as well as every small improvement and improvement in daily work, study and life. Positive personality traits need to be cultivated. Positive psychology advocates that individuals construct their own virtues and strengths and apply them in their daily lives to develop their own personality traits. Positive psychology believes that human beings have six virtues: wisdom and knowledge, courage, benevolence, justice, temperance, and spiritual excellence. The six virtues correspond to the 24 strengths. The path to virtue is called strength. By cultivating and learning these strengths, virtues can be realized.

Investigation and analysis of public-funded normal students engaged in teaching profession

Investigation and analysis of the status quo of the training of public-funded normal students

Selection of survey objects

Since the implementation of public-funded normal student education in 2016, a total of four colleges and universities in Shandong Province have undertaken the task of training public-funded normal students majoring in history. They are S Normal University, Q Normal University, L University, and J University. Among them, L University and J University have only begun to accept public-funded normal students of history majors in 2018. Therefore, this article selects the four grades of S Normal University and Q Normal University from 2016 to 2018, and the two grades from 2018 to 2019 of L University and J University as the survey objects. A total of 425 questionnaires were distributed in this survey, 418 valid questionnaires were recovered, and the effective recovery rate of the questionnaire was 98.35%. This survey is mainly carried out and carried out from four aspects: students' understanding of training goals, satisfaction with curriculum, learning initiative and employment expectations. The distribution of the number of respondents is shown in **Table 2**.

Results of the current situation of cultivation

From **Figure 6**, we can find that most of the students think that the current course of the first major is more reasonable. 25.7% of the students believed that the current curriculum can fully help them realize the professional study of history subjects, and they were very satisfied with this. 45.9% of the students were satisfied with it. 23% of the students believe that there are some problems in the current curriculum, and it is not possible to realize the professional learning of history, and they are not satisfied. 5.4% of the students think that it is completely impossible to achieve, and the current curriculum is not helpful to them, and they are very dissatisfied with this.

TABLE 2 Statistical map of the distribution of the number of respondents.

	2016	2017	2018	2019	Sum
S normal university	35	38	65	45	183
Q normal university	33	32	48	36	149
L university	–	–	40	31	71
J university	–	–	12	10	22
Amount to	68	70	165	122	425

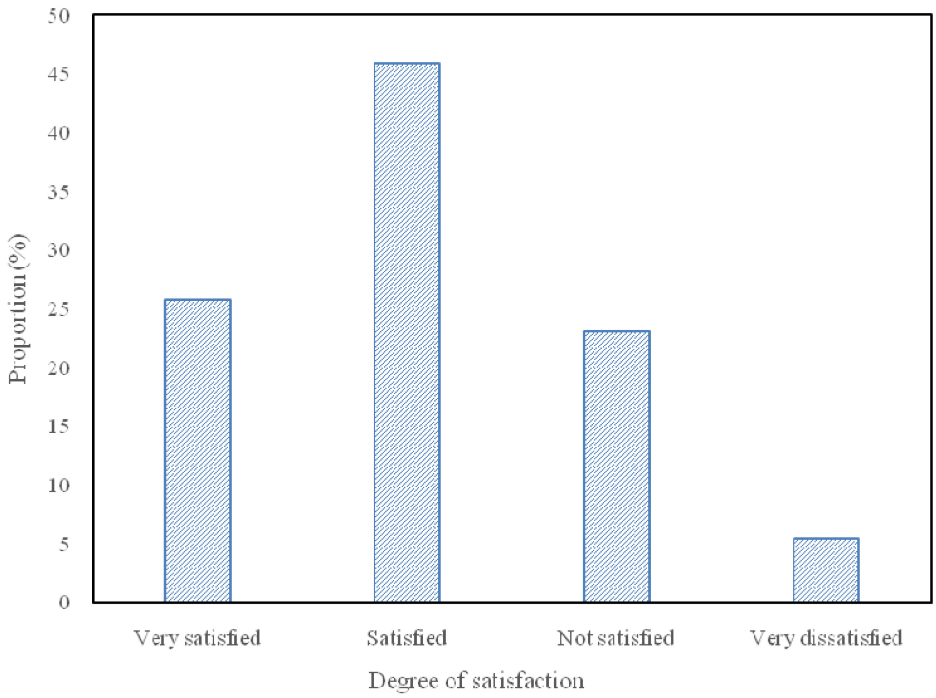

FIGURE 6
Statistical chart of the satisfaction data of the first major course setting.

According to Figure 7, we can see that students whose second major is Chinese are more satisfied with the curriculum, and 21.5% of the students are very satisfied. 49.6% of the students were quite satisfied, while 20.4 and 8.5% of the students were not very satisfied and very dissatisfied with the curriculum, respectively. Students whose second major is English are relatively less satisfied with the curriculum. Only 17.5% of the students were very satisfied with the curriculum, and 24% were quite satisfied. The proportions of not very satisfied and very dissatisfied reached 31 and 27.5%, respectively.

According to Figure 8, we can see that 33.5% of the students can preview frequently, and 26.5% of the students can preview occasionally. 17.6% of the students basically do not preview, and 22.4% of the students never preview. In terms of class concentration, 18.2% of the students were very focused in the class, and 21.6% of the classmates were relatively focused in the class. 33.2% of the students are not very focused in the classroom, and 27% of the students have a low degree of concentration in the classroom. In terms of after-class review, 33.5% of the students regularly review the knowledge they have learned, and 35.4% of the students review occasionally. 15.4% of the students basically do not review after class, and 17% of the students never review what they have learned. In terms of after-school learning, 19.5% of the students often study by themselves after class, and 22.4% of the students occasionally study by themselves after class. 27.3% of the students basically do not learn by themselves after class, and 30.8% of the students said they would never learn by themselves. From this, we found that public-funded normal students majoring in history are more proactive in pre-class preview and after-class review. They are not very active in classroom concentration and after-school self-study, and need to be further improved.

According to the degree of willingness in Figure 9, 72.4% of the students expressed their willingness to become a history teacher with "one specialization and multiple abilities." Only 27.6% expressed their unwillingness to become a "one-specialized and multi-skilled" history teacher. Through interviews, the author found that most of the students believed that as a teacher, they should master more skills and improve their own comprehensive quality, which is beneficial to their professional development in the future.

According to Figure 9, the willingness to take root in the township shows that only 11.9% of the students are very willing to take root and serve the township education, and 44.9% of the students are more willing. There are 31.9% of the students who are not willing to go to townships to teach, and even 11.3% of the students are very reluctant to go to townships for education. From the above analysis, it can be seen that most public-funded normal students are willing to become "one-specialized and multi-skilled" history teachers who are capable of teaching multiple subjects. However, they are unwilling to accept the living and working environment of township education and become history teachers who take root and serve township education. Therefore, in general, most students have low expectations for teaching in towns and villages in the future.

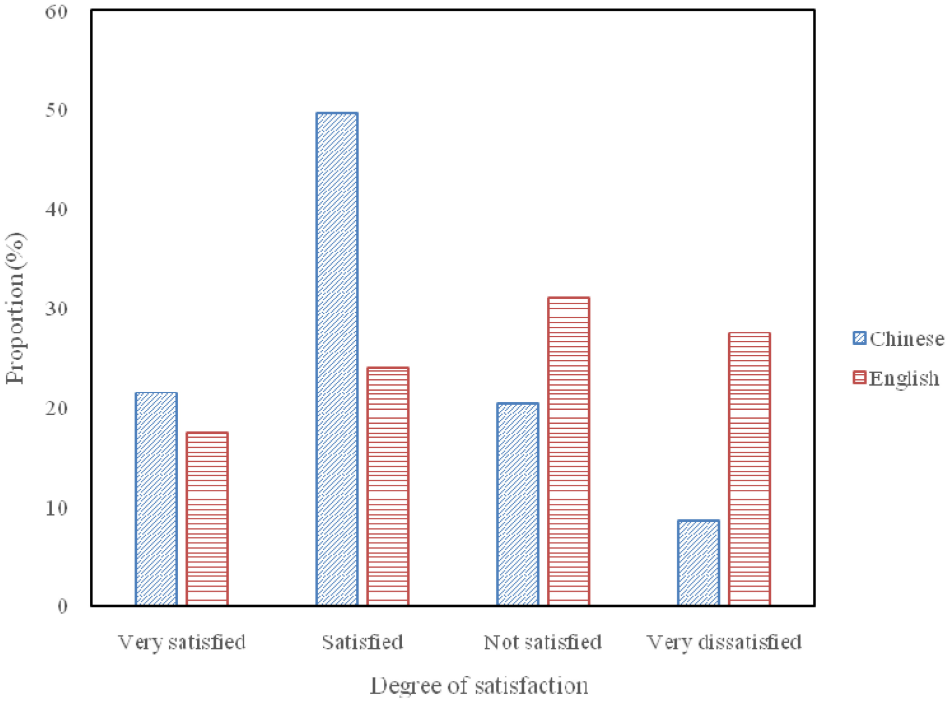

FIGURE 7
Statistical chart of the satisfaction data of the second major (Chinese/English) curriculum setting.

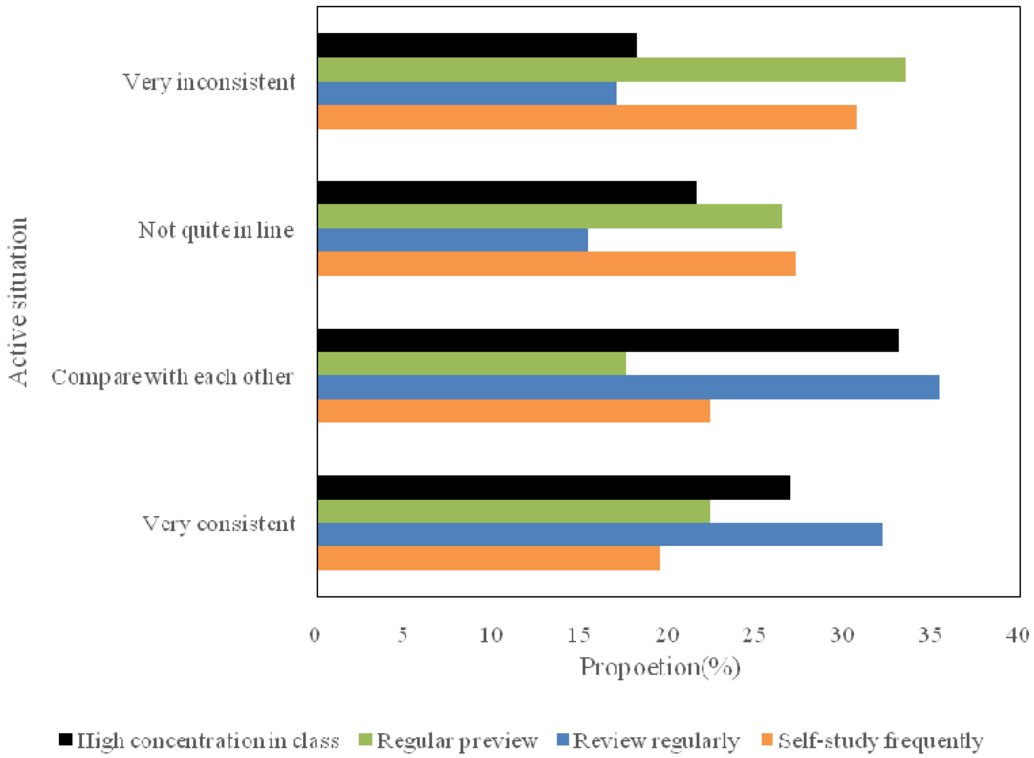

FIGURE 8
Statistics chart of learning initiative situation.

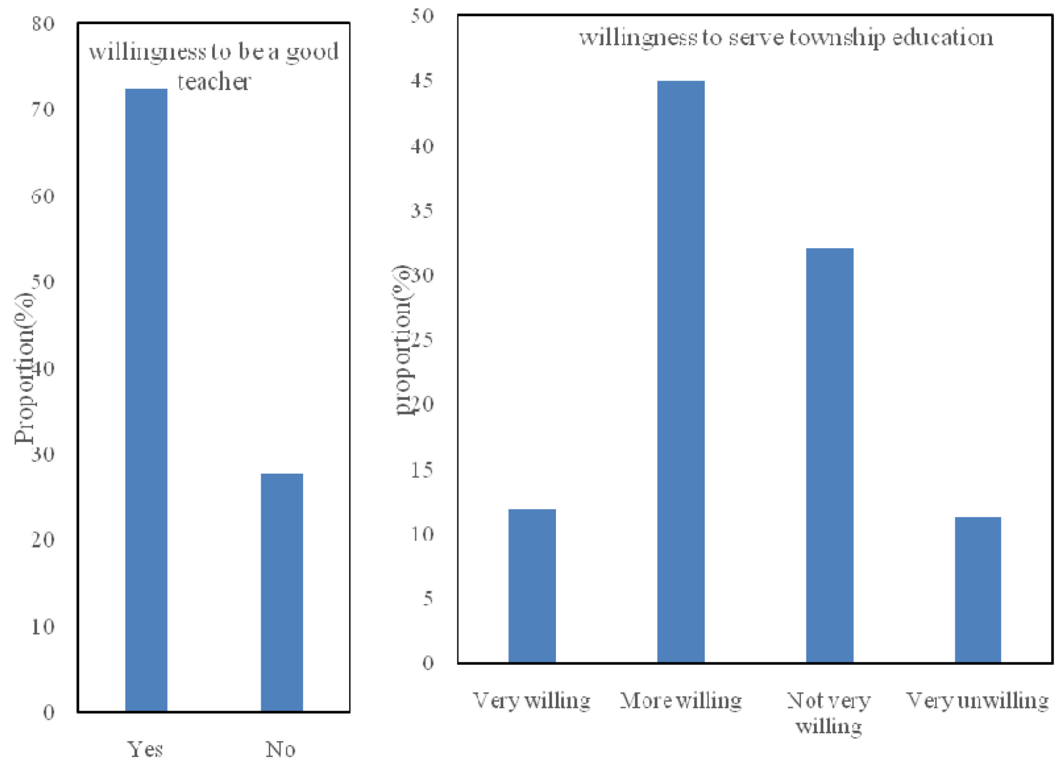

FIGURE 9
Employment expectations.

TABLE 3 List of questionnaires.

Project	Category		
Questionnaire list	Effective questionnaire 88%	Invalid questionnaire 4%	
Gender	Man 47.7%	Woman 52.3%	
Academic degree	Undergraduate course 86%	College for professional training 11%	Postgraduate 2%
Education experience	Under 5 years 26%	5–10 years 56%	More than 10 years 17%

Publicly funded normal students engaged in teachers' occupational psychological problems

Survey data

The subjects of this survey are first-line full-time young teachers under the age of 35 in 11 primary and secondary schools in a county. It does not include school leaders and non-teaching staff. Among them, there are six schools in urban areas and five schools in townships. The purpose of the investigation is to understand the current situation of the mental health and psychological support system of young teachers in primary and middle schools, find out the reasons for the existing problems, and propose countermeasures and suggestions for solving them. A total of 350 questionnaires were distributed and 320 were returned. Among them, there were 308 valid questionnaires, accounting for 88% of the total questionnaires issued. Among the 308 respondents, 147 were male and 161 were female, accounting for 48 and 52%, respectively. There are 100 primary school students, 100 junior high school students and 108 high school students. 43 people with less than 3 years of employment accounted for 14%, 40 with 3–5 years accounted for 13%, 173 with 6–10 years accounted for 56%, and 52 with more than 10 years accounted for 17%. There are 264 undergraduates accounting for 86%, 35 junior college students accounting for 11%, and 7 graduate students accounting for 2%. The details are shown in Table 3.

The research tool includes a social support rating scale with a total of 10 items. It includes three dimensions: objective support, subjective support, and the degree of utilization of social support. Objective support refers to the material assistance, group participation and social network that an

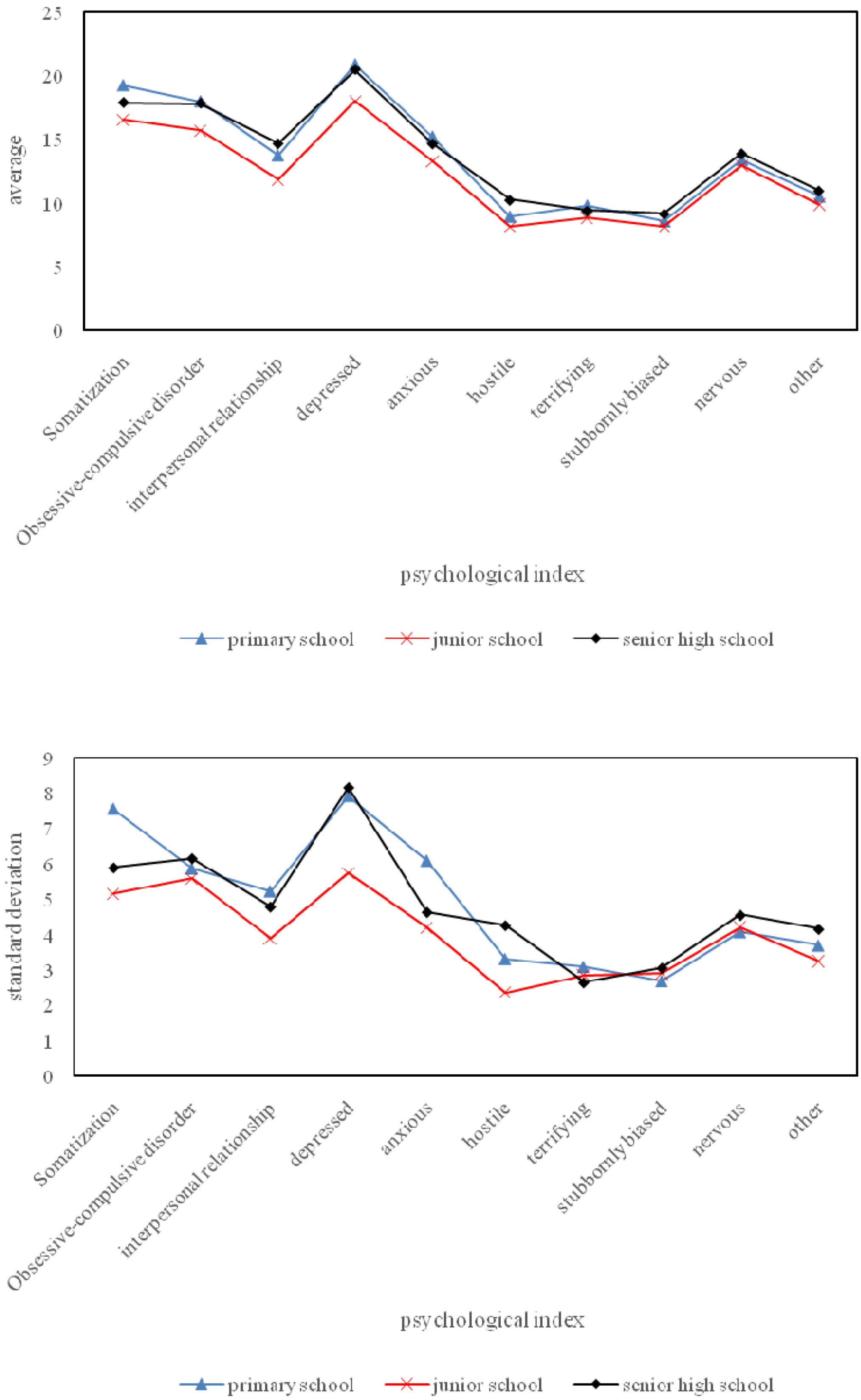

FIGURE 10
Differences in SCL-90 factors of teachers in three grades.

TABLE 4 Correlations of SCL-90 factors of teachers in three grades.

	F	*t*
Somatization	4.615*	0.011
Obsessive-compulsive disorder	4.860**	0.008
Interpersonal relationship	9.800**	0
Depressed	4.513*	0.012
Anxious	3.853*	0.022
Hostile	9.942**	0
Terrifying	2.875	0.058
Stubbornly biased	3.047*	0.049
Nervous	1.242	0.29
Other	2.227	0.11

* and ** represent the size of the statistical difference, and ** represents a larger statistical difference.

individual obtains, including material assistance and direct services. Subjective support refers to the sense of security, satisfaction, respect, and positive emotional experience that an individual feels. Utilization of support refers to the utilization of social support by individuals according to their actual situation. Those who refuse to help will respond negatively to social support, and the support they receive will be greatly reduced. People who actively seek help will receive more social support. The scale has good reliability and validity.

Survey results

The symptom self-rating scale is the SCL-90, which is suitable for minors over the age of 14 and all adults. It has a total of 90 items, including a wider range of psycho-symptomology content. It involves from feeling, emotion, thinking, consciousness, behavior to living habits, interpersonal communication, diet, and sleep. It uses 10 factors to reflect the symptoms of 10 aspects. These are: somatization, obsessive-compulsive symptoms, interpersonal sensitivity, depression, anxiety, hostility, terror, paranoia, psychosis, others. The first 9 assess whether individuals have psychological problems in the dimensions of perception, emotion, thinking, and physiology. "Other" reflects the individual's diet, sleep, and so on. It adopts a five-point scoring system, ranging from 1 to 5, indicating none, very mild, moderate, severe, and very severe. The scale has good reliability and validity. The SCL-90 questionnaire was collected and processed using SPSS statistical software. The results are as follows.

Statistical analysis results from Figure 10 and Table 4: There were significant differences in the total scores of somatization, obsessive-compulsive disorder, interpersonal relationship, depression, anxiety, hostility, paranoia, and mental health among teachers in high school, junior high school, and elementary school. From the mean point of view, the teachers in the junior high school have the lowest performance scores in various symptoms and the best mental health. Teachers in high school and elementary school are on a par, and their mental health is generally poor.

Statistical results of *post hoc* tests in Table 5: According to different indicators, it is found that there are significant differences in the groups of teachers in primary schools, junior high schools, and high schools. In somatization, there are significant differences between primary school teachers and junior high school teachers. In obsessive-compulsive disorder, there are significant differences between junior high

TABLE 5 Post-inspection situation table.

Dependent variable	(I) Grade	(J) Grade	Mean difference (I-J)	Significance
Somatization	Primary school	Junior school	2.704*	0.011
		Senior high school	1.372	0.291
Obsessive-compulsive disorder	Junior school	Primary school	−2.310*	0.022
		Senior high school	−2.152*	0.032
Interpersonal relationship	Junior school	Primary school	−1.920*	0.016
		Senior high school	−2.826*	0
Depressed	Primary school	Junior school	2890*	0.023
		Senior high school	0.419	920
Anxious	Primary school	Junior school	1920*	0.028
		Senior high school	0.563	0.723
Hostile	Senior high school	Primary school	1299*	0.025
		Junior school	2.099*	0
Stubbornly biased	Junior school	Primary school	−0.400	0.622
		Senior high school	−0.985*	0.051
Aggregate score	Junior school	Primary school	−15.200*	0.029
		Senior high school	−15.965*	0.017

*represents the statistical difference.

school teachers and primary school teachers, and between junior high school teachers and high school teachers. In interpersonal relationships, there are significant differences between junior high school teachers and primary school teachers, and between junior high school teachers and senior high school teachers. In depression, there is a significant difference between primary school teachers and junior high school teachers. In terms of anxiety, there is a significant difference between primary school teachers and junior high school teachers. In hostility, there are significant differences between high school teachers and primary school teachers, and between high school teachers and junior high school teachers. In paranoia, there is a marginally significant difference between junior high school teachers and high school teachers. In the total score of mental health, there are significant differences between junior high school teachers and primary school teachers, and between junior high school teachers and high school teachers.

Conclusion

Mental toughness can improve teachers' mental health in today's increasing pressure on teachers, so that teachers can be relieved from setbacks and pressures as soon as possible, so that teachers can maintain their enthusiasm for education and teaching. The study found that in the actual education and teaching situation, teachers' psychological toughness has not received corresponding attention. Based on positive psychology as the theoretical support, this article studies the psychological support system for the special group of young teachers in primary and secondary schools, and expands the application horizon of positive psychology. However, limited to the theoretical and academic level of researchers, it is difficult to conduct in-depth research. There are many unsatisfactory points in the paper, which need to be further revised and improved in the future. Therefore, further research will be carried out in this area in the future.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work, and approved it for publication.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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An empirical analysis of sport for mental health from the perspective of a factor analysis approach

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Mental health is a kind of emotional state, a good psychological state can have a positive impact on a person, physical exercise can have a positive impact on the psychological state of college students, prevent the generation of negative emotions, improve the bad emotional state, and then promote the mental health of college students. Health is an inevitable requirement to promote the all-round development of people and a basic condition for economic and social development. Health education should be incorporated into the national education system to promote the national health of the people through sports. Young people are the main force and backbone of national and social development. In order to realize the Chinese dream of great rejuvenation, we must attach importance to the development of young people and the physical and mental health of young people. In the process of compulsory education, middle school and high school period is a key stage in the gradual formation and development of students' psychology and body, but due to the large audience of China's education, the competition is more intense, which inevitably causes a lot of students to focus on exam-oriented education and neglect physical health, especially in recent years, the mental health issues of increasing concern. Through the research situation of mental health in China and the concept of mental health quality, this paper analyzes the problems of sports and mental health, and puts forward some corresponding suggestions for the problems, which has reference significance for promoting students' mental health.

KEYWORDS

factor analysis, physical education and sports, mental health, psychology and body, students' mental health

Introduction

At present, with the rapid development of science and technology, the rapid progress of society, the demand for talent is growing, through the college entrance examination, the baton shunt, become a watershed between talent flow, middle school students face examination choice, academic pressure and the main contradiction between the physical and mental health, how on the premise of easing the pressure on students, promote students' physical and mental health become one of the main problems at this stage. Faced with these pressures, it brings a great negative effect on the life and growth of secondary school students, who are not physically healthy enough and become psychologically fragile, which affects their normal life and school learning, and eventually leads to poor learning ability and a continuous low quality of life. According to the current international common understanding, the so-called health is not only physical health, but also includes psychological, moral, having good sociability and communication skills in social life, etc., which all belong to the category of health (Song, 2021). Therefore, the adjustment of physical and psychological health of secondary school students is taken as a research direction and an attempt is made to explore the way in which sports can adjust and promote the development of physical and mental health of secondary school students (Wang, 2021).

The issue of mental health has only been taken seriously in recent years and has been recognized as an important component no less than physical health (Zhang, 2021). Mental health is, in a way, more important than physical health, as it is a matter of the environment in which a person lives and whether it affects the harmony and stability of the surrounding society, and is an important topic in all aspects of family, work and life. Especially as secondary school students who are under great academic pressure, their mental health is becoming more and more important (Gou, 2021). However, the characteristics of sports to meet the psychological needs of college students. Long-term engaged in sports can effectively relieve the psychological pressure from study, interpersonal life, emotion and other aspects of college life, enhance the social adaptability of college students, and cultivate their self-esteem and self-confidence. Sports is also very suitable for college students to improve their emotions and release them. Exercise in the rhythm and melody of the exercise, the state of tension and fatigue is adjusted.

The investment in sports facilities has become more abundant, and the sale of sports products has gradually increased, as detailed in Figures 1, 2.

The fact that sports have such rich results in promoting mental health quality is attributed to two reasons: firstly, there is still great potential for research on the psychological effects of sports on human body as an effective means of health; secondly, the issues related to mental health quality are still a hot spot worthy of in-depth research, although most of the opinions think that mental health quality contains contents inseparable from the four aspects of Although most of the opinions think that the content of mental health quality is inseparable from the four aspects of “knowledge, emotion, intention and action”, as scholars go deeper, new connotations are constantly incorporated, and some contents are also questioned, so the specific content of mental health quality of college students is still inconclusive (Wang and Wu, 2021). On the basis of existing studies, it was found that such studies suffer from two deficiencies: first, mental health benefits are considered as a direct result of physical activity, with less attention paid to the influence of dummy additional variables and the control of additional variables; second, studies of mental health quality are mostly localized, focusing on examining the positive effects of physical activity on emotions, while considering the results of emotional responses unilaterally as the structure of mental health quality (Brown et al., 2020). Secondly, studies on mental health quality have focused on examining the positive effects of physical activity on emotions from a local perspective, while considering emotional response outcomes as the main dimension in the structure of mental health quality, while ignoring the theoretical structure and mechanisms of action of physical activity for mental health quality (Bhasin et al., 2021). Therefore, this paper studies the current situation and the concept of mental health quality, analyzes the problems of sports and mental health, and does the work of promoting students’ mental health.In view of this phenomenon, it is urgent to build a lifelong physical education teaching mode (as shown in Figure 3), through the interaction between teachers and students, comprehensive in-class teaching and extracurricular teaching, to carry out various sports activities in and out of class, so as to cultivate students’ lifelong sports habits.

Relevant theoretical basis

The current situation of domestic research

At present, although China has made certain achievements in promoting sports at the secondary school level, there are still various problems and potential drawbacks due to the development of the education system to a greater or lesser extent. At present, some university campuses in China cannot highlight the main position of college students in physical education teaching, but in the traditional physical education teaching mode: traditional physical education teaching is mainly teachers teach, students learn, students’ passivity is more obvious, they blindly learn under the mechanical guidance of teachers. Teaching effect directly affects the effect of students ’learning, but the present some colleges and universities for physical education although poured some effort, excessive emphasis on formalism in teaching, in the long run, physical education cannot achieve effect, students’ learning efficiency is low, lead to the overall decline of physical education teaching quality in colleges and universities, this phenomenon and the development of sports slogans. Through the combing and review of China’s education system, it is possible to provide a more intuitive way of thinking about the promotion of sports at the secondary school level. Since the introduction of quality education in China, more and more provinces have put on the agenda how to strengthen sports at the secondary school level, advocating reforms to strengthen the physical and humanistic qualities of our young generation. However, due to the influence

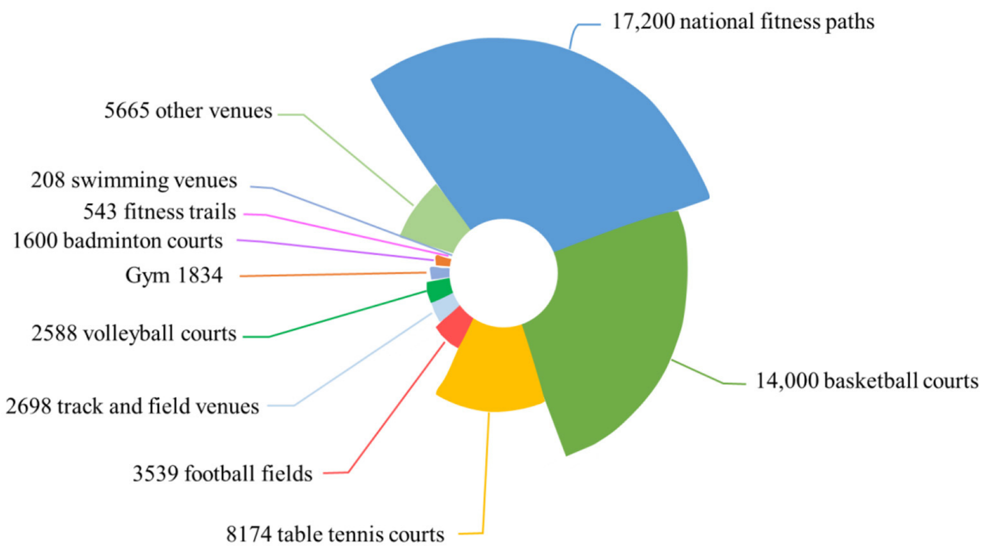

FIGURE 1
Sports field.

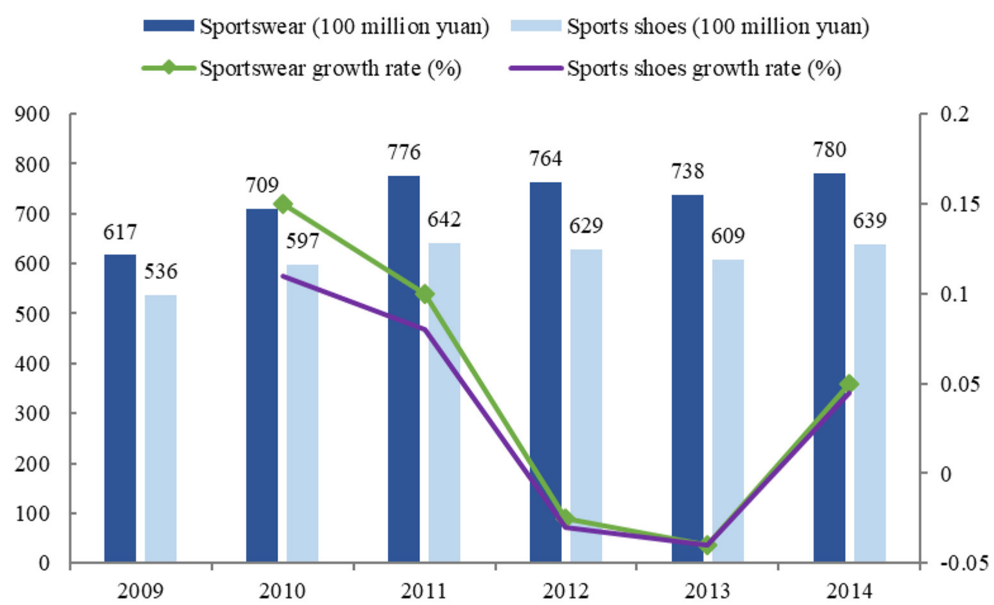

FIGURE 2
Sports equipment.

of the secondary and high school exams, a large part of the reform is still a formality, and it is still difficult to get secondary school students to truly integrate into sports by changing the soup (Mittmann et al., 2020). In some provinces and cities, the examinations of the secondary school examinations have been changed from hard to soft, and the tests have been changed to physical fitness tests in order to reduce the burden on students. The result is a deepening lack of attention to physical education and sport at the secondary level, which is contrary to the goals of the reform. In addition, the lack of attention to physical education and sport in schools, and the persistence of the "unspoken rule" that physical education makes way for culture classes, has led to a reduction in students' enthusiasm for physical education and sport in secondary schools, resulting in a lack of sport as a final consequence (Kyle et al., 2021).

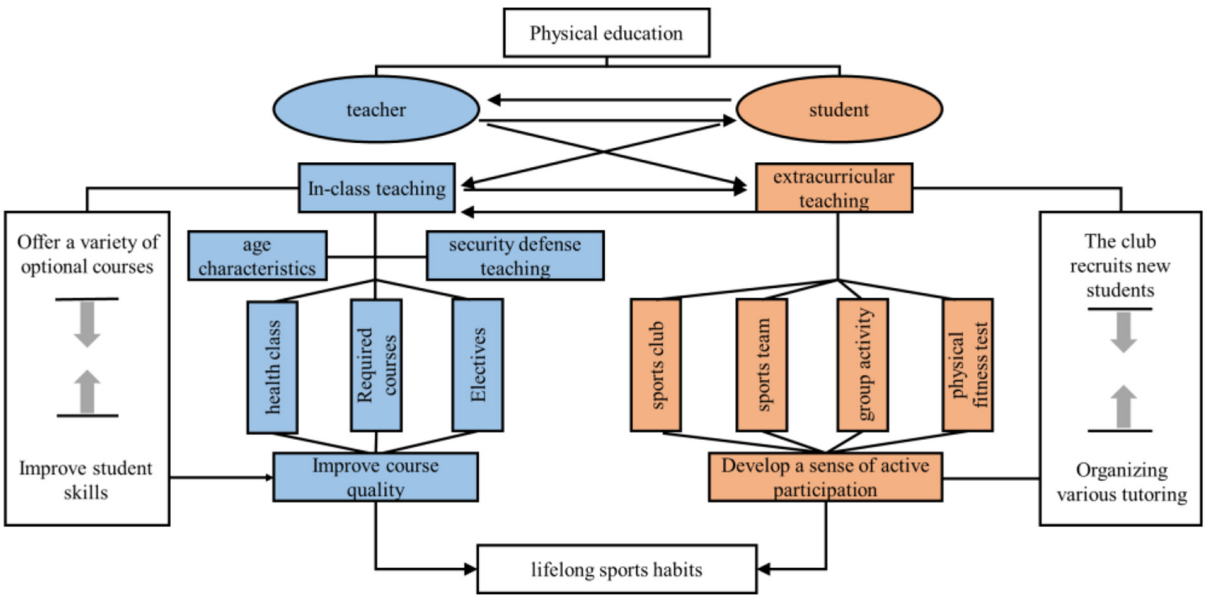

FIGURE 3
The lifelong physical education teaching mode runs through it.

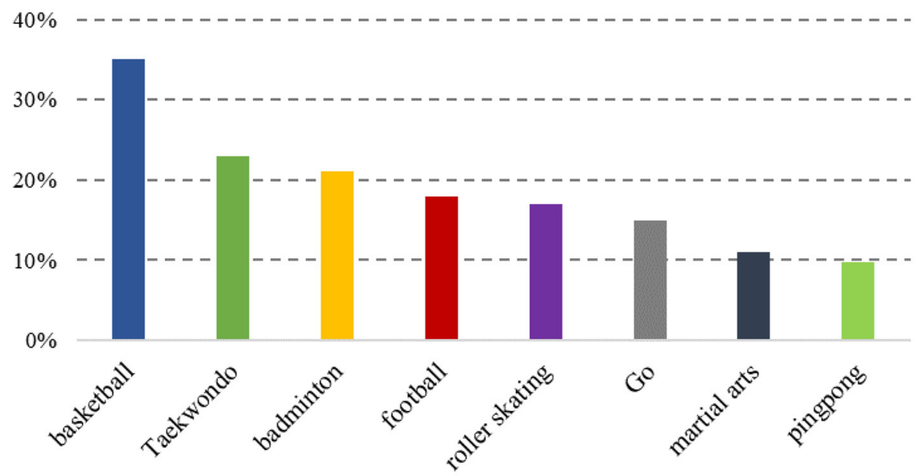

FIGURE 4
Selection of intended sports items.

Current status of foreign research

The results of international scientific research in this area show that sports and activities on campus can be very good at influencing the psychological state of secondary schools and maintaining the development of students' psychological health, and that the current choice of sports by students is mainly focused on basketball and taekwondo (see Figure 4). The human body in a healthy state affects the psychological health state of individuals at certain levels, and researchers have put forward a series of hypotheses that could provide an explanation for this situation (Zhang, 2020).

Hypothesis of cognitive behavior

This hypothesis is based on the premise that we assume that secondary school students have the appropriate cognitive abilities, which means that when we analyze their behavior, we assume that they have positive thinking patterns and good emotional perceptions, and that they can make their own

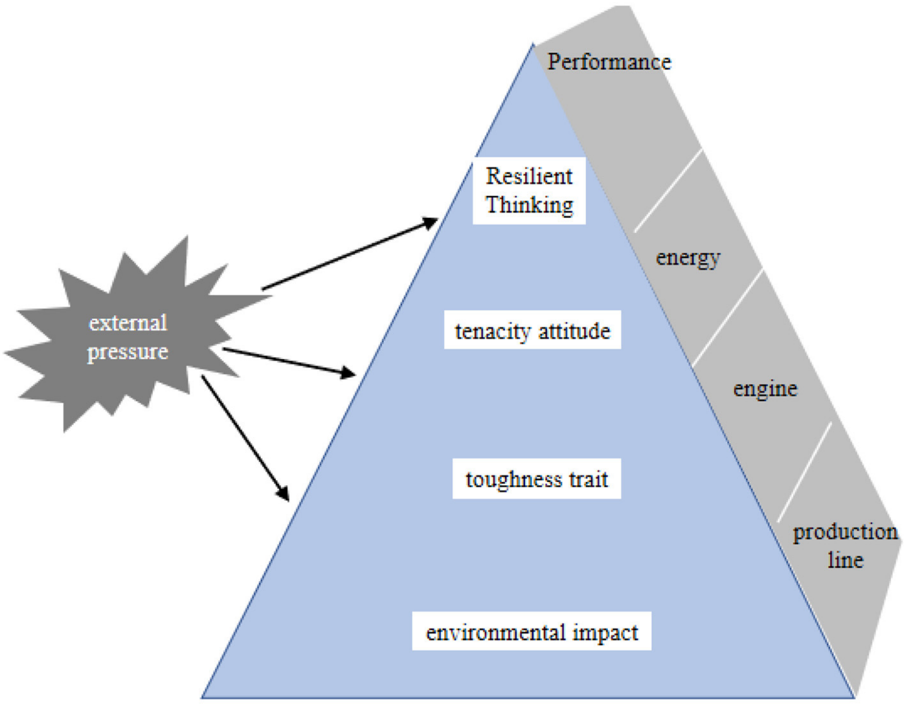

FIGURE 5
Teacher salary satisfaction level.

judgments and analyses of all aspects of the outside world, right and wrong. The theory of self-efficacy proposed and explained by the scholar Bantulla is similar to the theory of cognitive behavior, which believes that people have demands on their own behavior and will continue to try things that are still in progress, including the foreseeability of things. Self-efficacy is "the degree of people being confident that they can use their skills to complete a job behavior". Bandura believes that there is an efficacy expectation. Outcome expectation refers to a person's speculation that some behavior will lead to a certain result. At the same time, he believes that when people accomplish something they find difficult, overcoming this difficulty will lead to a further increase in cognition and a further experience of self-affirmation, which will lead to the affirmation of their own value (Bidaisee et al., 2020). When this theory is applied to sports, i.e., when people overcome their bad states, such as inability to persist, feeling tired, etc., in the sports state, and thus achieve self-transcendence, then for their bad emotions that are not conducive to mental health, such as irritability, anxiety, depression, etc., are effectively discharged.

Based on the research prompt, Bull took cricketers' mental toughness as the research object, proposed that the mental toughness of the athletes in this sport includes five aspects, and divided the content elements of mental toughness into four levels with reference to the logic of the concept, from bottom to top, they are environmental factors, toughness traits, attitudes and thinking, thus establishing the pyramid model of mental toughness; the model emphasizes the importance of environmental factors in the development of mental toughness, and the importance of mental toughness in the development of mental toughness. The model emphasizes the importance of environmental factors in the development of mental toughness, and points out that the intrinsic pyramid model will eventually stabilize with the growth of experience, which provides important theoretical insights for cultivating and improving mental toughness (see Figure 5). From this study, we can see that students 'mental health or mental resilience is mostly determined by the environment they live in, because the environment of sports is relatively relaxed, so sports can promote students' mental health.

The hypothesis of distraction

This hypothesis is based on the idea that secondary school students provide some support for other behaviors in the learning process so that they can focus on other things and can make a temporary distraction from their attention, which in turn makes them depressed, anxious and other undesirable emotions decrease quickly in a short period of time (Meng et al., 2020). Sports such as jogging, brisk walking, swimming, and yoga can put students in a more natural, calm and relaxed environment, so that they can easily repeat the reinforcement without thinking too much and shift their attention through activities such as meditation, so that they can detach themselves from their previous negative emotions and enter normal thinking again. Such a shift in attention and focus can be a good way to regulate one's emotions. It has been found that if one can persist in sports for a long time, it can effectively maintain and improve one's mental health.

Social interaction hypothesis

To be able to interact with people around us normally, and to feel the way between people and feel happy, which can promote their own mental health, this is a premise of the social interaction hypothesis. This is a premise of the social interaction hypothesis, that is, the interaction between us and other people brings us a feeling that is not completely in a state of pleasure, there will be anxiety, sadness and other negative emotions, then it will have a negative impact on our physical and mental health. And participate in sports is a kind of social communication, because sports needs to cooperate with friends, the practice standard research, sports is let oneself in a relaxed and comfortable state of a basic and fast way, negative is almost zero, insist on exercise is not only good for physical health, for mental health.

Dopamine hypothesis

Some studies have shown that our neurotransmitters contain chemicals that produce certain improvements in mental health when they are secreted and transmitted between the neuromuscles and nerves. When a person's mental state is negative or not very pleasant, the secretion of these substances decreases, while when a person is in a pleasant or more relaxed state, the secretion of these substances increases, thus maintaining the physical and mental health of the person. Then, we can study from a medical point of view, it can be concluded that people participate in sports, through some physical activities can promote the secretion of such substances, and then achieve a relaxed and comfortable and physical and mental state we want, and thus play a protective role for our mental health.

Hypothesis of cardiovascular health

A review of medical and psychological literature shows that cardiovascular health plays a significant role in a person's mental health. Because depression, long-term stress, anxiety, anger, pessimism, and unhealthy life are associated with potentially harmful biological responses, including heart rate/arrhythmias, digestive system discomfort, increased blood pressure, and inflammation, and decreased blood flow to the heart. Studies have shown that when people play sports, the permeability and contraction of their cardiovascular system increases compared to normal, which promotes the flow of the blood circulation system, thus making the blood circulation system smooth and conducive to the maintenance of its health and the normal conduction of the nerve fiber system, which has a good effect on the maintenance of personal physical and mental health.

The concept of mental health quality

Mental health quality is a local concept born in the process of promoting "case quality education" in China, and it is also a new research idea based on the reflection of the traditional mental health research at home and abroad. On the one hand, to some extent, the essence of mental health quality is the stripping of the healthy and positive aspects of the composition of mental quality, which is part of the mental quality that helps to form a healthy mental state; on the other hand, in the embarrassing situation that the research on mental health is often questioned and controversial, the issue of mental health standards has not reached a consensus among scholars, while the research on mental health quality derived from it has become On the other hand, the issue of mental health standards has not reached a consensus among scholars, and the research on mental health quality has become an important breakthrough and new attempt to explore mental health and quality education. To understand the concept of "mental health quality", we need to start from quality, psychological quality and mental health, which firstly originated from psychopathological research with biological basis, but as the research progresses, the single genetic theory is gradually overturned, and it is pointed out that "quality is the genetic basis of the individual. The quality is formed through the interaction of practical and mental activities and environmental factors, and eventually internalized into relatively stable, basic and implicit qualities of the individual (Nordgreen et al., 2021). Psychological quality is a subordinate concept based on the concept of quality, which is also the core and key link of quality education. Psychological quality originates from the background of local quality education and, compared to physical quality, is proposed as a psychological quality with stable, basic and derivative characteristics that is eventually internalized through the continuous strengthening of psychological aspects when interacting with the external environment. There are differences in the understanding of psychological quality due to different research directions, and there are views that summarize psychological quality as the unity of mental health quality and intellectual quality, and emphasize that psychological quality is the guarantee for individuals to maintain a psychologically healthy state in life, study and work. The study of mental health quality is not only an expansion of the positive psychology research trend abroad, but also a new breakthrough in the study of college students' mental health in China. Mental health quality and mental health are essentially two sides of the same coin describing the phenomenon of mental health, and the concepts and criteria of both are inseparable from the analysis of the basic psychological structure of human beings. Mental health quality refers to the intrinsic and basic psychological qualities of human beings, focusing on "quality", which is reduced to the description of psychological quality and ability, reflecting that individuals with a high level of mental health quality will have more stable psychological characteristics and are less likely to be disturbed by external factors and have psychological problems; while mental health is a state of mental Mental health is a state of mental well-being, which is characterized by sound cognitive function, normal intelligence, stable and positive emotion, sound personality, perfect will and good social adaptation, and harmonious interpersonal relationships, focusing on the description of "state". Mental health quality is closely related to mental health state, and mental health is the ideal mental function pursued by mental health quality, which includes the basic indicators of mental health from the conceptual level, which also indirectly clarifies the relationship between mental health and mental health quality, that is, mental health is the external expression and extension of mental health quality, and mental health quality is the internal foundation and direction of mental health formation.

Interview survey on mental health status

Research instruments

According to the requirements of psychometrics, the quality of a questionnaire or scale is generally assessed by its reliability, which is determined by the reliability coefficient and the model fit index. +The smaller the value, the better the model fit is, and the indices of GFI, AGFI, CFI, IFI, NFI, etc. are above 0.9, which indicates the better the model fit is. The following are the results of the reliability analysis of the research instruments used in this study.

This result shows that the questionnaire has good reliability. The results of exploratory factor analysis of the data using principal component analysis and maximum variance method showed that the KMO value was 0.90 and the significance level of Barlett's sphericity test reached 0.000, indicating that the data of this study were suitable for factor analysis. The results of the principal component analysis showed that the eigenvalues of the eight items corresponding to psychological resilience were all >1, and the factor loadings ranged from 0.75 to 0.83, all of which were >0.4, with a cumulative contribution of 63.00%. The factor loadings of each question item are shown in Table 1.

Table 2 shows the results of descriptive statistics of college students in terms of exercise volume, mental toughness and mental health qualities, which indicate that college students are at a moderately low level of exercise volume, at a moderately low level of mental toughness and at a moderately high overall level of mental health qualities (Lavingia et al., 2020).

TABLE 1 Factor loading diagram.

Item	Factor loading
I believe I have the ability to achieve my goals.	0.75
When performing tasks, I can control the focus of my attention.	0.80
I worked hard and persevered in overcoming difficulties.	0.83
I strive for every success.	0.83
In most cases, I can find the positive side.	0.80
I can master my emotions and express them in the way I want.	0.75
I am able to apply appropriate skills and knowledge when facing challenges.	0.80
I effectively use the knowledge and skills I need to achieve my goals.	0.79

TABLE 2 Levels of exercise, mental toughness and mental health qualities.

	Min	Max	M	SD
Amount of exercise	0.00	100	27.51	21.53
Mental toughness	1.00	7.00	3.80	1.44
Mental health diathesis	2.15	4.49	3.38	0.32

Table 3 shows the results of the test for differences in exercise among college students in different grades, from which it can be seen that the main effect of grade on exercise was significant ($F = 5.06$, $p < 0.01$). Subsequent two-by-two multiple comparisons, shown in Table 4, showed that there was a significant difference between senior year and the other three grades ($P < 0.01$). This is mainly because the senior students began to be busy finding a job or postgraduate entrance examination, no time to do sports, on the other hand, the school does not require the senior students' sports, only for other grade students have sports requirements.

Suggestions for enhancing students' mental health

School sports should be implemented in practice

The high academic demands of students and the unsatisfying after-school life make it difficult for them to have the energy for sports, and the lack of supervision of academic level tests makes students hold a relaxed state for physical education and give up sports, which leads to the weakening of their physical fitness in the process of self-indulgence. This objective factor, based on the traditional examinations in our country, makes the teaching format of physical education still more traditional and unchanged (Semlyen and Ellis, 2020; Salkovskis,

TABLE 3 Test for differences in exercise volume by grade.

	Freshman	Sophomore	Junior	Senior	*F*	*P*
Amount of exercise	27.19 ± 19.8	30.48 ± 22.1	29.03 ± 20.5	22.20 ± 23.1	5.06	0.00

TABLE 4 Test for differences in exercise volume by grade.

	Freshman and sophomore (*t*)	Freshman and junior (*t*)	Freshman and senior (*t*)	Sophomore and junior (*t*)	Sophomore and senior (*t*)	Junior and senior (*t*)
Amount of exercise	−3.29	−1.84	4.99*	1.45	8.28**	6.93**

* and ** respectively represent that the corresponding coefficient statistics are significant at the level of 10% and 5%.

2021; Alanna et al., 2022). Schools need to implement physical exercise attendance. Students are not allowed to be absent, late or leave early when participating in various physical exercise activities organized by the school. Students who cannot ask for leave in advance; those who are absent without reason shall be considered absent, and those who leave the school shall be dismissed early. And seriously implement the "two exercises", "two lessons" routine. When ringing the preparatory bell, the PE committee shall be responsible for counting and counting the number and making written records; after ringing the bell, report the number to the PE teacher; meanwhile, strictly implement the physical exercise discipline. Students to participate in a variety of physical exercise activities, to wear appropriate, action to be quickly, exercise seriously, discipline to be strict.

Mental health quality is a positive psychological quality inspired by the development of positive psychology. For the college students who have frequent psychological problems nowadays, the development of mental health quality can, to a certain extent, influence the physiological, psychological and social functions of college students and promote the better adaptation of college students to the development of society. Based on the results of the previous study, it is clear that the mental health quality of college students is significantly correlated with the level of sports and mental toughness, therefore, the development and improvement of mental health quality of college students can actively intervene in the mental quality of college students in Korakan education. Therefore, the first step to improve the mental health of college students is to improve their perceptions and attitudes in multiple ways and strategies, and to develop a school-based culture with special features, such as campus and classroom culture and activities. Colleges and universities can create school-based cultures with their own characteristics of mental health quality, and different disciplines or classes can also carry out special activities according to the characteristics of their disciplines to create a positive and healthy cultural atmosphere, so as to cultivate proper cognition of mental health quality among college students and encourage students to know themselves objectively and be happy with themselves. Secondly, college students should manage their emotions appropriately and maintain positive and optimistic emotions. Positive emotions can infect the students around them, and it is necessary to properly express and transmit positive emotions, as well as to regulate and control negative emotions at the right time. Again, university is an important stage to cultivate students' sound personality, and the main task of university education is to teach students how to behave, which means to cultivate students' independence and integrity of personality, and the independence of personality will motivate students to maintain a more positive attitude toward people. As Confucius said, "I have to reflect on myself three times a day. Always reflect on your own shortcomings, correct your shortcomings and discover your own strengths, improve your motivation to achieve, cultivate your sense of success, and gradually improve your will quality under the impetus of your goals. Finally, students are encouraged to actively participate in group activities to improve their interpersonal skills. Collective activities, in which everyone is working toward a common goal, whether it is winning or innovating, can make the collective environment more dynamic, and this dynamism makes the whole group more cohesive and centripetal, and also promotes the interaction between the members of the group and enhances students' interpersonal skills. Through the combined efforts of all aspects of the content, ultimately in order to promote the development and improvement of the quality of mental health of college students (Deluca et al., 2021).

Enhancing the diversity of physical education and sports through the leverage of examination

At present, the physical education examination in Wuhan focuses on the physical quality of students, and a comprehensive score is given through the combination of the usual results and the examination results. In the assessment items, the items set can indeed make a more scientific assessment of students' physical quality to a certain extent, but the relevant items lack a certain degree of sport, which cannot attract students to promote physical and mental health development through sports in the after-school period. In some cities in China, when physical education is included in the secondary school examinations, a combination of compulsory and optional items is adopted, so that students, in addition to passively completing the physical education items required by the school, can also take the initiative to select subjects that they are relatively interested in and like to train, and gradually change from passive to active, their independent initiative is fully mobilized, so that students do The purpose of physical education is not only to improve their performance in exams, but also to improve their physical function and quality.

Establishing the guiding ideology of "health first"

The guiding ideology of "Health First" is proposed in the "Physical Education and Health Curriculum Standards" formulated by the Ministry of Education, and this ideology makes all staff members pay attention to physical education, whose ultimate role is not only for academic exams but also for the physical and mental health of students, and should avoid taking up classes. It is important to avoid the idea that physical education is a sub-course or that it is not important, and to design and teach methods and techniques that take into account the curriculum standards, the students' own situation, and the school's hardware and facilities, so that students do not fall behind in physical education, but can also achieve all-round development through reasonable and effective sports that promote both mental and physical health (Abdullah et al., 2021). From the perspective of schools, the cultivation of teachers in this field can be increased, and more people can be engaged in this industry with relevant policies or supportive policies. At the same time, talents in the professional field can also avoid students due to substandard sports movements, or excessive injuries, resulting in losing interest in sports.

Students can be organized to receive frustration education courses or start experiential training outside of teaching and classroom, in which they are guided to cope with optimism and positive attitude in this experiential life, and through experiencing frustrating life, students' perseverance and self-confidence are enhanced, and they are motivated to cope positively when they encounter frustration or challenges, so as to improve their mental toughness (Iwahori et al., 2022). Through various measures and strategies, college students can gradually improve their own mental toughness level through subtlety.

Conclusion

The characteristics of sports can meet the psychological needs of college students. Long-term engaged in sports can effectively alleviate the university life from learning, interpersonal, emotional psychological pressure, sports is conducive to improve their mental health level, sports is very suitable for college students to improve mood, release emotions, sports is conducive to college students to improve interpersonal relationship. Sports provides a special platform for everyone's communication and communication. Physical education in colleges and universities should give full play to the unique attributes of sports, actively guide college students to adjust their psychological state, and avoid and overcome psychological diseases. Make its mental and physical healthy growth. This paper discusses the validity of the influence of sports on college students 'mental health, the results show that college students in exercise, psychological tenacity and mental health quality described statistical results, the results show that the college students' exercise in medium low level, psychological tenacity in the moderate level, the mental health quality level average, but the exercise has significant differences in grade. This paper has important reference significance for promoting the development of students 'mental health work and improving students' mental health quality.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the patients/ participants or patients/participants legal guardian/next of kin was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

LZ and S-HL contributed to the writing of the manuscript and data analysis. YC supervised the work and designed the study. All authors have read and agreed the final version to be published.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Application of data mining technology in college mental health education

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In order to improve education and teaching methods and meet the "heart" needs of college students in the era of big data, this paper analyzes the application of data mining technology in college mental health education, and introduces database technology and decision tree algorithm to support college mental health work. This process verifies the feasibility of this kind of system with the help of an example. Using the test standards outlined in this document, 1.5 previous test tasks were completed within the timeframe. During the system test, the error rate was 14% and the number of tests was 7%.However, the error rate in the development stage is 11%, which is lower than 19% of the old version. The error rate in the acceptance stage is 14%, which is lower than 5% of the old version. That is to say, most of the errors were found in time in the system analysis and design stage. 14% of the problems found in the development stage are basically small problems in the interface display, which do not need major changes. However, the old version also includes design defects found in the development stage, and only large-scale rewriting of the involved modules. In the research process, the work of mental health in Colleges and universities has been promoted. At this time, the law of psychological changes of college students has been summarized. Therefore, the support of data mining technology can better meet the needs of mental health education in Colleges and universities.

KEYWORDS

data mining technology, college students, mental health education, database technology, decision tree algorithm

Introduction

The rapid growth of information and information technology has brought new ideas and improvements to the traditional mental health education. How to adapt to the development of science and technology in the big data and how to find new ideas and approaches to the health of boys and college girls is a topic that needs to be discussed now. We need to make better use of the internet, rely on big data, use data mining technology as tools, use data platform as a platform, and learn about the "feelings" present of the mind. To drive the "mind" demand for data mining technology, the

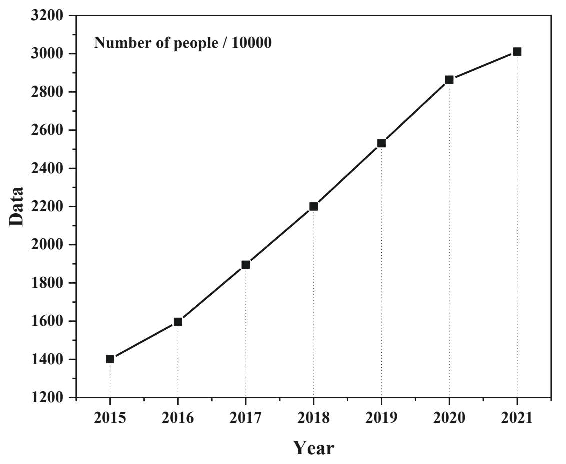

FIGURE 1
Proportion of college students' mental health problems.

"mind" type of "big data + psychology education" will be combined to create "mind" platform for the study of mental health combined with the "mind" of the school. The system identifies the "mind" benefits of current activity and seeks to achieve the goal of creating a "mind," identifying "mind" status of health. Mental illness in the term "mind." China's mental health problems are shown in **Figure 1** (Jiang et al., 2020).

According to the current situation, a large number of adverse events occur frequently among college students. A series of problems, such as "suicide by jumping off a building," "Majiajue incident," "online love" and "Internet addiction," which are frequently reported in the newspapers, have sounded the alarm for people—the top students in the ivory tower are ill and seriously ill (Zheng and Zhou, 2021). The health of college students is a concern throughout the community, because college students are the last stage of national education planning, and they performance determines the level of technological development in our country. They are not only about the future of the country, but also about the development of the country. Their expertise determines the speed and quality of China's reform process, and its overall impact on China's future. Only by examining the current state of mental health of college students in China today in a timely and legal manner can we solve their mental health problems. According to the goals and objectives and the development of new technologies in our country (Sang, 2021).

Based on the above criteria, this article has been selected as a tool to assess the mental health of two new students from various regions to better understand mental illness of modern college students in China. It also helps them deal with their mental health problems in a timely manner, take care of their health and wellbeing, have a positive outlook on life, complete their education, complete their education and work for their country. At the same time, we hope that the results of this study will be of great benefit to the relevant agencies of China in developing measures affecting the mental health of young men. The study focused on specific areas and had statistical data of 4738. 63 percent of boys are 2,983 and 1,755 or 37 percent of girls. Highlights of student resources: major cities are the top cities in the state, small cities and middle are state-level cities and towns, and cities are cities, cities, and towns. Of these, 1,174 came from major cities, accounting for 24.8% of the total students, 1,575 students from small and medium-sized cities, 33.2%, and 1,989 students from the population, rural, 42% (see **Table 1**; Meng et al., 2020).

Symptom checklist was used in the investigation. The scale contains 9 factors and 90 items, including physical maladjustment, interpersonal relationship, depression, anxiety, hostility, terror and so on. The validity of the questionnaire was $v = 0.78$ and the reliability was $a = 0.83$. Learn about the state of mental health in modern colleges. Published 4,752 questionnaires and scored 4,738 points. The return rate is 99.7%, valid and 100%. Conduct an analysis of current data on impact issues, document, compare and compile data on current issues, and create scenarios for further research (Barrett and Twycross, 2020; Wan and Wang, 2021).

Literature review

Data mining is often associated with computer science, and these goals can be achieved in a number of ways, including statistics, data recovery, validation standards, analysis. Online, professional, and technology training. Many problems have arisen since the development of data mining technology. The following describes several different definitions of data mining: One definition is the extraction of a hidden, previously unknown, important piece of data; another topic is research to extract useful information from multiple sources or data. The goal of data mining is to effectively organize the existing information and obtain valuable and difficult to find information and the association between information. It is based on many disciplines such as statistics and artificial intelligence. It realizes intelligent analysis of data, infers and summarizes information, finds potential laws, predicts customer behavior, helps the organization's decision makers correctly predict upcoming scenarios, adjust strategies, reduce risks, and make correct decisions (Zhou and Yang, 2021). Data mining is often used in data analysis, such as intelligence, but it is a rich term used in many ways. Its relationships to KDD are: KDD is the process of identifying models that are cost-effective, innovative, cost-effective, and ultimately understandable from data (Liu et al., 2021); Data mining means that KDD generates special data in the agreement including constraints by a special algorithm. In fact, these two terms are often used illegally in modern literature. The structure of data mining technology is shown in **Figure 2** (Li, 2021; Zhang, 2021).

TABLE 1 Statistics of surveyed students.

	Boys	Girls	Big city	Small and medium-sized city	Countryside
Number (person)	2,983	1,755	1,174	1,575	1,989
Percentage%	63	37	24.8	33.2	42

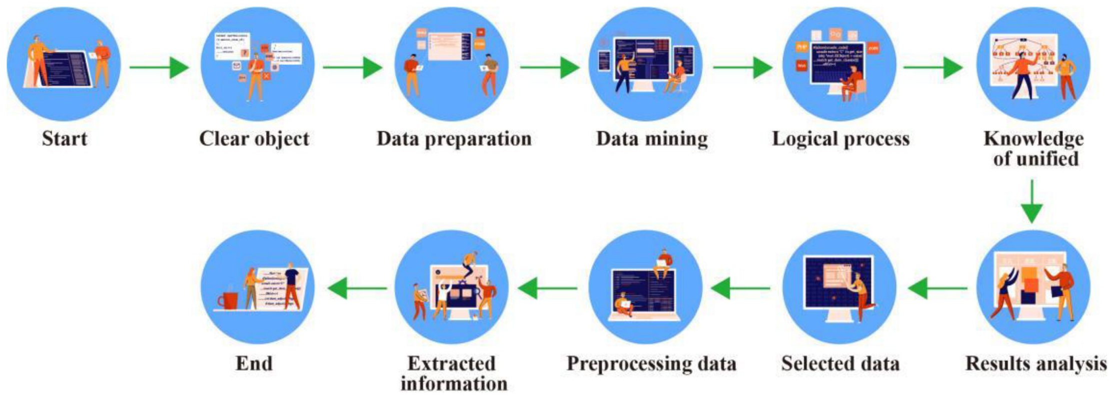

FIGURE 2
Data mining technology process.

Previously unpredicted information refers to the information that has not been and is not easy to speculate or guess. That is, one of the tasks of data mining is to find the internal relations that are not easy to rely on empirical reasoning, or even the experience or knowledge that is contrary to intuition. However, once the information mined is more contrary to people's experience, it is more likely to be more valuable. The most classic example of the application of data mining in real life is that a chain store found the close relationship between children's diapers and beer in data mining. Data mining and data warehouse have a very important relationship. In most cases, data mining must first import data from the data warehouse into the data mining library or data mart, as shown in **Figure 3** (Bai and Zhou, 2021; Ngussa et al., 2021). For example, the inconsistency of all data will not occur. Therefore, the organic combination of data warehouse and data mining will greatly improve the ability of enterprises and institutions to reorganize and reuse information, so that information can better serve decision-making.

FIGURE 3
Data mining library obtained from data warehouse.

Unsupervised learning, description and clustering, supervised learning, shopping basket analysis and relationship grouping are all important methods of data mining. Among them, supervised learning method includes classification, prediction and estimation. Data mining often uses web page mining, deviation analysis, association rules, features, changes, clustering and other methods in data analysis. These methods can enable data mining to mine data from different aspects. These data mining methods are introduced below. *Classification method*. Classification is to compare the similarity of data objects in the database and classify the data with the same or similar characteristics into a set. In this way, the data in the database can be mapped to different sets through the classification method. *Regression analysis method*. Regression analysis is an analytical method to clarify the relationship between multiple variables. Cluster analysis method. The first step of cluster analysis is to divide a group of data into several different categories. *Association rule method*. Association rule method is usually used to describe the degree of association between various data items in the database, that is, to judge the probability that the occurrence of an item in a transaction may cause the occurrence of other items in the transaction, that is, to mine the internal association between data. Feature analysis method. The function of feature analysis method is to extract the features of the data in the database and express them in a suitable way. *Change and deviation analysis method*. There are a lot of potentially interesting knowledge involved in the change and bias analysis method. Its purpose is to find

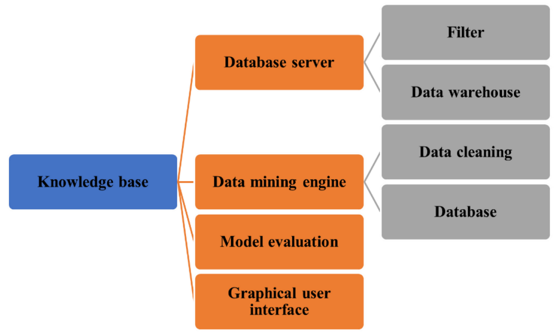

FIGURE 4
Data mining system structure.

the difference between the observed results and the reference quantity (Iammarino et al., 2020).

Data mining, also known as information mining, uses automatic or semi-automatic methods to find potential and valuable information and rules in data. Data mining technology comes from database, statistics and artificial intelligence. The composition of data mining system mainly includes the following aspects: Data mining is an important step in the process of learning about data. Knowledge acquisition consists of the following steps: Data cleaning, data collection, data selection, data transfer, data mining, data analysis, and instruction. A similar model for data is only shown in **Figure 4** (Aronson and Jaffal, 2022).

Materials and methods

Solutions

Overall system architecture

Based on the in-depth study of data mining technologies such as cluster analysis and association rule mining, and based on the demand analysis of student behavior, a student behavior analysis system based on cluster analysis. We can have a comprehensive understanding of students, provide decision support for students, and have self-evident practical significance for further understanding students' behavior characteristics and decision support of school management. For the convenience of function display and user interaction, the system adopts b\s architecture, and the system structure is shown in **Figure 5** (Soares et al., 2022). It mainly includes data layer, processing layer and application layer. The specific features are as follows: the data comes from student scores, consumption records and personal information, providing a data basis for subsequent analysis. The processing layer is the core business part of the system, which is responsible for processing the requests of the browser and realizing the data analysis functions such as clustering analysis of student data and association rule mining. Realize user registration, login and display of data analysis results.

The overall framework of the system starts with each data source in the school data, and stores the data in each data source in our database after preprocessing and integration. In the processing layer, the data in the database is extracted, different behavior data are selected through the behavior division module, and the cluster analysis technology is used to cluster the students from different behavior angles, so as to obtain the classification of all students in different behaviors, and have a clear division of the student group. Then, in the behavior association analysis module, combined with the clustering results and the original student data, combined the student behavior characteristics, and used the association rule mining technology to analyze, extract the frequent patterns between different behaviors, and find the association relationship between different behaviors. Then, the results of the student division module and the behavior association analysis module are displayed in the application layer through visualization technology for users to observe and analyze (Lindell et al., 2021; Berman et al., 2022).

Database design

Database is a very important part of the system. It is responsible for the storage and management of the data required by the system. Only with the support of database can the corresponding functions of the system be completed. The system processes the data through corresponding scripts. First, clean the data in the data source to remove the null data in the data source. For more effective data analysis, the system converts some data in the data source. For example, the student gender "male" and "female" are replaced by "1" and "0," respectively. Since the student grades in the data source record the grades of each course respectively, we average the students' grades in each semester, and then record them in the database. At this time, we also integrate the student consumption data. According to the architecture of the student behavior analysis system, in order to complete the corresponding functions, the database is designed, with a total of 8 tables. The following describes the tables and their relationships. The field description of the student basic information table is shown in **Table 2** (Posselt, 2021).

Experimental method of validation scheme

Decision tree algorithm

Data mining processes include structured thinking, decision trees, genetic algorithms, neural networks, and more. There are three types of wood cutting. The algorithm is based on data theory and uses levels of data entropy and data gain as a standard

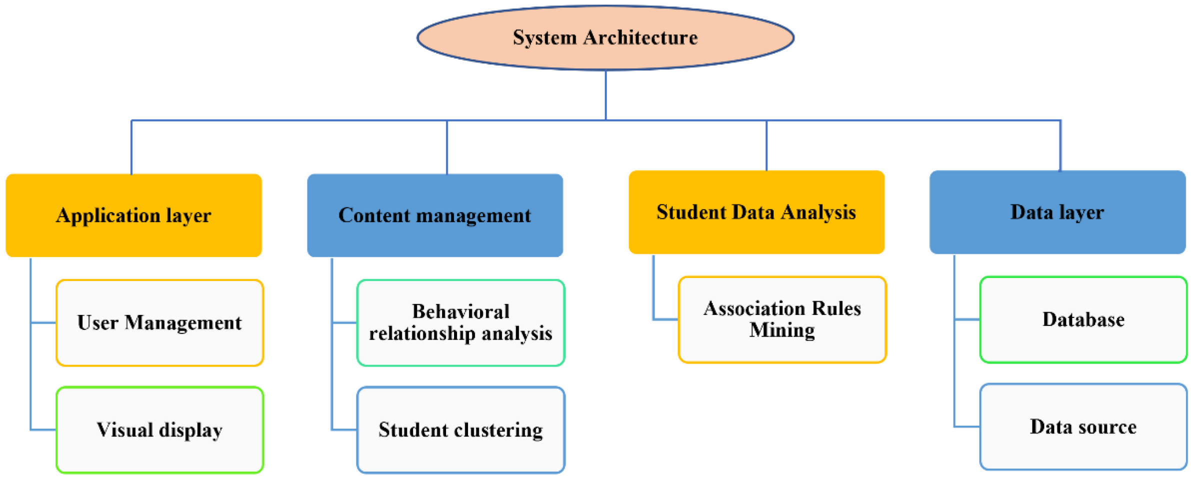

FIGURE 5
System structure.

TABLE 2 Field description of student basic information table.

Field name	Field type	Field description
SID	VARCHAR(255)	Student ID, primary key
Sex	Int	Gender, 1 for male, 0 for female
College	Int(255)	College to which the student belongs
Start-year	Timestamp	Year of enrollment

measure for using inductive data distribution. The training set S (Kondo et al., 2021).

$$(S) = \sum -p\,(I)\,2p\,(I)) \tag{1}$$

Here P (I) is the proportion of S belonging to class I. Σ is the sum of C. If all s belong to the same class, the range is 0 (classification completed) to 1 (completely random). Note: S is not only an attribute but also the entire sample set.

$$(S, A) = \sum \frac{|S_v|}{|S|} \times (S_v) \tag{2}$$

Here Σ is all possible values V of attribute A; Sv = subset of S with v value for attribute A, |Sv| = number of elements in SV,|S| = number of elements in S.

(S, A) is the information gain of attribute A on subset S, which is defined as

$$(S, A) = (S) - (S, A) \tag{3}$$

(T, A) refers to the reduction of entropy after the value of attribute a is known. The larger the Gain (S, A), the more information the test attribute a provides for classification (Cage and Howes, 2020).

Data mining

During data mining, it is first necessary to create an appropriate determination tree using the algorithm, and first determine the number of positive P samples and the number of negative structure n. The top 15 students with good grades are defined as positive examples, and the last 35 students with poor grades are defined as negative examples. Combined with the above settings, the following formula can be obtained:

$$P = 15, N = 35 \tag{4}$$

$$I\,(p, n) = -\frac{15}{50_2}\frac{15}{150} - \frac{35}{50_2}\frac{35}{50} = 0.881 \tag{5}$$

$$E = \frac{24}{50}I\,(p^1, n) + \frac{7}{50}I\,(p^2, n^2) + \frac{19}{50}I\,(p^3, n^3) =$$

$$\frac{24}{50}I\,(11, 13) + \frac{7}{50}I\,(4, 3) + \frac{19}{50}I\,(0, 19) = 0.616 \tag{6}$$

$I(p, n) = -E = 0.881-0.616 = 0.265$(7)Extra points for experiment report

$I(p, n) = -E = 0.881-0.801 = 0.08$(8)Extra points for experiment class

$I(p, n) = -E = 0.881-0.879 = 0.002$(9)Extra points for final assessment

According to the calculation, the experimental report bonus has the maximum information gain, so the experimental report bonus is selected as the root node and expanded downward to finally generate the decision tree, as shown in **Figure 6** (Xu et al., 2021).

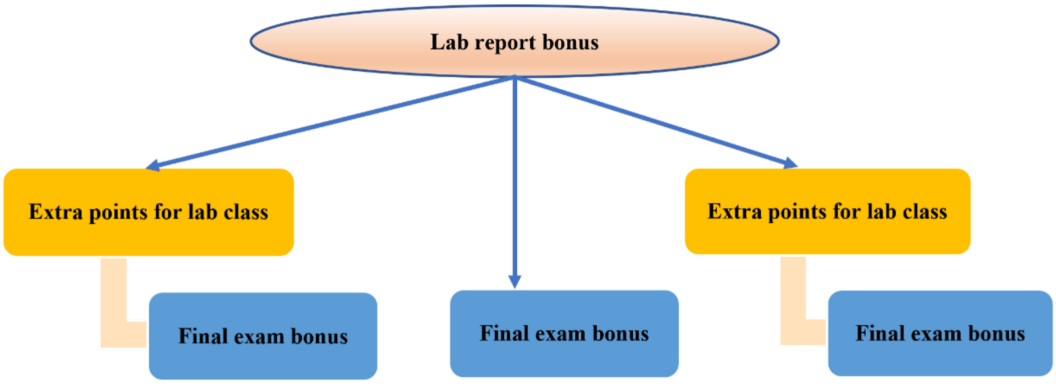

FIGURE 6
Score analysis decision tree.

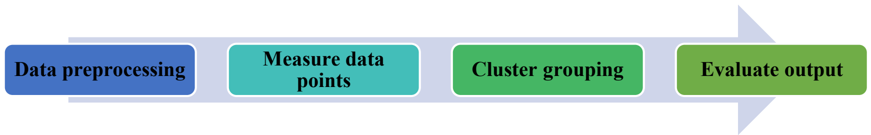

FIGURE 7
Clustering analysis algorithm.

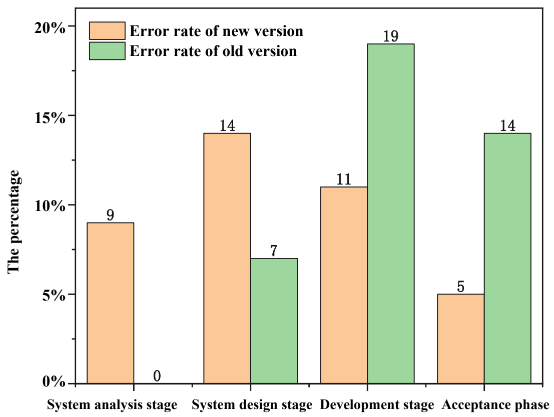

FIGURE 8
Data comparison between old and new software in different software development periods.

Clustering algorithm

In general, the important method used by people to understand things is to classify the objects of knowledge. Things divided into the same class tend to have more similar characteristics. The so-called clustering is not a descriptive task to divide a group of objects into a series of meaningful subsets according to the similarity of objects without training data samples (Bradha et al., 2021). The classical partition clustering methods include k-means algorithm, PAM algorithm, Clara algorithm and clarans algorithm. The classical clustering algorithm is K-means and extended algorithm, which divides object d into a group of clusters:

$$\{C_1, C_2 \ldots C_k\} \tag{7}$$

Here:

$$\overset{k}{\underset{i=1}{U}}\ ti = D \tag{8}$$

Where K is the number of clusters to be obtained. This algorithm only classifies an object into one cluster at most, and each cluster is a subset of all objects.

Using cluster analysis algorithm to analyze students' archives can provide a strong scientific basis for the management of college students. It can also adopt the way of questionnaire to students, and cluster analysis and processing the students' personal preferences, living habits, learning habits and other information, so as to provide scientific basis for school management and facilitate scientific management. The main steps of clustering analysis algorithm are shown in **Figure 7** (Liu et al., 2015).

Test case

During the development of a new version of an information management platform, the improved model mentioned in this paper is used. According to experience, the development cycle of the new version takes 1 month, half of which is for various

TABLE 3 Specific data.

	System analysis phase	System design stage	Development phase	Acceptance phase
Error rate of new version	9%	14%	11%	5%
Error rate of old version		7%	19%	14%

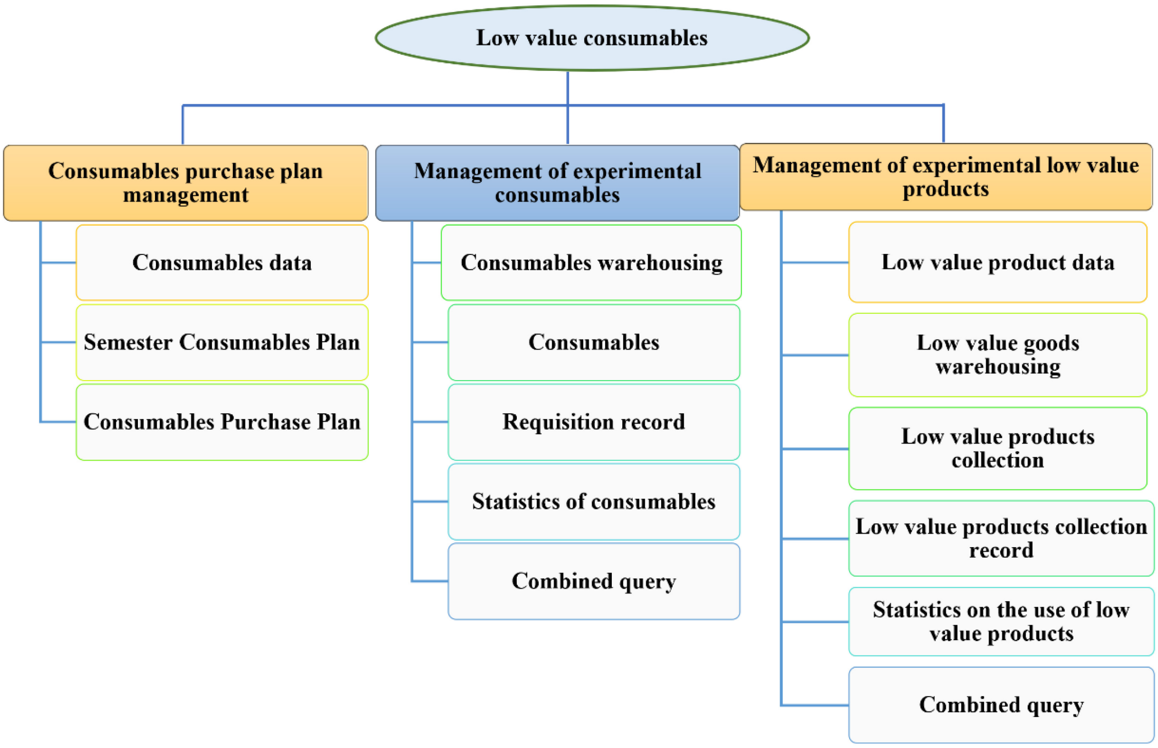

FIGURE 9
Teaching management system (laboratory part).

tests. In the test of the project, the problems faced are that the new functions to be added are twice as many as those of the previous version, and several modules need to design more in-depth test cases to rewrite the original function modules on a large scale. Neither the personnel nor time invested in testing can increase the time required by users (Huang et al., 2021). The software test engineer stepped in, conducted demand-based tests on the business requirements put forward by customers, and developed acceptance standards with customers at the same time. During system design, software test engineers and system designers work together to write technical test cases and acceptance based test cases, find out defects and errors in the design, and avoid bringing errors in the design into the software development stage. Because such errors are often fatal and cannot be remedied, unit tests and related integration tests will be carried out once the program fragments are written in the development phase, and software changes are tested and developed repeatedly and alternately. However, exploratory testing has found some unpredictable errors to some extent. Special attention is paid to that in the whole testing process, technical testing and acceptance testing are always independent routes due to their different purposes, which ensures the quality of the software. Compared with the old version, the whole software development period is shortened, the software development cost is reduced, the customer's satisfaction with the software is greatly improved, and the later maintenance work of the software is greatly reduced, which frees the company from a large number of later maintenance work. **Figure 8** data comparison between old and new software in different software development periods (Xie et al., 2021).

The error rate in the system analysis stage is 14%, and the number of test cases is 7%. However, the error rate in the development stage is 11%, which is lower than 19% of the old version. The error rate in the acceptance stage is 14%, which is lower than 5% of the old version. That is to say, most errors have been found in time in the system analysis and design stage. 14% of the problems found in the development stage are basically small problems in the interface display, which do not need major

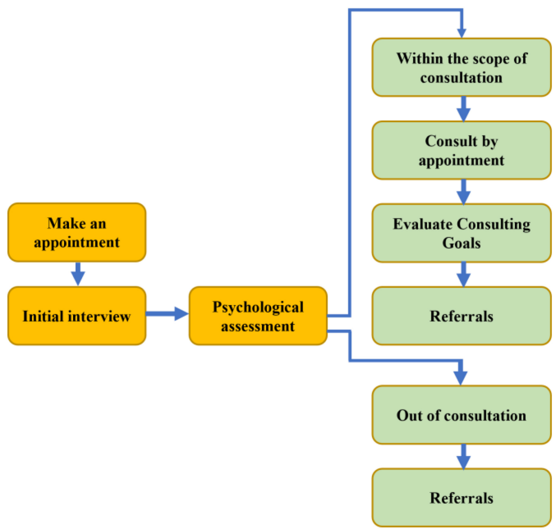

FIGURE 10
Psychological counseling and counseling process.

changes. However, the old version also includes design defects found in the development stage, and only large-scale rewriting of the involved modules (see Table 3 for details).

Results

To address the shortage of mental health educators, strengthen the capacity of educators, improve the quality and effectiveness of staff, and improve the quality of education. standard current operation; Changing existing teaching strategies, improving instruction, providing instructional materials and instruction, changing international assignments, increasing grades, completing classes in college, and increase teaching hours. Activities for practicing student skills; Change the form of teachers' classes and keep the course content up to date. Teachers can adopt the online + offline course learning mode, and the offline courses can independently choose the content of mental health education; On the other hand, it can break the time and space constraints, establish an online communication and teaching platform, timely understand students' psychological status, and provide psychological related services online, so as to achieve point-to-point, heart-to-heart and practical psychological early warning and consultation, enhance the "heart" effectiveness of psychological education, and make the results of psychological education work benefit more teachers and students.

Integrating data resources is to effectively combine students' basic family information, learning of teaching management system, campus card consumption, campus network browsing, campus life track and other relevant data. In the first stage, we collect basic information, and in the second stage, we analyze important data to assess, identify, and classify the characteristics of mental illness and the patterns of students. College, developing mental health information for college students, and collaborating. Creating and sharing mental health information. The data obtained through the screening and analysis platform has expanded the screening indicators of students' mental health education screening, and promoted the dynamic supervision of students' psychological early warning data; On the other hand, an early warning and tracking mechanism can be established. Teachers can use the relationship between relevant data to visually observe the data comparison of students under normal and abnormal conditions by integrating various data resources. On this basis, through the comparison and analysis of data, we can formulate relevant counseling and intervention programs for students who may have psychological problems, timely help students adjust themselves, effectively improve the identification of psychological crisis and the efficiency and quality of mental health education, provide personalized services for mental health education, and highlight the "heart" characteristics of mental health education. The teaching management system (laboratory part) is shown in Figure 9.

At present, the "Post-95" and "Post-00" students in Colleges and universities are in the majority. They are more inclined to obtain information, understand information and remove doubts from the Internet, so they will turn to the Internet at the first time. The creation of a new media platform is in line with the "heart" demand of the rapid development of new media at present. It also injects the "heart" concept and "heart" vitality into the mental health education in Colleges and universities, and creates a "heart" platform for students' psychological help and consultation at the first time. We will develop a "heart" system for mental health education, and implement the management of four levels of grid mental health supervision and screening: schools, colleges, classes and dormitories. The head of each dormitory is responsible for filling in the daily psychological barometer of the dormitory members. The psychological committee members of each class are responsible for collecting and checking the psychological conditions of students in each class every week. The college plans and manages the psychological conditions of students in the college. The school (psychological center) is responsible for psychological counseling and counseling of extremely abnormal students (Figure 10). Finally, the daily, weekly and monthly reports are formed to open up the last kilometer of mental health education in the school. Through the psychological survey results and relevant resources of students in the University, integrate the data for reasonable and scientific analysis. Push more targeted learning, life, interpersonal psychology knowledge, self-emotion regulation and stress relief adjustment methods through the new media platform.

Through the big data analysis of knowledge learning and students' mental health on the new media platform for mental health education, some psychological activities can be planned regularly, such as student psychological activity reception day, counselor psychological salon, sand table group counseling, psychological quality development activities, psychological drama situational drama competition, 21 day mental health punch in activities, so as to achieve the effect of new media publicity. Through these activities, it is helpful to build a bridge between teachers and students and improve the effect of mental health practical education.

Conclusion

Colleges and universities need to improve their knowledge of mental health, improve their education and teaching, move from the "mental" mode to "big data + knowledge" in real time, and create a "spiritual" bridge for students. Meets the "critical thinking" needs of college students when it comes to mental health and education. Psychiatrists use this information to inform psychiatrists about their health, to compensate for the lack of mental illness during the "high" in colleges and universities, serve as the spiritual protector of the growth of students, and protect the "high" life. The spirit and "mind" of high school students creates a "trust" environment that puts their energy and education to work in college. After more than 10 years of development and refinement, data mining technology has been successfully developed in many fields. In today's world of science, technology, and more and more, it is very difficult to find data that can be used to determine big data-based research. *Research, as always with standard procedures.* Encourage research and decision-making knowledge, based on data mining technology to use data mining technology to extract knowledge and data from multiple data and real laws really hidden inside information.

Data availability statement

The original contributions presented in this study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

XS contributed to the writing of the manuscript and data analysis, supervised the work, and designed the study.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Understanding, Investigating, and promoting deep learning in language education: A survey on chinese college students' deep learning in the online EFL teaching context

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This study aims to (1) develop and validate the four-dimension model hypothesis of deep learning to better understand deep learning in language education; (2) investigate and promote deep learning by conducting a survey involving 533 college students in the online learning English as a foreign language (EFL) teaching context in China. Concretely, this study initially synthesized theoretical insights from deep learning in the education domain and related theories in the second language acquisition and thus proposed the four-dimension model hypothesis of deep learning involving the motivation of deep learning, the engagement of deep learning, the strategy of deep learning, and the directional competence of deep learning. This study subsequently undertook a questionnaire survey utilizing a standardized instrument to confirm the model hypothesis and further investigate the current status and salient differences in students' deep learning in online EFL teaching. Exploratory factor analysis (EFA), confirmation factor analysis (CFA), and Pearson's correlation test validated a positively correlated four-dimension model of deep learning with high composite reliability and good convergent validity. Moreover, the descriptive and inferential statistics revealed that the level of students' deep learning marginally reached the median, with the lowest mean of directional competence and the highest mean of motivation; students manifested more instructional motives, neglect of deploying skilled-based cognitive strategies, and deficiency of language application skills, etc.; there existed some significant differences between deep learning and four sub-dimensions across the grade, English proficiency, EFL course, and vision groups. Eventually, this study proffered primary reasons and five appropriate strategies to scaffold and promote students' deep learning in online EFL teaching. Hopefully, this study will be a pioneering effort to clear away the theoretical muddle of deep learning construct in language education and be illuminating to further improve effectiveness in the online EFL teaching context.

KEYWORDS

deep learning, the motivation of deep learning, the engagement of deep learning, the strategy of deep learning, the directional competence of deep learning, online EFL teaching context, language education

Introduction

Riding the wave of deep integration of information and communication technology (ICT) and language education, online English as a foreign language (EFL) teaching, which de facto breaks through constraints of time and space between teaching and learning, still suffering from salient difficulties in attaining high teaching quality and ideal learning effect (Panigrahi et al., 2018; Luo et al., 2020). Especially during the COVID-19 pandemic, universities in China have launched sequential semesters of online teaching, proliferating a series of new yet intriguing circumstances worth reflecting on and summarizing: How effectively do students learn in online EFL teaching? How can teachers reduce students' mechanical, surface, and passive learning to scaffold and boost their deep learning in online EFL teaching? Recent trends in the application of online learning through management systems (LMSs), namely Blackboard, have led to a proliferation of studies, ensuring the utility of Blackboard by measuring the perception and use tends to be pivotal to improve the outcome of online EFL learning, especially in the Saudi context (Almekhlafy, 2020; Moawad, 2020). In China, due to the less extensive application of Blackboard in online EFL teaching, studies switch more attention to the urgent need for improving the effectiveness of online EFL teaching by providing supports from teachers or establishing effective learning frameworks (Han et al., 2021; Zhao et al., 2021; Du and Qian, 2022). However, very few studies have been shored up by data-driven analysis of large-scale investigation on the current holistic status of students' language learning in online EFL teaching. As a key trend to boost higher education development in the next 5 years or even longer (Becker et al., 2017), deep learning has become the ultimate target for the integration of ICT and education, as well as a vital dimension to measure learners' learning effect, which is receiving considerable critical attention. Hence, this study attempted to address the aforementioned issues and provide new insights into enhancing teaching quality and learning effect in online EFL teaching through conducting a survey on the current status of deep learning based on an in-depth exploration of the four-dimension model of deep learning and proffering instructional strategies to boost deep learning in the online EFL teaching context.

Deep learning embraces dynamic and versatile theoretical definitions in the education domain. It is conceptualized as a learning method opposite to surface learning (Marton and Säljö, 1976). Subsequently, it is described as a learning process, in which individuals apply learned knowledge in a new context (NRC, 2012). To date, it amounts to an essential competence that students must possess for working and living a civil life in the twenty-first century (Huberman et al., 2014). However, few attempts have been made to clarify the deep learning construct in language education. Although Tochon (2013) has defined a deep approach to language learning as "deep, reflective language learning," and some researchers have drawn our attention to deep clusters of language learning strategies (Tragant et al., 2013; Zhan et al., 2021); the validity of the theoretical model of deep learning rarely seems to be explored but just to interpret "deep" literally or ignore potentially interwoven correlations between deep learning and Second Language Acquisition (SLA) theories. Similarly, without shrugging off the uncertainty of deep learning construct in language education, scholars in china have explored theoretical teaching modes and frameworks to promote deep learning mostly in high school EFL teaching since 2016 (Luo et al., 2021; Wang et al., 2021). Overall, previous studies have suffered from a lack of clarity in the deep learning construct in language education. On this occasion, few large-scale empirical studies have been performed to investigate students' deep learning with standardized measurement instruments in the EFL teaching context. Consequently, the effectiveness of the modes and frameworks proposed would not be empirically assessed.

The paper begins by reviewing considerable literature on the concept, measurement, investigation, and promotion of deep learning. It will then go on to explicate the four-dimension model hypothesis of deep learning by incorporating correlative SLA theories, considering situated characters of online EFL teaching context. Thereafter, it will present how exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were exploited in a survey to validate the aforementioned model. It will also summarize the main findings of the additional survey aiming to investigate the current status of deep learning and salient differences in some variables in the online EFL teaching context. The discussion section ties together up all various theoretical and empirical strands to shed light on the four-dimension model of deep learning, survey results, and deep learning promotion strategies.

Literature review

The concept of deep learning

As previous studies suggest, deep learning is originally conceptualized as a learning method. The concept of deep learning is first proposed by Marton and Säljö (1976), which is the opposite of surface learning. It has been noted that students who adopted deep learning methods tend to extract meaning, connect prior knowledge, and think critically. Subsequently, scholars further develop and enrich their theoretical definitions in the education domain: Entwistle and Ramsden (1983) argue that deep learning and comprehension can be displayed in the process of solving and exploring complex problems in unfamiliar situations by combining prior and new knowledge. More attention has also been drawn to the process and essential conditions when explicating deep learning, for example, the learner's identity and connection with the world (Fullan et al., 2019), or learners' motivation and teachers' scaffolding roles (Tochon, 2013). Inspired by "twenty-first-century skills," the twenty-first century has witnessed the results-oriented research of deep learning, which emphasizes the cultivation of learners' critical thinking and problem-solving ability, creativity and innovation, and communication and cooperation (Asikainen, 2014; Esteban-Guitart and Gee, 2020; Faranda et al., 2021). It is He and Li (2005) who first introduced the concept of deep learning to the education domain in China. Although theoretical research into the deep learning concept from diverse perspectives in the education domain has been deepened, the theoretical muddle of deep learning construct in language education in China has not been cleared away. This study attempted to establish the theoretical model of deep learning in online EFL teaching context and explore the potential theoretical connections between deep learning in the education field and the realm of SLA.

The measurement and investigation of deep learning

There has been a considerable amount of research in the measurement and investigation of deep learning by mainly measuring the learning results and process. To illustrate, Biggs (1987) deployed a learning process questionnaire, SPQ, to measure motivation and learning strategies from three different dimensions (i.e., deep approach, surface approach, and achieving approach), which is later revised by removing the achieving approach (Biggs et al., 2001). Different from aforesaid methods and scales, emphasizing the quality and needs of talents cultivation in the twenty-first century, incorporating the interpersonal and individual capacities into measurement, American Institutes for Research(AIR) has built a six-dimension measurement framework to break through the cognitive boundaries of deep learning in the canonical sense (Huberman et al., 2014). In China, some attempts have been made to develop localized scales to measure deep learning more specifically and pertinently in ICT-assisted education in China, albeit a limited amount. For example, Li et al. (2018) creatively incorporate learning engagement into the measurement model to measure students' deep learning in blended teaching at universities. However, in-depth studies on well-established measurement models and standardized scales of deep learning in the realm of language education, especially in the context of online EFL teaching, are relatively scanty. In effect, the Revised Study Process Questionnaire (R-SPQ) (Biggs et al., 2001) has been directly deployed to measure language learners' deep learning (Jiang, 2008), which may suffer from the slightly weak theoretical foundation of SLA and neglect of situated characters of EFL teaching in China, although the R-SPQ is a well-established scale in education *per se*. To address these gaps, this study constructed a deep learning measurement model and drew on a self-developed questionnaire based on the in-depth theoretical exploration of deep learning in language teaching.

Furthermore, to date, a large and growing body of studies has attempted to unravel whether and how some influential factors, such as individual variables (e.g., age, experience, etc.), capacities (e.g., learning, reflection, communication, etc.), self-efficacy, teacher autonomy, or emotional support, etc., influence deep learning (Groves, 2005; Papinczak et al., 2008; Leung et al., 2012; Yang, 2018; Liu et al., 2021; Zhao and Qin, 2021). So far, there have been fewer systematic discussions on deep learning differences across variables in online EFL teaching, for instance, learners' language proficiency, EFL courses, grades, visions, etc., which would be tentatively explicated in this study.

Promoting deep learning in language education

Additionally, there is a consensus among many empirical studies that deep learning can be boosted by conducting efficient instructional strategies along with information technology, for example, educational games, creative podcasts, etc. (Vos et al., 2011; Pegrum et al., 2015). Pertaining to language education, with ubiquitous technology application, growing attention is paid to the supporting impacts of technologies on deep language education and learning (Beckett and Iida, 2006; Tochon et al., 2014; Du and Qian, 2022). To illustrate, Tochon et al. (2014) analyzed the impact of online personalized learning on developing deeper levels of language apprenticeship. Likewise, the recent 6 years in China have witnessed a growing amount of theoretical exploration on promoting language learners' deep learning (Luo et al., 2021; Wang et al., 2021). Surprisingly, from the perspective of deep learning strategy, Zhan et al. (2021) conducted an empirical study to elaborate on the interaction between learning motives and self-efficacy in using deep language learning strategies, which is one of few empirical studies aiming to promote learners' deep learning in EFL teaching and is one of little research based on the in-depth and comprehensive theoretical interpretation of SLA theories. Conversely, in the vast majority of aforementioned studies, teaching strategies and modes are proposed theoretically without data-driven analysis and theoretical integration with SLA. Realizing gaps in the extant literature, more multivariate empirical research with sufficient data support and a solid theoretical basis is needed to unravel how to enhance learners' deep learning, especially in the context of online EFL teaching.

The four-dimension model hypothesis of deep learning in the online EFL teaching context

By tracing the theoretical development of deep learning in the education domain, deep learning can be considered as a multi-faceted competence that comprises specific learning behaviors and approaches aiming to attain the ultimate goal and can further be extended as a pivotal goal of teaching technology and educational reform, as well as a mainstream orientation of talent cultivation in the twenty-first century. Looking at the complete process of language learning, incorporating diverse definitions of deep learning in previous literature, the present study suggested that deep learning in language education is usually driven by language learning motivation, aims to acquire an in-depth understanding of language knowledge, and attain comprehensive language application skills, complex problem-solving skills in an authentic context, language knowledge transfer and application, critical and higher-order thinking, etc., through performing active involvement and effective learning strategies in the whole process. In this sense, the current study presumed that deep learning in the online EFL teaching context has considerable potential as a multi-dimension model that meaningfully units four main components, namely the motivation of deep learning, the engagement of deep learning, the strategy of deep learning, and the directional competence of deep learning (model hypothesis). Based on the literature on deep learning, incorporating related SLA theories and situated traits of the online EFL teaching, this model would be delineated in a logical and exhaustive manner below. This study also proposed a deep learning measurement model to verify the hypothesis empirically and to further investigate the current status of deep learning, which will be elaborated in the Method section.

The motivation of deep learning

As Entwistle (2013) argues, the motivation of deep learning aims to energize and direct learners to pursue the meaning of knowledge. With the support of motivations, learners can consciously establish connections among different knowledge and maintain interest in the learning process, otherwise, it tends to become challenging to access deep learning. It is similarly highlighted that deep learning involves interest and willingness to experience and participate in the learning (Biggs, 1987). Furthermore, the motivation of deep learning can be perceived as intrinsic motivation (Ryan and Deci, 2000b) or a strong sense of identity around goals or passions in deep learning (Fullan et al., 2019). Coincidentally, language learning motivation is considered a vital factor resulting in the sustained process of language learning (Gardner, 1985; Ellis and Ellis, 1994). Therefore, intense learning motivation can become the driving force for deep language learning, which signifies that the motivation of deep learning is one indispensable component. Based on Gardner (1985) motivation theory, the motivation in this study incorporates an integrative motive, which concerns the openness to and respect for targeted cultural groups and ways of life, and gradually develops as the extended or metaphorical or imaginary integration (Dörnyei, 2006). Moreover, considering EFL course curriculum, current talents training needs, societal employment factors, etc., instrumental motive, which is related to concrete benefits that language proficiency might generate (Swann et al., 2010), such as passing a standardized college English test (CET4/CET6), is also taken into account.

The engagement of deep learning

Ryan and Deci (2000a) endorse that deep learning is a process of active learning, in which students' active participation and investment are very important (Biggs, 1987). Nevertheless, regarding online EFL teaching, it is usually disturbed by inevitable factors such as long-distance separation, hardware equipment malfunction, network information interference, etc., which can more easily undermine students' long-term and high-quality engagement and result in a high rate of dropping out (Chapelle, 2019). Consequently, it is difficult for students to comprehend knowledge deeply, and even more challenging to further apply, resulting in the failure of attaining deep learning. Hence, the engagement of deep learning is another key component in this model, which mainly concerns behavioral engagement, one aspect of the three-dimension study engagement constructs proposed by Fredricks et al. (2004). It concretely refers to involvement and learning behaviors in academic and social or extracurricular activities aiming to attain positive outcomes (Fredricks et al., 2004). As a whole, online EFL teaching can be seen as a "combo" comprising three stages, namely pre-class, in-class (i.e., online-teaching), and after-class. Thus, pre-class engagement and after-class engagement, for instance, students preview content before online class and revise key questions after class, should not be ignored. The reason why the other two aspects (i.e., emotional engagement and cognitive engagement) are not referred to here is that their definitions, to some extent, overlap with what is portrayed in the motivation dimension and the strategy dimension in this study. As Fredricks et al. (2004) argue, interest and value in emotional engagement overlap considerably with constructs used in motivational literature. Cognitive engagement may suffer from a similar dilemma where the overlap exists in the learning strategy literature.

The strategy of deep learning

As Marton and Säljö (1976) argue, learning strategy in deep learning is not mechanical processing in surface learning, but oriented to deep learning, for instance, combining thoughts into a whole structure, critically evaluating the knowledge, reflecting, etc. Similarly, language learning strategy (LLS) is regarded as one of the key factors determining EFL learning (Oxford, 2016) and is considered as "actions chosen by learners (either deliberately or automatically) for the purposes of learning or regulating the learning of language" (Griffiths, 2015). Deep LLS, different from surface LLS, requires the use of high-order skills rather than memorization and repetition (Tragant et al., 2013). Previous studies have demonstrated that deep LLS, namely metacognitive and cognitive strategies, are more applied by successful language learners than memory strategies (Lai, 2009; Gerami and Baighlou, 2011), which to some extent demonstrates the capacity of deep LLS in promoting efficient and deep language learning. However, few studies have further verified which specific type of deep LLS can have a direct predicting role in deep language learning. It is assumed that aiming to access deep learning, learners would tend to exploit more deep LLS. Based on the six-group strategy inventory for language learning (SILL) (Oxford, 1996), which is extensively used to categorize language learning strategies, the strategy of deep learning in the current study mainly refers to deep LLS, including cognitive and metacognitive strategies, social and emotional strategies. Concretely, the cognitive strategies might refer to utilizing in-depth analysis, generalization, induction, deduction, etc., to enhance comprehension of knowledge and promote further application; the metacognitive strategies might underscore regulating individual language learning process through assessing, reflecting, monitoring, etc.; emotional and social strategies might be exploited to manage feelings in language learning or involve in interaction with others aiming to promote mutual learning. It is noteworthy that this study intentionally added surface LLS (e.g., memory strategies) to the follow-up measurement mode of the strategy dimension to be analyzed by EFA and CFA, for better empirically exploring if deep LLS can play an exclusive role in helping learners access deep learning rather than surface LLS.

The directional competence of deep learning

Result-oriented deep learning studies pay more attention to attaining the ultimate goals of deep learning, namely cultivating of competencies of deep learning aiming to meet talents requirements of social development (Esteban-Guitart and Gee, 2020), as exemplified by a considerably systematic and compatible six-dimension framework of deep learning competence proposed by AIR (Huberman et al., 2014). Those competencies can also be concretely identified as a broader understanding of knowledge, seeking meaning between content, connecting ideas with prior knowledge and daily experience, collaborating with others, and other various advanced competencies (Asikainen, 2014; Faranda et al., 2021). Therefore, the directional competence acquired by learners through deep learning is the last component. Additionally, pertaining to online language education, a considerable amount of literature has underlined the significance of cementing students' language knowledge, cultivating their 2L proficiency and cross-culture communication, promoting learner autonomy, etc. (Chen and Yang, 2016; Plonsky and Ziegler, 2016; Lai, 2019; Tseng et al., 2020). Hence, in the online EFL teaching context, the directional competence of deep learning can be embodied in a solid foundation of language knowledge and comprehensive language application competence, namely, an in-depth understanding of language knowledge, a capacity to apply language knowledge in specific situations to solve novel practical problems, learning autonomy, English critical thinking, etc.

Purpose of the study

The main purpose of this study is to develop and validate a four-dimension model of deep learning in the online EFL teaching context with considerable theoretical and empirical evidence to better understand deep learning in language education. The present study also attempts to investigate the current status of college students' deep learning and assess the effects of diverse variables on deep learning, as well as propose appropriate instructional strategies to boost students' deep learning in the online EFL teaching context in China, hopefully shedding new light on promoting teaching quality and learning effect in the realm of ICT-assisted language education. Specifically, the present study attempts to validate one model hypothesis and address five research questions:

- Model Hypothesis: The four-dimension model of deep learning in the online EFL teaching context units four main components, namely the motivation of deep learning, the engagement of deep learning, the learning strategies of deep learning, and the directional competence of deep learning.
- RQ1: What are the dimensions and internal correlations of deep learning in the online EFL teaching context?
- RQ2: What is the overall current status of college students' deep learning in the online EFL teaching context in China?
- RQ3: Are there statistically significant differences in deep learning or other sub-dimensions across the grade, English proficiency, EFL course, and vision groups?
- RQ4: What might be the main reasons behind survey results?
- RQ5: What are efficient strategies to boost students' deep learning in the online EFL teaching context?

To achieve above the aims, this study principally conducted a survey by a self-developed and standardized questionnaire method and also drew on EFA, CFA, descriptive analysis, independent sample *t*-test, and ANOVA to analyze the quantitative data, which would contribute to deeper insights into deep learning in the online EFL teaching context.

Materials and methods

Participants

Participants of this questionnaire were college students attending online EFL courses this spring semester at one university in Tianjin, China. Since EFL courses are exclusively compulsory for freshmen and sophomores according to national initiatives in China, the stratified random sampling was just conducted in the above two grades. In total, 533 students in two grades (52.1% freshmen and 47.9% sophomores), 4 institutes, and 10 majors were selected as samples. The sample was 72.3% women and 27.7% men with ages ranging from 17 to 20. The sample distributions were relatively balanced. Concretely, participants were attending three types of EFL courses: 81.8% public college English course (PCE); 0.09% ELS course targeting students in the international program; and 0.09% basic English course targeting students majoring in teaching Chinese as a foreign language (TCFL). Participants also reported their English proficiency as 71.5% primary level (non-passing CET-4 test); 26.1% intermediate level (passing CET-4 test); and 0.02% intermediate and advanced level (passing CET-6 test). Three sorts of visions after graduation were presented: hunting for a job (49.58%); further studying for a master's degree in the domestic or overseas (45.99%); and self-employment (4.43%). In total, 533 questionnaires were issued online and 474 valid questionnaires were retrieved, with the effective response rate being approximately 88.93%. Therefore, this data analysis results were representative.

Instrument

College students' deep learning in online EFL teaching questionnaire

The questionnaire comprises two main parts: basic information questions (i.e., gender, grade, English proficiency, EFL course, and vision) and closed-ended questions on deep learning, of which responses are provided using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Posited on model hypothesis, the deep learning measurement model involves four sub-dimensions, namely the motivation, the engagement, the strategy, and the directional competence. The second part of this questionnaire was developed based on the above measurement model. Some related scales with good reliability and validity were referred to when compiling items. The items were translated into Chinese for higher readability and comprehension and were adjusted and contextualized for authentic online EFL teaching contexts. More details are demonstrated below.

The motivation measurement sub-dimension aims to measure learners' language learning motivation directed to deep learning, which mainly involves integrative motive and instrumental motive (Gardner, 1985), based on definitions and classification of 2L motivation in SLA. Referring to motivation questionnaire (Dörnyei and Taguchi, 2009), considering situated characters of the online EFL teaching in China, items were revised and contextualized. The sample item of integrative motives is "I think it's important to learn English to know more about the culture and arts of its speakers." The sample item of instrumental motives is "I study English diligently to pass standardized English tests (e.g., CET4, CET6, TOEFL, IELTS, etc.)."

The engagement measurement sub-dimension aims to measure participants' behavioral engagement. Items were adapted from the National Survey of Student Engagement 2020, which is a well-confirmed and widely used study engagement questionnaire for college students and can also be applied in online teaching (Robinson and Hullinger, 2008). Engagement in three stages of online EFL teaching was portrayed in specific items. The sample item is "After online class, I review and summarize key ideas or concepts."

The strategy measurement sub-dimension aims at measuring cognitive and metacognitive strategies, along with social and emotional strategies according to deep LLS research in SLA (Tragant et al., 2013). Items were adapted from SILL, some of which were simplified and adjusted for better understanding. A sample item of metacognitive is "I regularly reflect on my English learning to avoid making similar mistakes." A sample item of cognitive strategy is "I look for words in my own language that are similar to new words in English." A sample item of social strategy is "I participate in group discussions with students to better understand learning content from different perspectives." A sample item of emotional strategy is "I watch inspiring online English videos (e.g., speech, motive, social media video, etc.) to encourage myself in English learning." Aiming to test the exclusively crucial effect of deep LLS in promoting deep learning, some surface LLS items were added to the questionnaire for further discussion on the results of CFA and EFA. A sample item of memory strategy is "I use online English learning apps to remember new words."

The directional competence measurement sub-dimension aims to measure various advanced competences acquired by learners. Based on six dimensions of deep learning competence proposed by AIR (Huberman et al., 2014), combined with the main teaching objectives of online EFL teaching, items were compiled as the following samples: "I think I have mastery of basic English language knowledge (i.e., vocabulary, grammar, etc.)," "I think I can solve practical problems in English in a specific context."

Procedure

After demonstrating the research goals and procedures and asking for permission at the university, a pilot test of the questionnaire with 50 participants was conducted to note any points of confusion. An adapted version was afterward filled out online by 533 participants anonymously, honestly, and voluntarily. None posed any questions or confusion on this questionnaire during the whole process, which indicated that it was properly organized and easy for them to use.

Data analysis

A total of 474 pieces of valid data were collected online and then quantitatively analyzed on SPSS.25. and AMOS.24. Specifically, EFA and CFA were initially conducted to test the reliability and validity of the questionnaire and measurement mode, to further verify the model hypothesis. Afterward, Pearson's correlation test was deployed to unravel the internal correlation between four sub-dimensions. Descriptive analysis was conducted to investigate the current status of deep learning in EFL online teaching. Additionally, Independent sample t-test and ANOVA were used to explore whether these variables (i.e., grade, English proficiency, EFL course, and vision) can cause statistically significant differences in deep learning.

Results

Exploratory factor analysis

Table 1 shows that the KMO value was 0.922(>0.50), and Bartlett's spherical chi-square value was 5647.469 ($p = 0.000 < 0.05$), indicating that the questionnaire's factor structure was suitable for EFA (Tabachnick and Fidell, 2001). Through principal component analysis and Varimax with Kaiser normalization rotation method, according to the principle that the eigenvalue is greater than 1, as Table 3 presents, 4 factors with 22 variables were extracted sequentially by deleting variables with less salient loadings (<0.40), cross-loading variables, and factors with less than two variables with less related content to the questionnaire (Dörnyei, 2007). It also corresponded to the four-factor solution in the scree plot in Figure 1, which demonstrates that a useful model for these data may have 4 factors. The standard factor loadings of variables ranged from 0.551 to 0.844 and the total interpretation rate was 63.207% (>50%) in Tables 2, 3.

Moreover, as Table 4 shows, Cronbach's alpha coefficients of each factor ranged from 0.799 to 0.907 (>0.70) and Cronbach's alpha coefficient of the overall questionnaire was 0.926 (>0.70), indicating that each sub-dimension and whole questionnaire had high re liability and internal consistency.

TABLE 1 KMO and Bartlett's test.

The Kaiser-Meyer-OlKin measurement of sample adequacy		0.922
Bartlett's test of sphericity	Approx. Chi-Square	5647.469
	df	231
	Sig.	0.000

Confirmatory factor analysis

Confirmatory factor analysis was conducted on AMOS.24. to confirm hypothesized factor structure, namely the four-dimension model of deep learning(H1). The model fit statistics indicate a good model fit: $\chi^2 = 643.236$ ($p = 0.002$); IFI = 0.921 (>0.9); TLI = 0.909 (>0.9); CFI = 0.920 (>0.9); PCFI = 0.809 (>0.5), PNFI=0.780 (>0.5); CMIN/DF = 3.169 (3<NC<5) and RMSEA = 0.068 (<0.08) (MacCallum et al., 1996). Table 5 and Figure 2 report that the Cronbach's alpha coefficients of each factor were greater than 0.7, corresponding to above Cronbach's alpha reliability test results in EFA, reconfirming the high reliability of the scale. Moreover, the standard loadings of 22 variables in four factors ranged from 0.599 to 0.834 in CFA, similar to the results in EFA. Table 5 and Figure 2 also present that the Composite Reliability values (CR) of each factor were all greater than 0.7, indicating that the model had good composite reliability, and the average variance extracted values (AVE) of each variable were greater than 0.5, except for the F4 (AVE = 0.445), which was still in the acceptable range (0.36–0.50), signifying that the model had good convergent validity.

Pearson's correlation test

Aiming to explore internal correlations in four factors of deep learning and evaluate the strength and direction of association with each other, Pearson's correlation test was conducted. As Table 6 suggests, four factors displayed a positive pairwise correlation: engagement had a positive correlation with motivation ($R = 0.457$, $p < 0.01$) and competence had a positive correlation with strategy ($r = 0.547$, $p < 0.01$). Engagement was positively related to competence ($r = 0.388$, $p < 0.01$) and strategy ($r = 0.656$, $p < 0.01$). Motivation was positively related to competence ($r = 0.434$, $p < 0.01$) and strategy ($r = 0.528$, $p < 0.01$). Additionally, four factors all displayed a positive correlation with deep learning, respectively ($r > 0.70$, $p < 0.01$). It is the strategy that demonstrated the

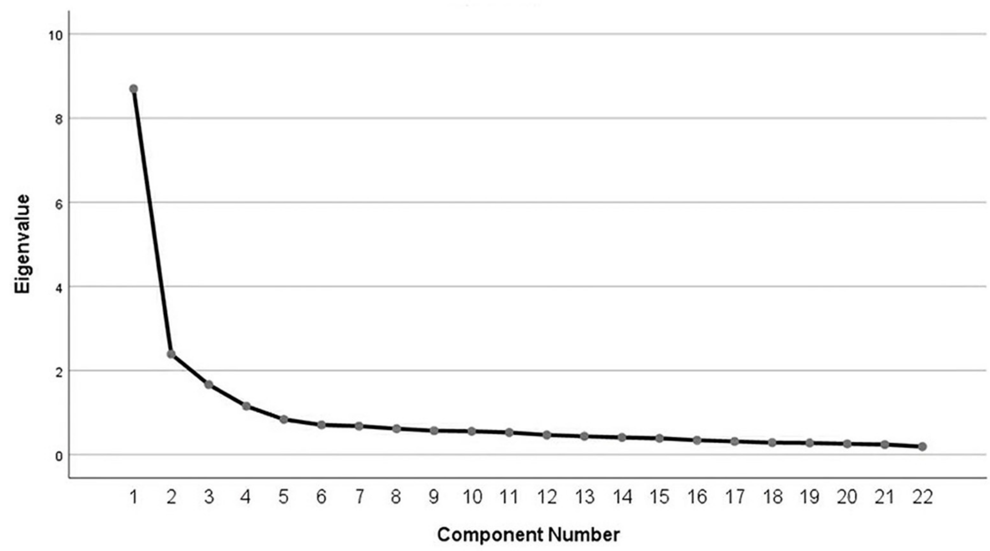

FIGURE 1
Screen plot.

TABLE 2 Total variance explained.

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
t	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	8.697	39.532	39.532	8.697	39.532	39.532	4.173	18.968	18.968
2	2.390	10.862	50.394	2.390	10.862	50.394	3.576	16.254	35.222
3	1.665	7.568	57.962	1.665	7.568	57.962	3.282	14.919	50.141
4	1.154	5.245	63.207	1.154	5.245	63.207	2.874	13.066	63.207
5	0.837	3.806	67.013						

Extraction method: Principal component analysis.

highest positive correlation with deep learning (r = 0. 870, $p < 0.01$).

Descriptive analysis

Table 6 suggests that the mean of deep learning, which equals the average of scores on overall 22 variables in scale, marginally reached the median value (M = 3.272, SD = 0.52395). The mean of motivation (M = 3.9241, SD = 0.59438) was higher than other sub-dimensions, with the highest score (M = 4.2743, SD = 0.85075) in instructional motive (M3) and the lowest score (M = 3.5865, SD = 0.75125) in integrative motive (M1) (see Appendix). In contrast, the mean of competence (M = 2.9170, SD = 0.70221) was the lowest, even lower than median value, with the highest score (M = 3.1709, SD = 0.81627) in learning autonomy(C3) and lower scores (M < 0.3) in basic language knowledge, language application skills, problem-solving skills, critically thinking, etc. (C1, C2, C6, C4,) (see Appendix). In strategy dimension, the score in skilled-based cognitive strategies (S10) is the lowest (M = 2.8165, SD = 0.87608). Additionally, students performed lower levels in some behavioral engagement (E6, E7), involving interaction and discussion with teachers and peers in or after online class (see Appendix).

Comparative analysis

An independent sample t-test was conducted to compare scores of two grade groups in deep learning and four sub-dimensions. In Leven's test, except for motivation ($p < 0.05$), the study referred to results of assume equal variance in engagement, strategy, competence, and deep learning ($P < 0.05$). Table 7 suggests the scores of motivation (P = 0.013), engagement (P = 0.024), strategy (P = 0.004), and deep learning (P = 0.006)

TABLE 3 Rotated component matrix[a].

Variables	1	2	3	4
C2	0.844			
C4	0.801			
C5	0.789			
C3	0.772			
C6	0.765			
C1	0.717			
S11		0.727		
S3		0.698		
S12		0.687		
S10		0.664		
S2		0.648		
S9		0.619		
E5			0.806	
E6			0.779	
E4			0.764	
E7			0.704	
E2			0.551	
M2				0.728
M3				0.719
M5				0.698
M1				0.657
M4				0.652

Extraction method: Principal component analysis. Rotation method: Varimax with Kaiser normalization. [a]Rotation converged in five iterations.

TABLE 4 Cronbach's alpha coefficients for four sub-dimensions and the overall scale in exploratory factor analysis (EFA).

	Factor	Alpha coefficients	N of Items
1	Competence	0.907	6
2	Strategy	0.868	6
3	Engagement	0.858	5
4	Motivation	0.799	5
	Deep learning	0.926	22

of freshmen were statistically higher than those of sophomores. There was no significant difference in scores of competence, which were relatively low for the two groups.

ANOVA was conducted to compare scores across three English proficiency groups in deep learning and four sub-dimensions. Leven's test shows except for deep learning ($p < 0.05$), the LSD method can be used for multiple comparisons in others dimensions. In Table 8, ANOVA suggests that in motivation ($P = 0.002$), strategy ($p = 0.030$), competence ($P = 0.000$), and deep learning ($p = 0.000$), there were at least one significant difference amongst the group means. The *post-hoc* test reveals significant differences between PL and IL groups in motivation ($P = 0.006$), strategy ($P = 0.010$), competence ($P = 0.000$), and deep learning ($P = 0.000$): the scores of the IL group were significantly higher than the PL group counterparts. Moreover, the scores of IAL group in motivation ($P = 0.015$), competence ($p = 0.011$), and deep learning ($p = 0.000$) were significantly higher than IP group counterparts. There were no significant differences between the three groups in engagement.

In order to examine whether three EFL course groups differ in deep learning and four sub-dimensions, ANOVA was conducted. Leven's test does not show any significant differences in all dimensions ($P < 0.05$), so the LSD method can be used for multiple comparisons. In Table 9, ANOVA suggests that in motivation ($P = 0.018$), engagement ($p = 0.000$), strategy ($P = 0.010$), and deep learning ($P = 0.005$), there was at least one significant difference among the group means. The *post-hoc* test reveals significant differences between PCE and BE groups for motivation ($P = 0.005$), engagement ($p = 0.000$), strategy ($P = 0.006$), and deep learning ($P = 0.009$): the score of BE group was significantly higher than the PCE group counterparts. Besides, the ELS group had higher scores in engagement ($P = 0.026$) than the PCE group, but lower scores in motivation ($P = 0.045$) compared with the BE group. There were no significant differences among the three group in competence.

At last, ANOVA was used to explore differences in deep learning and four sub-dimensions among three vision groups. Leven's test shows a significant difference in motivation ($P < 0.05$), Tamhane method was conducted to multiply and compare three groups in this dimension, whereas others resorted to the LSD method. In Table 10, ANOVA shows that three group differed significantly in motivation ($P = 0.000$), strategy ($P = 0.048$), competence ($P = 0.001$), and deep learning ($P = 0.001$). As the LSD and Tamhane demonstrate, the scores of the HJ group in motivation ($P = 0.000$), strategy ($P = 0.030$), competence ($P = 0.000$), and deep learning ($P = 0.000$) were, respectively, much lower than the FS group counterparts. FS group also performed better than the SE group in motivation ($P = 0.000$) and competence ($P = 0.044$). There were no statistically significant differences between the HJ group and SE group in the above dimensions. In addition, the three groups did not differ from each other significantly in engagement.

Discussion

The four-dimension model of deep learning in the online EFL teaching context

Utilizing EFA and CFA, this study first empirically validated the four-dimension model hypothesis of deep learning involving the motivation of deep learning, the engagement of deep learning, the strategy of deep learning, and the directional competence of deep learning in the context of online EFL

TABLE 5 Confirmatory factor analysis (CFA).

			Estimate	Std. estimate	S.E.	C.R.	P	Cronbach alpha	AVE	CR
C6	←	F1	1.013	0.758	0.060	16.900	***			
C5	←	F1	0.984	0.775	0.057	17.330	***	0.907	0.621	0.907
C4	←	F1	1.102	0.812	0.060	18.291	***			
C3	←	F1	0.982	0.785	0.056	17.598	***			
C2	←	F1	1.070	0.834	0.057	18.840	***			
C1	←	F1	1.000	0.760						
S12	←	F2	1.000	0.719						
S11	←	F2	1.072	0.793	0.066	16.350	***			
S10	←	F2	0.887	0.608	0.071	12.554	***			
S9	←	F2	0.958	0.710	0.065	14.666	***	0.868	0.531	0.871
S3	←	F2	1.067	0.760	0.068	15.703	***			
S2	←	F2	1.071	0.766	0.068	15.817	***			
E7	←	F3	1.000	0.714						
E6	←	F3	1.063	0.716	0.073	14.565	***			
E5	←	F3	1.116	0.814	0.068	16.427	***	0.858	0.558	0.862
E4	←	F3	1.181	0.840	0.070	16.877	***			
E2	←	F3	0.892	0.632	0.069	12.882	***			
M5	←	F4	1.000	0.731						
M4	←	F4	1.023	0.729	0.073	13.976	***			
M3	←	F4	0.888	0.599	0.076	11.684	***	0.799	0.445	0.799
M2	←	F4	0.896	0.646	0.071	12.548	***			
M1	←	F4	0.810	0.619	0.067	12.053	***			

F1, competence; F2, strategy; F3, engagement; F4, motivation. ***$p < 0.001$.

teaching. In particular, engagement, motivation, and strategy were included in this deep learning model, which was congruent with the general definitions of deep learning from cognitive perspectives in the education domain (Marton and Säljö, 1976; Biggs, 1987). The directional competence further underpinned the "results-oriented" concept of deep learning, which is defined as an essential competence for students when working and living a civil life in the twenty-first century (Huberman et al., 2014). Overall, the four-dimension model of deep learning in online EFL teaching well echoed the dominant theoretical conceptualizations of deep learning from both cognitive and talent training needs perspectives in the literature. It is also noteworthy that some emotional factors (e.g., the sense of interest) were implicitly subsumed under the motivation dimension, which, to some extent, shored up the deep learning model including cognitive emotional experiences proposed by Liu et al. (2021). Additionally, Pearson's correlation test demonstrates that these four dimensions interacted with each other in a positively correlated way. Surprisingly, among these four internally correlated dimensions, the strategy had a relatively stronger positive correlation with deep learning than others. To some extent, this suggests that language learning strategies, especially deep LLS, exerted an important role in L2 attainment, but its mechanism in the complex process of learning deserves further exploration (Dörnyei, 2006). Table 11 presents definitions and components of the four dimensions of the deep learning model and more details will be explicated, respectively, below.

To start with, the motivation of deep learning was one component of the model, referring to learners' strong interests, subjective willingness to learn, and a strong sense of identity around goals or passions, integrative or instrumental, directed to deep language learning, which further supported general definitions of deep learning (Biggs, 1987; Ryan and Deci, 2000b; Fullan et al., 2019; Esteban-Guitart and Gee, 2020), and highlighted the directing and energizing role of motivation in the long-term process of language learning (Gardner, 1985; Dörnyei, 2006; Tochon, 2013). Results also reveal that the motivation of deep learning comprised integrative motive and instrumental motive, which was in accordance with the long-lived conceptualization of L2 motivation from psychological perspectives (Gardner, 1985; Swann et al., 2010). The rather intriguing finding in the descriptive analysis might be that students may be driven by more instructional motives than integrative motives in deep language learning, for instance, passing English tests, improving overall competitiveness, etc., which was generally in line with those of previous studies (Chen et al., 2005; Liu, 2007; Zhan et al., 2021). To some extent,

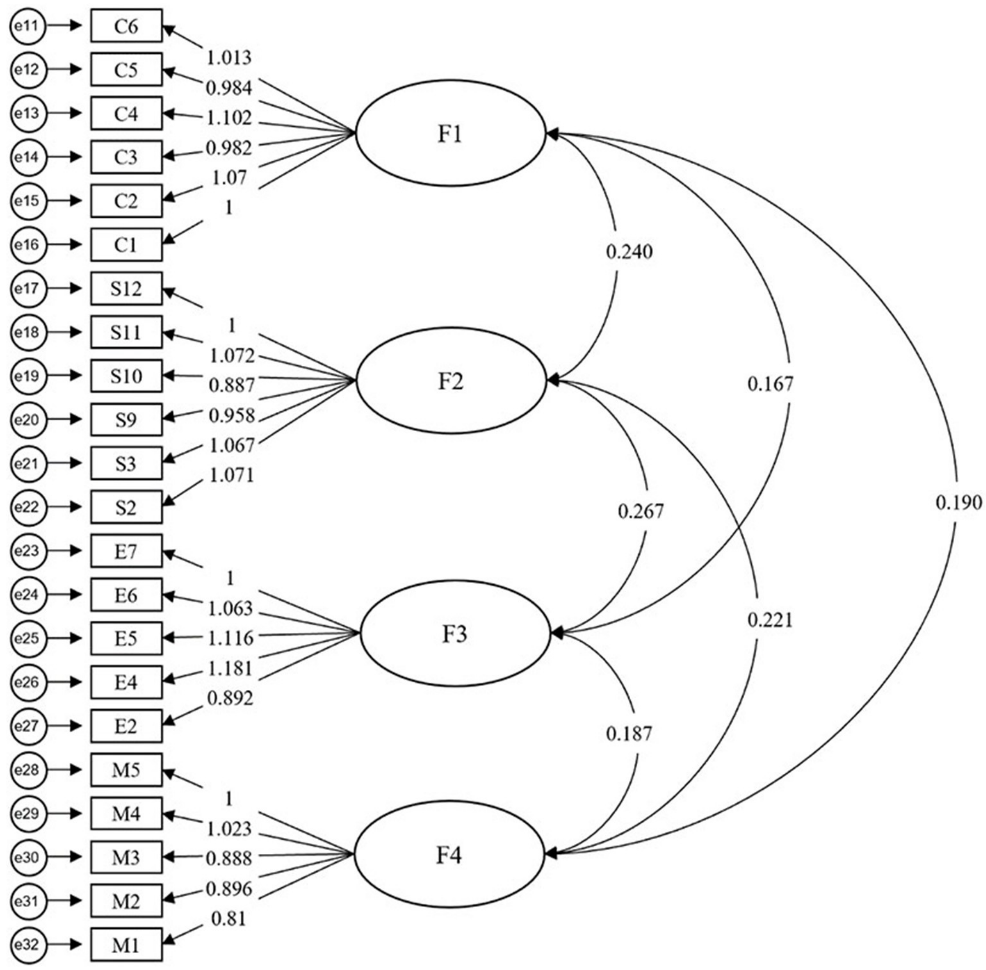

FIGURE 2
Confirmatory factor analysis (CFA): F1, competence; F2, strategy; F3, engagement; and F4, motivation.

TABLE 6 Descriptive statistics and correlation among variables.

Variables	N	Mean	SD	M	E	S	C	Deep learning
M: motivation	474	3.9241	0.59438	1				
E: engagement	474	3.1046	0.68929	0.457**	1			
S: strategy	474	3.2222	0.64887	0.528**	0.656**	1		
C: competence	474	2.9170	0.70221	0.434**	0.388**	0.547**	1	
Deep learning	474	3.2718	0.52395	0.731**	0.780**	0.870**	0.778**	1

**$p < 0.01$.

this finding also mirrors that instructional motives will act out a more promoting role in instructional learning situations especially without any direct contact with native speakers, while "integrative metaphor simply did not make sense" (Swann et al., 2010). Nevertheless, regarding recent 2L motivation studies from a complex dynamic perspective, the current study may be limited to exploring dynamic characters and temporal variation of motivation, which is worthy of further discussion.

The strategy of deep learning was another critical component, referring to deep language learning strategies deployed by learners to access deep language cognitive process, which was opposite to surface learning strategies underscoring

TABLE 7 Independent samples *t*-test of students' deep learning across grade groups.

Variables	Grade	N	M	S D	T	df	Sig(2-tailed)
Motivation	F	247	3.9895	0.53834	2.495	442.144	0.013
	S	227	3.8529	0.64357			
Engagement	F	247	3.1733	0.66119	2.271	472	0.024
	S	227	3.0300	0.71258			
Strategy	F	247	3.3036	0.57893	2.871	472	0.004
	S	227	3.1336	0.70798			
Competence	F	247	2.9548	0.69428	1.222	472	0.222
	S	227	2.8759	0.70998			
Overall	F	247	3.3347	0.48271	2.748	472	0.006
	S	227	3.2032	0.55846			

F, freshmen; S, sophomores.

TABLE 8 ANOVA for comparison of students' deep learning across English proficiency groups.

	M(SD)				
Variables	PL ($N = 339$)	IL ($N = 124$)	IAL ($N = 11$)	F	LSD/Tamhane
Motivation	3.8690 (0.59551)	4.0403 (0.58434)	4.3091 (0.30151)	6.27*	PL<IL ($P = 0.006$), PL<IAL ($P = 0.015$)
Engagement	3.0791 (0.67789)	3.1645 (0.72181)	3.2182 (0.67204)	0.85	
Strategy	3.1726 (0.65294)	3.3481 (0.63616)	3.3333 (0.48305)	3.525*	PL<IL($P = 0.010$)
Competence	2.7915 (0.69655)	3.2245 (0.62903)	3.3182 (0.41803)	20.68*	PL<IL ($P = 0.000$), PL<IAL ($p = 0.011$)
Deep learning	3.2057 (0.52088)	3.4300 (0.51427)	3.5248 (0.18109)	9.999*	PL<IL ($P = 0.000$), PL<IAL ($p = 0.000$)

*$p < 0.05$.
PL, primary level group (non-passing CET-4 test); IL, intermediate level group (passing CET-4 test); IAL, intermediate and advanced level group (passing CET-6 test).

TABLE 9 ANOVA for comparison of students' deep learning across English as a foreign language (EFL) course groups.

	M(SD)				
Variables	PCE ($N = 388$)	ELS ($N = 43$)	BE ($N = 43$)	F	LSD
Motivation	3.8985(0.59498)	3.9116 (0.66376)	4.1674 (0.45759)	4.025*	PCE<BE($P = 0.005$), ELS<BE ($P = 0.045$)
Engagement	3.0412 (0.68044)	3.2837 (0.66222)	3.4977 (0.64641)	10.488*	PCE<BE ($p = 0.000$), PCE<ELS ($P = 0.026$)
Strategy	3.1813 (0.64872)	3.3488 (0.64428)	3.4651 (0.59713)	4.676*	PCE<BE ($p = 0.006$)
Competence	2.9003 (0.69499)	3.0853 (0.72134)	2.8992 (0.74192)	1.360	
Deep learning	3.2358 (0.52232)	3.3901 (0.52601)	3.4778 (0.48108)	5.433*	PCE<BE ($P = 0.009$)

*$p < 0.05$.
PCE, Public College English course group; ELS, ELS course group; BE, Basic English course group.

mechanical processing (Marton and Säljö, 1976). Inspired by the deep LLS concept concerning high-order skills strategies (Tragant et al., 2013), referring to the six-group SILL (Oxford, 1996), this study assumed that cognitive and metacognitive strategies, along with social and emotional strategies, constituted the strategy of deep learning. Since few works of literature empirically suggest deep LLS can exclusively promote deep learning in the online EFL teaching context, memory strategies were intentionally included in the initial measurement model to verify the above assumption. As expected, EFA reveals that items related to memory strategies (S1, S4, S6, and S7) were not retained due to less salient loadings (<0.4) on each factor or cross-loading variables, which empirically suggests that surface LLS focusing on memorization and repetition may not contribute to deep language learning. Nevertheless, the most striking finding in EFA was that one factor with just two items about emotional strategies (S8 and S5) was excluded for a much higher total interpretation rate since this factor did not seem to fit the conceptually interpretable four-factor solution. This unexpected finding indicates that from the perspective

TABLE 10 ANOVA for comparison of students' deep learning across vision groups.

Variables	M(SD)			F	LSD/Tamhane
	HJ (N = 235)	FS (N = 218)	SE (N = 21)		
Motivation	3.7932 (0.62590)	4.0862 (0.53512)	3.7048 (0.35563)	16.221*	HJ<FS (P = 0.000), SE<FS (P = 0.000)
Engagement	3.0791 (0.65636)	3.1367 (0.73606)	3.0571 (0.54458)	0.445	
Strategy	3.1610 (0.64455)	3.2936 (0.66355)	3.1667 (0.46547)	2.456*	HJ<FS (P = 0.030)
Competence	2.8106 (0.70405)	3.0497 (0.67503)	2.7302 (0.74624)	7.534*	HJ<FS (P = 0.000), SE<FS (P = 0.044)
Deep learning	3.1905 (0.52198)	3.3716 (0.52095)	3.1450 (0.39642)	7.600*	HJ<FS (P = 0.000)

*$p < 0.05$.
HJ, hunting for a job group; FS, further studying group; SE, self-employment group.

TABLE 11 The four dimensions of the deep learning model in the online EFL teaching context.

Dimensions	Definitions	Components
The motivation of deep learning	Learners' strong interests, subjective willingness to learn, and a strong sense of identity around goals or passions, integrative or instrumental, directed to deep language learning	Integrative motives and instrumental motives
The strategy of deep learning	Deep language learning strategies deployed by learners to access deep language cognitive process	Cognitive strategies, metacognitive strategies, and social strategies
The engagement of deep learning	Learners' concrete involvement and learning behaviors aiming to attain positive academic outcomes and avoid alienation at three stages in online EFL teaching	Pre-class engagement, in-class engagement, and after-class engagement
The directional competence of deep learning	The ultimate advanced language competences nurtured in deep language learning	In-depth mastery of language knowledge, language application skills, English critical thinking, problem-solving capacity, learning autonomy, and online English information processing capacity

of learners, strategies to manage feelings in language learning may not play an essential role in attaining deep learning in the context of online EFL teaching. One possible explanation for this might be that compared with emotional strategies deployed by learners on their own, perceived teacher emotional support might perform efficiently in promoting students' deep learning in practical teaching contexts (Karagiannopoulou and Entwistle, 2019; Liu et al., 2021). Therefore, the strategy of deep learning in this study involved cognitive and metacognitive strategies, as well as social strategies, which can be considered as deep LLS contributing to deep learning in the online EFL teaching context.

Additionally, the engagement of deep learning was the third component, referring to learners' concrete involvement and learning behaviors aiming to attain positive academic outcomes and avoid alienation across three stages in online EFL teaching, namely pre-class engagement, in-class engagement, and after-class engagement. This confirmed that deep learning is a process of active learning, in which students' active participation and investment are very critical (Biggs, 1987; Ryan and Deci, 2000a). Concretely, pre-class engagement referred to learning behaviors, such as previewing content and maintaining an active mood before online class. In-class engagement included participation in online academic activities and active interaction with teachers and peers. After-class engagement covered learning behaviors, such as revising and summarizing key knowledge, etc. In addition, the directional competence of deep learning was the last component of the model, referring to the ultimate advanced language competencies nurtured in the deep language learning. In online EFL teaching, these competencies involved in-depth mastery of language knowledge, a capacity to apply language knowledge in specific situations to solve novel problems, learning autonomy, English critical thinking, processing online English information, etc., which are generally agreed with deep learning conceptualization in the literature on result-oriented deep learning (Asikainen, 2014; Huberman et al., 2014; Faranda et al., 2021).

The current status of college students' deep learning in online EFL teaching context

Descriptive analysis demonstrates that the current level of students' deep learning in online EFL teaching was marginally median, of which the mean was slightly lower than that in previous surveys in traditional face-to-face general teaching

(Yang, 2018). Thus, it is still challenging for college students to access deep learning in the online EFL teaching context, especially during the COVID-19 pandemic. Moreover, results also demonstrate that even though students had strong motivation, they still lacked advanced language competencies, especially language application skills and problem-solving skills. One reason for this might be ascribed to the underestimated self-evaluation of academic success, which was explained as the influence of Chinese modesty (Wan and Lee, 2017; Zhan et al., 2021). But if we offer a glimpse into the strategy dimension, we found that students tended to neglect to deploy skill-based cognitive strategy (S10) during deep learning, thereby hindering the development of language application skills and problem-solving skills. In addition, students presented relatively low engagement regardless of distinct English proficiency and visions, and similarly low competence across grade and EFL course groups, which will be elaborated in the following comparative analysis section. Overall, it is urgent for EFL teachers to seek possible antidotes to the above problems.

Comparative analysis

Regarding grade groups, the striking finding was that freshmen performed visibly better than sophomores in motivation, engagement, strategy, and overall deep learning. A possible explanation for this might be that freshmen who just attended National College Entrance Examination (NCEE) and completed an arduous senior year in high school, possibly maintained such intense learning momentum and routines resulting in stronger motivation to learn, higher investment, and more active participation in learning, as well as the higher level of deep learning. In contrast, sophomores may mostly pay more attention to core course learning than EFL learning. Moreover, there existed a significant difference in strategy dimension across grade groups, which was generally in agreement with Tragant et al. (2013), who found that language learning strategies used were significantly different for the two age groups. Concretely, freshmen tended to make more attempts to employ strategies to learn deeply possibly due to intense 3-year instructed language learning in high school aiming to attain high scores in NCEE. However, there was no significant difference in competence, indicating that it might be challenging for both grades to attain advanced language competence in the online EFL teaching context.

In terms of English proficiency groups, results revealed that the higher level of English proficiency students had the higher levels of motivation, strategy, competence, and deep learning. The finding was partly consistent with some research discovering that more proficient EFL learners used deep language learning strategies more frequently than less proficient counterparts (Lai, 2009; Gerami and Baighlou, 2011; Zhan et al., 2021). In this vein, due to the internal positive correlation of four dimensions, more proficient EFL learners seemed to perform better in other dimensions. However, there was no significant difference in engagement across the three English proficiency groups. One possible explanation might be that behavioral engagement in online EFL teaching might be influenced by numerous external factors, such as comparatively weaker supervision mechanism than face-to-face classroom teaching, instability of network and equipment, low efficient interaction, delayed online instruction, etc. (Chapelle, 2019; Du and Qian, 2022). It is also worth considering, as some research indicates, that a lower level of students' engagement was an inevitable problem during the COVID-19 pandemic (Yang et al., 2020) since perceived COVID-19 event strength and perceived stress can negatively influence learning engagement (Zhao et al., 2021). Nevertheless, this survey did not observe such impacts caused by external events and internal pressures, which needs to be further explored.

This survey also uncovered that motivation, engagement, strategy, and deep learning did differ between students in BE and students in PCE groups. One of the main possible reasons might be distinct curricula based on different talent training programs. BE is a core course for students who majored in TCFL, focusing on increasing mastery of language knowledge, language application skills, and cross-cultural competence, whereas PCE is a public general English course for non-English major students aiming to teach vocabulary, grammar, text, etc., and develop basic language skills. In this vein, students in BE might pay more attention and effort to EFL learning, which is visibly related to their future professional development, thereby contributing to a higher level of motivation, engagement, strategy, and deep learning. Similarly, students in ELS, which is designed to develop academic communication to ensure future academic success at overseas universities, also performed better than the PCE group in engagement. In addition, although students in PCE struggled with passing CET-4 and CET-6, in the short term, a relatively less strong correlation with their majors might undermine their efforts and attention in EFL learning, resulting in low motivation, engagement, strategy, and deep learning. Interestingly, there was no difference in competence across the three groups, even if the average rate of passing CET-4 in BE groups is higher than in others. This might be due to the underestimated self-evaluation as we discussed above.

Since some literature has demonstrated that visions are instrumental in driving human behavior in the present (Markus and Nurius, 1987), this study considered vision as one of the variable to observe its impact on deep learning in online EFL teaching. The vision here was initially set as three types of dreamed future states after graduation: hunting jobs, further studying, and self-employment, which imply different requirements for English proficiency. Results suggest that students in FS had a higher level of motivation than other groups, suggesting that students having a vision of being more proficient English speakers (i.e., FS group) presented stronger motivation to learn. This finding partly supported the motivational self system (L2MSS) theory advocated by Dörnyei (2009), highlighting the motivational potential of vision in the field of SLA. Moreover, it was discovered that students with a vision of being more proficient in English had a higher level of strategy, competence, and deep learning, which indicate that a strong vision might galvanize them to conduct deep learning strategy. Consequently, advanced competencies became much easier to acquire, and ultimately students were more inclined to access deep learning. This further confirmed the capacity of a vision of an ideal L2 self to motivate learning (Henry, 2011; You and Dörnyei, 2016). However, no significant differences in engagement existed across the three groups, similar to the results in English proficiency groups, which have been discussed above.

Promoting deep learning in the online EFL teaching context

Based on findings in this survey, referring to the four-dimension theoretical model of deep learning in online EFL teaching, this study proposed five proper instructional strategies to promote students' deep learning. First, teachers should give top priority to cultivating students' directional competence of deep learning by organizing creative multi-facet online tasks and activities incorporating four main language application skills, or through conducting situational teaching approach and project-based approach to promote internalization and application of language knowledge, or by designing online learning navigation to gradually guide students' thinking, perceiving and behaving toward deep learning goals. Additionally, teachers can increase the number of open-ended questions in tests to develop students' English high order thinking and critical thinking. Second, teachers should take efficient measures to improve students' engagement in three stages of online EFL teaching. Specifically, teachers can make full use of ICT-assisted teaching platforms in China context or LMSs (e.g., Blackboard) to manage and supervise class by randomly taking online attendance, asking questions, interacting, giving tests, etc. Teachers can also establish a highly interactive and harmonious learning community with more teachers' emotional support to meet students' learning needs and promoting investment (Liu et al., 2021). Additionally, during the COVID-19 pandemic, strengthening students' growth mindset and reducing students' perceived stress can promote students' engagement (Zhao et al., 2021). Third, teachers should make efforts to help students exploit deep LLS, especially skill-based cognitive characters, which may be realized during implicit or explicit instruction in online EFL teaching, for example, choreographing online learning tasks and projects (e.g., self-reflection, KWL chart) to provide abundant opportunities for students to practice and evaluate strategies (Gerami and Baighlou, 2011). According to the comparative analysis, less proficient students, students in PCE course, and students with less strong English-related vision need more attention. Moreover, attempts to maintain an all-English environment in online or offline classes can also contribute to practicing skill-based strategies. Fourth, teachers need to create and maintain students' diverse language learning motives directed to deep learning through providing high-quality online materials and resources about English society, culture, customs, etc., to stimulate students' integrative motives. Teachers can also increase students' expectancy of success and goal-orientedness (Dörnyei, 2001) or utilize ICT to build and enhance vision to energize and maintain deep language learning (Adolphs et al., 2018). Fifth, since deep learning may differ across variables, teachers should exploit ICT and big data as well as LMSs (e.g., Blackboard) to manage, track, and record students' learning behaviors and analyze their various learning preferences, aiming to conduct individualized online EFL teaching to promote students' deep learning effectively.

Limitations and future research

It is significant to recognize potential limitations of the study, which may hopefully amount to directions for future research. First, although the correlated four-dimension theoretical model of deep learning was supported by ample literature and confirmed through EFA and CFA, suggesting the fit of the model was adequate, we still hope that the fit of the model can be further replicated in larger diverse sample sizes to establish the generalizability for different countries/regions or in various contexts of EFL teaching focusing on specific skills (listening, reading, etc.). Longitudinal research is also needed to validate the model in the future. Second, theoretic junctions of deep learning dimensions (e.g., the motivation, the strategy) and related cutting-edge SLA theories may become promising research directions to further explore, to illustrate, from a complex dynamic perspective, whether or how the motivation of deep learning is related to language learners' motivational directed currents (DMCs) (Muir and Dörnyei, 2013). Third, regarding the survey, the self-reported measurement might result in overrating or underrating real status, therefore, classroom observations and interviews can be adopted to collect more qualitative data to comprehensively investigate deep learning and dig into more in-depth reasons behind survey results. Fourth, unfortunately, the COVID-19 pandemic limited the scope of investigation in this study, which needs to be expanded in the future relevant surveys.

Conclusion

This study exerted pioneering efforts to understand, investigate, and promote deep learning in the online EFL teaching context. The present study proposed the four-dimension model hypothesis of deep learning involving the motivation of deep learning, the engagement of deep learning, the strategy of deep learning, and the directional competence of deep learning, which was empirically validated as a positively correlated model with high composite reliability and good convergent validity by using EFA and CFA. An additional survey reported that the current level of college students' deep learning in online EFL teaching context reached median value, with the lowest mean of directional competence and the highest mean of motivation; students presented more instructional motives, neglect of deploying skilled-based cognitive strategies, and deficiency of language application skills and problem-solving skills; there existed some statistically salient differences in deep learning level and other four sub-dimensions across grades, English proficiency, EFL course, and vision groups; students presented relatively low engagement regardless of distinct English proficiency and visions and similarly low directional competence across grade and EFL course groups. In the end, this study attempted to explicate the main results and proffered five promotion instructional strategies to boost students' deep learning in the online EFL teaching context.

Overall, this study tries to clear away theoretical muddle in deep learning construct in language education and prove the latent rationality of the converge of deep learning concept and SLA theories, hopefully, proffering new insights into the theoretical and empirical development of deep learning in language education. The survey findings and instructional strategies may be useful for EFL teachers to implement efficient and individualized online EFL teaching to boost students' deep learning and further remedy problems of low effectiveness in ICL-assisted EFL teaching. The standardized instrument developed in the present study may also serve as a valuable tool for other researchers interested in this domain.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving human participants were reviewed and approved by College of Humanities and Arts, Tianjin University of Finance and Economics Pearl River College. The patients/participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

RJ was fully in charge of reviewing literature, conceiving the study, conducting a questionnaire survey, analyzing statistics, writing and revising the manuscript, etc.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Psychological emotions-based online learning grade prediction *via* BP neural network

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With the rapid development of Internet technology and the reform of the education model, online education has been widely recognized and applied. In the process of online learning, various types of browsing behavior characteristic data such as learning engagement and attitude will be generated. These learning behaviors are closely related to academic performance. In-depth exploration of the laws contained in the data can provide teaching assistance for education administrators. In this paper, the random forest algorithm is used to determine the importance of factors for the relationship between 11 learning behavior data and students' psychological quality test data, a total of 12-dimensional feature data and grades, and extracts six factors that have a greater impact on grades. Through the research of this paper, the method of random forest is innovatively used, and it is found that the psychological factor is one of the six important factors. This paper innovatively uses BP neural network as the prediction model, takes six important factors as input, and establishes a complete method of online learning performance prediction. The research in this paper can help teachers monitor students' learning status, detect abnormal learning behaviors and problems in time, and make timely and effective teaching interventions and adjustments in advance according to the abnormal status of students found.

KEYWORDS

online learning, psychological emotions, BP neural network, learning status, prediction psychological

Introduction

In 1988, Professor Will Smith from Harvard University proposed the concept of online teaching. In 2003, some educational institutions in China gradually began online teaching. In the stage of rapid development of information techniques, online teaching has become a prominent way of learning (Abu Saa et al., 2019). Online learning is well accepted by teachers and students due to its following three characteristics. First, online learning is not affected by the separation between time and space. Second, online learning helps teachers and students make full use of fragmented time. Last but not least, ways of online learning are more flexible. The overall development of online education in China is on the rise since 2016. In 2016, the number of users reaches 104 million, exceeding 100 million for the first time. In 2020, the number of users increases rapidly and reaches 259 million due to the effects of COVID-19, and it was predicted to hike to 446 million in 2021 (Almeda et al., 2018). Many studies indicated that the learning behaviors of learners have a high correlation with learning effects. Traditional face-to-face education utilizes the result-based evaluation method for students. This evaluation method is usually based on the weighted results of usual grades and grades of the final exam, which does not establish close associations between learning behaviors and learning grades of learners. In summary, the result-based evaluation method has one-sidedness to a certain extent, so it fails to fully reflect learners' attitudes and learning habits. Different from traditional face-to-face tutoring, online education can record students' various types of data of learning behaviors in real time to generate learning big data for students. The recorded data are the reflection of students' learning status at that time and their unconscious learning behavior habits formed over a long period of time. A deep study of the learning behaviors helps discover the most authentic learning thinking and learning situations. The activities of comprehensively tracking the learning process of learners, accurately grasping the learning status, and evaluating the learning effects in actual teaching scenarios help teachers take effective measures according to students' status and abilities to realize early identification, early prevention, early intervention, timely, and effective teaching adjustment, so as to greatly improve the teaching quality and students' learning effects.

With the wide application of online education, more and more teachers and students participate, resulting in the generation of great amount of various types of data on platforms. The generated data reflect students' learning behaviors. It is a hot spot to fully mine the patterns hidden in data and to transform structured data as well as unstructured data into effective information. Data mining is applied to the domain of online education by more and more researchers (Chen et al., 2021) to mine the online learning behaviors as well as the correlation between behavior patterns hidden in data and learning effects, to understand the learning behaviors of learners, and to predict the levels of learners to master their knowledge (Elena et al., 2018). However, the prediction for learners' learning grades is complex. The reasons are illustrated as follows. First, learning grades are usually affected by various impact factors such as learners' backgrounds, previous learning performance, the interaction between learners and teachers, and psychological characteristics of learners. Moreover, the types and levels of impact factors are different in different situations (Guo and Liu, 2018). With the help of the research on the impacts of behavior data of learners on learning effects, teachers can monitor the learning status of learners to discover unusual learning behaviors and problems, in order to make timely and effective teaching interventions and adjustments in advance. This study aims to improve the quality of online teaching by predicting students' learning grades, raising students' learning grades, and strengthening online teaching management. The random forest algorithm is applied to recognize important features from various recorded behavior data in platforms. The BP neural network is applied to build a model of online learning behavior and effects according to the selected important behavior data. The built model can predict grades according to learning behavior data during the learning process to monitor learning behaviors, which helps to guide students to carry out beneficial learning behaviors and further improve teaching quality.

Related work

Online learning behaviors are closely related to learning grades. Learning behavior is an important representation of predicting learning performance. In order to study the impacts of online learning behaviors of learners on their learning grades, the related researches mainly focus on the following categories.

Many studies on impact factors of learning grades

During the process of online education, large quantities of behavior data are recorded by platforms. Some data have a high correlation with learning grades, while some data have a low correlation. Many researchers have conducted a large number of studies (Abdi, 2010). Shi and Ge (2018) pointed that learning investment and interaction behavior had impacts on grades by reviewing current papers. The authors applied the structural equation model to study the relationship between learning investment (interaction behavior) and grades. Researchers selected behavior data based on previous research findings, which shows subjectivity to a certain extent. Moreover, researchers ignore the impacts of other factors and do not make full use of behavior data recorded by platforms. Zheng et al. (2020) utilized data from the online learning management system (LMS), grades of the final exam, level factors of teachers and classes to study the relationship between learners' activities (teachers' features, class design elements, etc.), and online learning grades. The results indicated that the learning effects will be better when students study courses. Moreover, more times to login and a longer duration of login also lead to better learning effects. Sun and Feng (2019) built models by using neural network, decision tree, and linear regression to study impact factors of online learning grades. It is indicated that learning attitudes (number of subjective and objective questions completed), timely level (the first time to learn courses, etc.) as well as investment (average video viewing progress and times) are the main factors that affected learning achievements. Moreover, the level of frustration tolerance (persistence) has a second-level influence. In addition, the level of interaction (number of posts, replies, and followers), the level of positivity (aggressiveness, etc.), and the stage effect (quality of subjective question completion) showed no correlation with learning grades. Li et al. (2016) used multiple linear regression to analyze 21 online learning behavior indexes. The result indicated that four indexes of the number of assignments submitted, the total number of times when the time interval between each submission of assignments was less than the average time interval of the whole class, the contribution rate of the number of posts, and the average number of browse forum topic posts logged in each time were significantly helpful for predicting grades of courses. Guo and Liu (2018) studied the correlation between seven aspects of online learning behaviors (usual grades, online learning time, online test, forum activities, etc.) and learning effects. These researchers have made full use of online behavior data recorded on platforms to analyze impact levels of behavior data. However, they only use data in platforms, without considering the impacts of individual conditions such as psychological quality on grades.

Research on relationship between impact factors of learning and grades

With the wide and deep application of information techniques, more and more researchers begin to study the relationship between online learning behaviors of learners and learning grades. Shen et al. (2020) used online learning behavior data to build online learning behavior and learning evaluation model for MOOCAP by using various methods, namely, Delphi, expert ranking, and expert. Shen et al. (2019) used sampling stepwise regression to build the evaluation model for online learning behavior and performance. The impacts of online learning behaviors on learning grades were analyzed. Zhao et al. (2017) utilized multiple regression analysis to determine early warning factors influencing the learning performance of students. The Delphi method is a kind of subjective scoring method. The effectiveness of this method depends on the experts' familiarity with the target industry. The applicability of the regression analysis method is limited because the model structure needs to be estimated first. In addition, the model is also limited by the diversity of factors and the unpredictability of some factors. Sun and Feng (2019) applied neural network, decision tree, and linear regression to build models and recognized the importance of online learning behaviors for learning grades. The authors conducted a quantitative study on the relationship between learning behaviors and learning grades.

Many studies on models building for learning grade prediction

With the wide application of big data, learning grade prediction has become the important content of data mining for online education. The prediction model is built by discovering the relationship between learning behavior features and grades. The built model can be used to predict the learning grades of learners and further provide an important basis for academic warning, teaching strategy adjustment, and learning plan formulation. Section "Research on relationship between impact factors of learning and grades" recognizes important impact factors but does not validate these factors and applied them to practical scenarios. Song et al. (2020) construct an academic warning model based on the RBF neural network which was optimized by the genetic algorithm. AHP is used to analyze the weights of the impact factors affecting the learning crisis extracted by teachers and experts. The main impact factors are modified according to the weights and then used as the model input for academic early warning. In this case, the recognized important factors are applied to practical scenarios. In the actual process of building models, the redundant or irrelevant features should be reduced without significantly affecting the performance of the model (training time, complexity, and accuracy) (Sun and Feng, 2019). Methods such as AHP, PCA, and methods that select important features by analyzing the influence of different correlations and features on the tags of datasets can be used to reduce the dimensions of model inputs (Tsang et al., 2021). However, AHP and PCA have the shortcoming of strong subjectivity, which is closely related to the familiarity of teachers and experts in this field. As a highly flexible machine learning, the random forest has good accuracy and generates grades for the important attributes during the process of analyzing data. Moreover, unlike algorithms such as SVM, random forest does not need to perform super parameter tuning. The random forest algorithm shows its progressiveness and has been widely applied to practical scenarios.

Data and methods

Research object

The Blackboard platform is the online education platform that is currently used in a university in Guangzhou. This platform will store records of users during the process of teaching and learning, namely, course learning statistics records, students' learning records, and teachers' records of accessing and using the platform. Totally 117 courses are provided for students on the platform. The course "Research on mobile applications" in the platform is selected for the research in this paper. In the second semester of the 2019–2020 academic year (March–June 2020), 137 students registered for the study. Totally 11

TABLE 1 Factors of learning behaviors.

Category of online learning behavior	Typical behavior
Clicking feature	X1: Number of visits during current semester
	X2: Number of visited pages during current semester
	X7: Number of times to click announcements
	X8: Number of times to click tasks
	X9: Number of times to click "my grades"
	X10: Number of times to click general review questions
	X11: Number of times to click review courseware
Homework test	X3: Number of homework participated during current semester
	X4: Number of tests participated during current semester
Interaction feature (learning emotion)	X5: Number of self-assessment and mutual assessment homework participated
	X6: Number posts during current week
Psychological quality	X12: Psychological quality of a student

dimensions of online learning data, including data on average online time backstage, are collected. Except for the online data, the offline grades of the final exam after learning are also included. This paper considers the influences of both online learning behaviors and students' psychological quality which is evaluated by using a questionnaire survey method.

Data processing and analysis

Indexes of 11 dimensions are achieved by transforming the extracted data from the platform. The indexes are shown in Table 1. The selected course is registered by 137 students. Four students do not participate in the course after registration, so their behavior data and grades are both zero. The sample data of the four students are removed. Moreover, sample data of another student are also removed because the grade of this student is lower than 20 and far lower than the average grades of students in his/her class. This student can answer some subjective questions correctly according to their original knowledge level or by luck to get such a grade even if he/she does not attend the course. The processed data of 132 students are divided into a training set and testing set. The training set is used to establish the prediction model, and the testing set is used to evaluate the prediction accuracy of the model.

Good mental health is conducive to the development of learning potential. This paper comprehensively considers the influences of both online learning features and psychological quality of students on learning grades. The questionnaire for testing students' psychological quality is the college students' psychological quality questionnaire (simplified version) designed by Zhang and Zhang (2018). The questionnaire contains three factors, namely, cognition, personality, and adaptability, and 27 issues. The three factors have nine issues. The questionnaire adopts 5-level scoring. The grades of 1–5 points represent the opinions from "very inconsistent" to "very consistent." Higher grades indicate a better psychological quality of the tested students. Totally 137 questionnaires were distributed, and 137 valid questionnaires were recovered to obtain the students' psychological quality data. The data are obtained by adding the grades of each issue in the questionnaire and are represented as X12 in Table 1.

The main impact factors are analyzed as follows.

- **Number of visits during the current semester (X1):** The total number of times that a student visits an online platform during the current semester. This index is a reflection of online learning habits and basic learning attitudes. A large number of visits indicates high acceptance of students on the way online teaching and reflects that a student is active in learning and is able to study and review on time.
- **Number of visited pages during the current semester (X2):** The total number of times that a student visits course pages and course-related pages during the current semester. A large number of visited pages indicates a high learning investment (Zhao et al., 2017) of a student and reflects that the student is active in learning.
- **Number of homework participated during the current semester (X3):** This index is the total number of homework that is arranged for a student by teachers during the current semester. This index reflects a student's basic learning attitudes, and the status that the student participates in online learning on time and masters the course progress and content from time to time. At the same time, the student is able to timely consolidate the content of the course through homework.
- **Number of tests participated during the current semester (X4):** This index is the reflection of the basic learning attitudes of students and the total number of tests that are arranged for a student by teachers. The tests are helpful for students to find out his/her weakness in mastering knowledge check the leak and fill the vacancy in the his/her knowledge system.
- **Number of self-assessment and mutual assessment homework participated (X5):** Subjective questions for a student from most online courses can be self-assessed or assessed by other students. The number of self-assessment and mutual assessment homework participants reflects a student's learning enthusiasm. The process of assessing homework is the process of consolidating and further understanding knowledge.

- **Number of posts during the current week (X6):** The number of posts that a student sends during the process of learning a course reflects his/her active participation in the interaction. A large number of posts during the current week indicates a high level of a student's thinking and interactive initiative. This index reflects whether the student thinks seriously in the learning process, whether he/she can actively request help for encountered problems and solve the problems in time.
- **Number of times to click announcements (X7):** This index is the reflection of a student's online learning habits. Generally speaking, a student with good online learning habits will actively check announcements, and he/she will manage to master related activities of courses and complete related tasks for activities in time.
- **Number of times to click tasks (X8):** This index is the reflection of a student's online learning habits. A student with good learning habits usually checks task notifications carefully and timely and completes tasks according to corresponding notifications. On the contrary, a student who seldom pays attention to task notifications is unable to complete tasks arranged by teachers and does not attach importance to learning.
- **Number of times to click "my grades" (X9):** Total number of times that a student checks his/her grades on tests and the final exam. This index reflects the student's attention to learning and his/her sense of honor in learning.
- **Number of times to click general review questions (X10):** This index reflects a student's learning habits of reviewing before an exam, and the time invested by the student for an exam. A larger number of times to click general review questions generally indicates better grades the student will receive.
- **Number of times to click review courseware (X11):** This index reflects a student's learning habits of reviewing after class, and the time spent by the student learning a course after class. A large number of times to click review courseware indicates better grades the student will receive.
- **Psychological quality of a student (Zheng et al., 2020) (X12):** Good mental health is conducive to the development of learning potential. A student with good psychological quality has positive learning attitudes. He/she is optimistic and confident and good at affirming himself/herself. Moreover, he/she will seek help from teachers and other students to solve problems and is good at relieving anxiety. Good psychological quality helps a student to raise his/her learning grades. A student with poor psychological quality may abandon himself/herself due to criticism and dissatisfaction from teachers or parents and lose learning interests. Worse still, he/she may lose confidence or even give up education. A student with good psychological quality can adjust his/her mentality in time when he/she encounters difficult test questions and uses reasonable answer strategies to make full use of his/her knowledge to the greatest extent. On the contrary, a student with poor psychological quality may fall into anxiety because of a certain problem and cannot adjust his/her state in time, which will affect the performance of dealing with subsequent problems, and will not fully reflect his/her ability, so that his/her learning grades are seriously affected.

Random forest and behavior feature selection

Random forest is an ensemble learning algorithm and it is developed by using the decision tree as a base classifier. The basic idea of random forest is to train multiple decision trees by using data subsets to achieve the voted classification result. Random sampling with replacement is conducted repeatedly to generate K training sample sets N. Each training sample subset corresponds to a decision tree. This process is called the bagging method. The K decision trees created by the bagging method are different from each other, which decreases the correlation between decision trees in random forest and further decreases the error rates of random forest. In random forest, the number of decision trees K and the characteristics of randomly selected node splitting determine the prediction performance of the model. It is one of the characteristics of random forest to estimate the importance of variables. This paper calculates the importance of variables based on the out-of-bag error rate (OOB error). Definition of OOB error estimates (Mitchell, 2011): in random forests, there is no need for cross-validation or a separate test set to get an unbiased estimate of the test set error. It is estimated internally, during the run, as follows: each tree is constructed using a different bootstrap sample from the original data. About one-third of the cases are left out of the bootstrap sample and not used in the construction of the *k*th tree. Put each case left out in the construction of the *k*th tree down the *k*th tree to get a classification. In this way, a test set classification is obtained for each case in about one-third of the trees. At the end of the run, take *j* to be the class that got most of the votes every time case *n* is OOB. The proportion of times that *j* is not equal to the true class of *n* averaged over all cases is the OOB error estimate. This has proven to be unbiased in many tests.

If $x_j(j = 1, 2, \cdots, 12)$ is the input variable, then the importance of the *k*th tree $I_k(j = 1, 2, \cdots, 12)$ is the mean of estimated error of out-of-bag data before and after randomly replacing variables. The importance is given by Formula (1).

$$I_k(x_j) = \{\sum_{n=1}^{N_{OOB}} I[f(x_n) = f_k(x_n)] - \sum_{n=1}^{N_{OOB}} I[f(x_n) = f_k(x'_n)]\} / N_{OOB} \tag{1}$$

The importance of variable x_j in random forest is given by Formula (2).

$$I(x_j) = \sum_{k=1}^{K} I_k(x_j)/K \tag{2}$$

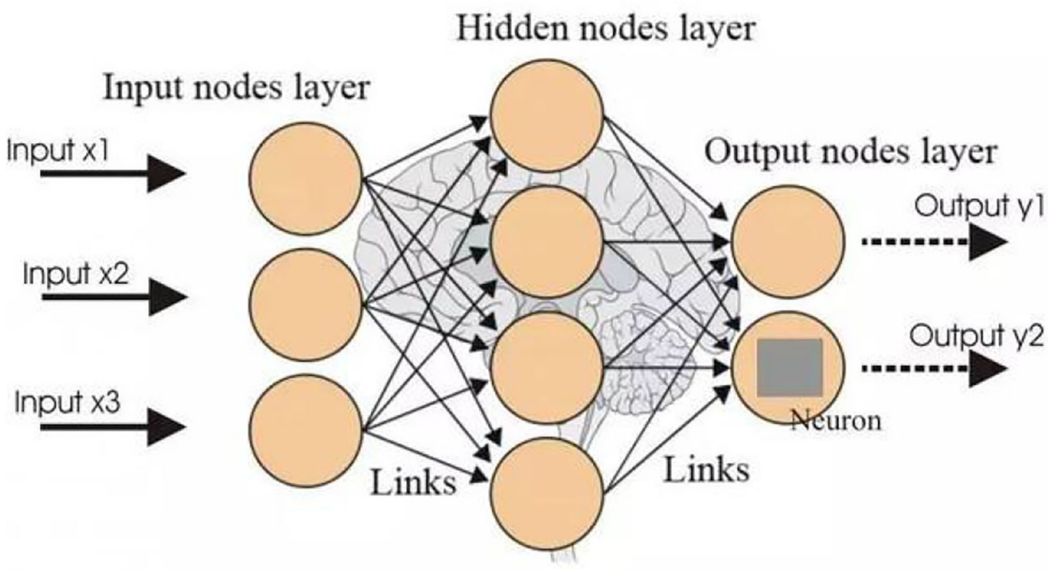

FIGURE 1
BP neural network structure.

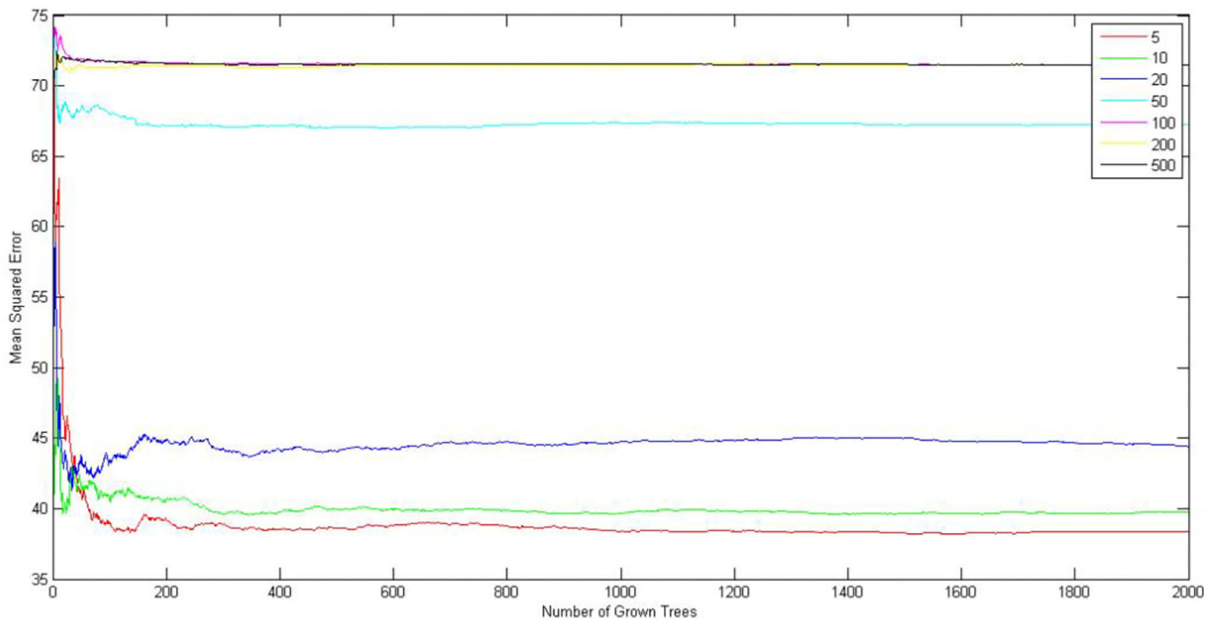

FIGURE 2
Curve of optimal numbers of leaves and trees in random forest.

N_{OOB} is the number of out-of-bag sample data. $f(x_n)$ is the nth sample value of out-of-bag data. $f_k(x_n)$ and $f_k(x'_n)$ are the estimated value of the nth sample before and after replacing variables. $I(\cdot)$ is the discriminant function whose value is set as 1 when the condition in parentheses is valid and 0 otherwise.

BP neural network and prediction model design

BP neural network (Ding et al., 2011) is one of the most widely used neural network models. It can learn and store a

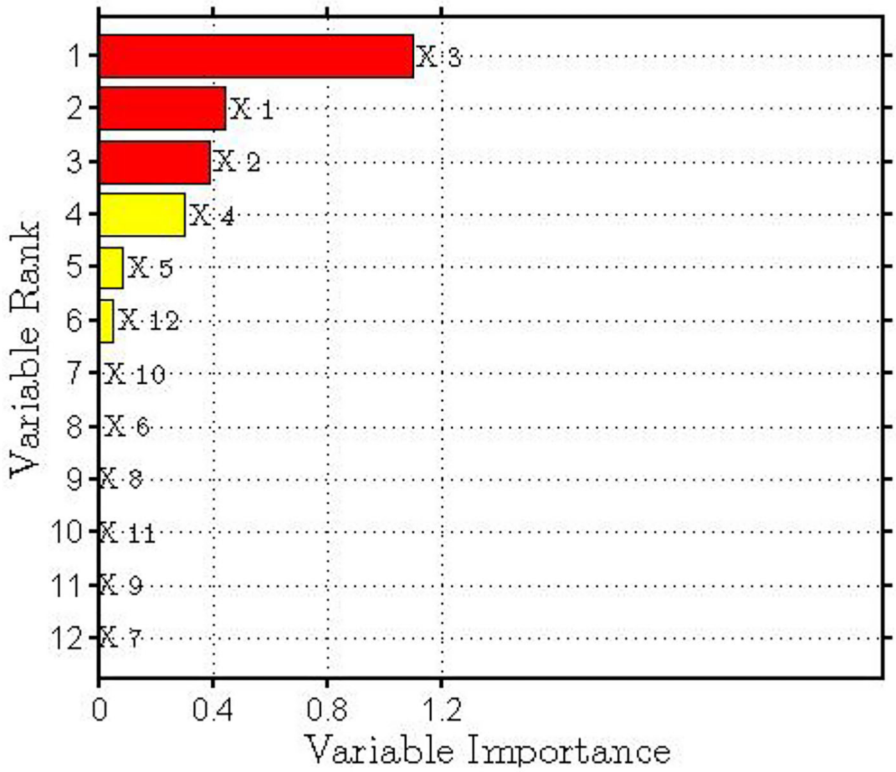

FIGURE 3
The importance of online behavior features.

large number of input–output pattern mapping relationships without revealing the mathematical equations to this mapping relationship in advance. It is outstanding in describing non-linear function relationships. A three-layer BP neural network can describe non-linear relationships of any complexity. Its structure is shown in Figure 1.

The selected important behavior feature data of students in Section "Random forest and behavior feature selection" are utilized as the input of the neural network to build a model and conduct prediction. Sigmoid function is selected as the activation function for hidden layers. The parameter setting of the BP neural network is to carry out multiple rounds of tests according to the initial value, continuously optimize to ensure the minimum error, and determine the parameter value through the iterative operation. The number of nodes is set as 7. The output layer generates the grades of students. In this paper, the parameter threshold of the BP neural network model is set as 0.001, the maximum number of training times is set as 6,000, and the learning rate is set as 0.05. When the calculation error is lower than the threshold or the number of training times exceeds the set maximum number, the training is terminated.

Results and analysis

This paper starts with the relationship between learning behaviors and learning grades to investigate features that influence the learning grades of students. The dimensions of behavior data influencing students' grades are reduced to several typical factors which are helpful to improve students' grade prediction by analyzing the importance of behavior data to retain useful features and remove redundant features. The important behavior feature data are selected as the input to construct BP neural network for students' grade prediction. Based on the aforementioned model design, online behavior data, data of psychological quality, and data of grades of the course "Research on mobile applications" which were offered at the beginning of the semester and learned by 137 students are collected to construct the dataset. The dataset contains valid data from 132 students. About 70% of the dataset is used as a training set, while the other 30% is used as a testing set for evaluating the trained model. The software MATLAB is used as a tool to build the model. This paper is based on the modeling method of random forest. The introduction of random forest (Shi and Horvath, 2006) is as follows.

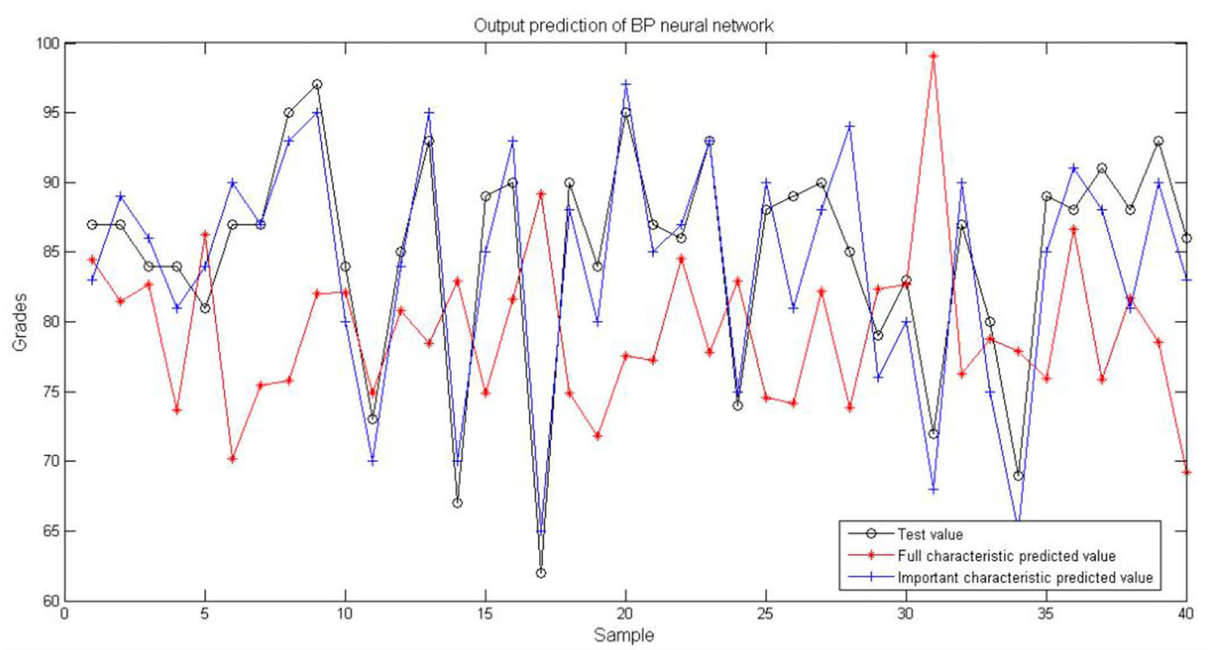

FIGURE 4
Prediction result of BP neural network.

TABLE 2 Comparison of two prediction models.

Prediction model	Maximum prediction error	Minimum prediction error	Mean square error of predicted value	Training time
Full characteristic model	−32.1144	−0.1412	14.1928	0.060903 second
Important characteristic model	−9.1750	−0.0419	3.5468	0.036974 second

Random forest is built a forest in a random way. There are many decision trees in the forest, and each decision tree in the random forest is not related. After getting the forest, when a new input sample enters, let each decision tree in the forest make a judgment to see which class the sample should belong to, and then see which class is selected the most, it is predicted that the sample belongs to that class.

A decision tree (Patel and Prajapati, 2018) is a tree structure (can be binary or non-binary). Each non-leaf node represents a test on a feature attribute, each branch represents the output of the feature attribute on a certain value range, and each leaf node stores a category. The process of using a decision tree to make decisions is to start from the root node, test the corresponding feature attributes in the items to be classified, and select the output branch according to its value until it reaches the leaf node, and the category stored in the leaf node is used as the decision result. The analysis of the data in this paper is as follows.

First, initial numbers of leaves fall in the range (5, 10, 20, 50, 100, 200, 500). The 132 original data of students are used to select the optimal numbers of leaves and trees. The result is shown in Figure 2. It is indicated that the mean square error of random forest reaches a minimum value when the number of leaves is set as 5, so the optimal number of leaves is 5. By observing the abscissa, it is found that the number of leaves decreases steadily when the number of trees K is 400, so the optimal number of trees is 400.

Behavior data and psychological quality data of 132 students after the online learning semester are collected to build random forest model with optimal numbers of leaves and trees and the importance of learning behavior features for grades is achieved. The features are sorted and highlighted according to their importance in Figure 3. It can be observed that a total of six features have a significant correlation with learning grades, while the other six features show an insignificant correlation. The six key behavior data, that is, number of visits during

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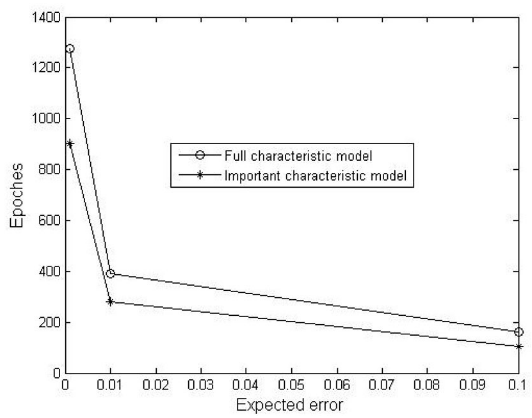

FIGURE 5
Training effects of two prediction models.

current semester (X1), number of visited pages during current semester (X2), number of homework participated during current semester (X3), number of tests participated during current semester (X4), number of self-assessment and mutual assessment homework participated (X5), and psychological quality of a student (X12) are the optimal feature variables for predicting students' grades. The more frequent appearance of these behavior features, the more energy and efforts are invested by students to achieve learning goals and better achievements. According to the above discussion, the six important behavior features are selected as input for BP neural network to train the model and predict students' grades.

The recognized six important behavior features are utilized to build the grade prediction model. The 30% (around 40 groups) of the original data are used for the model test. The result is shown in Figure 4. The black curve shows the test sample data. The red curve is the prediction curve using the data of 12 features. The blue curve is the test curve using the important features as input. Obviously, the blue curve achieves better prediction performance because its overall trend is basically consistent with the original sample data. However, the red curve achieves poor prediction performance.

It is indicated in Table 2 that the mean square error of the BP model which is constructed by using important feature data (important characteristic model) is only 3.5468, while the mean square error of the BP model which is constructed by using all the features (full characteristic model) is 14.1968. The former decreases by 75% compared with the latter. For training speed, the training time of the important characteristic model is 0.036974, while the training time of the full characteristic model is 0.060903. The former decreases by nearly half compared with the letter. The comparison of training speed indicates great improvement in the training speed of the prediction model which is constructed using important feature data. The improvement will be more significant in the case of large quantities of data, which greatly reduces computing expenses.

In order to validate the running effects of model, full characteristic model and important characteristic model are trained under the condition that training errors are set as 0.1, 0.01 and 0.001, while other parameters are consistent. The performance of models is shown in Figure 5. It can be observed that the number of iterations of the important characteristic model is obviously smaller, indicating that the training speed becomes faster after the redundant behavior features are removed.

Conclusion

Based on previous scholars' theories, this paper selects 12 factors that affect students' online learning behavior for research. Using the random forest identification method, six important learning behaviors with significant correlations between students' performance were selected for in-depth analysis. The six important learning behaviors are used as the inputs for BP neural network to build the grade prediction model. The built model removes redundant features, which increases the speed of algorithm, and effectively improves the training speed of network and prediction accuracy.

This paper compares the full feature prediction model and the important feature prediction model. The empirical study also shows that the prediction error of the model established by using the important features is greatly reduced, and the training speed is greatly improved. The model can be used in actual teaching management. Teachers can monitor students' learning behaviors, find abnormal students' behaviors, and conduct teaching interventions in a timely manner, thereby improving the quality of teaching and the effectiveness of students' learning.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving human participants were reviewed and approved by Department of General and Formative Education, Guangzhou Nanfang College. The patients/participants provided their written informed consent to participate in this study.

Author contributions

JX responsible for writing manuscripts, collecting, and analyzing experimental data. HT responsible for language polishing of articles and emotional analysis of learning behavior. HW responsible for the progress supervision and technical guidance of the overall article. JT responsible for the collection and analysis of data. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The approaches and methods of music psychology in the relationship between music emotion and cognition in music teaching activities

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In order to further improve the effect of music teaching, more music psychology should be applied in music teaching to assist teaching, and students should better understand the emotional elements reflected in music through music emotion and cognitive teaching. This essay starts from the relationship between music emotion and cognition, to deeply explore the application of music psychology in teaching activities, through the construction of music education psychological regulation function model to explore the effect of the application of psychology in music teaching. The results showed that the scores of positive emotions were significantly improved, while the scores of negative emotions were significantly decreased. The difference between the improvement and reduction of positive emotions was significant (p<0.01, p<0.01). The results show that psychology based on the relationship between emotions and people is helpful to improve the effectiveness of music teaching. And on this basis put forward the music teaching activity innovation path.

KEYWORDS
music teaching, psychology, emotion and cognition, positive emotion, negative emotion

Introduction

As a special subject, music itself has the deepest power of the people. Music can wash and immerse the heart. Music course is also an important way to implement esthetic education in the process of quality-oriented education, which can better enrich students' minds, develop students' phenomenal power, and further enhance students' phenomenal space and creativity (Au and Lau, 2021). In addition, music can deeply affect students, help students form a correct attitude toward objective facts, enhance students' moral concepts and moral feelings, and better regulate students' behavior. The realization of these needs to use the emotional guidance and cognitive concept of music, through the emotional and cognitive guidance of music psychology to better have a profound impact on students' thoughts, enhance students' good moral sentiment, increase wisdom and improve health, and promote students to develop good ideological morality (Topal et al., 2021). Music education is not only needed for the construction of socialist spiritual civilization, but also an important means to stimulate students' musical ability and individualized and comprehensive development. Based on this, from the perspective of music psychology, this essay deeply discusses the application path of the relationship between emotion and cognition in music teaching activities.

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Rahiem et al. believe that in the overall activity of music practice, music appreciation is the receiving link of music creation and performance. In the final analysis, the activities of composers and performers, which are for the audience to enjoy, are always centered around the audience. Without music appreciation, music creation and performance will lose their fundamental significance (Rahiem, 2021). An et al. put forward that music appreciation is not only a passive accepting behavior, but also an active and subjective creative activity (An et al., 2022). With the in-depth study of music esthetic practice, modern music esthetics especially turns its attention to the link of music acceptance, and examines the acceptance of music to the same important degree as music creation and performance from a new perspective. Music appreciation is the product of the image activity of the appreciator. Ostendorf et al. pointed out that the emotions expressed or inspired by music are certain, but such certain emotional movement forms may be generated by different people's attitudes toward different time, so people in emotional movement will seek or recall things that cause similar emotional movement in their own experience. In this way, the definite musical mood also produces the uncertain musical content (Ostendorf et al., 2020). Therefore, when students appreciate the same piece of music, due to their different life experiences, they cannot associate or imagine the music content is exactly the same. Xu et al. believe that the esthetic education function of music is mainly to enrich the emotional experience of esthetic subjects, so as to improve the ability of music appreciation and performance. In the teaching of music appreciation, it is necessary to arouse the enthusiasm of the appreciator, that is, the esthetic subject, so that he can actively, actively and consciously participate in the process of psychological experience. Junior high school students are exposed to a lot of music and have formed certain esthetic standards. Unlike primary school students, they are not easy to accept the esthetic content arranged by teachers (Xu et al., 2021). Moreno, M. et al. pointed out that in music appreciation activities, esthetic subjects always judge esthetic objects with certain esthetic standards. For music works that do not meet their own esthetic standards, they often fail to attract their esthetic attention, resulting in the inability to complete the psychological process of music appreciation (Moreno and Woodruff, 2022). Due to the differences in esthetic personality between junior high school students and teachers, teachers do not pay good attention to the esthetic psychology of teenagers and lack of understanding of the needs of teenagers. As a result, junior high school music appreciation materials are not comprehensive enough, and it is often difficult to arouse the interest of junior high school students in music appreciation class.

An experimental study of music psychology in regulating students' psychological function and promoting teaching effect

Experimental hypothesis and design

> *Hypothesis 1*: In terms of music type, there are differences between soundscape music stimulation and non-soundscape music stimulation in the influence of skin electricity, skin temperature, heart rate and EMG of subjects.
>
> *Hypothesis 2*: In terms of music listening methods, abdominal breathing and chest breathing have different effects on skin electricity, skin temperature, heart rate and electromyography.
>
> *Hypothesis 3*: When abdominal breathing is used in music listening, the effect of listening to soundscape music is more significant than that of non-soundscape music in inducing positive emotions.
>
> *Hypothesis 4*: When listening to soundscape music stimuli, abdominal breathing is more effective than chest breathing in inducing positive emotions.

This experiment was a multi-factor completely randomized experimental design (2 × 2 factor experimental design/two-factor experiment), and each subject was treated with four experimental conditions. To avoid the order effect, a 4 × 4 standard Latin square design was adopted (Jannusch et al., 2021). The independent variables of this experiment were two levels of music selection (soundscape music and pure non-soundscape music) and two levels of music listening style (abdominal breathing and chest breathing; see Table 1).

Respiration is the process of gas exchange between the human body and the outside world, and respiration rate represents the number of individual breaths in a unit of time, the unit is times/min. In this study, "breathing" was determined as an independent variable, and the effects of two levels of breathing, "chest breathing" and "abdominal breathing," on the physiological indicators of the autonomic nervous system of each subject were investigated (Hashemi et al., 2022). When the emotional state is stressed, the respiratory rate increases. On the contrary, it decreases, and about 70 times/min is the respiratory rate of healthy subjects.

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TABLE 1 Variable selection design table.

		Listening style (B)		
	Soundscape music (a1)	Abdominal breathing (b1)	Thoracic breathing (b2)	
Music choice (A)		O1:b1a1	O2: b2a1	Oa1
	Non-soundscape music(a2)	O3:B1a2	O4: B2a2	Oa2
		Ob1	Ob2	

The subjects were college students. A total of 32 subjects, including 12 males and 20 females, aged 18–25 years with an average age of 22.5 years (SD = 1.25 years) were recruited by means of voluntary registration through notices and advertisements. All subjects had no cardiovascular or respiratory diseases, and did not do strenuous exercise 2 h before the test. The scale used in this study is the positive and negative Emotion Scale (Kirk et al., 2022). He revision of PANAS-R scale was based on the theory of affective loop model, and the items of the scale were collected and selected, and a series of experimental tests were carried out. Exploratory factor analysis was used to screen the emotional word items of the scale, and then factor analysis was carried out. The KMO value was 0.781, and the Chi-square value of Bartletts spherical test was 2645.024 ($p < 0.001$). By calculating the CR value, the discrimination degree of each item was tested. The results showed that the CR value of all emotional word items was significant at the level of $p < 0.001$ (see Table 2), indicating that the discrimination degree of items was good.

The experimental process

Preparation: Breathing exercises and pre-test of PANAS-R self-report scale

The behavior laboratory in which this experiment was conducted was quiet and tidy. In the preparation stage of the experiment, indoor temperature and light should be adjusted. Close the blackout curtains and adjust the lighting rheostat to minimize the lighting brightness of the room and create a safe and comfortable music listening atmosphere for the subjects. The indoor temperature is kept at 22°C ± 2°C by air conditioning (Fraenkel, 2020). To avoid interference with music listening and experimental data signals, participants were required to remove necklaces, rings, bracelets, and mobile phones on silent or airplane mode. The subjects sat on the sofa and adjusted to a comfortable posture. The subjects wore the experimental equipment for the subjects. Before the start of the experiment, the subjects read the "Subjects Need to Know," which included the procedure, abdominal breathing methods and precautions. The experimenter instructed the subjects to perform abdominal breathing exercises.

TABLE 2 Factor loads, commonality and CR values of PANAS-R items.

Project	Load factor PA	NA	Common degrees	CR value
Active	0.861		0.740	7.602
Enthusiastic	0.859		0.762	13.361
Happy	0.809		0.770	12.752
Elated	0.798		0.669	13.866
Excitedly	0.773		0.599	16.102
Proud	0.763		0.602	12.173
Delighted	0.739		0.565	15.539
Energetic	0.712		0.512	12.827
Grateful	0.567		0.388	14.723
Ashamed		0.750	0.563	8.475
Sad		0.748	0.587	7.386
Afraid		0.745	0.554	10.635
Nervous		0.712	0.509	7.250
Terrified		0.683	0.468	10.420
Guilty		0.572	0.331	8.978
Irritable		0.554	0.335	7.687
Jittery		0.529	0.386	8.283
Irritated		0.461	0.389	6.646

PA, positive emotion; NA, negative emotion; CR value is significant at $P < 0.001$ level. The revised PANAS-R scale included nine words for describing positive emotions and nine words for describing negative emotions, and participants were required to describe the experience of emotional words on a 5-point Likert scale. The internal consistency coefficients were 0.79 and 0.80, respectively.

Implementation: Baseline and experimental measurements

The data of this experiment were measured one by one by the subjects, and the experimental program was compiled by E-PRIME2.0 software. The procedure consists of three components: baseline data collection, positive emotion induction and PANAS-R scale filling. The duration of each stage was 127 s, and the scale was filled out after each item of positive emotion was evoked. The experimental conditions for each subject were randomly presented as Latin squares. The specific experimental process is shown in Table 3.

Experimental period

In the positive emotion induction stage, the subjects would listen to four musical stimuli in turn, and four beats of the same pitch would appear at the beginning and the end of the music to remind the beginning and the end of the music (Dunbar et al., 2022).

Results and analysis

Self-rating scale report results and analysis

The results of multivariate analysis of variance in Table 4 show that music type and breathing style have significant effects on emotion induction, indicating that corresponding emotions are successfully evoked. The differences between positive emotion and negative emotion induced by different listening methods

TABLE 3 Experimental process arrangement.

Conditions	Process							
	127 s	127 s	127 s	127 s	127 s	127 s	127 s	127 s
1	Baseline 1	Soundscape music	Baseline 2	Non-soundscape music	Baseline 3	Soundscape music	Baseline 4	Non-soundscape music
2	Baseline 1	Soundscape music	Baseline 2	Non-soundscape music	Baseline 3	Non-soundscape music	Baseline 4	Soundscape music
3	Baseline 1	Non-soundscape music	Baseline 2	Soundscape music	Baseline 3	Soundscape music	Baseline 4	Non-soundscape music
4	Baseline 1	Non-soundscape music	Baseline 2	Soundscape music	Baseline 3	Non-soundscape music	Baseline 4	Soundscape music

TABLE 4 Self-rating scale reports the results of ANOVA.

Emotional type	The mean square	The *F*-value	Sig.
Active	44.681	35.006***	0.000
Enthusiastic	38.234	25.392***	0.011
Happy	39.011	29.865**	0.022
Elated	42.568	40.335**	0.031
Excitedly	39.082	22.484*	0.041
Proud	31.220	32.609***	0.122
Delighted	30.992	26.804*	0.023
Energetic	41.221	32.469***	0.015
Grateful	30.145	22.557*	0.063
Ashamed	0.841	6.358*	0.108
Sad	0.216	3.781*	0.197
Afraid	1.292	5.880**	0.098
Nervous	1.414	4.589**	0.235
Terrified	0.291	10.220*	0.645
Guilty	1.541	5.667*	0.891
Irritable	2.385	3.475**	0.100
Jittery	3.013	0.691*	0.092
Irritated	2.991	0.407*	0.450

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

TABLE 5 Difference of positive emotion and negative emotion before and after test under different conditions.

Conditions	Positive emotions ($n = 32$)			Negative emotions ($n = 32$)		
	Pre-test (M ± SD)	Posttest (M ± SD)	Sig.	Pre-test (M ± SD)	Posttest (M ± SD)	Sig.
I	15.89 ± 4.22	23.91 ± 6.14	5.62***	14.97 ± 3.49	12.95 ± 2.94	−3.54**
II	16.07 ± 5.09	21.64 ± 7.45	4.99***	14.33 ± 4.58	13.27 ± 3.96	−3.86**
III	16.79 ± 4.22	21.01 ± 6.14	5.62***	15.97 ± 3.49	12.95 ± 2.94	−3.54**
IV	14.97 ± 5.09	15.02 ± 7.45	4.99***	15.33 ± 4.58	15.57 ± 3.96	−3.86**

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

(abdominal breathing and chest breathing) and different music types (soundscape music and non-soundscape music) were compared, and the difference test was shown in Table 5. Condition I represents soundscape music × abdominal breathing, condition II represents non-soundscape music × abdominal breathing, condition III represents soundscape music × chest breathing, and condition IV represents non-soundscape music × chest breathing.

As can be seen from the above table, in the four experimental conditions of I, II, III, and IV, the scores of positive emotion before and after the test were improved to varying degrees, while the scores of negative emotion before and after the test were decreased to varying degrees, and the difference between the two was significant ($p < 0.01$, $p < 0.001$; Guo and Xiao, 2021). Therefore, the results of the difference test indicate that the manipulation of the four experimental conditions is effective.

In the process of inducing positive emotions, the values of positive emotions before and after the four experimental conditions have been significantly increased. As can be seen from

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Figure 1, condition I (soundscape music × abdominal breathing) increased the most (pretest =15.89 ± 4.22, posttest =23.91 ± 6.14), followed by condition II (non-soundscape music × abdominal breathing; pretest =16.07 ± 5.09, posttest =13.27 ± 3.96), and condition III again. Soundscape music × chest breathing (pre-test =16.79 ± 4.22, posttest =12.95 ± 2.94), and condition IV, non-soundscape music X chest breathing (pre-test =14.97 ± 5.09, posttest =15.02 ± 7.45) had the smallest increase (Ajmani and Kumar, 2022).

In the process of inducing negative emotions, the values of negative emotions before and after the four experimental conditions all decreased significantly and to different degrees. As can be seen from Figure 2, condition III (soundscape music + chest breathing) had the largest reduction (pretest =15.97 ± 3.49, posttest =21.01 ± 6.14), and condition I (soundscape music + abdominal breathing) had the second largest reduction (pretest =14.97 ± 3.49, posttest =12.95 ± 2.94). Condition II, non-soundscape music + abdominal breathing (pretest =14.33 ± 4.58, posttest =21.64 ± 7.45), and condition IV, non-soundscape music + chest breathing (pretest =15.33 ± 4.58, posttest =15.57 ± 3.96) had the smallest reduction (Garg et al., 2022).

Test and analysis of significant differences in physiological indicators

Table 6 shows the descriptive statistical results of skin temperature (STS), galvanic skin (SCR), heart rate (BVP) and electromyography (EMG) of the dependent variables of this study, including mean (M) and standard deviation (SD).

Skin temperature (STS) index difference test analysis

According to the results of ANOVA (Table 7), in terms of STS index, there was a significant difference in music condition between the two experimental conditions ($p < 0.005^{***}$), while there was no significant difference in breath between the two experimental conditions ($p > 0.05$). There was no significant interaction between music type and breathing mode ($p > 0.05$; Guimares, 2021).

The difference test and analysis of electric skin (SCR) index

According to Table 8, in terms of SCR index, the intervention effect of soundscape music was better than that of non-soundscape music under the two conditions ($p < 0.005^{***}$). There were

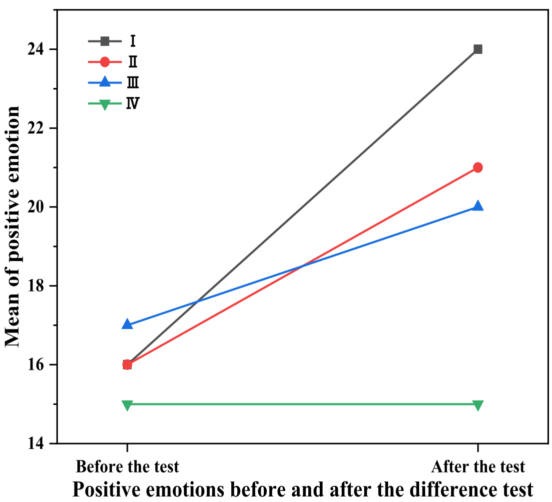

FIGURE 1
Difference of positive emotion before and after test under different conditions.

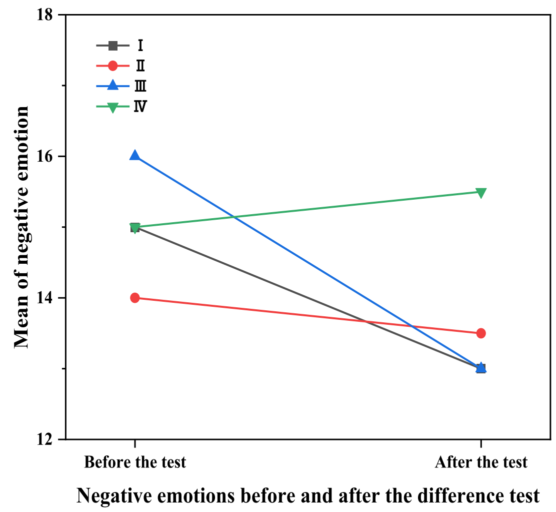

FIGURE 2
The difference of negative emotions measured before and after different conditions.

TABLE 6 Descriptive statistical results of physiological indicators.

	Soundscape music ($n = 32$)				Non-soundscape music ($n = 32$)			
	Abdominal breathing		Thoracic breathing		Abdominal breathing		Thoracic breathing	
	M	SD	M	SD	M	SD	M	SD
STS	1.9531	1.2468	1.66647	0.9332	0.113888	1.71809	−0.009783	0.75689
SCR	−7.02722	2.061785	−5.014174	2.0639674	−3.396138	2.0639679	−1.574833	1.529027
BVP	−8.056602	1.3467893	−3.772575	1.4263564	−2.58998	1.5641307	−0.0737	1.093805
EMG	−10.22204	3.0723889	−4.759364	3.6875054	−4.879805	2.2548016	0.580964	2.5944441

TABLE 7 Results of within-subject effect test of skin temperature (STS) index.

The source	Type III sum of squares	df	The mean square	F	Sig.	Partial Eta square
Music	98.868	1	98.868	75.667	0.000	0.709
Error (music)	40.501	31	1.300			
breath	1.344	1	1.346	0.723	0.402	0.024
Error (breath)	57.653	31	1.860			
Music * breath	0.214	1	0.211	0.204	0.655	0.007
Error (music * breath)	32.412	31	1.045			

TABLE 8 Results of intra subject effect test of electroskin (SCR) index.

Test for intra-subject contrast in SCR

The source	Type III sum of squares	df	The mean square	F	Sig.	Partial Eta square
Music	399.931	1	399.935	77.941	0	0.714
Error (music)	159.054	31	5.132			
Breath	117.627	1	117.622	21.571	0	0.410
Error (breath)	169.045	31	5.453			
Music * breath	0.293	1	0.294	0.095	0.758	0.003
Error (music * breath)	95.232	31	3.075			

TABLE 9 Results of within-subject effect test of heart rate (BVP) index.

Test for intra-subject contrast of BVP

The source	Type III sum of squares	df	The mean square	F	sig.
Music	672.063	1	672.068	450.21	0.000
Error (music)	46.271	31	1.492		
Breath	369.946	1	369.945	214.20	0.000
Error (breath)	53.541	31	1.727		
Music * breath	25.001	1	25.002	11.023	0.002
Error (music * breath)	70.296	31	2.268		

TABLE 10 Test results of paired samples of heart rate (BVP) index.

Paired sample *T*-test		M	sD	Standard error of the mean	95% confidence interval		t	df	Sig.
					The lower limit	Upper limit			
1	SM AB vs. TB	−4.2840353	2.1212586	3,749,892	−5.0488304	−3.5192398	−11.425	31	0
2	NSM AB vs. TB	−2.5162085	1.8680951	3,302,358	−3.1897285	−1.8426887	−7.619	31	0
3	AB SM vs. NSM	−5.4666992	1.9948600	3,526,430	−6.1859191	−4.7474792	−15.502	31	0
4	TB SM vs. NSM	−3.6988725	1.8817799	3,326,549	−4.3773263	−3.0204184	−11.119	31	0

significant differences between abdominal breathing and thoracic breathing under the two music conditions ($p < 0.001$***), but no significant interaction ($p > 0.05$).

Heart rate (BVP) index difference test analysis

According to the descriptive statistical results (Tables 9, 10), there was a significant difference between the two experimental conditions of music type and breathing mode ($p < 0.005$***), and the main effect was significant ($p < 0.005$***) in BVP index (Raj et al., 2021). Further paired sample *t*-test showed that there was a significant difference between chest breathing and abdominal breathing under soundscape music condition ($p < 0.005$***). The difference between chest breathing and abdominal breathing was significant ($p < 0.005$***) under the condition of non-soundscape music. In chest breathing condition, there was a significant difference between soundscape music and non-soundscape music ($p < 0.005$***). In abdominal breathing condition, the difference between soundscape music and non-soundscape music was significant ($p < 0.005$***).

TABLE 11 Results of intra-subject effect test of electromyography (EMG) index.

Test for intra-subject contrast of BVP

The source	III type of sum of squares	df	The mean square	F	Sig.
Music	912.932	1	912.931	94.566	0.000***
Error (music)	299.275	31	9.653		
Breath	954.571	1	954.58	109.830	0.000***
Error (breath)	269.438	31	8.692		
Music * breath	2.87E-05	1	2.87E-05	0.000	0.998
Error (music * breath)	181.984	31	5.871		

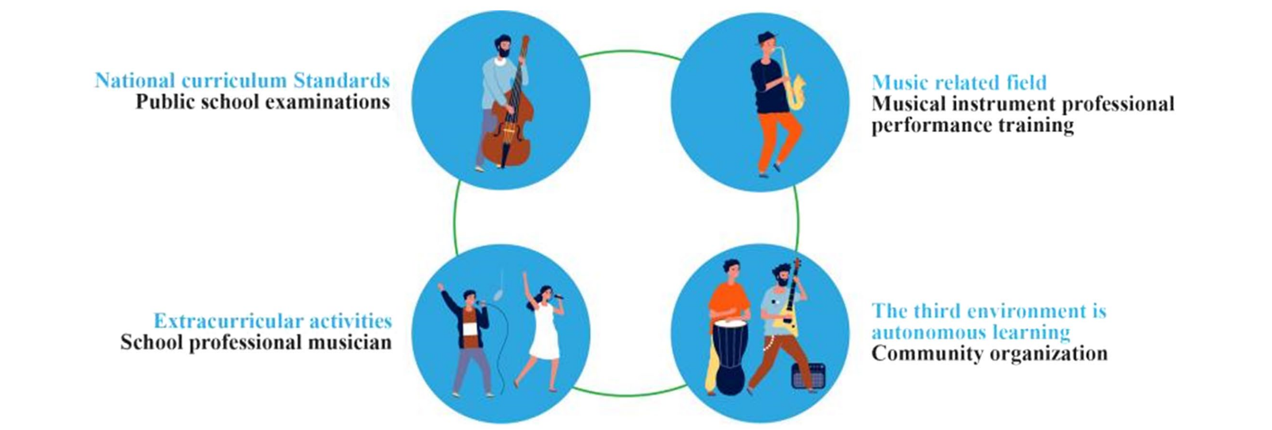

FIGURE 3
Hargreaves' model of music education resources.

According to the descriptive statistical results of EMG indexes (Table 11), there was a significant difference between the two intervention conditions of soundscape music and non-soundscape music in EMG index ($p < 0.000$***), but no significant interaction ($p > 0.05$). The intervention effect of SM was better than that of NSM in AB and TB respiratory conditions ($p < 0.000$***). In SM and NSM, there was a significant difference between abdominal breathing and chest breathing ($p < 0.000$***), and the effect of abdominal breathing was better than that of chest breathing ($p < 0.000$***).

The path and method of music psychology in music teaching

Improve the teaching effect by regulating function model of music psychological education

The music education resource model (Figure 3) is built on the basis of students' age development and ability level. The content reflects the potential scope and target of music education inside and outside the school, that is, all the resources that music education can provide for students. The latent function model of music education (Figure 4) shows the influence of primary music education on individual students and the relationship among various dimensions (Chaturvedi et al., 2021).

The music education resource model is built on three polar dimensions. First, the vertical dimension of the model represents a series of formal resources for the institutionalized training of music education and a variety of other informal resources; Secondly, the horizontal dimension separates the resources inside and outside the school of music education. The resources inside the school represent the prescribed resources provided by the school, while the resources outside the school represent the resources that students can choose independently. Third, in the "professional-general" dimension, it includes professional resources and general resources in music education (Das and Satpathy, 2021).

The realization of the music education psychological adjustment function model (see Figure 5) includes two dimensions: measurement method and influencing factors. The measurement methods of music-induced emotions include self-report scale measurement, physiological index measurement and behavioral intervention measurement. The measurement results are reflected in the three influencing factors of music-induced emotions, which are individual factors, music ontological characteristics and breathing mode characteristics.

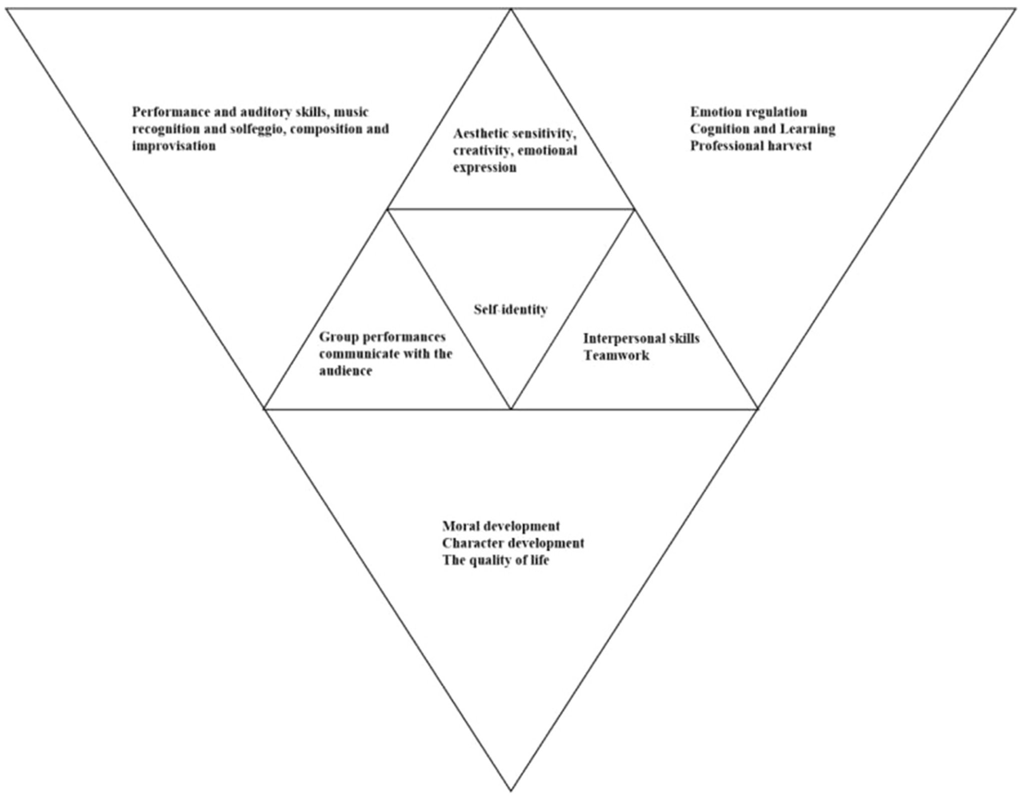

FIGURE 4
Hargreaves' potential functional model of music education.

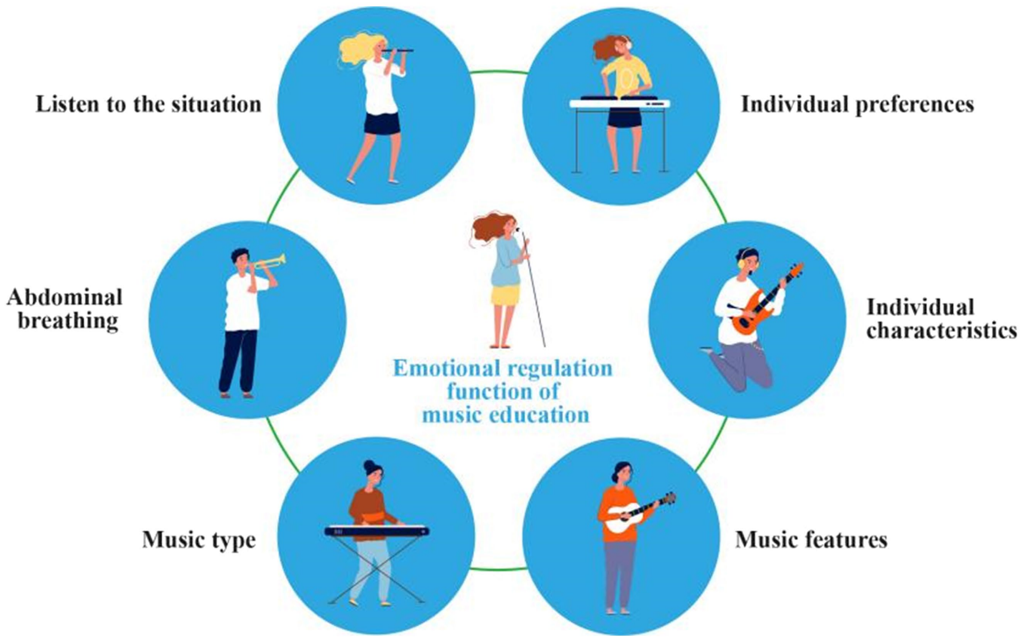

FIGURE 5
Psychological adjustment function model of music education.

Strengthen the understanding and cognition of music works appreciation practice

Inspire the initiative of students' esthetic thinking

Some teachers in the music appreciation class always in a commanding attitude, stiff and rigid to teach students what the music is the background of The Times, what is the expression of thoughts and feelings, how to understand the music and so on. Such rational analysis and blunt loss is often very easy to make students lose interest, resulting in the generation of students disgust and weariness. Therefore, in the process of teaching, the teacher and the educatees should and are allowed to have certain differences in the emotional understanding of music works, which is the law of human understanding of objective things. If you insist on consistency, it is tantamount to swallowing dates in a circle and mass production (Huang and Yang, 2022). Therefore, students should be appropriately encouraged to show their individuality, encourage students to expand their imagination with music, enter the rich emotional atmosphere of music works, and enhance the inside information. In music education, it is of special significance to pay attention to the development of students' personality. Music is an experiential subject, only the active participation and independent experience of students can feel the happiness of learning and accumulate learning results. In the teaching of music appreciation, teachers guide students to participate actively, give full play to their main role, mobilize the enthusiasm and initiative of students' active participation in learning, so that students can really get audio-visual, singing, thinking ability and imagination exercise in music appreciation, and deepen their own music perception and esthetic power in emotional experience. In addition, because of the strong practicality of music art, it is closely related to other forms of practical activities. In appreciation class, attention should be paid to students' participation and practice, to students' feelings, experience, understanding and expression of music emotion, and to students' feelings, experience, performance and appreciation of music beauty, so that students can understand music through profound experience rather than preaching (Davies et al., 2021). We should appreciate the teaching, understand the expressive force of music works, experience the rich spiritual feelings that music brings us, cultivate students to understand the ability of human beings to understand the world with music mode. The teaching effect of music appreciation is directly related to the effect of music education and whether our education can achieve those positive social effects we want.

Protect the freedom of students' esthetic imagination

It is normal for people to have different understandings of music. It is the non-semantic nature and uncertainty of music that provide a wide space for people's different imagination and association, laying the foundation for creative musical thinking activities. Many people, including music teachers, agree that music education should cultivate students' imagination in theory, but there is often no space for students' imagination to play in concrete teaching practice. There are many reasons for this situation, but the fundamental reason is that students cannot be treated correctly, treated as learning subjects and given equal status in music learning (Bakerjian et al., 2020). As a matter of fact, due to the open growing environment and diversified ways of receiving education, today's students may understand all kinds of new things and new knowledge more quickly and widely than adults, so that they have more information mastery and understanding of new things than adults. They have no inherent views, and there is often no framework for music learning and understanding, and no discipline rules and regulations. However, with the advantages of sensitivity to new culture, recognition and acceptance ability, they show a natural nature and vitality of learning. Some students said their feelings about music learning like this, "I think the school music class is boring, I feel like learning. There are steps, there is analysis, there is what there is a formula for what this music is like, right (Zhao et al., 2019). Why is it not what I think, and why is it wrong? "Some students think that" for music, I think I only need my own feeling, which is not clear, and maybe it will bump into the feeling in my heart inadvertently. To achieve this feeling, I cannot restrict my "freedom," freedom from external interference. If everyone had to understand music by "rules," then "music would not have a feel." It can be seen that students' "rebellion" against music education in the traditional sense is not a whim, but a positive thinking based on independent learning, full of critical spirit, and there is no lack of insight.

Cultivate students' music esthetic ability by creating teaching situation

Create situations with instrumental props to stimulate students' interest

In the music class, the use of small and convenient instruments to assist teaching is conducive to students' immersive experience of music. The necessary piano in the traditional music classroom can no longer satisfy students' curiosity about the timbre of various Musical Instruments. The use of small instruments in teaching can stimulate students' interest in learning. When using small instruments, students can easily immerse themselves in the real music situation and feel the charm of Musical Instruments (Ebrahimi et al., 2022). The sound of some small instruments is clear and pleasant, and it is easy to express the happy mood of music works. At the beginning of the class, students are first exposed to the small instruments that can express the emotion of the works, so that they can experience the emotional content of the textbook in advance by using the situation created by physical instruments, and further enhance their esthetic experience.

Use things around you to create a situation, stimulate learning enthusiasm

Music comes from life, and students' life is full of music. When teaching, if students can choose music that is familiar with and related to teaching content as an intermediary, they will get twice the result with half the effort. When introducing the content, we should also pay attention to the methods and methods, and when selecting the content, we should try our best to select the content that students feel close to, so as to create a teaching situation close to the content of the work and students' preferences, and stimulate strong enthusiasm for learning.

Teaching stories creates situations and arouses students' interest

An interesting story is easy to arouse students' interest. When preparing lessons, the author will create story situations related to the content of music textbooks in advance to make students intoxicated as much as possible, and then transfer their interest to the music works to be learned. The story should not be long, but it should be relevant to the book.

Set up questions to arouse students' enthusiasm

Junior high school students have the psychological characteristics of curiosity and competitive, teachers can use this psychological characteristics to set up suspense, guessing links. When teaching, the author also asks students to listen to music segments and release pictures of Musical Instruments to ask what kind of Musical Instruments are played (Sharma and Kumar, 2019). This fully mobilized the competitive heart of students, and they have been scrambling to answer, actively participate in the music esthetic activities. Students also gain a better understanding of the timbre of different Musical Instruments, laying a solid foundation for future music study.

Set up game links to create situations and activate the teaching atmosphere

Setting up interesting games in music teaching can greatly ignite students' interest in learning. In the teaching practice, the author also set up a lyric filling game combined with the teaching content. These interesting games greatly stimulated the enthusiasm of students to learn this course.

Explore the musical emotional elements in music works

Analysis of music elements

Music classroom takes music esthetic education as the core, and teachers' teaching goal is to improve students' esthetic appreciation level as the main goal. Only by letting students understand the specific content of many musical elements of music and how different forms of expression of the elements reflect the emotion of the work can they experience the beauty of music to the greatest extent. The movement form of music is similar to the movement state of human psychology, so music can express people's mental state and emotional thoughts in an abstract way. In order to cultivate students' esthetic ability by listening to and appreciating music, it is not enough to allow them to listen to and appreciate the psychological fluctuations. It is necessary to guide them to master the internal association between music sound and its object of expression, and understand how the specific operation of music expression affects the changes in the emotional content of the object of expression. Therefore, only staying in the physiological perception cannot meet the students' esthetic needs for music. It is necessary to conduct systematic study to master the basic elements of music and the importance of music elements to the expression of content. The enhancement of students' music esthetic experience and the cultivation of esthetic ability need to start with the basic elements of music ontology in works.

Understand the cultural background

Music belongs to the category of human culture. While teaching music knowledge and skills in music classroom, the cultural and historical background related to music should not be underestimated. Teachers need to expand the cultural connotation as much as possible, so that students can actively obtain the cultural content contained in the works in the process of music esthetics, further cultivate artistic sentiment, and improve the overall quality (Hekmati et al., 2021). Understanding the historical background of music works is to enhance the horizontal connection between music lessons and other disciplines. It is the main way to improve the esthetic understanding of music. It can help students deepen their perception of music through the understanding of history and culture, and understand the characteristics of music styles in different times. This is the most common way to teach a musical composition and the life of a musician. Through the teacher's teaching, students can accept the historical background, humanistic influence and the composer's life experience when the work was created. It is easy for students to understand the mood of the composer when he created the work, which is helpful for students to understand and analyze the emotion of the work.

Conclusion

This research focuses on the realization of the psychological regulation function of music education, which is the core issue, and takes music education activities to induce positive emotions as the realization approach. The selection and design of research methods strictly follow the norms of mixed method research. First of all, the main conclusions of this study are summarized as a whole: this study defines relevant concepts on the basis of searching, sorting, analyzing and commenting on "music education function research" and "music evoked emotion research." Then mixed methods are used to carry out the main research, among which the experimental research on the psychological regulation function of music education belongs to the quantitative research stage of mixed methods, and the qualitative intervention research on the psychological regulation function of music education belongs to the qualitative research stage. The analysis of the factors influencing the realization of the psychological adjustment function of music education based on the two methods is an integrative study in the mixed method. The hybrid method provides the methodological support for the main part of the whole research, and also provides the theoretical basis for the research findings. The research findings include the model construction of the psychological regulation function of music education and the prospect of the educational value of this model. The mechanism of music education activities to induce positive emotions is the sublimation of the theoretical basis of music education psychological regulation function. Based on the literature review of "music education function" and "music evoked emotion," the mechanism of music education activities to induce positive emotion originates from the further interpretation of the mechanism of music evoked emotion. Specifically, music education activities induce positive emotion mechanism is mainly manifested in the relationship between music and emotion of four models (in theory), including music clues consistency model, music expectation model, music emotion of synergy theory and multiple mechanism model, in which multiple mechanism model, including seven kinds of independent existence mechanism, they are brainstem reflex, rhythmic synchronization, evaluative reflex, emotional infection, visual imagination, episodic memory and musical anticipation.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

NJ contributed to the writing of the manuscript and data analysis. CY supervised the work and designed the study. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Emotion recognition and achievement prediction for foreign language learners under the background of network teaching

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At present, there are so many learners in online classroom that teachers cannot master the learning situation of each student comprehensively and in real time. Therefore, this paper first constructs a multimodal emotion recognition (ER) model based on CNN-BiGRU. Through the feature extraction of video and voice information, combined with temporal attention mechanism, the attention distribution of each modal information at different times is calculated in real time. In addition, based on the recognition of learners' emotions, a prediction model of learners' achievement based on emotional state assessment is proposed. C4.5 algorithm is used to predict students' academic achievement in the multi-polarized emotional state, and the relationship between confusion and academic achievement is further explored. The experimental results show that the proposed multi-scale self-attention layer and multi-modal fusion layer can improve the achievement of ER task; moreover, there is a strong correlation between students' confusion and foreign language achievement. Finally, the model can accurately and continuously observe students' learning emotion and state, which provides a new idea for the reform of education modernization.

KEYWORDS

emotion recognition, network teaching, achievement prediction, CNN-BiGRU, multimodal fusion

Introduction

The new generation of intelligent teaching system integrates artificial intelligence, learning analysis and personalized recommendation technology, which can not only promote the problem-solving ability of learners in autonomous environment, but also help to regulate learning emotion and enhance learning motivation. Learning emotion is an important part of learner modeling. More and more researchers pay attention to the effective detection of learning emotion and targeted intervention and guidance of negative learning emotion to improve teaching effect and teaching quality. Research shows that solving the confusion in learning in time can change the negative learning emotion into positive emotion, which is helpful to improve the learning achievement (Liu et al., 2018). However, the implicit learning confusion is strong, how to effectively detect it has become an important issue for current researchers. With the development of affective computing technology, effective detection and discovery of learning emotions will become a reality.

Among them, learners' confusion in language learning is particularly prominent, which refers to the negative anxiety reaction produced by language learners in specific situations. Horwitz et al. (1986) believed that if all normal people have innate language acquisition mechanism, then acquired trigger input is very important, and the process of obtaining this input is closely related to personal learning motivation, anxiety, personality type, attitude, and other emotional factors. Emotional development includes the attention to students' emotions and moods and the different effects of emotional changes on their studies. Emotion is a complex and transient internal reaction activated by external environment or internal stimulation (Gross, 2015). Positive emotions can bring positive and highly active subjective feelings to individuals, while negative emotions tend to bring negative and low active subjective feelings to individuals.

Achievement prediction is one of the most important research issues in the field of educational data mining, which is a hot issue that many researchers at home and abroad pay attention to. Through the prediction of student achievement, it can provide timely warning information for educators. Kriegel et al. (2007) pointed out that the application prospect of machine learning method in the field of education is very wide, and the data modeling of learning achievement can be carried out by using this technology to realize the prediction of learning achievement (Kriegel et al., 2007). However, the current prediction modeling of academic achievement mainly focuses on the construction of the achievement prediction model, the analysis of the prediction model and the evaluation of the prediction model. In fact, emotional state has a great impact on learners' academic achievement, such as the widespread confusion in the learning process. If the learners are in a state of confusion for a long time, they will have a sense of frustration, which is not conducive to the effective learning of knowledge. Persistent confusion will lead to the decline of learners' interest in learning and the lack of learning motivation, which will affect their academic achievement. Especially for online learning, the more confused the learners are about the course content, the lower the retention rate of the course, and thus the completion rate of the course is affected (Baker et al., 2012; Vail et al., 2016).

The purpose of this paper is to apply the ER of foreign language learners in the process of language learning to the construction of online learning environment, so as to improve the learner model, provide technical support for the realization of emotional interaction, and mine learning behavior. Therefore, this paper constructs a multi-modal ER model based on CNN-BiGRU, and puts forward a achievement prediction model based on emotional state assessment, so as to further explore the correlation between confused emotion and academic achievement.

Related works

Confusion in foreign language learning

Linguists have studied language learning anxiety from different perspectives. For example, Horwitz et al. (1986) pointed out that foreign language anxiety is related to language learning in classroom, and is generated in the process of language learning. It is a unique and complex self-awareness, belief, emotion and behavior in language learning, including communication fear, test anxiety and fear of negative evaluation; Rajitha and Alamelu (2020) pointed out that language anxiety is the main factor affecting the affective factors of second language learners, and the factors causing language anxiety include various types of examination results, oral narration, written expression, self-confidence and self-esteem in the process of language learning (Rajitha and Alamelu, 2020); The interdisciplinary theories and methods introduced by Dewaele (2005) can promote the gradual development of emotion research in second language acquisition; Bielak and Mystkowska-Wiertelak (2020) used the situational experiment method to study the use of emotion regulation strategies in English learning of Polish college students.

The research mainly focuses on the influence of positive or negative emotions on English learning and introduces the appropriate adjustment measures. Han and Xu (2020) adopted emotion-oriented, assessment-oriented and situational-oriented adjustment strategies for different students' emotions, and studied the emotional changes of second language learners in the writing process and the adjustment strategy scheme. Li (2020) pointed out that the study of language learners' emotion in learning is an essential teaching practice in the study of foreign language learning psychology. Wang (2014) carried out cognitive reconstruction on 32 undergraduate students under the guidance of rational emotional behavior therapy with the help of psychological outpatient technology for the treatment of general social anxiety. The results show that rational emotional behavior therapy is helpful to reduce learners' oral English anxiety.

ER of learners

Different researchers pay attention to different models of learning emotion, and the focus is also different. Wu et al. (2008) applied learning emotion to distance learning system, and proposed a new learning emotion modeling method based on OCC emotion model and two-dimensional emotion model, to realize the interaction between cognition and emotion in Distance Teaching. In order to solve the shortcomings of traditional learning model (Wang and Gong, 2011) introduced learning style and learning emotion and other factors to construct a perfect

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e-learning student model to solve the emotional lack of online teaching system, and improve the intelligence and personalized role of the system. Shi et al. (2007) designed experiments to collect biological signals such as skin conductivity, blood pressure and brain waves to construct a circular emotion model. They found that participation and confusion are the two most frequent emotions in e-learning learning activities, which improve the learning effect in e-learning.

The emotion modeling of learners needs machine learning model to model the multimodal data such as picture physiology and text collected by researchers, so as to realize the recognition and discovery of learning emotion of complex data. Kapoor et al. (2007) established an emotion model based on the collected facial expression images and heart rate data, and realized the detection of learning emotion based on Dynamic Bayesian network. With the improvement of data processing technology, researchers can obtain better ER results by processing and analyzing multimodal data, and improve the accuracy of Emotion Modeling (Ling et al., 2021). In addition, the data of learning emotion come from various learning scenes, including facial expression pictures, physiological data and text data. Ekman and Lavoué (2017) developed a set of emotion coding system based on facial action features. The system can identify six emotions, including happiness and surprise, by encoding facial features according to the achievement differences of different faces. This study provides important inspiration for Learning Emotion Modeling with facial expression pictures (Ekman and Lavoué, 2017). Jin et al. (2016) constructed a learning emotion measurement model, including user data module, analysis and diagnosis module, emotion integration module and feedback module, aiming to solve the problem of lack of emotional communication in online learning.

The emerging deep learning methods in recent years have well made up for the defects of the two methods based on machine learning and sentiment dictionary. Yin and Schütze (2016) used multi-channel convolutional neural networks of different sizes for sentence classification. Chen et al. (2018) proposed a multi-channel convolutional neural network model, which used multiple convolutional neural networks to extract the multi-faceted features of sentences, and achieved good results in the sentiment analysis task of Chinese microblog. However, CNN-based sentiment classification has the problem that it cannot consider the semantic information of sentence context. Alayba et al. (2018) proposed a combination of CNN and LSTM model for Arabic sentiment analysis and achieved good classification results. Zhang et al. (2018) used the Convolution-GRU model to discriminate the sentiment polarity of Twitter hate comment text. Yuan et al. (2019) proposed a sentiment analysis model based on multi-channel convolution and bidirectional GRU network, and introduced an attention mechanism on BiGRU network to automatically pay attention to features with strong influence on sentiment polarity. In view of the excellent performance of the neural network model integrating attention mechanism, this paper also introduces attention mechanism in the task of text sentiment orientation analysis, so that the network model can pay more attention to the words that contribute a lot to the text sentiment polarity.

Prediction of learners' achievement

In this paper, we propose a learning model based on Bayesian neural network and Bayesian regression model. Yuan and Zhu (2021) based on the data of various factors of students' English learning, the researchers used random forest algorithm to model scores and predict the passing rate of CET-4. Wu (2017) collected data on Online Learners' demographic information, autonomous learning behavior and writing learning behavior, and constructed multiple learning achievement prediction models using decision tree, support vector machine, neural network, Bayesian network and other machine learning algorithms. Such models can provide advance organizers and strengthen learning discussion supervision to promote effective teaching strategies (Wu, 2017). Sun et al. (2016) used k-means algorithm to cluster students' degree English scores, determined a more specific score distribution interval, and used C5.0 classification algorithm of decision tree to carry out achievement prediction modeling and analysis, so as to realize the prediction model of students' degree application achievement. Through this model, the coping strategies between undergraduate students' English learning level and adult English test scores were proposed, which helps to improve the learning effect (Sun et al., 2016).

Although studies have shown that there is a strong correlation between learners' emotions and academic achievement, few scholars have focused on exploring the internal relationship between them. Research made a prediction based on learning behavior, while the prediction based on learning emotion is still less. Therefore, the purpose of this study is to explore the internal relationship between learning confusion and academic achievement, so as to uncover the quantitative model relationship between confusion and correct test questions, and to establish relevant prediction models.

Multimodal ER based on CNN-BIGRU

Overall structure

In this paper, a tensor fusion method based on low rank decomposition is introduced. This method can focus on the information inside and between modes, and aggregate the interaction between modes, so that the features of facial expression and pulse signal are more complementary. The framework of MA-TFNet is shown in Figure 1.

Firstly, the high-dimensional features of facial expressions and speech signals are extracted, and the high-dimensional features are input into Bi-GRU network for training. Then, using the output of Bi-GRU network of two modes, the attention

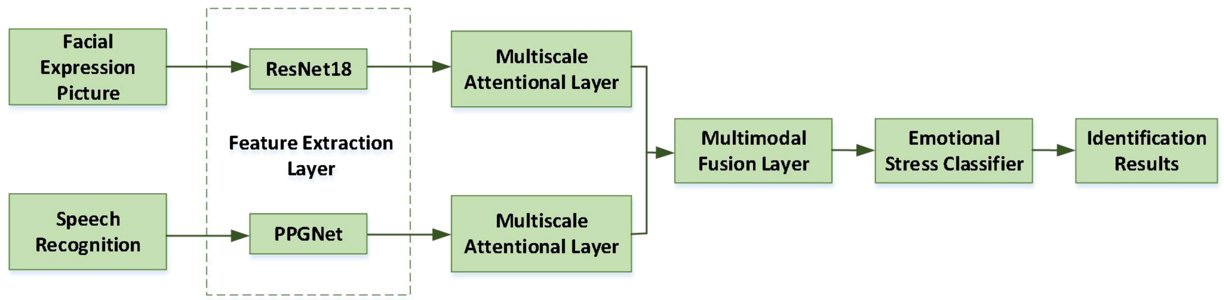

FIGURE 1
Multimodal ER framework.

distribution of each mode at each time is calculated. The feature vectors of two modes with attention weight are input into the multimodal feature fusion module, and the fused eigenvectors are used as the input of the fully connected network. After training, the data to be identified is input into the network to get the output of ER.

Feature extraction

For feature extraction of facial expression image sequence, res net18 network is used in the model. ResNet based on residual structure has a strong ability of feature extraction. In computer vision tasks, it is often used as a basic convolution neural network to extract image features. Moreover, it has a strong generalization ability and can perform well in different data sets. At present, ResNet has been widely used in various image-related tasks, where, as shown in Figure 2, BasicBlock is a residual structure formed by two 3×3 convolution.

The basic idea of Bi-GRU is to set two different data flow directions for input data, forward propagation and backward propagation, which connect the same output layer. Through this structure, the network can not only pay attention to the information of the past time of the input data, but also focus on the information of the future time of the input data. Bi-GRU focuses on the information of past time and future time of input data by setting forward calculation and backward calculation, where the order of information flow in the forward calculation layer is from the past to the future, receiving the input of the current time and the output of the hidden layer at the previous time; while the order of information flow in backward calculation layer is from the future to the past, receiving the input of the current time and the hidden layer of the next time. Finally, the output layer outputs two hidden layer States, one from the forward computing layer and the other from the backward computing layer, as shown in Figure 3.

The image features $f = \{f_1, f_2, f_3, \ldots, f_t\}$ is input into Bi-GRU network, and $\text{Forward}(\cdot)$ is defined as the Forward computation function of the network, while $\text{Backward}(\cdot)$ is the Backward computation function of the network, as shown in Equations (1), (2):

$$\vec{h}_t = \text{Forward}\left(f_t, \vec{h}_{(t-1)}\right) \tag{1}$$

$$\overleftarrow{h}_t = \text{Backward}\left(f_t, \overleftarrow{h}_{(t+1)}\right) \tag{2}$$

Among them, the $\vec{h}_t$ is network layer before t time to calculate the output, $\overleftarrow{h}$ is the network layer to calculate the output after t time. $\vec{h}_{(t-1)}$ and $\overleftarrow{h}_{(t+1)}$ represent the network in $t-1$ h after the forward calculation of the output layer and to calculate the output layer. When the timing information of the high-dimensional features of the input data is fully learned by the network, the state information of the network is output as follows:

$$H = \left[\left[\overleftarrow{h}_1, \vec{h}_1\right], \left[\overleftarrow{h}_2, \vec{h}_2\right], \ldots, \left[\overleftarrow{h}_t, \vec{h}_t\right]\right] \tag{3}$$

Define the input of facial expression Bi-GRU subnet as $x_{\text{face}_1}, x_{\text{face}_2}, \ldots, x_{\text{face}_t}$.

Then the output of the hidden layer of Bi-GRU network is:

$$H = \left[\left[\overleftarrow{h}_1, \vec{h}_1\right], \left[\overleftarrow{h}_2, \vec{h}_2\right], \ldots, \left[\overleftarrow{h}_t, \vec{h}_t\right]\right] \tag{4}$$

Therefore, the hidden layer output of facial expression Bi-GRU is:

$$H_i = \left[\left[\overleftarrow{h}_{\text{face}_1}, \vec{h}_{\text{face}_1}\right], \left[\overleftarrow{h}_{\text{face}_2}, \vec{h}_{\text{face}_2}\right], \ldots, \left[\overleftarrow{h}_{\text{face}_t}, \vec{h}_{\text{face}_t}\right]\right] \tag{5}$$

The hidden layer output of speech signal Bi-GRU is:

$$H_p = \left[\left[\overleftarrow{h}_{ppg_1}, \vec{h}_{ppg_1}\right], \left[\overleftarrow{h}_{ppg_2}, \vec{h}_{ppg_2}\right], \ldots, \left[\overleftarrow{h}_{ppg_t}, \vec{h}_{ppg_t}\right]\right] \tag{6}$$

When designing the temporal attention mechanism, we hope to ensure that the unique information of each mode will not be lost, and at the same time, the information of the other mode can be combined. Therefore, this paper calculates the input

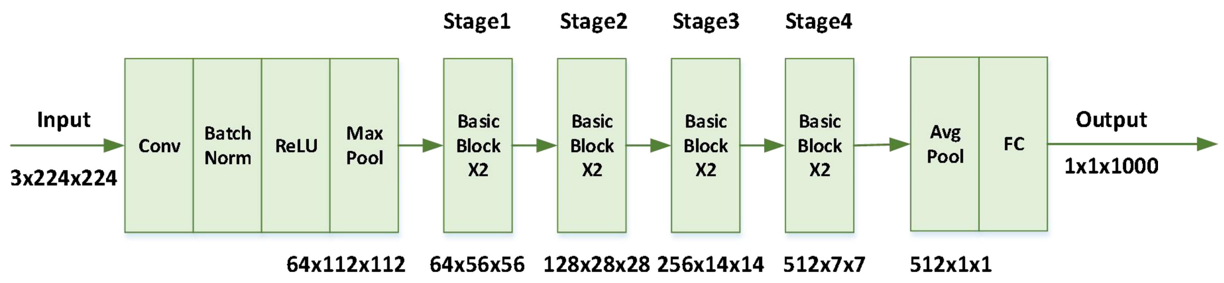

FIGURE 2
Network structure of resnet18.

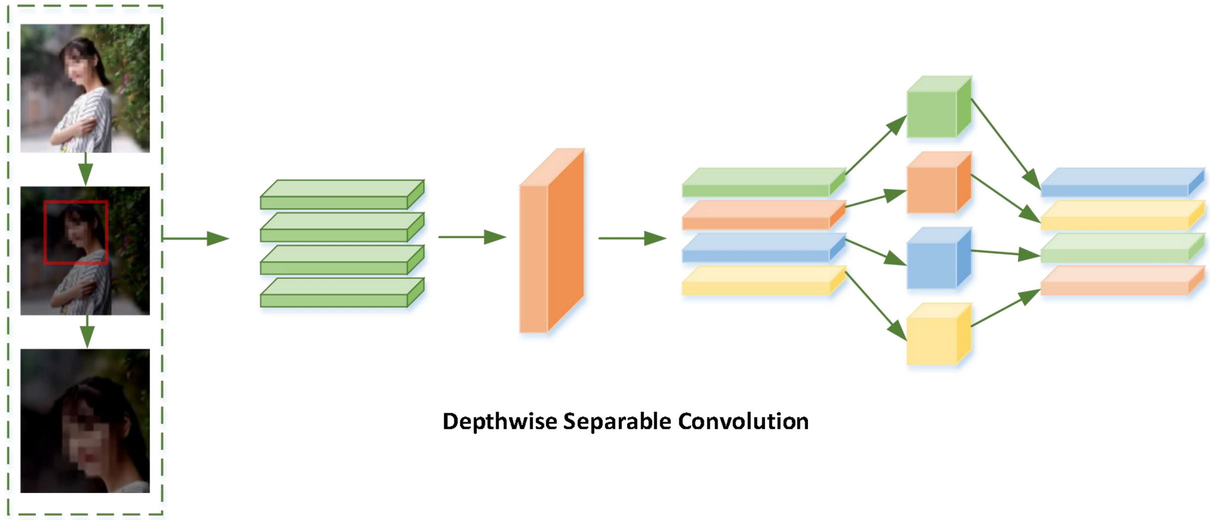

FIGURE 3
Bi-GRU process.

information of the two modes according to different proportions. At the same time, the proposed attention mechanism can combine the context information of temporal information and refer to the practice of ECA-Net in the network structure design, where the input of the two modal information will pass through the global average pooling layer and the one-dimensional convolution layer, and then calculate the attention weight.

The specific attention calculation methods are as follows:

Input $\vec{h}_{face} \in \mathbb{R}^{T\times d}, \overleftarrow{h}_{face} \in \mathbb{R}^{T\times d}$, which, respectively, represent the two facial expressions of bidirectional GRU order and reverse order.

Input $\vec{h}_{ppg} \in \mathbb{R}^{T\times d}, \overleftarrow{h}_{ppg} \in \mathbb{R}^{T\times d}$, which are the hidden vectors of speech signals.

Feature fusion

For the j -th recognition classification, the new classification probability $\mathrm{q}_j(x)$ obtained after processing according to the Rule can be expressed as follows:

$$\mathrm{q}_j(x) = q_j^{'}(x) / \sum_j^m q_j^{'}(x) \tag{7}$$

Where the calculation equation of $q_j^{'}(x)$ is as follows:

$$q_j^{'}(x) = \mathrm{rule}\left(p_{ij}(x)\right) \tag{8}$$

Finally, the classification label is obtained as follows:

$$w(x) = \mathrm{argmax}\left(q_j(x)\right) \tag{9}$$

The classification corresponding to the largest value is the final classification result. That is, $q_j^{'}(x)$ can be expressed as

$$q_j^{'}(x) = \sum_{i=1}^{n} p_{ij}(x) \tag{10}$$

Learners' achievement prediction model based on emotion state assessment

Multi polarization emotional state assessment

Based on the vectorized representation of foreign language learners' multi-polarized emotion, the multi-polarized emotion vector of foreign language learners in each class hour t can be calculated, and the multi-polarization emotion state matrix can be constructed to evaluate the change characteristics of their multi polar emotional state. On this basis, it can further analyze the phased dominant emotion of learners in class hour t, so as to assess the emotion tendency of learners, and then provide targeted personalized teaching intervention for learners with different emotion tendencies.

Step 1: Calculate the multi-polarization emotion state matrix of learners, as shown in Equation (11)

$$\mathrm{Mat}(L_i) = \begin{bmatrix} v_{1,1} & \cdots & v_{1,\mathrm{utn}} \\ \cdots & v_{i,t} & \cdots \\ v_{8,1} & \cdots & v_{8,\mathrm{utn}} \end{bmatrix} \quad (11)$$

Where $\mathrm{Mat}(L_i)$ represents the i-th learner's multi-polarization emotion state matrix; utn represents the current class progress, and $u\,\mathrm{tn} \in Z^+$; $v_{i,t}$ represents the emotional intensity value of the i-th emotion in t period, and $v_{i,t} \in v_t$.

Step 2: Calculate the dominant emotion in stages. Based on the multi polar emotion vector analysis of learners, it can be found that learners usually show a single polarity emotion type at the same time. Therefore, through the vectorization of learners' periodic multi polarization emotions, we can further analyze the learners' phased dominant emotions $Dmt_{pst}(v_t)$. When the intensity value of a certain emotion is the largest element in v_t, the phased dominant emotion of the learner $Dmt_{pst}(v_t)$ in class period t is defined, as shown in Equation (12):

$$Dxt_{pst}(v_t) = \max(v_t) \quad (12)$$

Where $Dmt_{pst}(v_t)$ represents the key value pair of emotional polarity and intensity of the first learner's dominant emotion in t period.

Step 3: Construct a multi-polar emotional state change chain. Based on the phased dominant emotion calculation, the multi-polar emotion states of each course stage can be obtained, and thus the multi-polar emotion state change chain can be constructed, as shown in Equation (13):

$$Dmt_{pst} - \mathrm{chain} = \left[Dmt_{pst}(v_1), Dmt_{pst}(v_2), \ldots, Dmt_{pst}(v_t), \ldots, Dmt_{pst}(v_{utn})\right] \quad (13)$$

Where $Dmt_{pst} -$ chain is the multi-polar affective state change chain of the i-th learner in the current course progress. $Dmt_{pst}(v_t)$ is the key pair of emotion polarity and intensity.

Step 4: Identify the emotional tendency of learners. The traditional method to judge the user's emotional orientation is based on the positive and negative of the calculation results by means of superposition calculation of the user's emotional intensity. However, the limitation of this method is that local extreme emotions can easily counteract or even cover the global dominant emotions, which leads to the low classification accuracy of the method. Therefore, this paper counts the frequency of each polarity's phased dominant emotion in the course progress, and the most frequent emotional polarity is the learners' emotional inclination, as shown in Equation (14).

$$\mathrm{Sent}_{\mathrm{tend}}(L_i) = m\left(Dmt_{pst,p} - \mathrm{freq}\right) \quad (14)$$

Where $\mathrm{Sent}_{\mathrm{tend}}(L_i)$ represents the i-th learner's emotional tendency; $Dmt_{pst,p} - \mathrm{freq}$ represents the frequency that the emotion with polarity of p dominates the stage in the current class schedule.

Achievement prediction

Through emotional feature selection, this paper uses C4.5 algorithm to predict student assembly. The algorithm selects features based on information gain rate, and uses the maximum information gain rate as the branch standard of decision-making features until all subsets have the same class of data. Let the sample training set D have d emotion state data and m different categories, the m different categories are defined as $L_i(i=1,2,\cdots,m)$. Let d_i be the number of samples in class L_i, and the expected information amount of emotion state data set D is:

$$\mathrm{I(D)} = \mathrm{I}(d_1,\ldots,d_m) = -\sum_{i=1}^{m} P_i \times \log_2(P_i) \quad (15)$$

Where P_i represents the probability that the sample belongs to class L_i, that is, $P_i = \frac{d_i}{d}$.

Set emotion features H has n different discrete values $\{h_1,h_2,h_3,\cdots,h_n\}$, the data set D is divided into n subset $\{D_1,D_2,D_3,\cdots D_n\}$. Let d_{ij} be the number of samples belonging to L_i class in subset D_j. Then, the entropy of H partition sample subset is:

$$E(H) = \sum_{j=1}^{n} \frac{|D_j|}{d} \mathrm{I}(\mathrm{d}_{1j},\ldots,d_{mj}) \quad (16)$$

The expected information of subset D_j is:

$$I\left(d_{1j},\ldots,d_{mj}\right)=\sum_{i=1}^{m}P_{ij}\times\log_2\left(P_{ij}\right) \tag{17}$$

Where $P_{ij}=\dfrac{d_{ij}}{|D_j|}$ is the probability that each data sample in subset D_j belongs to category L_i.

Therefore, the information gain of H as a branch node for sample training set partitioning is:

$$G(H)=I(D)-E(H) \tag{18}$$

Experiment and analysis

Data set

The selection of data set is very important for ER. Because seven categories of ER is used, THCHS30 data set is selected as sound data set,[1] which is an open Chinese speech data set that released by the Center of Speech and Language Technology (CSLT) of Tsinghua University. For video data set, FER2013 Kaggle Challenge data set is used.[2] The face data is composed of 48×48 pixels, and each picture has a corresponding label, a total of seven expressions, numbered from 0 to 6. The original database has 73,500 images of learners' facial expressions, each image has a corresponding label, a total of seven expressions, numbered from 0 to 6. At the same time, the platform automatically annotates the emotion type and intensity of each image. For example, in 0001_02_03_0004, 0001 represents the subject number, 02 represents the emotion type, 03 represents the emotion intensity, and 0004 represents the image number.

Results and discussion

Model validation

The loss function of the model changes with the number of iterations as shown in Figure 4.

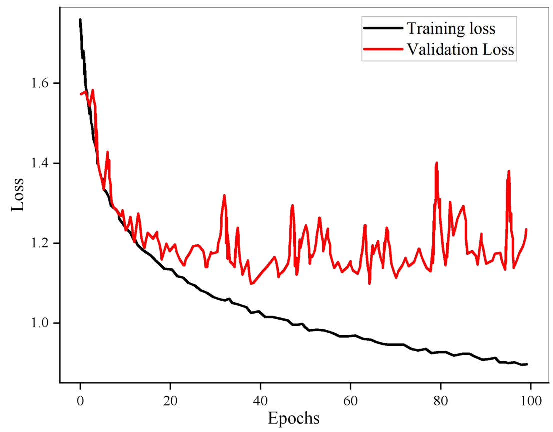

FIGURE 4
Results of model training.

It can be found from the figure that the accuracy of the test set is not much different from that of the training set, and the loss value of the test set is also consistent with the loss value of the training set, indicating that the model can be applied in practice. Bi-GRU structure enables the network to access the information of past time and future time in multimodal data at the same time, capture the change of emotional stress, and fully learn the information.

ER results

The confusion matrix of ER results based on the fusion of decision level is shown in Figure 5. Its accuracy rate is higher than that of ER based on single mode such as voice or facial expression.28708 test charts were selected from the FER2013 dataset, and the training set of THCHS30 data set was trained. The results showed that the average recognition rate was 82.1%. Compared with the single-mode ER results of speech and image, it is found that the accuracy of the multi-modal ER results after fusion has been greatly improved, which shows that the algorithm can be applied to classroom teaching. At the same time, in foreign language class, learners' confused emotions are widely distributed and need to be focused on.

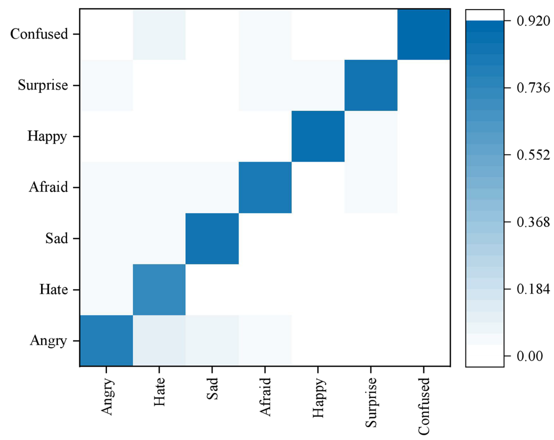

FIGURE 5
Confusion matrix of different ER.

In addition, when multi-scale attention layer and multi-modal fusion layer are included, the accuracy rate of learners' ER is high, which shows that the self-attention layer and multi-modal fusion layer proposed in this paper can improve the achievement of multimodal ER task by superposition, proving the effectiveness of the method.

1 http://www.openslr.org/18/
2 https://www.kaggle.com/

Learners' emotional changes based on time characteristics

This paper analyzes the video data of Multimedia English teaching class in a university in Xi'an. After 6 weeks of teaching application, students' emotions are collected, as shown in Figures 6, 7.

It can be clearly seen from the figure that students' emotions are different in each cycle. In the first week, students' learning emotions are mainly natural. Combined with the actual situation of teaching, it is found that the basic structure of grammar teaching is the content of this class, and teachers mainly teach. While in the sixth week, the teachers found that the students' enthusiasm for learning was greatly stimulated by the interaction between the teachers and the students in the classroom.

Correlation between learners' emotional state and achievement

As mentioned above, language learners' confusion is particularly prominent, which can bring low active subjective feelings to learners. The section "ER results" also confirm this view. Therefore, this study uses two variable indicators, namely learning confusion and view resolution, to predict the right and wrong of the test questions of learners, so as to achieve the purpose of predicting achievement. Self-report is often used to define emotional labels in learning emotion detection, where students can determine whether their emotional state is in a state of confusion according to the options of self-report. It can be seen from Figure 8 that the quadratic curve equation fitted by linear regression can better reflect the relationship between learners' confused emotion and achievement.

When the number of confused questions was more, the score also decreased significantly. From this we can draw the following conclusions: learning confusion has a more obvious impact on learning achievement, too much learning confusion will lead to the increase in the number of errors, reduce the accuracy rate, and lead to the decline of the overall score; The learners who are puzzled by the increasing number of test questions may not grasp the whole knowledge firmly enough, which leads to greater difficulty in choosing almost all knowledge points, thus affecting the whole judgment. Therefore, if we can help learners to solve the current confusion in a timely manner, it may help learners to have a new understanding of learning, so as to improve their academic achievement.

Learning behavior has a great impact on learning achievement. Learning behavior indirectly reflects the level of learners' emotional state. If some behaviors can be seen that learners are in a relatively negative emotional state, they will further affect their academic achievement. Learning confusion is positively related to the change of students' achievement.

Application scenarios

The experimental results show that the multimodal foreign language learners' ER model proposed in this paper can accurately

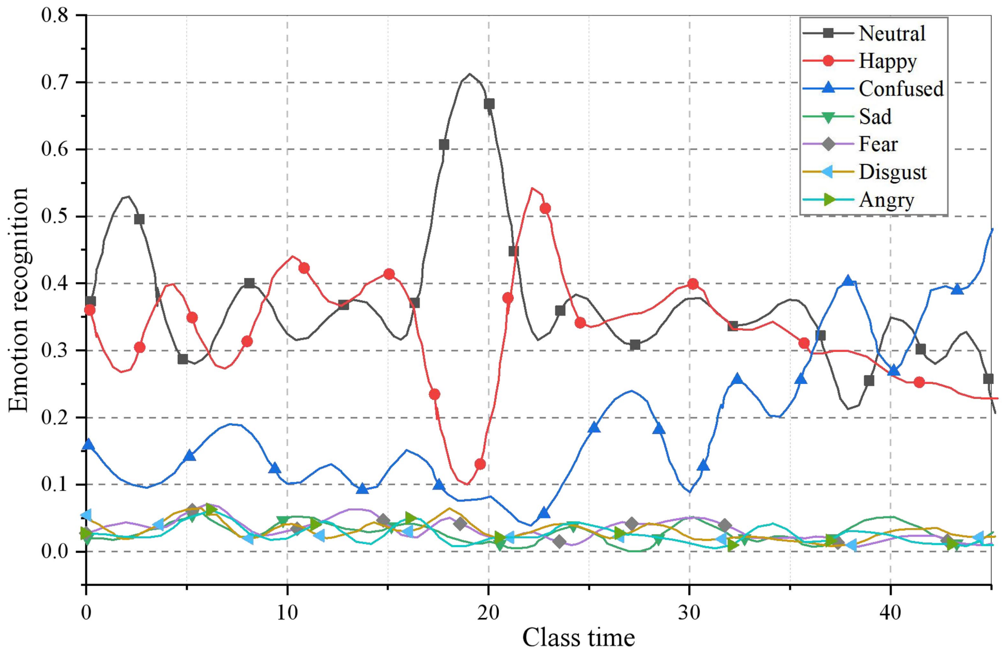

FIGURE 6
Results of students' ER in the first week.

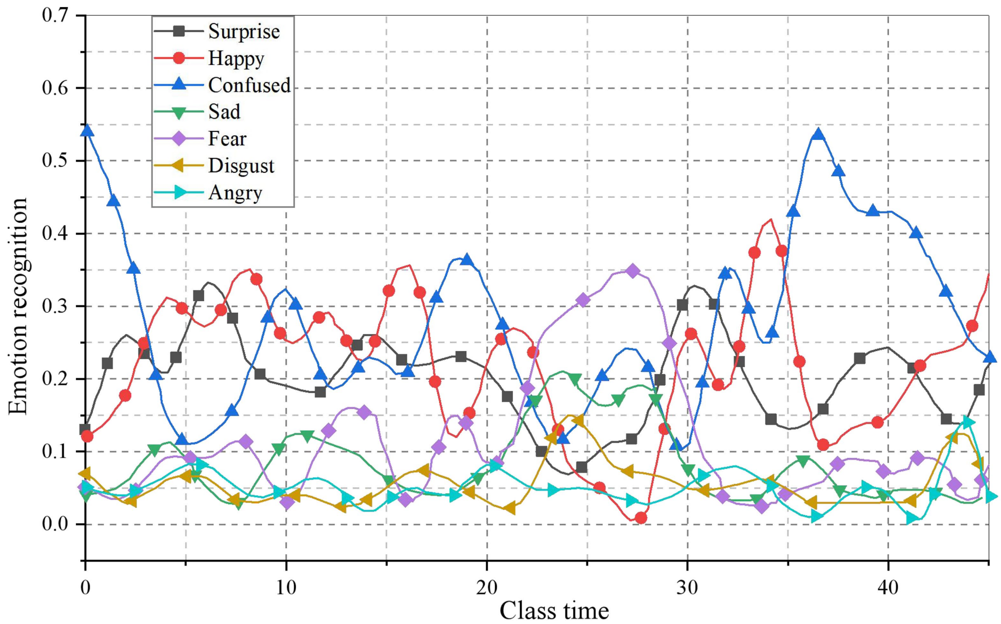

FIGURE 7
Results of students' ER in the sixth week.

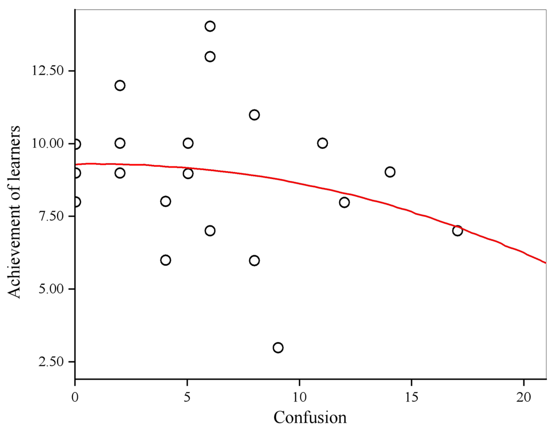

FIGURE 8
Fitting curve between learners' confusion and achievement.

and continuously observe students' learning emotions and states. Therefore, the analysis module of learning state and learning emotion can be added to the existing network teaching system of colleges and universities. As shown in Figure 9, the deployed system consists of learning module, teaching module, learning state and learning emotion analysis module, and server module. These four parts exchange data through the cloud to ensure the normal operation of the network teaching system.

The system starts to implement after the course starts. It collects the learners' learning state and learning emotion information according to the time period, and records the collected effective data. Then the data are preprocessed and analyzed by the algorithm to get the feedback result. Finally, according to the feedback results, data analysis is carried out to make a positive impact on learners.

Conclusion

This paper constructs a multi-modal ER model based on CNN-BiGRU, and proposes an achievement prediction model based on emotional state assessment to further explore the relationship between confused emotion and academic achievement. Moreover, it analyzes the influence of learners' emotional state on learning process from different levels. The results show that in the learning of foreign language, learners' confusion is widely distributed and needs to be focused on; while too much confusion will lead to more mistakes and lower correct rate. In the characteristics of time and space, the change of teaching methods can affect students' emotional changes. Finally, in the future, the model can be integrated into the existing network teaching system of colleges and universities to accurately and continuously observe students' learning emotions and states, and then help teachers adjust teaching strategies in time.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

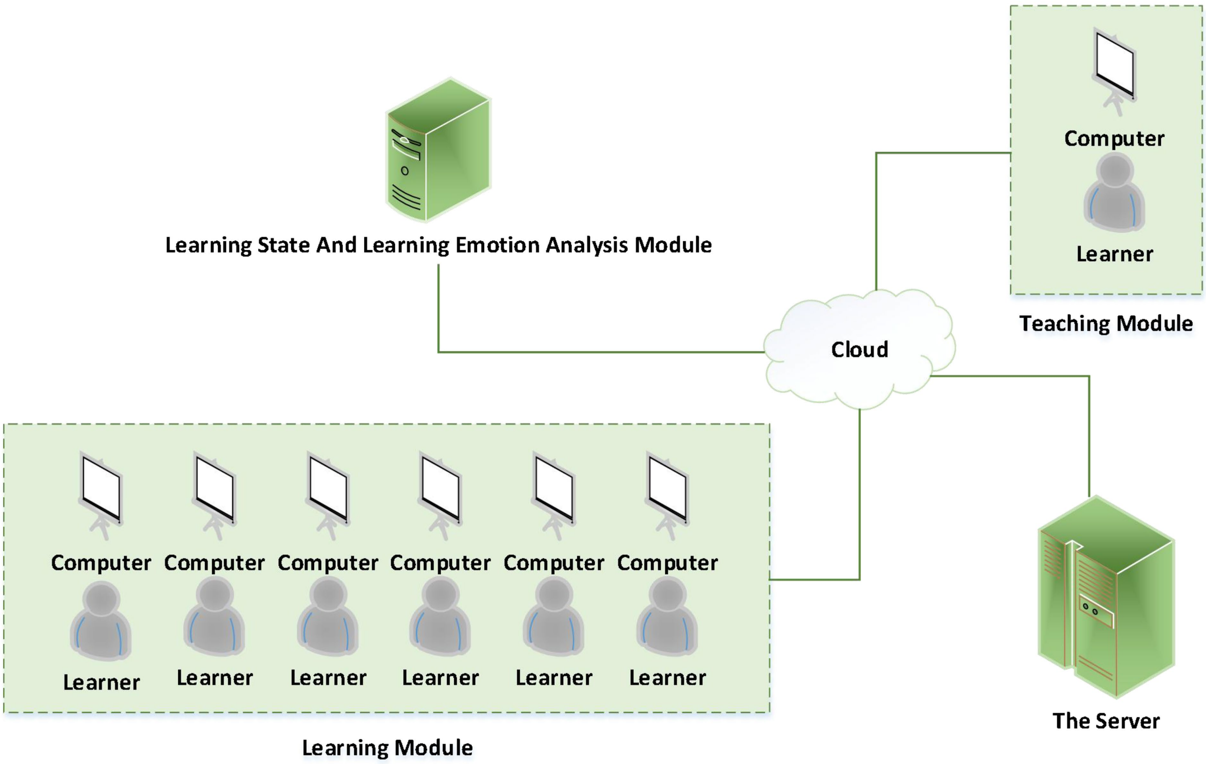

FIGURE 9
Deployment of emotion analysis module in network teaching system.

Ethics statement

This study were reviewed and approved by School of Languages and Cultures, Shijiazhuang Tiedao University. The participants provided their written informed consent to participate in the study.

Author contributions

YD was responsible for the conception of research ideas. WX was responsible for data collection. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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How does artificial intelligence empower EFL teaching and learning nowadays? A review on artificial intelligence in the EFL context

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The booming Artificial Intelligence (AI) provides fertile ground for AI in education. So far, few reviews have been deployed to explore how AI empowers English as Foreign Language (EFL) teaching and learning. This study attempts to give a brief yet profound overview of AI in the EFL context by summarizing and delineating six dominant forms of AI application, including Automatic Evaluation Systems, Neural Machine Translation Tools, Intelligent Tutoring Systems (ITSs), AI Chatting Robots, Intelligent Virtual Environment, and Affective Computing (AC) in ITSs. The review furthermore uncovers a current paucity of research on applying AC in the EFL context and exploring pedagogical and ethical implications of AI in the EFL context. Ultimately, challenges from technical and teachers' perspectives, as well as future research directions, are illuminated, hopefully proffering new insights for the future study.

KEYWORDS

artificial intelligence, AI in the EFL context, affective computing, English as foreign language (EFL), EFL teaching and learning

Introduction

With Artificial Intelligence (AI) consistently penetrating all domains of human life, recent years have witnessed the dramatic growth of AI in education (AIEd) (Hwang et al., 2020). Specifically, AIEd is anticipated to grow by 43% from 2018 to 2022 (Becker et al., 2018), whereas the Horizon Report 2019 (Alexander et al., 2019) predicts AI applications of teaching and learning will develop even more significantly. As one key issue discussed by UNESCO (2019), AIEd proliferates surging scientific output (Hinojo-Lucena et al., 2019). Likewise, various AI applications integrating analytical techniques [e.g., Machine Learning (ML), Natural Language Processing (NLP), Artificial Neural Networks (ANNs), Affective Computing (AC)], have been widely harnessed in English as Foreign Language (EFL) context and are exerting profound impacts. Particularly in the upheaval of teaching modes in the COVID-19 pandemic, video conferencing tools (e.g., Zoom) and learning management systems (e.g., Blackboard) supported by AI technologies have been widely opted to implement online EFL teaching and learning (Layali and Al-Shlowiy, 2020). A large and growing body of literature has suggested that AI can benefit language teaching and learning (Gao, 2021; Pikhart, 2021; Klimova et al., 2022), and ameliorate the quality of online EFL learning especially during the COVID-19 pandemic (Zitouni, 2022). To date, many reviews on AIEd have emerged (Chen et al., 2022). Nevertheless, to our knowledge, reviews concentrating on AI in the EFL context tend to be comparatively scarce. Accordingly, this paper attempts to explore how AI empowers EFL teaching and learning nowadays through critically reviewing research into the application of AI technologies solely in the EFL context, hopefully inspiring more fresh ideas in this future domain.

An automated method (Guan et al., 2020) was used to initially retrieve related publications from 2000 to 2022 in four databases (i.e., WOS, Scopus, ERIC, and Google Scholar) by searching AI-related terms (e.g., Chatting Robots) and EFL-related terms (e.g., EFL/English Teaching and Learning). Afterwards, the publication relevance was assessed by experts (Chen et al., 2022) to determine targeted research samples in this review. Manual coding and keyword analysis, along with computer-assisted content analysis (i.e., NVivo), were deployed to profoundly analyze the highly-related publications ($N = 245$). Consequently, the following six dominant forms of AI in the EFL context were summarized, including Automatic Evaluation Systems, Neural Machine Translation Tools, Intelligent Tutoring Systems, AI Chatting Robots, Intelligent Virtual Environment, and Affective Computing in ITSs. Moreover, this review teased out AI in the EFL context in the literature from learner-facing and teacher-facing perspectives. Finally, the paper endeavors to shed new light on challenges from technical and teachers' perspectives and future research directions of AI in the EFL context.

Automatic evaluation systems

Automatic Evaluation Systems (AESs) are generally based on big data and NLP technologies (e.g., automatic speech recognition, word sense disambiguation, etc.) to evaluate the input information and provide automatic revision opinions, which are mainly applied in EFL writing and speaking contexts. Current commercialized applications using AESs in EFL writing, namely Criterion and Pigai, are proved to bolster writing accuracy and motivate learners to do more writing practice and revision (Bai and Hu, 2017; Gao, 2021). Likewise, AESs in EFL speaking, such as English 60 Junior and Eye speak, are confirmed to improve oral proficiency, frequency, and pronunciation (Ahn and Lee, 2016). In the covid-19 context, AESs can also facilitate EFL teaching by integrating online evaluation with automatic response and grading (Zitouni, 2022). However, from teachers' perception, they may remain vaguely optimistic about the use of AESs. Some underscore that AESs can't replace human raters in EFL writing instruction (Bai and Hu, 2017; Qian et al., 2021) due to relatively low accuracy (Liu and Kunnan, 2016), insufficient high-quality comment on collocation errors and syntactic use (Gao, 2021), the frustrating levels of recognition, and the lack of convenience (McCrocklin, 2019). Since teachers' adoption of AI is determined by its effectiveness and efficiency (Du and Gao, 2022), from technical perspectives, more technical efforts need to be exerted to improve the assessment accuracy of AESs; from instructional perspectives, teachers are required to fully deploy the potential of AESs to improve their effectiveness in diverse EFL contexts.

Neural machine translation tools

Neural Machine Translation (NMT) is an end-to-end learning approach for automated translation. Unlike the traditional statistical MT, NMT aims to build a single neural network to maximize translation performance and overcome many weaknesses of conventional phrase-based translation systems (Bahdanau et al., 2014; Wu et al., 2016b). Google Translate, the Microsoft Translator (Bing), etc., are nowadays widely used NMT tools in diverse language education, of which performance is evaluated and compared from different linguistics perspectives (Vanjani and Aiken, 2020; Koh, 2022), still unveiling pressing problems, for instance, being incapable of conveying the proper sense and implication at the discourse level, containing errors of discontinuous expressions, word orders, etc., and requiring humans' intensive post-editing (Groves and Mundt, 2015; Koh, 2022). Notwithstanding the drawbacks of NMT tools revealed in some literature (Bahri and Mahadi, 2016), a considerable amount of literature suggest that NMT tools can benefit EFL students' learning: from the cognitive and linguistic perspective, they promote self-directed learning (Godwin-Jones, 2015), improve mastery of lexico-grammatical knowledge (Doherty and Kenny, 2014; Bahri and Mahadi, 2016), and develop productive (L2 writing) and receptive (reading comprehension) language skills (Alhaisoni and Alhaysony, 2017). It is noteworthy that from the affective perspective, they may lower language anxiety (Bahri and Mahadi, 2016). Conversely, Zhu et al. (2020) recently found that NMT may inhibit learning motivation. Moreover, some research reveals that NMT tools are especially suitable for advanced L2 learners (Klimova et al., 2022). Pertaining to NMT tools' pedagogical implications, they can be exploited to conduct comparison activities of original and machine-translated texts (Chen et al., 2020) and engage students in analytical language tasks or awareness-raising tasks (Valijärvi and Tarsoly, 2019). Overall, the use of MNT tools in the EFL context remains controversial, especially in the teaching context (Delorme Benites and Lehr, 2022). Future research can focus on the following two unanswered questions: considering EFL learners, whether NMT tools can benefit all English proficiency levels require more empirical research to investigate thoroughly; for EFL teachers, how to effectively exploit NMT tools to maximize their effectiveness and adaptability in EFL classroom requires more in-depth exploration.

Intelligent tutoring systems

As computer-based learning systems, Intelligent Tutoring Systems (ITSs) are designed to promote personal tutoring and facilitate learning based on learner models, algorithms, and neural networks. Through providing proper and immediate feedback and tailoring instructional materials, various applications of ITSs, such as Pigaiwang (for Chinese students English writing), Your Verbal Zone (for Turkish students English vocabulary learning), and Robo-Sensei (for Japanese), are widely adopted in EFL fields, which have yielded learning effectiveness, for instance, improving grammar learning (Abu Ghali et al., 2018) and reading comprehension (Xu et al., 2019). ITSs can also be adapted to various teaching contexts to maximize their effectiveness. Concretely, embedded in the flipped classroom, ITSs help students solve problems (Mohamed and Lamia, 2018); assisting Self-Regulatory Learning (SRL), ITSs are proved to improve speaking skills (Mohammadzadeh and Sarkhosh, 2018); in COVID-19 context, ITSs can build students' performance profiles to assist teachers in adapting online teaching modes and content wisely (Nagro, 2021). Surprisingly, few attempts have been made to detect EFL learners' affective state when applying ITSs, although Affective Computing (AC) has been widely embedded in ITSs in other education domains. Hence, it may be pedagogically significant to integrate AC into current ITSs in the EFL context to identify and classify learners' emotions and give adequate emotional support to motivate EFL learning.

AI chatting robots

AI Chatting Robots (AI chatbots) are computer programs with AI to promote intelligent human language interaction in a written or spoken form, which can provide a more fluid user experience by updating their knowledge and perception from previous conversations (Haristiani, 2019). Many empirical studies have confirmed the effectiveness of AI Chatbots in EFL fields. Concretely, AI Chatbots can not only strengthen EFL learners' mastery of language knowledge, including grammar and new vocabularies (Wang and Petrina, 2013), but also can improve English application skills, namely oral communication skills, listening and reading skills, and high-quality argumentative writing skills (Hong et al., 2016; Kim et al., 2019; Guo et al., 2022). Additionally, some research reveals that AI Chatbots can boost students' motivation, self-confidence, and interest in learning (Kim et al., 2019). However, whether AI Chatbots benefit all English proficiency levels remains controversial: some research argues that chatbots are ineffective for beginners, while some claim that all students can benefit (Kim, 2016). Additionally, it's noteworthy that some minor pronunciation errors along with grammar and spelling mistakes seem challenging for present AI Chatbots to interpret and diagnose in EFL fields. As Lotze (2018) argues, AI diagnostic systems still need to meet some key criteria (i.e., spontaneity, creativity, and shared knowledge) before they can serve as a real-life language teacher. Hence, along with providing more technical support to upgrade diagnostic systems of AI chatbots, future work is required to empirically investigate their adaptability to different language proficiency levels and various instructional contexts.

Intelligent virtual environment

It is during the last two decades that Virtual Reality (VR) tools have been widely adopted in foreign language education (Rau et al., 2018; Wang et al., 2020), exemplified by Google Earth (Chen et al., 2020), Google Tour Creator (Nobrega and Rozenfeld, 2019), and Google Expeditions (Xie et al., 2021). Multiple benefits of applying VR tools in the EFL context have also been validated, for instance, improving vocabulary learning and retention (Lai and Chen, 2021; Tai et al., 2022), enhancing English speaking and willingness to communicate (Ebadi and Ebadijalal, 2020), building ideal 2L self (Adolphs et al., 2018), and improving English learning motivation to reduce anxiety (Chien et al., 2020). With AI technologies maturing enough to interact with a virtual environment, Intelligent Virtual Environment (IVE) is proposed as "a combination of intelligent techniques and tools, embodied in autonomous creatures and agents, together with effective means for their graphical representation and interaction of various kinds" (Luck and Aylett, 2000). As one typical application of IVE, virtual agents (avatars) can upgrade user presence in the virtual and promote collaboration (Yin, 2022). Particularly in the EFL context, 3D avatars are reported to improve listening performance (Lan et al., 2018). Similarly, some empirical evidence suggests that using avatars can decrease foreign language anxiety and encourage learners to communicate more successfully (Melchor-Couto, 2017; York et al., 2021). IVR can also serve as an effective means to engage EFL students virtually in Zoom virtual classroom teaching in covid-19 pandemic (Obari, 2020). However, some scholars still express some reservations about the effectiveness of using avatars in the EFL context, considering technical factors such as interacting with avatars outside the scripted application areas (Lotze, 2018), the acceptability of virtual avatars (Repetto, 2014). Additionally, the affordability and limited access to networks still stump the implementation of IVE in the EFL context (Cowie and Alizadeh, 2022). Thus, there is a call for more new technological frontiers to address the aforementioned technical problems, along with an appeal for EFL teachers' professional training to exploit IVE and avatars properly from technical and pedagogical aspects.

Affective computing in ITSs

There is a consensus that emotion significantly impacts cognitive activities (e.g., learning) (Wu et al., 2016a, 2022; Ma and Lin, 2017). Particularly, the close connection between emotions and language learning motivation is also empirically verified (Yu et al., 2022). Affective computing (AC) is currently one of the most promising research topics (Tao and Tan, 2005), referring to "computing that relates to, arises from, or deliberately influences emotion or other affective phenomena" (Picard, 1997). By recognizing learners' emotions from physiological, facial, and textual data, AC is widely embodied in ITSs and applied in various educational domains. To illustrate, the Affective Tutoring System (ATS) combining emotional expressions and AC, can detect learners' emotional expressions, determine learners' learning state, and give interactive feedback (Lin et al., 2012; Hasan et al., 2020). A large volume of published studies has verified that ATS can improve learning motivation and outcomes (Lin et al., 2012; Sionti et al., 2018; Wang and Lin, 2018; Hasan et al., 2020). Particularly in language education, Ma and Lin (2017) discover that ATS can make Japanese learning more interesting and provide an adaptive learning environment. Similarly, Wu et al. (2022) note that the affective mobile language tutoring system (AMLTS) can deepen content understanding, promote engagement in peer interaction, and generate positive emotions. So far, ATS has been mainly applied in foreign language education, particularly in Japanese learning, whereas there are few studies on the use of ATS in the EFL context. Therefore, there is abundant room for further research exploring ATS's pedagogical and ethical implications in the EFL context and for further studies developing more effective applications utilizing AC to detect learners' emotions and proffer sufficient affective interaction and support in the EFL context.

Learner-facing and teacher-facing AI in the EFL context

Aiming to present a more in-depth overview of AI in the EFL context, this review teased out published studies from two perspectives, namely learner-facing and teacher-facing AI applications (Baker and Smith, 2019). Generally, NMT tools, AI Chatbots and ITSs are related to learner-facing AI applications, which can promote adaptive or personalized learning, while AESs, IVE, and AC in ITSs can be concerned as teacher-facing systems, which can support teaching and reduce workload by automating administration, assessment, feedback, and data detection. However, in the authentic EFL context, some AI applications may play intertwined roles in promoting both teaching and learning. For instance, AESs, NMT tools, and ITSs can serve as monitoring and tutoring tools in the EFL instruction to promote EFL learning mainly from cognitive and linguistic perspectives (Groves and Mundt, 2015; Abu Ghali et al., 2018; Gao, 2021; Koh, 2022). EFL teachers can also harness IVE to construct an interactive and collaborative virtual reality learning environment to scaffold EFL learning (Melchor-Couto, 2017; Lan et al., 2018).

Additionally, it's noteworthy that the majority of published studies investigate EFL performance when applying AI in the EFL instructional settings, for instance, scaffolding argumentative writing by using AI chatbots (Guo et al., 2022), and improving speaking ability by deploying ITSs (Mohammadzadeh and Sarkhosh, 2018). Conversely, less research offer glimpse into the sheer EFL instruction behaviors from teachers' perspectives, although teachers' perceptions (e.g., willingness, attitude) of AI begin to draw attention (Sumakul et al., 2022). Similarly, teachers' consideration of ethical implications and risks when applying AI haven't been treated in much detail. These review results are in accordance with previous findings that there is a paucity of studies of AIEd from teachers'/teaching perspectives (Zawacki-Richter et al., 2019). Thus, more research is require to unravel AI's pedagogical potential to address muti-faceted EFL teaching issues (e.g., developing curriculum and materials, optimizing teaching modes, etc) and unfold new ethical implications and risks dwelling in AI inherently.

Discussion

This review foregrounds that AI has empowered current EFL teaching and learning primarily in six forms and achieved relatively satisfactory effects and feedback, echoing related discussions (Sumakul et al., 2022), while some technical drawbacks and improper manipulation in authentic instruction still retain long-term conservative attention. Overall, the application of AESs, NMT Tools, ITSs, and AI Chatting Robots in the EFL context has made steady progress in promoting EFL teaching and learning, while IVE and AC in ITSs (e.g., ATS) still need to transcend current technical handicaps to fully spur their pedagogical potential and expand the breadth and depth of the application in the EFL context. Surprisingly, very few studies have explored AC in ITSs in EFL context. Moreover, other striking findings in this review are the dramatic paucity of empirical studies exploring pedagogical implications of AI in the EFL context from teachers' perspectives as well as less attention on ethical implications and risks when applying AI. Therefore, the following discussion will dig deeper into the challenges of AI in the EFL context from technical and teachers' perspectives and future research directions.

Challenges from technical perspectives

With the deep learning (DL)-based AI techniques developing rapidly (Dong et al., 2021), DL has earned research attention in AIEd, especially in the EFL context. Traditional ML-based techniques mainly rely on experts' domain knowledge, whereby AI algorithms can be specifically designed for a given task, such as language recognition algorithm based on support vector machine (Campbell et al., 2004). In contrast, DL-based techniques are based on artificial neural network, e.g., convolutional neural network (Gu et al., 2018) and recurrent neural network (Mikolov et al., 2011), which can be easily adapted to handle different tasks. Moreover, multi-task learning methods have been developed using one DL model to cover different tasks (Dong et al., 2015), e.g., recognition and translation. However, DL-based techniques in existing AI-based EFL applications tend to analyze specific single signal, e.g., text for writing and audio for speaking. Accordingly, more severe challenges are arising from analyzing the multi-modal signals, namely text, audio, facial micro-expression and body actions, to promote the effects of EFL teaching and learning. To this end, large-scale Transformer (Shvetsova et al., 2022) can be pre-trained based on a large amount of multi-modal signals in self-supervised learning of multi-modal embedding space. For AI techniques in the EFL context, it is meaningful and challenging to adapt the large-scale multi-modal pre-training model to EFL teaching and learning.

This review also uncovers that existing AI-based EFL tools and systems are targeted to EFL performance and outcome from linguistic and cognitive perspectives, neglecting the emotions or mood during the learning process. In this vein, we suggest that affective computing (AC) is a potential solution to monitor the affective status of students to promote effectiveness in the EFL context (Lin et al., 2012; Hasan et al., 2020). In particular, students' emotions can be recognized and analyzed based on the physiological signal, e.g., audio, vision and even electroencephalo-graph, using AC techniques (Schoneveld et al., 2021), which can feed back to teachers or ITSs for further monitoring and improving the EFL learning. Considering the natural multi-modal property of physiological signals, the fusion of multi-type signals can also benefit from self-supervised learning in large-scale pre-training model but remains unresolved, when developing AC techniques for EFL fields. Besides aforementioned technical challenges, ethical issues of applying AC should be well addressed when collecting and analyzing multi-type physiological signals in a real-time manner to identify and measure learners' emotions during the entire learning process. In this sense, ethical implications were explored below from two perspectives, i.e., instructor and learner. On the one hand, AC should be properly used by the instructor for teaching (Wu et al., 2016a). Also when designing AI algorithms, AC for EFL should be strictly restricted to analyzing learning status, avoiding emotional manipulation or other commercial bias analysis. On the other hand, the learner's autonomy should be respected (Engel et al., 2017). For the private physiological signals, personal raw data should only be used in local personalized AI system, and cannot be uploaded to the public big data pool without authorization.

Personalized EFL tools and systems also require more focus, by which every student can be specifically guided by updating the DL model based on the learning process rather than sole English proficiency. Continual learning (Aljundi et al., 2019) can be adopted to adaptively update the DL model to satisfy personalized requirements and tasks in the EFL context. Continual learning and AC can also be integrated to adaptively finetune the DL model to explore both proficiency levels and emotional states in the EFL context. To this end, personalized EFL tools and systems based on Continual learning and AC would be the future direction, and they are undoubtedly facing head-on ethical challenges for avoiding the emotional manipulation, respecting autonomy, and protecting data privacy.

Challenges from teachers' perspectives

The review highlights that teachers' attitudes to applying AI in the EFL context tend to vary from being positive, which is in accord with Sumakul et al. (2022)'s findings, toward being conservative, as noted by Holstein et al. (2017) and Lin et al. (2017) that less-experienced instructors usually struggle to execute effective responses to analytics, leading to their reluctance and lower acceptance. Hence, from teachers' perspective, it's essential to relieve negative emotions and promote AI acceptance, aiming to deploy AI's pedagogical potential shored up by numerous empirical studies. Suggestions on improving AI acceptance *via* boosting confidence in applying AI and extending knowledge of AI are proffered and briefly explored below. Concretely, more future research foregrounded by ample empirical and theoretical evidence are still required to be conducted, aiming to highlight the effectiveness and potential of AI in the EFL context then galvanize confidence and motivation to utilize AI. Additionally, high-quality theoretical and practical profession training in AI can prepare teachers for AI-empowered EFL teaching, of which forms can be question-oriented practicums or workshops with modules of diverse EFL instructional contexts integrating multiple teaching modes rather than one-size-fits-all approach. It's noteworthy that improving teachers' awareness of ethical implications and risks when applying AI is compulsory (Russell, 2010). Finally, more access to engagement in interdisciplinary research with

AI scholars can also provide technical support to EFL teachers, aiming to bolster the understanding and using of AI to maximize its pedagogical potential.

Future research directions

Notwithstanding a proliferation of studies on AI in the EFL context in recent years, there is a relative paucity of longitudinal studies investigating the effectiveness of AI in the EFL context *via* robust experiments with a larger amount of participants, strict assessment, competent instructors and supporting institutions, as well as a mechanism to protect data privacy. Besides, further research should be undertaken to investigate the adaptability of AI to different EFL learners with L2 individual differences (i.e., personal traits, language aptitude, motivation, learning styles, learning strategies) and to diverse learning and teaching contexts (e.g., online teaching, blended teaching, the flipped classroom). Additionally, there is abundant room for further progress in exploring students' emotional state by utilizing AC in the EFL context, hopefully contributing more evidence to detecting relationships between emotions and learning in the EFL context. Finally, future work is required to shed new lights on pedagogical implications as well as ethical implications and risks of AI in the EFL context.

Author contributions

In the study, RJ was fully in charge of collecting and reviewing literature, writing, and revising the manuscript, etc.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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System quality, information quality, satisfaction and acceptance of online learning platform among college students in the context of online learning and blended learning

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The paper was based on the User Satisfaction and Technology Acceptance Integration Theory (USATA). The authors analyzed the factors that affect college students' acceptance and satisfaction of online learning platform, as well as the differences in the relationship between various factors in blended learning scenario and online learning scenario. The results showed that the quality of online learning platform and information quality affect user satisfaction, and satisfaction affects usefulness and ease of use, and then affect attitude and intention. The comparison between the two groups showed that there were significant differences in the impact of information quality on information satisfaction and the impact of perceived usefulness on usage intention. In the online learning scenario, the endogenous latent variables of the model had higher explanatory power, which indicates that learners are more dependent on the quality and relevant characteristics of the learning platform in the online learning scenario.

KEYWORDS
online learning platform, online learning, blended learning, system quality, information quality, USATA

1 Introduction

Since 2019, the novel coronavirus (COVID-19) disease has been pandemic in the world. The whole world has taken many measures to prevent the spread of COVID-19. The relevant measures have had a great impact on our social, economic life, health, work, and learning (Clark et al., 2021). The United Nations Education, Scientific and Cultural Organization (UNESCO) pointed out that the COVID-19 has affected the world's education system (UNESCO, 2020). In order to reduce the impact on students' learning during school closure, many countries used information technology and online learning platforms or tools to carry out massive online teaching and learning (Varalakshmi and Arunachalam, 2020). The Chinese Ministry of Education has launched the initiative of "Disrupted Classes, Undisrupted Learning" to provide students with flexible online learning (Huang et al., 2020).

During the COVID-19, online learning became an alternative to face-to-face learning in schools. Online learning platform had become an important way and tool for learners to learn in the completely home-based online learning environment. This had led to a large number of studies focusing on learners' acceptance and satisfaction with the online learning platform in the online learning environment. For example, some researchers used the extended Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT) to study learners' acceptance of online learning or online learning platform during the COVID-19 (Aguilera-Hermida, 2020; Mailizar et al., 2021; Raza et al., 2021). During the period of COVID-19 and school closure, online learning platform is a key factor for the massive online learning. These studies showed that learners' acceptance and satisfaction with online learning platforms will affect learners' intention to use online learning platforms and online learning effect.

In the blended learning scenario during the non-COVID-19 period, learners also need to use the online learning platform to carry out online learning. Unlike online learning, blended learning includes not only online learning, but also face-to-face learning. Many studies had explored learners' acceptance and satisfaction with online learning platforms in blended learning environments. For example, some researchers use the extended TAM model (Padilla-Meléndez et al., 2013; Al-Azawei et al., 2017), Expectation Confirmation model (Cheng, 2014), and the Unified Technology Acceptance and System Success model (Zhang et al., 2020) to investigate the intention of college students to use the blended learning system. Some researchers use similar models to investigate the acceptance and satisfaction of knowledge management systems in blended learning environments (Bervell and Umar, 2020; Ustun et al., 2021).

In conclusion, blended learning and online learning scenarios are widely used. The teaching scenarios have an important impact on students' learning experience and learning quality (Lim and Morris, 2009; Gómez-Rey et al., 2016). In both learning scenarios, online learning platform is an important learning resource and tool. At present, most researches focus on the acceptance or satisfaction of a learning scenario, less on the combination of satisfaction and acceptance, and pay attention to the differences in different learning scenarios. This study attempts to analyze the college students' acceptance, satisfaction and influence factors of online learning platform in the two scenarios of blended learning and online learning, and compare the differences in the relationship between various factors in the two scenarios. This study aims to provide theoretical basis for the development of online learning platform and the design of teaching resources in online learning platform.

2 Literature review

2.1 User satisfaction theory

Previous studies focusing on the success factors of information systems have found that system quality, information quality and user satisfaction are the key factors that affect the success of information systems (DeLone and McLean, 1992). In a specific context, the satisfaction is the sum of a person's feelings toward various factors that affect the situation (Schwab and Cummings, 1970). User Satisfaction in this study is defined in the specific context of using information systems or platforms. Satisfaction is the sum of a person's positive and negative reactions to a series of factors. User Satisfaction Model mainly lists some attributes of system and information design, which are used as factors affecting satisfaction (Wanous and Lawler, 1972).

Through the comprehensive analysis of the researches on the evaluation tools of user information system satisfaction, it is found that the common dimensions of information system user satisfaction measurement tools are system quality and information quality. System quality includes five sub dimensions, namely reliability, flexibility, integration, accessibility and timeliness. Information quality includes four sub dimensions, namely integrity, accuracy, format and currency (Bailey and Pearson, 1983). Reliability refers to the reliability or stability of system operation. Flexibility means that the system can meet the changing needs of users. Integration refers to the integration or compatibility of the system, allowing the integration of data from different sources. Accessibility refers to the ease of use of the system, which is convenient to access the system or extract information. Timeliness refers to the system's timely response to user requests. Integrity means that the information provided by the system is necessary and comprehensive. Accuracy refers to the scientific and correct information provided by the system. Format refers to the standard and reasonable presentation of information provided by the system. Currency means that the information provided by the system is updated in time (Ives et al., 1983; Baroudi and Orlikowski, 1988). It can be seen that the user satisfaction model focuses on the characteristics of the system and information. User satisfaction is regarded as the attitude of users toward information systems, and it can also be regarded as an object-based attitude (Ajzen and Fishbein, 1980). User satisfaction is mainly measured by various object-based beliefs such as the quality of system technology and services, and the quality of information carried and transmitted by the system (Wixom and Todd, 2005). However, user satisfaction cannot predict users' use of the system well, that is, users who are satisfied with the system and information do not necessarily use the system (Barki, 1994).

In this study, online learning platform is regarded as an information system. Therefore, based on the above literature review, the following hypotheses are put forward by the authors:

> H1: Information Quality positively influences Information Satisfaction.

> H2: System Quality positively influences System Satisfaction.

2.2 Technology acceptance theory

The commonly used model for investigating technology acceptance is the TAM proposed by David. The TAM model mainly includes the following variables and relationship of variables: (1) Whether users use the system depends on the user attitude toward the system. (2) User attitude toward the system will affect users' intention to use it. (3) Attitude is mainly influenced by behavioral beliefs such as perceived usefulness and perceived ease of use. (4) Perceived ease of use will affect perceived usefulness (Davis, 1985). Perceived usefulness refers to the extent to which a person believes that using a specific system can improve job performance. Users think that if using a system can help improve job performance, they think it is a system with high perceived usefulness. Perceived ease of use refers to the degree to which a person thinks that using a particular system will save effort. Users think that if this system is easier to use, it will be more easily accepted by users (Davis, 1989). The TAM model is widely used in the research of understanding people's attitude toward technology use, and is mainly used to predict the users' use of information technology and tools. The TAM model only provides suggestions on how to improve users' use by designing and perfecting the system (Taylor and Todd, 1995). Based on this model, the designer can generally receive user feedback on the ease of use and usefulness of the system or platform, but will not receive feedback on the characteristics of the system or platform itself, such as flexibility, integration, reliability, information integrity, etc.

Therefore, based on the above literature review, the following hypotheses are put forward by the authors:

> H3: Perceived ease of use positively influences perceived usefulness.

> H4: Perceived usefulness positively influences user attitude.

> H5: Perceived usefulness positively influences usage intention.

> H6: Perceived ease of use positively influences user attitude.

> H7: User attitude positively influences usage intention.

2.3 User satisfaction and technology acceptance integration theory

Among the relevant TAM studies, some studies have focused on the key factors that affect ease of use and usefulness, such as gender, social impact and other factors (Gefen and Straub, 1997; Venkatesh and Morris, 2000). Venkatesh et al. (2003) empirically compared eight models in the field of information system technology acceptance, including rational behavior theory, technology acceptance model, motivation model, planned behavior theory, a model combining TAM and planned behavior theory, personal computer utilization model, innovation diffusion theory and social cognition theory, and developed the UTAUT. At the same time, based on the Technology Acceptance Model, they verified the external variables that affect the behavioral intention of digital libraries, such as individual differences and system characteristics. System characteristics mainly include relevance, terminology, and screen design. Individual differences and system characteristics have significant effects on perceived ease of use, thus affecting behavioral intention. System characteristics have significant effects on perceived usefulness, thus affecting behavioral intention. In particular, the relevance of system characteristics has the greatest effect on perceived usefulness (Hong et al., 2002).

According to the expectancy-value theory (Wigfield and Eccles, 2000), external variables will affect the user belief in performing a certain behavior, thus affecting the attitude of performing a certain behavior. Attitude will affect the

TABLE 1 Cronbach's alpha, composite reliability, average variance extracted (AVE), factor loadings of the constructs and items in the research models of BL and OL.

	Cronbach's alpha/Composite reliability/AVE		Factor loadings		M		SD	
	BL	OL	BL	OL	BL	OL	BL	OL
Information quality (INQU)	0.906/0.941/0.842	0.931/0.956/0.879						
INQU1			0.931	0.946	5.350	5.313	1.096	1.007
INQU2			0.924	0.937	5.448	5.306	1.053	1.013
INQU3			0.898	0.930	5.294	5.284	1.087	1.016
System quality (SYQU)	0.920/0.950/0.863	0.916/0.947/0.857						
SYQU1			0.937	0.931	5.273	5.231	1.127	0.957
SYQU2			0.942	0.917	5.357	5.336	1.141	0.925
SYQU3			0.907	0.929	5.357	5.336	0.989	0.934
Information satisfaction (INSA)	0.820/0.918/0.848	0.910/0.957/0.917						
INSA1			0.918	0.957	5.573	5.313	0.968	0.953
INSA2			0.923	0.959	5.336	5.336	1.041	0.973
System satisfaction (SYSA)	0.862/0.936/0.879	0.886/0.946/0.898						
SYSAT1			0.938	0.948	5.357	5.306	1.058	0.952
SYSAT2			0.937	0.947	5.343	5.328	1.015	0.899
Usefulness (USEF)	0.898/0.936/0.831	0.942/0.963/0.896						
USEF1			0.906	0.937	5.476	5.343	0.999	0.982
USEF2			0.899	0.944	5.392	5.396	1.081	1.026
USEF3			0.929	0.958	5.350	5.410	0.959	0.990
Ease of use (EAOU)	0.804/0.884/0.717	0.871/0.921/0.795						
EAOU1			0.799	0.886	5.629	5.410	0.861	0.928
EAOU2			0.874	0.883	5.259	5.269	1.060	0.967
EAOU3			0.866	0.905	5.490	5.440	0.971	0.905
Attitude (ATTI)	0.855/0.912/0.775	0.921/0.950/0.863						
ATTI1			0.896	0.937	5.343	5.269	1.062	0.935
ATTI2			0.886	0.931	5.203	5.284	1.098	0.955
ATTI3			0.858	0.919	5.601	5.321	1.056	0.939
Intention (INTE)	0.922/0.951/0.866	0.919/0.949/0.861						
INTEN1			0.932	0.926	5.315	5.299	1.195	0.910
INTEN2			0.926	0.916	4.993	5.269	1.335	1.020
INTEN3			0.933	0.942	5.203	5.246	1.166	0.945

intention to perform the behavior, and ultimately affect the behavior itself. Under certain circumstances, satisfaction is the feeling toward these external factors (Ajzen and Fishbein, 1980). External factors such as system characteristics will affect behavioral beliefs such as perceived ease of use or perceived usefulness (Hong et al., 2002). It can be seen that user satisfaction is the feeling toward external factors such as system characteristics and information characteristics. The beliefs of system quality and information quality will affect user attitude toward the system or information, so it will affect behavioral beliefs about using the system, such as perceived ease of use and usefulness. The behavior belief of using system directly affects the user attitude, and finally affects the behavior intention (Wixom and Todd, 2005).

The TAM can predict users' intentions and behaviors in a specific context and time according to the specific behavior belief and attitude, but it cannot obtain feedback on the characteristics of the system itself. User Satisfaction Model can obtain the characteristics of the system and information, but it cannot predict user behavior well. The characteristics of information and system will affect their satisfaction. Satisfaction may affect their behavioral beliefs about the system or information, and then affect their behavioral attitude, thus affecting usage intention (Ajzen and Fishbein, 1980). Wixom and Todd (2005) proposed and verified the Theoretical Integration of User Satisfaction and Technology Acceptance (USATA), which can better integrate the advantages of User Satisfaction and Technology Acceptance Model, and build the relationship between the two models. Information quality and system quality represent object-based belief. Satisfaction with information and systems represents object-based attitude. Object-based attitude is external variable of behavioral belief such as perceived ease of use and perceived usefulness. Specifically, the higher the system satisfaction, the more users will feel that the system is easy to use. The higher the information satisfaction, the more users will feel that the application of this information is useful for their work. In the Technology Acceptance Model, perceived ease of use affects perceived usefulness. Consistent with this view, the model proposes that system satisfaction affects information satisfaction.

Therefore, based on the above literature review, the following hypotheses are put forward by the authors:

> H8: Information satisfaction positively influences perceived usefulness.

> H9: System satisfaction positively influences perceived ease of use.

> H10: System satisfaction positively influences information satisfaction.

3 Materials and methods

3.1 Participants

Two groups (BL group and OL group) were selected from a public university in Lanzhou, China; they came from the same educational technology major and were taught by the same lecturer. Two groups studied the same course in different years. BL group participants studied this course in blended learning environment, who started their university studies in 2015 and 2016. OL group participants studied this course in online learning environment, who started their university studies in 2017 and 2018. The two groups of participants had the same professional learning experience and were familiar with the online learning platform they used. BL group had 143 students (43 male students and 100 female students). OL group had 134 students (34 male students and 100 female students). When they studied this course, they were in their junior year, ranging in age from 19 to 21.

3.2 Setting

This study was conducted in the form of quasi-experiment. Both groups took the same courses, had the same teachers, and used the same online learning platform. They were just different in the design of the learning environment.

The course was called "Design and Development of Multimedia Curriculum Resources," which aims to enable students to master the design and development methods of different types of curriculum resources, so as to make curriculum resources suitable for future teaching. Teachers of this course had 11 years of teaching experience and was exploring new teaching methods. The online learning platform used in this course was Chaoxing Fanya Platform. It was an online learning platform developed by China Chaoxing company. Teachers could set up courses on this platform, add courseware, test questions, teaching videos and other course resources, and carried out online activities such as topic discussion, grouping tasks, assignments, and evaluation.

During the non-COVID-19 epidemic period, the author carried out blended learning method relying on the Chaoxing Fanya platform. Before the COVID-19, in October 2019, the author conducted a survey (called BL group) in order to find out the factors affecting user satisfaction and acceptance of the online learning platform in blended learning scenario.

Due to the COVID-19, the author's university carried out four times of complete online teaching at home. The authors find that the importance of online learning platforms becomes more prominent when learning is completely online. In complete online learning, learners can only rely on online learning platform to obtain course knowledge, so the quality of online learning platform will affect students' learning process. Therefore, in December 2021, the authors also conducted a survey (called OL group) on the user satisfaction and acceptance of the online learning platform for learners who used the same Chaoxing Fanya platform in online learning scenario.

3.3 Treatment

The BL group was taught before the COVID-19, using blended learning approach. When face-to-face teaching, the teacher mainly explained the key and difficult points of the curriculum theory and students' difficult problems. In addition, in the course practice part, students practiced the development process of teaching resources. Before or after class, students could preview or review relevant resources of the course with the help of Chaoxing Fanya Platform; complete the after-school grouping tasks, participate in group theme discussion, participate in the outcome evaluation and other activities. Teachers conducted online guidance and evaluation on students' grouping tasks.

The OL group was taught during the COVID-19, and adopted a complete online learning method. The author used the curriculum resources built by Chaoxing Fanya Platform, and carried out online learning with the help of Chaoxing classroom and live broadcast software. Before class, students learned relevant courseware and videos in the online platform, completed the test questions, and put forward learning questions in the discussion area. In class, Teachers used live broadcast software to answer students' questions before class; students presented their learning achievements and exchanged comments. After class, students could watch the live broadcast course playback and course materials, review the course content, complete the homework, group tasks, and participate in online evaluation.

3.4 Instruments

The survey scale of this study mainly referred to the measurement scales of the Theoretical Integration of User Satisfaction and Technology Acceptance (Wixom and Todd, 2005). The questionnaire was divided into eight dimensions, namely information quality (3 survey items), system quality (3 survey items), information satisfaction (2 survey items), system satisfaction (2 survey items), user attitude (3 survey items), use intention (3 survey items), perceived ease of use (3 survey items) and perceived usefulness (3 survey items), totaling 22 items (see **Appendix Table A1**). Each item on the scale was measured on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). According to the theme of this study, the information system was defined as the Chaoxing Fanya platform, and some modifications were made according to the Chinese background, which is more convenient for Chinese students to understand. All scales in this study have implemented the back-translation procedure (Brislin, 1970).

3.5 Why PLS-SEM

In this study, Partial Least Squares Structural Equation Modeling (PLS-SEM) method was used for data analysis, and the analysis tool was SmartPLS 2.0. The PLS-SEM algorithm was selected in this study mainly because the PLS-SEM algorithm is very suitable for the study of small-scale samples (Subramani, 2004; Urbach and Ahlemann, 2010). Rules of thumb given by previous researchers suggested that the sample size in PLS-SEM model should be five times the largest number of independent variables (Falk and Miller, 1992), or equal to 10 times the number of independent variables in the most complex regression in the PLS path model (i.e., considering both measurement and structural models) (Hair et al., 2021). Some researchers believe that in PLS-SEM research, the appropriate sample size depends on many factors, such as the psychometric properties of the items, the effect size of the model, and the characteristics of the raw data (Chin and Newsted, 1999; Marcoulides and Saunders, 2006). Chin and Newsted (1999) suggested that the PLS-SEM algorithm can get accurate parameter estimates at sample size as low as 20. In this study, the sample sizes of BL group and OL group were 143 and 134 respectively, which is enough. The data analysis process mainly includes two steps. The first step is to analyze the measurement model to evaluate the reliability, internal consistency reliability, convergence validity and discrimination validity of the model. The second step is to analyze the structural model to evaluate the goodness-of-fit, coefficient of determination, path coefficient and group comparison results of the model (Hair et al., 1998).

4 Results

4.1 Measurement model

The evaluation of the measurement model is carried out through four aspects: item reliability, internal consistency reliability, convergence validity and discrimination validity.

4.1.1 Item reliability

The item reliability was evaluated by the indicator loadings. The reliability of one structure is independent of other structures and calculated separately from the reliability of other structures. According to Chin's suggestion, the factor loadings should be greater than 0.7 (Chin, 1998). As showed in **Table 1**, all indicator loadings in this study met the requirement. The ranges of item loadings in BL group and OL group were (0.799, 0.942) and (0.883, 0.959) respectively, which were greater than the recommended value. Overall, the item reliability in research models of the BL group and OL group was supported.

4.1.2 Internal consistency reliability

Internal consistency was assessed by Cronbach's alpha (CA) or Composite Reliability (CR). The traditional standard for evaluating the internal consistency reliability is CA and a high alpha value indicates that all items in the same construct have the same meaning (Cronbach, 1951). As an indicator of internal consistency reliability, the composition reliability is more accurate than CA (Chin, 1998). CA believes that all indicators are equally reliable. Composition reliability focuses on the differences of different indicators, and different indicators

TABLE 2 Discriminant validity of the research models of BL and OL.

Construct	ATTI		EAOU		INQU		INSA		INTE		SYQU		SYSA		USEF	
	BL	OL	BL	OL	BL	OL	BL	OL	BL	OL	BL	OL	BL	OL	BL	OL
ATTI	**0.880**	**0.929**														
EAOU	0.758	0.872	**0.847**	**0.892**												
INQU	0.796	0.814	0.728	0.807	**0.918**	**0.938**										
INSA	0.752	0.872	0.686	0.833	0.698	0.858	**0.921**	**0.958**								
INTE	0.807	0.902	0.734	0.897	0.700	0.822	0.660	0.847	**0.930**	**0.928**						
SYQU	0.826	0.863	0.738	0.854	0.828	0.892	0.829	0.903	0.717	0.856	**0.929**	**0.926**				
SYSA	0.871	0.895	0.786	0.861	0.763	0.836	0.823	0.894	0.723	0.865	0.825	0.897	**0.938**	**0.947**		
USEF	0.810	0.884	0.772	0.888	0.756	0.806	0.671	0.849	0.725	0.910	0.734	0.851	0.759	0.874	**0.911**	**0.947**

The bold values in the diagonal row are the square roots of the average variance extracted for the constructs in both research models.

have different loading (Henseler et al., 2009). The CA should be greater than 0.8 and the CR should be greater than 0.7 (Nunnally and Bernstein, 1994). In this study, the CA ranges of BL and OL group were (0.804, 0.922) and (0.871, 0.942) respectively and the CR ranges were (0.884, 0.951) and (0.921, 0.963) respectively (see **Table 1**). The CA and CR were all greater than the recommended values. It showed that the internal consistency of the measurement model is good.

4.1.3 Convergent validity

The convergent validity reflects the degree of convergence of individual items of a construct compared with items measuring different constructs. A common criterion for convergent validity is the average variance extracted (AVE) (Fornell and Larcker, 1981). An AVE value should be greater than 0.5 to have sufficient convergent validity. In this study, the AVE value ranges of BL group and OL group were (0.717, 0.879) and (0.795, 0.917) respectively (see **Table 1**), which were larger than the recommended values.

4.1.4 Discriminant validity

Discriminant validity indicates the difference of measurement values of different constructs. It is to check whether the measurement items of one construct have inadvertently measured other constructs. The discriminant validity can be evaluated by two criteria. For the first measure, the square root of the AVE of each latent variable should exceed the correlation between this variable and all other latent variables (Fornell and Larcker, 1981). The second measure, the cross-loadings means that the loading of each indicator of this construct is higher than that of the other construct (Chin, 1998). In the measurement of BL group and OL group, the square root of the AVE of all constructs were greater than that of Pearson correlation coefficient with other constructs (see **Table 2**). The cross-loadings of BL group and OL group were shown in **Table 3**. The loading of each indicator on the designated construct was higher than that on other construct (see **Table 3**). These results show that the constructs of this study have sufficient discriminant validity.

4.2 Structural model

Structural models are mainly evaluated by checking the significance level of the path coefficient in the research model and the explanatory power (i.e., R^2). The validation results of the structural models for the two research designs were presented in **Figures 1, 2**.

In the structural model of the BL group, information quality and system quality were found to have a significant influence on information satisfaction and system satisfaction, respectively, therefore supporting H1 and H2. Perceived ease of use had a significant positive influence on perceived usefulness, therefore supporting H3. User attitude was significantly affected by perceived ease of use and perceived usefulness, therefore supporting H4 and H6. User attitude was found to have a significant positively influence on usage intention, therefore supporting H7. However, Perceived usefulness was not found to significantly affect usage intention, thus rejecting H5. Information satisfaction had a significant positive influence on perceived usefulness, and system satisfaction had a significant positive influence on perceived ease of use, therefore supporting H8 and H9. System satisfaction was found to have a significant positively influence on information satisfaction, therefore supporting H10. The path coefficient of the BL group model was shown in **Figure 1**. Meanwhile, in the OL group, all path coefficients were significant, therefore supporting all the ten hypotheses (see **Figure 2**).

The coefficient of determination (R^2) is the ratio of the interpretable variance of the endogenous latent variables to the total variance in the model, and it is one of the indicators to evaluate the prediction effect of the model. Chin (1998) suggested that when the R^2 of endogenous latent variable is 0.670, it means that the prediction effect of the latent variable is "large"; when the R^2 of the endogenous latent variable is 0.333,

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TABLE 3 Cross-loadings of the variables in the measurement models of BL and OL.

	ATTI		EAOU		INQU		INSA		INTE		SYQU		SYSA		USEF	
	BL	OL	BL	OL	BL	OL	BL	OL	OL	OL	OL	OL	OL	OL	OL	OL
Attitude (ATTI)																
ATTI1	**0.896**	**0.937**	0.663	0.792	0.737	0.748	0.679	0.844	0.690	0.829	0.741	0.801	0.815	0.826	0.728	0.809
ATTI2	**0.886**	**0.931**	0.672	0.825	0.715	0.758	0.705	0.826	0.724	0.842	0.764	0.821	0.778	0.858	0.681	0.844
ATTI3	**0.858**	**0.919**	0.665	0.811	0.650	0.763	0.601	0.760	0.716	0.844	0.676	0.785	0.707	0.812	0.728	0.811
Ease of use (EAOU)																
EAOU1	0.528	0.762	**0.799**	**0.886**	0.500	0.747	0.484	0.753	0.548	0.755	0.478	0.772	0.565	0.754	0.573	0.759
EAOU2	0.731	0.803	**0.874**	**0.883**	0.753	0.747	0.715	0.770	0.730	0.869	0.779	0.828	0.767	0.813	0.725	0.832
EAOU3	0.644	0.763	**0.866**	**0.905**	0.567	0.662	0.516	0.701	0.567	0.768	0.581	0.678	0.643	0.732	0.648	0.779
Information quality (INQU)																
INQU1	0.737	0.760	0.687	0.772	**0.931**	**0.946**	0.659	0.788	0.660	0.779	0.772	0.843	0.708	0.764	0.703	0.754
INQU2	0.743	0.749	0.657	0.741	**0.924**	**0.937**	0.657	0.786	0.640	0.747	0.718	0.825	0.700	0.787	0.711	0.735
INQU3	0.711	0.780	0.661	0.758	**0.898**	**0.930**	0.604	0.836	0.628	0.786	0.793	0.841	0.693	0.801	0.667	0.775
Information satisfaction (INSA)																
INSA1	0.665	0.823	0.627	0.787	0.616	0.805	**0.918**	**0.957**	0.561	0.809	0.731	0.836	0.736	0.859	0.622	0.794
INSA2	0.718	0.846	0.635	0.808	0.669	0.838	**0.923**	**0.959**	0.653	0.812	0.794	0.894	0.778	0.853	0.613	0.831
Intention (INTE)																
INTEN1	0.751	0.865	0.712	0.852	0.667	0.781	0.618	0.816	**0.932**	**0.926**	0.655	0.833	0.690	0.861	0.718	0.862
INTEN2	0.727	0.790	0.687	0.807	0.639	0.737	0.603	0.738	**0.926**	**0.916**	0.658	0.754	0.648	0.741	0.638	0.815
INTEN3	0.773	0.854	0.650	0.836	0.648	0.769	0.622	0.800	**0.933**	**0.942**	0.689	0.795	0.680	0.804	0.666	0.855
System quality (SYQU)																
SYQU1	0.761	0.792	0.677	0.804	0.791	0.819	0.764	0.830	0.650	0.794	**0.937**	**0.931**	0.777	0.812	0.650	0.779
SYQU2	0.803	0.828	0.724	0.810	0.783	0.818	0.762	0.827	0.700	0.796	**0.942**	**0.917**	0.773	0.841	0.704	0.8
SYQU3	0.735	0.778	0.655	0.758	0.732	0.839	0.785	0.851	0.649	0.789	**0.907**	**0.929**	0.749	0.838	0.691	0.784
System satisfaction (SYSA)																
SYSAT1	0.812	0.839	0.718	0.798	0.714	0.808	0.783	0.875	0.684	0.811	0.791	0.849	**0.938**	**0.948**	0.687	0.821
SYSAT2	0.821	0.858	0.755	0.834	0.717	0.776	0.759	0.818	0.672	0.829	0.756	0.851	**0.937**	**0.947**	0.737	0.835
Usefulness (USEF)																
USEF1	0.730	0.818	0.672	0.828	0.629	0.766	0.622	0.781	0.650	0.861	0.651	0.813	0.713	0.838	**0.906**	**0.937**
USEF2	0.755	0.855	0.715	0.848	0.716	0.760	0.578	0.817	0.654	0.848	0.669	0.802	0.663	0.816	**0.899**	**0.944**
USEF3	0.729	0.838	0.723	0.845	0.722	0.761	0.634	0.812	0.678	0.876	0.685	0.802	0.700	0.827	**0.929**	**0.958**

The bold values are the loadings of each item on its latent variable in both research models.

the prediction effect of the latent variable is “medium”; when the R^2 of the endogenous latent variable is 0.190, the prediction effect of the latent variable is “small.” In this study, in BL group, the R^2 for information satisfaction, system satisfaction, usefulness, ease of use, attitude and intention were 0.689, 0.681, 0.633, 0.618, 0.699, and 0.666, respectively (see **Figure 1**). In OL group, R^2 for information satisfaction, system satisfaction, usefulness, ease of use, attitude and intention were 0.839, 0.805, 0.827, 0.742, 0.818, and 0.872, respectively (see **Figure 2**). Thus, the research models had the predictive power of "medium" or above.

Although PLS-SEM analysis does not have any overall model fit indicators (Henseler et al., 2009). However, Tenenhaus et al. (2004) proposed a global goodness of fit ($0 < \text{GoF} < 1$) criterion for PLS-SEM analysis. It is calculated as the geometric mean of the average communality and average R^2 (Tenenhaus et al., 2004). Wetzels et al. (2009) proposed that the value of GoF is defined as small (0.10), medium (0.25), and large (0.36). The GoF values of BL group and OL group were 0.741 and 0.843, respectively. Therefore, the research models designed in this study had a high degree of fitting. This showed that the two models built in this study were acceptable.

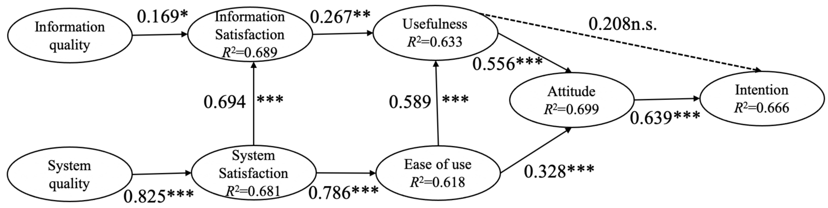

FIGURE 1
Structural model for the group of blended learning. *p < 0.05; **p < 0.01; ***p < 0.001; n.s. = non-significant.

4.3 Comparison of path coefficients between blended learning group and online learning group

The previous analysis confirmed the reliability and validity of the two groups of research models. In order to find out whether there is any difference in the research model before and during the COVID-19, this study conducted a multi-group comparative analysis. Generally, the method of comparing path models usually focuses on the differences in the structure level, especially the path coefficient (Sanchez, 2013). In this study, bootstrapping T-test was used to compare multiple groups (K = 5000). As shown in **Table 4**, there are differences between BL group and OL group in the paths of "information quality affects information satisfaction" (H1) and "perceived usefulness affects usage intention" (H5).

4.4 Satisfaction and acceptance comparison in two groups

Finally, this study compared the satisfaction and acceptance of college students on the online learning platform between the BL group and the OL group. The T-test analysis of the two groups from the three dimensions of information satisfaction, system satisfaction and usage intention showed that there was no difference in the satisfaction and acceptance of online learning platform between the two groups, as shown in **Table 5**.

5 Discussion

The purpose of this study was to investigate and analyze the influence factors of learners' satisfaction and acceptance of online learning platform based on USATA model, and focused on the comparative investigation and analysis of the differences in the context of online learning and blended learning. The results of data analysis showed that there was no significant difference in college students' satisfaction and acceptance in both groups, but the information quality of online learning platform had a greater impact on college students' information satisfaction during the home-based online learning, and there was a significant difference between the two groups. In blended learning environment, the perceived usefulness of online learning platform had no significant impact on college students' intention to use the online learning platform. In online learning environment, the perceived usefulness of online learning platform significantly affected college students' intention to use the online learning platform, and the degree of impact was large.

5.1 Information quality and system quality affect user's online learning platform satisfaction

From the research results, we can see that in the level of students' satisfaction with online learning platforms, the proposed hypotheses 1, 2, and 10 have been supported, and the information quality has a significant positive impact on information satisfaction; System quality has a significant positive impact on system satisfaction; System satisfaction has a significant positive impact on information satisfaction. In online learning environment, the quality of learning resources provided by online learning platform will affect college students' satisfaction with online learning content. The quality of online learning platform itself will affect college students' satisfaction with online learning platform. These results have been supported in the research of information system satisfaction measurement, and are consistent with the existing research results (Doll and Torkzadeh, 1988). Online learning platform is also a specific form of information system. This study focused on whether students' satisfaction with online learning platforms was different in different learning environments.

Through investigation and analysis, it was found that there was a significant difference in the path of information quality affecting information satisfaction between blended learning and online learning environments. In online learning environment, information quality had a greater impact on user's information satisfaction. To some extent, this showed that college students had higher requirements for the quality of learning resources provided by the online learning platform during the home-based online learning. The quality of online learning resources

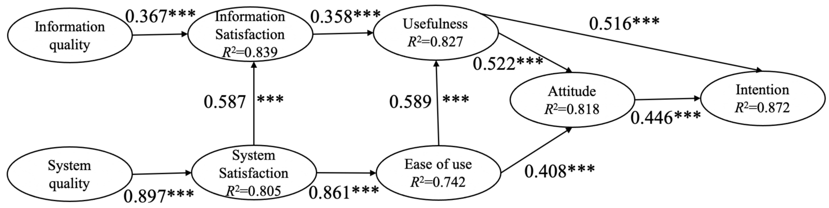

FIGURE 2
Structural model for the group of online learning. ***p < 0.001.

TABLE 4 Comparisons between BL and OL through bootstrapping.

Hypothesis	Path	Group: BL path coefficients	Group: OL path coefficients	Diff. abs	t	df	p	Sig. 05
H1	**INQU - > INSA**	**0.169**	**0.367**	**0.198**	**1.985**	**276**	**0.049**	**Yes**
H2	SYQU - > SYSA	0.825	0.897	0.072	1.565	276	0.120	No
H3	EAOU - > USEF	0.589	0.589	0.000	0.004	276	0.997	No
H4	USEF - > ATTI	0.556	0.522	0.034	0.247	276	0.805	No
H5	**USEF - > INTE**	**0.208**	**0.516**	**0.308**	**2.096**	**276**	**0.038**	**Yes**
H6	EAOU - > ATTI	0.328	0.408	0.080	0.556	276	0.579	No
H7	ATTI - > INTE	0.639	0.446	0.193	1.236	276	0.219	No
H8	INSA - > USEF	0.267	0.358	0.091	0.646	276	0.520	No
H9	SYSA - > EAOU	0.786	0.861	0.075	1.441	276	0.152	No
H10	SYSA - > INSA	0.694	0.587	0.107	1.052	276	0.295	No

Diff. abs, absolute difference; df, degree of freedom. The bold values are the values of two hypotheses with significant difference.

was directly related to learners' satisfaction with online learning. The previous studies on online learning and online learning platforms during the COVID-19 also showed that the learning method had changed from face-to-face learning to full online learning. The interaction between teachers and students and the acquisition of online learning resources in the online learning environment were particularly important (Almusharraf and Khahro, 2020; Tsang et al., 2021). The results of this study can be explained from two aspects. On the one hand, in face-to-face learning environment, online learning platform is not a necessary way for students to obtain information. It is more convenient for students to communicate with teachers and peers. Learning resources can be obtained through teacher-student conversation, or through libraries and other channels. However, during the period of full online learning at home, learning mainly relies on an online learning platform, and students will naturally obtain learning resources from the online learning platform. Therefore, college students have higher requirements for the quality of learning resources provided by the online platform. On the other hand, the data analysis results of this study verified the impact of system satisfaction on information satisfaction. This showed that personal satisfaction with the system may affect their satisfaction with the system information. Therefore, learners' satisfaction with the online learning platform will affect learners' satisfaction with the learning resources provided by the online learning platform. This result may be because college students are more satisfied with the online learning platform they use, and will be more accustomed to using the online learning platform to learn and obtain learning resources and information, so they will be more satisfied with the learning information provided in the platform.

5.2 Perceived usefulness and perceived ease of use affect user attitude and usage intention

The data analysis results of this study showed that in the level of students' acceptance of online learning platforms, the proposed hypotheses 3–7 have been supported in the OL group, while in BL group, except H5, H3, H4, H6, and H7 were also supported. Perceived usefulness and perceived ease of use will affect user attitudes toward online learning platforms, which will affect their intention to use. Perceived ease of use affects perceived usefulness. Students perceive that the online learning platform is useful or easy to use. In this way, students like to use the online learning platform and have a more positive attitude toward the online teaching platform, resulting in a stronger intention to use the online learning platform. Students perceive that online learning platforms are easy to use, which will also lead to the perception that online learning platforms are more useful. These results are consistent with those of the TAM (Davis et al., 1989; Davis and Wiedenbeck, 2001). The results of this study were also consistent with previous studies results of investigating the acceptance of other online learning platforms with the TAM model (Sánchez and Hueros, 2010; Zhou et al., 2022).

Through the comparative analysis of the models of blended learning and complete online learning, it was found that there was no significant difference between the two groups in the impact of perceived usefulness and perceived ease of use on user attitude, and there was no significant difference in the impact of perceived ease of use on perceived usefulness, but there was a significant difference in the impact of perceived usefulness on usage intention. In blended learning environment, the hypothesis that perceived usefulness affects learners' intention to use online learning platforms was not supported, which showed that user perception of the usefulness of online learning resources did not significantly affect learners' intention to use them. This is different from some previous studies. This difference may be caused by the fact that students mainly studied by face-to-face way in the classroom environment, and learners had many ways to obtain learning resources, so their dependence on online learning platforms was not obvious, that is, even if the learning resources provided by online learning platforms were very useful, students did not necessarily use them. In complete online learning environment, learners' perceived usefulness will significantly affect their intention to use online learning platforms, and the degree of influence is greater. This can explain that in the complete home-based online learning environment, online learning platform has become the important way for students to obtain learning resources. Learners pay more attention to the usefulness and quality of online learning resources. If the online learning platform provides high-quality and useful learning resources, learners are more willing to use the online learning platform. This result was consistent with the conclusion in the satisfaction survey that "the quality of learning resources affects learners' online learning satisfaction."

5.3 Online platform satisfaction affects the perception of usefulness and ease of use behavior beliefs, and then affects the usage intention

In this study, hypotheses 8 and 9 were supported in the relationship between college students' satisfaction and acceptance of online learning platforms. Research showed that information satisfaction affects user perceived usefulness and system satisfaction affects user perceived ease of use. If learners are satisfied with online learning resources, they think that learning resources are more useful; If learners are satisfied with the online learning platform, they will think that the platform is easy to use. These results were consistent with those proposed and verified by USATA model (Wixom and Todd, 2005). In the blended learning group, the impact of information satisfaction on perceived usefulness was slightly smaller than that in the online learning group, but there was no significant difference between the two groups.

TABLE 5 The two groups were analyzed by *T*-test in intention, information satisfaction and system satisfaction.

Construct	Group	N	M	SD	*T*-test
INTEN	BL	143	5.170	1.146	$t = -0.822, p = 0.412$
	OL	134	5.271	0.889	
INSA	BL	143	5.455	0.925	$t = 1.170, p = 0.243$
	OL	134	5.325	0.922	
SYSA	BL	143	5.350	0.971	$t = 0.291, p = 0.771$
	OL	134	5.317	0.877	

In addition, the study found that there was no significant difference in learners' satisfaction and acceptance of the online learning platform in two groups. The reason for this result may be related to the fact that the participants of this study are college students who usually have more contact with online learning platforms. These students have been using the online learning platform for blending learning in their professional learning, and are familiar with the online learning platform. Another reason may be related to the online learning platform investigated. The online learning platform investigated in this study was Chaoxing Fanya platform. The university where the respondents are located has been using this platform to carry out public network digital courses, and many professional courses also use this platform for auxiliary teaching. It can be seen that students are more accustomed to using the online learning platform at ordinary times, so it will be more acceptable to continue to use the online learning platform for online learning at home, and they will be more satisfied with the online learning platform and the learning resources it provides.

6 Conclusion and limitation

This study focused on college students' satisfaction and acceptance with the online learning platform and its key influence factors, and verified the USATA model in two learning environments. The study found that during the home-based online learning, the quality of learning resources provided by online learning platforms has a more significant impact on students' satisfaction and acceptance of online learning platforms. This study integrated learners' satisfaction and acceptance into a model to investigate learners' intention to use online learning platforms in different learning environments, which provides a new perspective for similar studies. Moreover, the results of this study also provided a basis for the design and development of online learning platform, that is, we should pay attention to the external factors that affect user's satisfaction and acceptance, and start from improving the quality of online learning platform itself and online learning information. Only by focusing on the quality of online learning platform and resources, and ensuring the ease of use of the platform and the usefulness of resources, can learners' satisfaction and acceptance of online learning be improved. In order to improve learners' satisfaction and acceptance of online learning platform, online learning platform designers and developers should focus on the quality of online learning platform itself and the information it provides, so as to improve the ease of use of online learning platform and the usefulness of learning resources.

The results of this study have two important implications for the practical activities of development and application of online learning platform. The first implication is that the quality of online learning platform affects learners' satisfaction and usage intention, so the design and development of online learning platform should focus on its quality. When developing online learning platform, developers can improve the quality of online learning platform from the aspects of reliability, accessibility, flexibility, comprehensiveness, timeliness and so on (Ives et al., 1983). First of all, we should ensure that the online learning platform is stable and reliable, without congestion and collapse, and convenient for learners to use. The second is to ensure that learners can easily obtain the required resources and tools through the platform. Third, enrich the functions of the online platform to meet different learning needs. Fourth, integrate the learning functions commonly used in online learning, collect different types of learning resources, and be compatible with the resources and tools of other learning platforms. Fifth, give timely feedback to learners' interaction to ensure smooth human-computer interaction.

The second implication is that the quality of online learning resources affects learners' satisfaction and intention to use resources. Therefore, the design and development of online learning resources should ensure their quality. Online learning resources can ensure the quality of resources from their integrity, standardization, accuracy, currency and ease of use (Bailey and Pearson, 1983). First, online learning resources should provide complete and rich resources for learners' needs. Second, online learning resources should be standardized in presentation style and clear in content design. Third, the accuracy of online learning resources should be guaranteed, and there should be no wrong content. Fourth, the content of online learning resources should be constantly updated to provide the latest learning content. Fifth, online learning resources need to be carefully designed, such as learning units, learning paths, learning activities, learning content presentation and so on, which need to be reasonably designed to ensure that learners can easily access and use.

This study has two limitations that should be addressed in future research. First, the online learning platform surveyed is relatively single. The online learning platform investigated in this study is Chaoxing Fanya platform, which cannot explain the quality of all online learning platforms. This research limitation is also reflected in the research results. The results of this study showed that there was no significant difference in students' satisfaction and acceptance of Chaoxing Fanya platform in two groups. This may be related to the fact that the respondent groups are familiar with the learning platform. The second limitation is that the level of respondents is not diverse enough to involve primary and secondary school learners. For primary and secondary school students who had less access to online learning platforms in face-to-face teaching at schools, their satisfaction and acceptance of online learning platforms may be more different. Although this study has some limitations, it also provides the research direction in related research fields to a certain extent. According to the idea of this study, it is necessary to investigate the USATA model of more other countries during the COVID-19 and after the normalization of the epidemic, analyze the factors that affect the satisfaction and acceptance of online learning platforms, and provide educational support to students in a wider range.

Data availability statement

The original contributions presented in this study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

XL conducted online teaching, found research problems, designed research plans, and conducted investigation research. WZ processed and analyzed the research data. Both authors participated in the writing, revision and submission of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix

APPENDIX TABLE A1 Dimensions and items of the research model.

Construct	Item
Information quality (INQU)	INQU 1. In a word, I highly evaluate the content on learning platform
	INQU 2. In short, I highly value the functions of the learning platform
	INQU 3. In short, the resources on the learning platform are of high quality.
System quality (SYQU)	SYQU 1. Regarding the product quality of learning platform, I give a very high evaluation.
	SYQU 2. In short, learning platform has high quality in terms of function.
	SYQU 3. In short, the resources provided by learning platform are of high quality.
Information satisfaction (INSA)	INSA 1. I am satisfied with the learning resources on learning platform.
	INSA 2. I am very satisfied with the learning resources provided by learning platform.
System satisfaction (SYSA)	SYSA 1. Considering all aspects, I am very satisfied with the learning platform.
	SYSA 2. I am very satisfied with the interactive experience with the learning platform.
Ease of use (EAOU)	EAOU 1. The learning platform is easy to use.
	EAOU 2. On the learning platform, it is easy to operate and realize the functions I want.
	EAOU 3. It is very easy to operate on the learning platform.
Usefulness (USEF)	USEF 1. Using the learning platform is helpful to improve my learning methods.
	USEF 2. Learning platform saves time and improves efficiency.
	USEF 3. Learning platform has improved my learning quality.
Attitude (ATTI)	ATTI1. I like the process of using learning platform very much.
	ATTI 2. In short, the experience of using learning platform is happy.
	ATTI 3. I am in favor of using learning platform.
Intention (INTE)	INTE 1. In the future, I plan to use more learning platform in my learning process.
	INTE 2. As long as I have the opportunity to use learning platform, I will seize every opportunity to use it.
	INTE 3. I plan to increase the frequency of using learning platform in the future.

The above scales were used for online learning and blended learning, respectively. The formulation of online learning and blended learning scenarios had been omitted in the table.