EnPress Publisher

Journal of Infrastructure, Policy and Development 2024, 8(9), 8037.
https://doi.org/10.24294/jipd.v8i9.8037

Article

A novel systematic macroscopic approach: Identifying secondary school students' learning psychological states through multimodal data application and advancing education and educational reform

Xinyu Ni, Baoyuan Yin*

College of Educational Science, Harbin Normal University, Harbin 150000, Heilongjiang Province, China
*** Corresponding author:** Baoyuan Yin, yinbaoyuan@hrbnu.edu.cn

CITATION

Ni X, Yin B. (2024). A novel systematic macroscopic approach: Identifying secondary school students' learning psychological states through multimodal data application and advancing education and educational reform. Journal of Infrastructure, Policy and Development. 8(9): 8037. https://doi.org/10.24294/jipd.v8i9.8037

ARTICLE INFO

Received: 19 February 2024
Accepted: 1 August 2024
Available online: 4 September 2024

Abstract: In the dynamic landscape of modern education, it is essential to understand and recognize the psychological habits that underpin students' learning processes. These habits play a crucial role in shaping students' learning outcomes, motivation, and overall educational experiences. This paper shifts the focus towards a more nuanced exploration of these psychological habits in learning, particularly among secondary school students. We propose an innovative assessment model that integrates multimodal data analysis with the quality function deployment theory and the subjective-objective assignment method. This model employs the G-1-entropy value method for an objective evaluation of students' psychological learning habits. The G-1-entropy method stands out for its comprehensive, objective, and practical approach, offering valuable insights into students' learning behaviors. By applying this method to assess the psychological aspects of learning, this study contributes to educational research and informs educational reforms. It provides a robust framework for understanding students' learning habits, thereby aiding in the development of targeted educational strategies. The findings of this study offer strategic directions for educational management, teacher training, and curriculum development. This research not only advances theoretical knowledge in the field of educational psychology but also has practical implications for enhancing the quality of education. It serves as a scientific foundation for educators, administrators, and policymakers in shaping effective educational practices.

Keywords: psychological learning habits; educational reform; multimodal data analysis; educational psychology; G-1-entropy method; secondary education

1. Introduction

The ongoing COVID-19 pandemic, persisting for over three years, has precipitated a profound psychological and mental health crisis among students, particularly affecting adolescents. This demographic is alarmingly susceptible to severe mental health issues, including self-harm and suicide. Recent surveys reveal a troubling trend in adolescent mental health, with approximately three-quarters of college students reluctant to seek help for mental health concerns. The 2021 American Mental Health Status Survey underscores this issue, reporting that 9.7% of young Americans suffer from major depression, a slight increase from 9.2% in the previous year. The situation appears even more dire in developing countries. Furthermore, research indicates that high school students are more prone to moderate to severe anxiety and depression during the pandemic than other age groups. Addressing and mitigating this mental health crisis among students has thus emerged as a critical global challenge. The psychological and psychiatric repercussions of the pandemic are likely to be long-term, necessitating urgent and comprehensive mental health education and services for students. This requires a collaborative effort involving governments, societies, schools, and families.

In response to this crisis, various countries have increasingly focused on the mental health of their citizens, particularly students. Both the United States and China have introduced significant policies to combat these challenges. In March 2021, the U.S. government enacted the Rescue Plan Act, allocating $122.7 billion in emergency relief for elementary and secondary schools. A portion of these funds is dedicated to enhancing child mental health through promotion, training, and provision of mental health education and services. This hopes to mitigate the pandemic's impact on the mental well-being of students and teachers. Additionally, the Bipartisan Safe Communities Act, passed in June 2022, includes provisions for funding school-based mental health services. In China, the Health China Initiative 2021–2022 Assessment and Implementation Plan, released in February 2022, incorporates key metrics such as the "rate of standardized management of patients with severe mental disorders" and the "proportion of primary and secondary schools with full-time mental health education teachers" into its evaluation criteria. By 2030, the plan aims for the standardized management rate of patients with severe mental disorders in China to reach 85%, surpassing the National Health Commission's 2021 target of 80%. Furthermore, the "Health China Action 2022 Work Highlights," announced on 23 March 2022, emphasizes the importance of summarizing and promoting the pilot construction of a social psychological service system and enhancing the mental health of children and adolescents.

The emerging focus of national policies on addressing youth mental health issues through educational reform highlights the need for timely and accurate identification of students' psychological states. This is a critical step in mitigating mental health concerns among young people. On one hand, many students with mental health issues are unaware of their conditions. On the other hand, teachers often find it challenging to discern changes in the mental state of each student, particularly in offline, multi-person classroom settings or discussions, and especially with students who are less interactive. The global COVID-19 pandemic has further complicated this issue. The necessity for students to wear masks during face-to-face interactions and the shift to remote learning modalities have made it increasingly difficult for educators to observe and assess students' mental states effectively. In response to these challenges, the focus has shifted towards the automatic detection of complex, learning-centered mental states during educational activities. Traditionally, mental state recognition relies on the analysis of single-modal information, such as facial expression recognition, physiological signal analysis (like EEG), and speech information recognition. However, these single-modal approaches often fail to provide a comprehensive understanding of mental states. Recent advances in intelligent sensing devices and artificial intelligence technologies, including natural language processing, computer vision, speech recognition, and physiological information recognition, have enabled the acquisition of multimodal data in intelligent learning environments. This advancement allows for more accurate psychological recognition of students based on multimodal data. Multimodal psychological recognition technology involves the integration of complementary information from various modalities, including visual, auditory, and textual data, to characterize students' behaviors, attention, emotions, engagement, and learning performance. This integrated approach facilitates more nuanced and accurate psychological state assessments than single-modal methods. The complexity and higher accuracy of multimodal psychological recognition technology mark a significant advancement in mental health education for primary and secondary school students. This technology paves the way for the development of a comprehensive mental health service system that caters to all students and gradually integrates with social governance systems, promoting the healthy development of primary and secondary school students.

This paper makes significant contributions in three key areas. Firstly, at the methodological level, it introduces a novel approach for evaluating the psychological state of learning using multimodal data and the G-1-entropy value method. This method, by integrating multiple data sources and employing an innovative evaluation technique, enables a comprehensive and objective analysis of students' psychological states in learning environments. It addresses the shortcomings of subjectivity and limitations inherent in traditional assessment methods, offering new insights and tools for examining students' psychological learning states. Secondly, from a research perspective, the study bridges the gap between the identification of students' psychological states in learning and macro-level educational reform. Through in-depth weighting analysis and the development of targeted strategies for school education management, teacher training, and curriculum design, the paper provides practical guidance and suggestions. These insights aim to support education administrators and teachers in implementing effective educational reforms, thereby enhancing the overall quality and effectiveness of education. Lastly, in terms of results output, this study demonstrates the practical applicability and validation of the proposed evaluation method in identifying students' psychological learning states and informing educational reforms. The findings of this research not only represent a novel application in the field but also offer practical guidance for enhancing learning outcomes and teaching strategies. Moreover, they serve as a scientific foundation for educational policymakers, contributing to the improvement of educational quality and advancing the field of education.

The structure of the paper is as follows: Part 2 presents a literature review, offering an in-depth analysis at three levels—the mental states and health of secondary school students, the impact of mental states on these students, and the identification and detection of students' mental states. Part 3 introduces the foundational theories, including quality function deployment theory, questionnaire survey methodology, and multimodal data methods for mental state identification. Part 4 outlines the technical route of this study. Part 5 analyzes the identification of secondary school students' mental states and the current state of experimentation. Part 6 proposes a model for educational reform based on quality function deployment theory. Part 7 discusses the significance of conducting this study, and Part 8 concludes the paper.

2. Literature review

This study delves into the identification of secondary school students' psychological states in learning and explores the intersections with educational reform.

It emphasizes the application of multimodal data methods, the development of a psychological state identification model, enhancement of mental health intervention programs, and the construction of a mental health assessment index system. The objective is to quantitatively analyze students' psychological states and their influencing factors, culminating in tailored opinions and recommendations. To provide a clear and structured overview of the literature review, we have developed a framework diagram (**Figure 1**), which visually outlines the thematic organization of our literature review. This framework is instrumental in elucidating the three-tiered approach of our review. These tiers encompass: student psychological research, student mental health and psychological state research, and psychological state impact on students and detection categories, which are reviewed as follows.

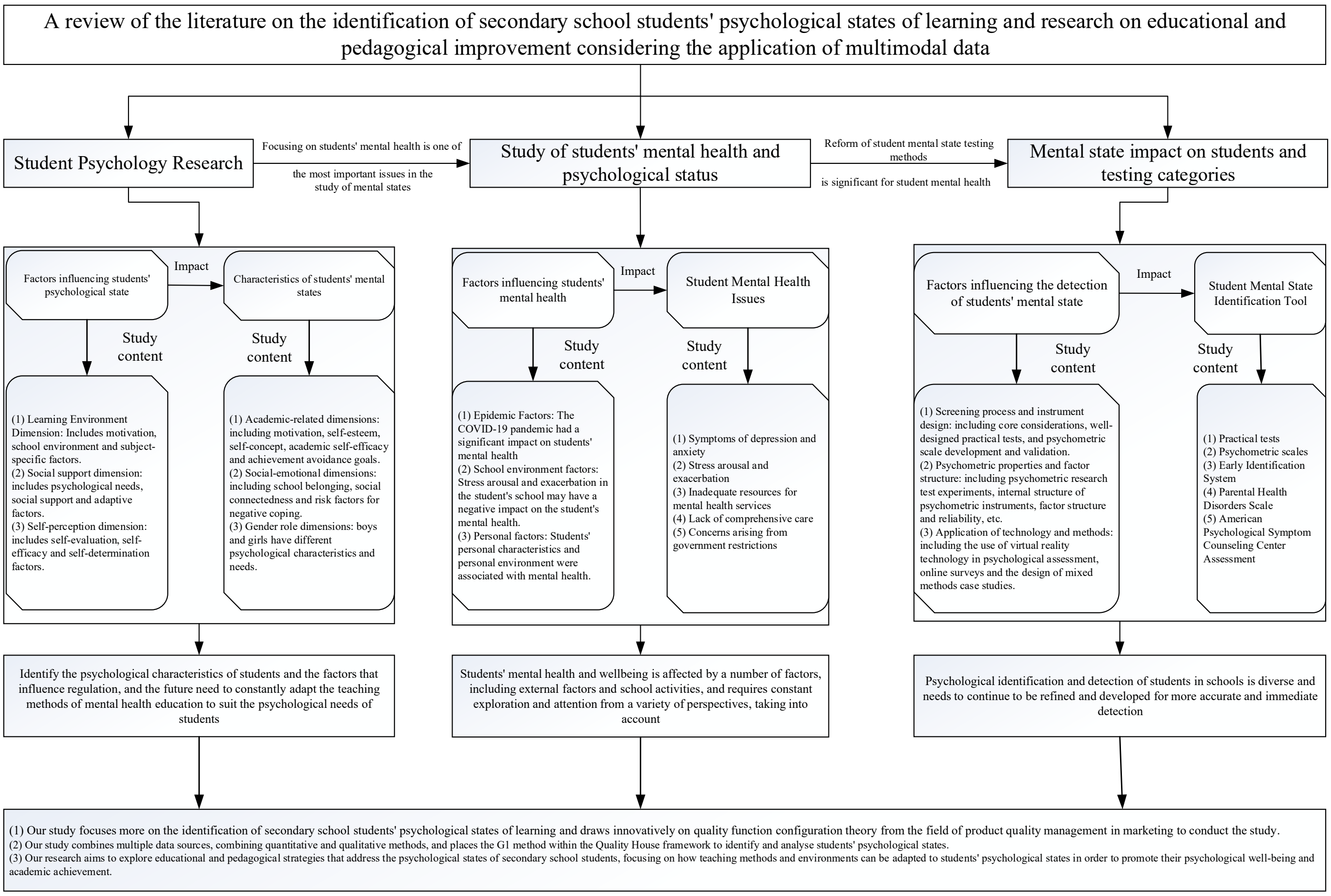


Figure 1. Literature review thought diagram.

In exploring the psychological states of secondary school students, the international literature presents a rich body of research. These studies predominantly focus on investigating various aspects of student psychology through qualitative analysis and empirical data experiments. Vsevolod and Franzis (2019) delved into the interplay between student motivation and self-esteem levels, uncovering significant insights through an independent longitudinal study. They highlighted the intricate connections between self-esteem, academic self-concept, self-efficacy, and achievement motivation. Korpershoek et al. (2019) examined the crucial role of school belonging in students' motivation, affect, behavior, and academic functioning in secondary education. Their findings underscore the significant impact of school belonging on students' overall school experience. Luisa et al. (2018) investigated the relationship between basic psychological needs and student engagement among Italian secondary school students. Jerusha et al. (2022) used self-report survey data to confirm the positive influence of student voice on student engagement. These studies collectively provide a macro perspective on the factors influencing student psychological states, demonstrating their critical importance in the realms of student learning and education. They also offer a valuable framework for constructing indicators to evaluate student psychological states. Xiaoxia et al. (2019) explored gender-specific factors affecting students' psychological states, finding that math proficiency directly influenced math anxiety, growth mindset, and career interests in male students, while math anxiety directly affected female students' career interests. Mikko et al. (2019) studied the relationship between students' basic psychological needs, motivational norms, and enjoyment in Finnish physical education classes. These studies provide a micro perspective, analyzing students' psychological states within specific classroom settings. While these studies do not directly link to the application of multimodal data, they offer insightful perspectives for constructing and understanding evaluation indicators of students' psychological states. They highlight the relationship between subject competence, context-specific psychological needs, and students' psychological states. During the COVID-19 pandemic, Caiyun et al. (2020) found that over one-fifth of middle and high school students in China experienced mental health impacts, with negative coping identified as a risk factor. (Jason C et al. (2018) conducted an extensive online survey to measure mental health among UK university students and identify key social determinants. Anniko et al. (2019) investigated anxiety as a mediator in the development of mental health problems in response to common adolescent stressors. These studies explore various influences on students' psychological states, indicating that these states are shaped by both internal factors (like individual abilities and gender) and external factors (such as social environment and educational setting). Hao et al. (2017) examined the relationship between teacher support and students' academic emotions, finding a stronger correlation in Western European and American students compared to East Asian students. Wan Har et al. (2018) analyzed the indirect relationships between students' perceptions of teacher learning support, self-efficacy, and adaptive competence. Cheon et al. (2019) discussed the benefits of autonomy-supportive teaching methods in secondary school physical education through a controlled experiment. These studies emphasize the effects of teacher interventions on student psychology, offering theoretical support for our research on identifying secondary school students' psychological states and educational reform under multimodal data applications. However, as these studies primarily rely on qualitative methodologies or context-specific analyses, the use of questionnaires may introduce recall bias or subjective evaluations. Therefore, the goal of this paper is to integrate qualitative and quantitative methods to validate and extend these findings. We acknowledge the value of these studies in providing the background and theoretical foundation for understanding the key factors influencing students' psychological states. Nonetheless, qualitative analysis alone may not yield comprehensive statistical evidence. Hence, in our study, we endeavor to employ quantitative analysis techniques, statistical methods, and other approaches to delve deeper into students' psychological states of learning and refine effective identification methods and educational strategies.

The international body of literature on student mental health is extensive, primarily employing qualitative and quantitative analyses to underscore the significance of focusing on student mental health across various settings. Sakinah et al. (2021) assessed the impact of the COVID-19 pandemic on Chinese children's mental health using questionnaires and multiple logistic regression analysis. Shuang-Jiang et al. (2020) conducted a cross-sectional study during the pandemic, employing an online survey to examine the prevalence and sociodemographic correlates of depression and anxiety symptoms among Chinese adolescents. These studies provide a critical understanding of the pandemic's impact on youth mental health. Kelly Dean et al. (2021) suggested that schools need targeted strategies to address stress-related issues in students exacerbated by the COVID-19 pandemic. Natasha et al. (2021) provided longitudinal evidence of a decline in adolescent mental health during the pandemic, linking concerns about government-imposed restrictions to increased anxiety, depressive symptoms, and decreased life satisfaction. These findings offer valuable empirical data for developing interventions and support services for students. Xiaosheng et al. (2021) identified a range of mental health problems among university students in Hubei, China, linked to personal, academic, and social environments. Eva et al. (2019) examined the role of peer belonging and its association with mental health, while Hyunlye et al. (2019) explored gender differences in the lifestyle and mental health status of senior high school students. Akihiro et al. (2021) summarized reports from a workshop on school-based mental health promotion in Southeast Asian countries, highlighting the limited scope of mental health training for teachers in most countries except Singapore. These studies are crucial for understanding the impact of the school environment on students' psychological states, aligning with the context of our research. Helen (2022) emphasized the importance of comprehensive care for children, addressing all their needs effectively. Tessa et al. (2017) reported on parental perceptions regarding barriers to adolescents' access to mental health treatment, suggesting improvements like increasing the availability of free services and providing flexible service options. These studies offer insights into the influence of family education on student psychology. This body of literature, focusing on mental health issues in children and adolescents across different settings, provides a theoretical foundation for constructing mental state identification indicators. It explores various research methods and technical applications, such as questionnaires and quantitative analysis, relevant to our study's use of subjective-objective assignment methods and the construction of mental state identification indices. However, there is a noticeable gap in studies that specifically consider the application of multimodal data, the development of a comprehensive mental state identification index system, and the use of quantitative techniques to address students' psychological issues. Our objective is to fill this gap by focusing on these aspects, contributing to the broader field of student psychological research and educational reform.

In the realm of student mental status detection, the existing international literature has explored a variety of psychometric instruments and methods, including scales, questionnaires, behavioral observations, assessments, and continuum models, to identify different student psychological problems. Stephanie et al. (2023) highlighted core considerations for equitable school mental health screening, offering guidelines for each stage of the screening process and facilitating the construction of equitable school mental health systems. Brann et al. (2021) employed a mixed methods case study design to explore multilevel determinants of implementation, comparing the scope of implementation before and after comprehensive screening. Their findings emphasize the importance of factors influencing implementation. Joanna et al. (2019) conducted an electronic literature database search and emphasized the need for well-designed pragmatic trials to establish the accuracy of models for identifying mental health difficulties in children and young people, as well as the effectiveness of linking students to appropriate support in real-world settings. Sophia et al. (2022) evaluated professional screening and interventions in relation to mental health service usage and risk status. These studies focus on equitable school mental health screening, aligning with the context of this paper. They provide valuable insights and methodologies, yet practical limitations exist. The overarching objective of this study is to extend these findings by integrating psychological state identification indicators for more accurate student assessments. Simms et al. (2019) proposed a Likert scale-based psychometric research test experiment, underlining its significance for scale development. Francis et al. (2021) evaluated the psychometric properties of the Early Identification System, finding it to be a promising, no-cost general screening tool for identifying students at risk of social-emotional and behavioral difficulties. Amanda et al. (2022) assessed the Strengths and Difficulties Questionnaire's reliability and validity, highlighting its potential as a screening tool for new immigrant Latino youth. I-Hua et al. (2020) validated the psychometric properties of three scales among elementary students in mainland China, focusing on online gaming, social media, and smartphone app addiction. Ting et al. (2022) developed a parental health disorders scale, emphasizing the need for increased financial and healthcare support for parents. Emma et al. (2017) employed a mixed methods case study design alongside an online survey. These studies offer diverse methodological options in psychological research; Roberts et al. (2019) summarized the benefits and potential issues of VR technology, proposing a customizable VR system for scalable psychological testing in a modifiable environment. While these psychometric measures are widely used in psychological testing, they have limitations when used in isolation. Our study plans to explore the development of new multimodal psychometric instruments to more accurately capture students' psychological states, combining quantitative and qualitative methods for a comprehensive analysis. Shu-Ping et al. (2020) found the Mental Health Continuum Model effective in helping undergraduates reflect on and improve their mental health. Emma et al. (2018) examined the feasibility and acceptability of the American Psychological Symptom Counseling Center Assessment, discussing its potential benefits in student counseling services. These models offer dynamic, diverse, and continuous approaches, providing insights for integrating and validating multimodal data in our study. Research in student psychological state detection has primarily focused on multiple psychometric instruments and methods. However, there is a gap in establishing a comprehensive multimodal mental health indicator system and using quantitative methods for educational reform. Our study is geared towards addressing these areas, building upon the existing research to provide foundational analysis and technical applications.

The array of studies discussed provides a wealth of theoretical and practical insights in education and psychology, significantly bolstering research on the identification of secondary school students' psychological states of learning through multimodal techniques. However, we recognize the need to delve deeper into the nuances of students' psychological characteristics across different cultural contexts and how these variations can be harnessed to devise more effective educational strategies and interventions. This leads us to identify key distinctions between our study and existing research in three main areas:

(1) Focus on Specific Psychological States in Learning Contexts: Our study specifically concentrates on identifying secondary school students' psychological states within learning environments. While existing research predominantly addresses the general spectrum of adolescent mental health issues, including depression, anxiety, and coping strategies, our approach is more targeted towards understanding the psychological dynamics that occur during the learning process.

(2) Integration of Multimodal Data: A distinctive aspect of our study is the incorporation of multimodal data. We aim to amalgamate diverse data sources, such as physiological, behavioral, and self-reported data, to provide a more holistic and accurate analysis of students' psychological states. This approach contrasts with the prevailing trend in current research, which typically relies on single data sources for psychological assessment.

(3) Focus on Educational and Pedagogical Strategies: Our study endeavors to explore specific educational and pedagogical strategies tailored to the psychological states of learning in secondary school students. The emphasis is on adapting teaching methodologies and learning environments to enhance students' psychological well-being and academic performance. This approach marks a departure from existing studies that primarily concentrate on identifying and intervening in mental health problems, rather than on the development of specific educational and teaching strategies.

3. Methodology

3.1. Quality Function Deployment (QFD)

Quality Function Deployment (QFD) is a comprehensive, customer-driven approach to product development. It emphasizes facets such as quality, technology, cost, and reliability. This method was introduced by the Japanese scholar Yo Jiakao in 1985, initially in the context of product quality management. QFD operates on the principle of gathering customer requirements through market research, focusing primarily on quality assurance. These requirements are then systematically broken down across various stages of product development and distributed among different functional departments. The process involves the use of matrix diagrams to facilitate this decomposition. The primary objective of QFD is to coordinate the efforts of each department to ensure that the final product not only meets but exceeds customer expectations. This approach is directed towards capturing the market with products that are developed rapidly, cost-effectively, and with superior quality. Over the years, the application of QFD has transcended its original domain and is now utilized in a wide range of social disciplines and applications. These include system risk assessment, financial investment decision-making, economic behavior analysis, enterprise strategic planning, and engineering quality management, among others. The core concept of QFD revolves around analyzing customer needs and understanding the correlation between these needs and the methods employed to fulfill them. QFD signifies a shift from traditional quality management approaches by prioritizing customer requirements and translating them into specific, actionable production solutions. The specific structure of QFD is depicted in **Figure 2** below. The operational process of QFD involves the construction of a 'Quality House' structure model. Into this model, customer demand factors are inputted. These are then subjected to quantifiable experiments, ultimately outputting results that reflect these demands. This process facilitates the conversion of abstract customer needs into concrete, implementable production solutions.

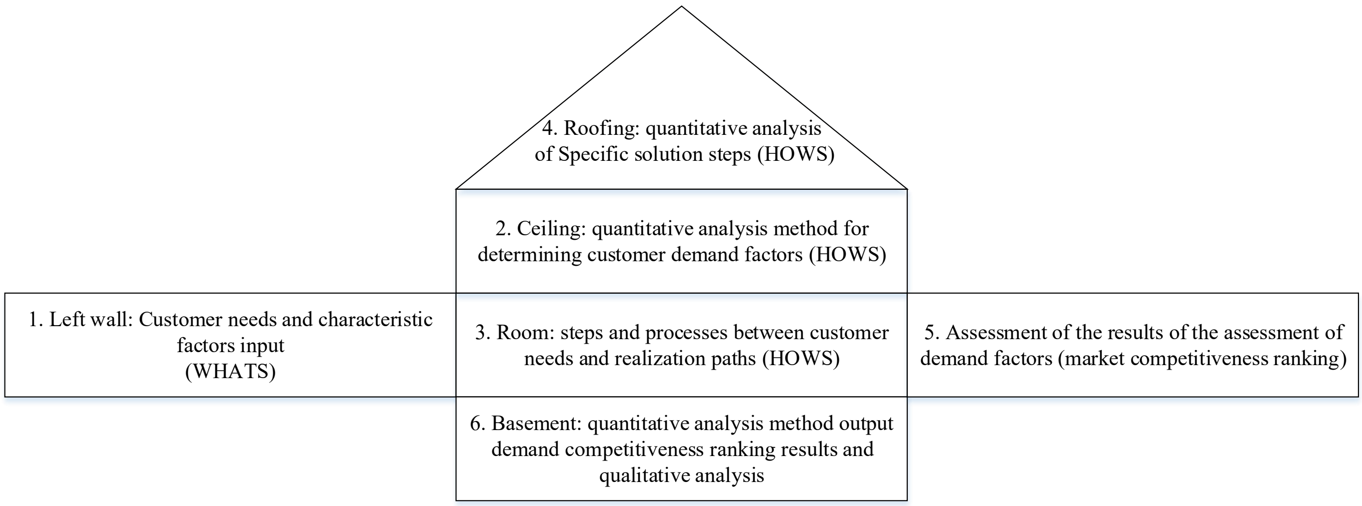


Figure 2. Schematic diagram of the general form of the mass house structure.

1) Left wall: represents the input factors of the client, indicating the social questionnaires, expert consultations and web information for the client's needs.

2) Ceiling: represents the determination of the quantitative analysis method of the social factors of the client's needs, and represents the qualitative analysis of how the client should go about transforming the needs into quantifiable technical methods.

3) Room: represents the steps and processes between the customer's needs and the ways to achieve them, and represents the correlation between the customer's needs and the ways to achieve them.

4) Roof: represents the specific solving steps and process of quantitative analysis, and represents the necessity of the quantitative analysis process unfolding between the customer and the technical pathway.

5) Right wall: represents the quantitative calculation result of the evaluation of the requirement factors, and indicates the result value of the requirement importance assessment based on the quantitative process.

6) Basement: represents the quantitative analysis method outputting the results of ranking the competitiveness of requirements and performing qualitative analysis, indicating the application of quantifiable methods to realize customer requirements as

well as giving the ranking results and qualitative solutions for the relationship between the degree of importance of customer requirement factors.

QFD, primarily understood as a qualitative analysis tool, is not a method for quantitative calculation. Instead, it serves as a conceptual framework used to logically analyze the relationships between customer needs, product characteristics, and the dynamics of need competition. In recent years, QFD has found extensive application in the realms of education management, education quality improvement, education reform, and model innovation. For instance, Yuanbin et al. (2022) utilized the QFD approach to design an industrial robotics training curriculum for secondary vocational schools. They identified the professional skills and competencies needed by robotics professionals and ranked these through a hierarchical analysis. Raissi (2019) applied QFD techniques for reflective assessments of university education quality, aligning these assessments with labor market requirements. Similarly, Yahia-Berrouiguet and Belabid (2022) employed QFD methods to identify key Quality Management System (QMS) needs affecting the service quality at the Faculty of Economic Sciences in Tlemcen. Kinker et al. (2022) leveraged fuzzy Kano and QFD methods to enhance the service quality of vocational education institutions in India. Singh and Rawani (2022) applied a QFD-TOPSIS approach in a case study of engineering education in India, aiming to improve the overall quality of engineering education. Misra Bakhru (2018) used the QFD approach to evaluate the effectiveness of various teaching and learning methods, proposing strategies for educational improvement.

These diverse applications of QFD in education demonstrate its effectiveness in identifying and addressing challenges within the educational sector. By facilitating systematic and comprehensive analysis of educational systems, QFD provides a robust theoretical and practical foundation for the continual improvement and development of educational practices and models.

While the development of indicator design in education and teaching reform research is crucial, it is ultimately the teaching indicators and curriculum quality data that are presented to the education and teaching management. QFD transcends its traditional role in product design and manufacturing to become a valuable tool in teaching research and experimental design exploration. This tool is capable of establishing a full-cycle experimental inquiry process, supporting educational and teaching management reforms, and facilitating informed decision-making.

In our research on identifying the psychological state of learning in secondary school students based on multimodal data and educational reform, we are venturing into an emerging technology field. Despite the extensive application of QFD, its integration with education remains relatively unexplored. Thus, we emphasize the necessity of this approach for several reasons:

(1) The use of multimodal data for mental state identification enables educators to acquire real-time insights into students’ emotions, attention, and cognitive load. Understanding these psychological states allows teachers to tailor their teaching methods and enhance teaching quality, thereby improving student learning effectiveness and experience.

(2) The psychological state identification method utilizing multimodal data offers a deep understanding of students’ diverse learning needs. This knowledge empowers educators to refine course design and teaching strategies in a targeted manner,

fostering student engagement and motivation, and enhancing the relevance and appeal of the curriculum.

(3) A psychological state identification method based on multimodal data provides a more comprehensive, objective, and real-time foundation for educational assessment. This approach enables educators to more accurately evaluate students' learning progress, comprehension, and challenges, thereby offering timely and appropriate feedback.

3.2. Mental state identification methods for multimodal data

Multimodal data-based mental state identification methods employ an array of sensors and data sources, integrating principles from biology, psychology, and computer science. These methods utilize various algorithms and techniques to detect and analyze individuals' mental states, identifying diverse states such as emotions, stress, and cognitive load. The key components of current multimodal data mental state identification techniques include:

(1) Physiological Parameters: This involves collecting physiological signals like heart rate, skin resistance, EMG, EEG, etc., to analyze changes associated with mental states. These signals are often closely linked to states such as mood, stress, and cognitive load.

(2) Facial Expression Analysis: By detecting facial expressions and micro-expressions, it is possible to determine an individual's emotional state. Techniques such as computer vision and deep learning enable automatic recognition and classification of expressions.

(3) Speech Feature Extraction: Features of speech such as pitch, rate, and volume are analyzed to identify emotions and mental states. Speech emotion recognition typically employs machine learning or deep learning algorithms.

(4) Text Mining: Textual data is analyzed using Natural Language Processing (NLP) to extract information on emotion and mental state. Techniques like sentiment analysis and topic modeling are instrumental in identifying individuals' mental states.

(5) Behavioral Pattern Analysis: Observing behavioral data, including posture, movement, and eye movements, can provide insights into mental states. Technologies like computer vision and sensors are used to capture and analyze these data.

(6) Information Integration: Data from various sensors and sources are fused to enhance the accuracy of mental state recognition. Common approaches to data fusion include feature fusion, decision fusion, and model fusion.

(7) Machine Learning and Deep Learning: Techniques such as support vector machines, random forests, K-nearest neighbors (in machine learning), and convolutional neural networks, recurrent neural networks, long- and short-term memory networks (in deep learning) are employed to train models for mental state recognition.

These multimodal data mental state recognition methods have broad applications across fields such as intelligent interaction, healthcare, psychotherapy, and education and training. Not only do they aid in enhancing individual mental health, but they also provide critical data and insights for psychological research, offering a comprehensive approach to understanding and addressing mental states.

3.3. G-1-entropy method

The G-1-entropy method is an innovative approach that combines subjective and objective assignment methods to compute index factors and weights for demand splitting and index system construction. This method aligns with the core idea of Quality Function Deployment (QFD)—demand splitting and importance ranking—by utilizing quantifiable technical means to output importance results. The G-1-entropy method integrates the G1 method's strengths in quantitative evaluation with the entropy method's credibility and accuracy, making it a powerful tool for quantitative analysis in various applications.

(1) Subjective empowerment method: G1 method.

The G1 method is a subjective assignment technique, an advancement over the traditional hierarchical analysis. It addresses the limitations of hierarchical analysis, such as extensive calculation requirements, cumbersome processes, and result inaccuracies, while maintaining the integrity of index consistency tests. The G1 method is particularly suitable for calculating index weights due to its streamlined and precise approach. The specific process of employing the G1 method for index weight calculation is illustrated in **Figure 3**.

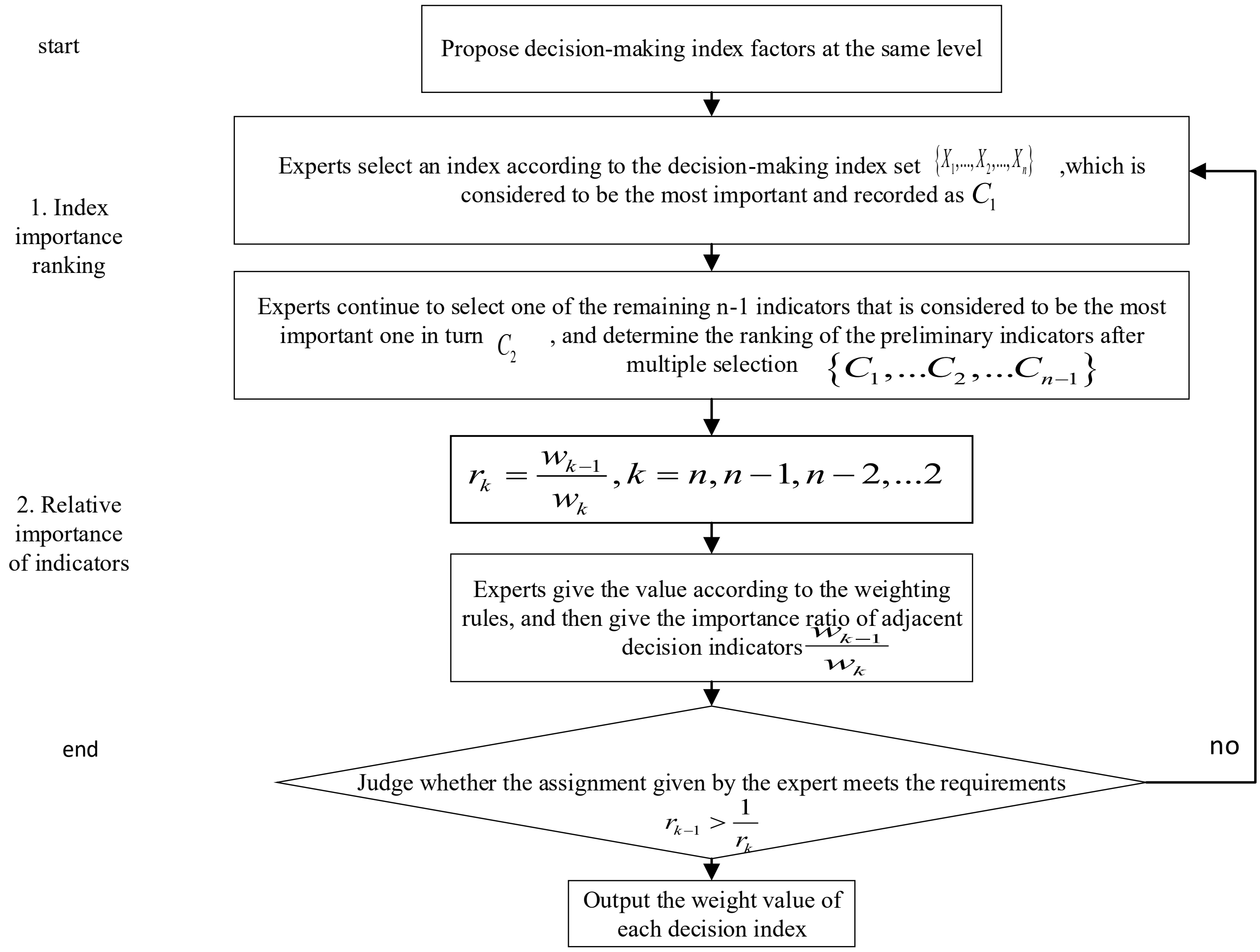


Figure 3. The weighting process utilizing the G1 method.

In the application of the G1 method within the G1-Entropy framework, as depicted in **Figure 3**, several key elements are defined to facilitate the weight calculation of indicators. These elements include the number of indicators (n), the weight of the k-th indicator (w_k), and the ratio of the importance of the previous indicator to the next indicator ($r_k = \frac{w_{k-1}}{w_k}$). These components are critical in determining the relative significance of each indicator within the analysis. The specific assignment of r_k, which is essential for calculating the weights of indicators, is detailed in **Table 1**.

Table 1. Assignment reference table r_k.

Outcomes	Description
1.0	Indicator $k-1$ is as important as indicator k
1.2	Indicator $k-1$ is slightly more important than indicator k
1.4	Indicator $k-1$ is apparently more important than indicator k
1.6	Indicator $k-1$ is strongly important compared to indicator k
1.8	Indicator $k-1$ is extremely important compared to indicator k

(2) Objective empowerment method: entropy method.

The entropy method, an objective assignment technique, is employed to impartially assign weights to decision indicators based on their information entropy. This method evaluates the weight of each indicator by assessing its relative change and its impact on the system as a whole. An indicator with a greater degree of relative change is assigned a higher weight. The specific steps involved in the entropy method are as follows:

Step 1: Collect and organize the initial dataset to form the evaluation system's primary data matrix.

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \quad (1)$$

Step 2: Data processing-standardized processing. The indicators are standardized as follows.

$$x'_{ij} = \frac{x_j - x_{min}}{x_{max} - x_{min}}; x'_{ij} = \frac{x_{max} - x_j}{x_{max} - x_{min}} \quad (2)$$

where χ_j is the value of the index j, x_{max} is the max value of the index j, x_{min} is the min value of the index j, x'_{ij} is the standard value index. If the value of the indicators used is larger, the former formula is chosen; if the value of the indicators used is smaller, the latter formula is chosen.

Step 3: Calculate the information entropy value of indicator e. The formula to calculate the information entropy value of the indicator j is

$$e_j = -K \sum_{i=1}^{m} y_{ij} \ln y_{ij} \quad (3)$$

where K is a constant, $K = \frac{1}{\ln m}$.

Step 4: Calculate the information utility value of indicator d. Formula for the information utility value of indicator j:

$$d_j = 1 - e_j \quad (4)$$

Step 5: Calculate the weights of evaluation indicators. The weights of the j −th indicator are.

$$w_j = \frac{d_j}{\sum_{i=1}^{m} d_j} \tag{5}$$

(3) Methodology for portfolio assignment calculation.

The amalgamation of the G1 methodology with the entropy approach in the computation of portfolio allocation endeavors to furnish a harmonized assessment of indicators, taking into account both subjective and objective elements. The G1 methodology's weights are indicative of expert knowledge and subjective discernments, whilst the weights derived from the entropy method epitomize the objective correlations existing amongst the indicators' values. To ensure a thorough and judicious evaluation, a linear weighting approach is adopted, amalgamating the advantages of both methodologies. This approach is delineated as follows:

$$w_j^* = \beta w_j^1 + (1-\beta) w_j^2 \tag{6}$$

where w_j^1 is the weight value calculated by G1method ， w_j^2 is the weight value calculated by entropy method. β is the subjective preference coefficient， $1-\beta$ is the objective preference coefficient, its specific value can be given by the decision makers after a collective agreement based on the actual situation and preferences.

Having outlined the comprehensive methodologies of QFD, multimodal data analysis, and the G-1-entropy method, we now turn our attention to the application of these innovative approaches in the nuanced identification of secondary school students' mental states. This next section delves into the practical implications of our theoretical groundwork, marking a pivotal transition from methodological foundations to empirical exploration and analysis.

4. Identification of the characteristics of secondary school students' mental states and the current state of experiments

4.1. Mental state characteristics identification methods

The exploration of secondary school students' mental states encompasses a range of methodologies, drawing on insights from psychology, education, and computer science. These methods vary in approach and focus, each offering unique insights into the mental states of students. The key methods include:

(1) Behavioral Observation-Based Methods: These involve learning behavior analysis and self-report questionnaires. They focus on observing students' behaviors and actions in a learning environment and rely on students' self-reported data to infer their mental states.

(2) Physiological Indicator-Based Methods: Techniques such as heart rate variability and electrical skin activity measurement fall under this category. These methods rely on physiological signals to deduce the mental states of students, offering a more objective perspective compared to self-reported data.

(3) Emotion Recognition-Based Methods: This category includes speech emotion analysis and facial expression recognition. By analyzing the tone, pitch, and modulation in speech, as well as observing facial expressions, these methods aim to identify the emotional states of students.

Each of these methods contributes to the preliminary identification and analysis of secondary school students' mental states, providing valuable insights into their psychological wellbeing. They enable educators and researchers to understand the complex interplay of emotions, behaviors, and physiological responses that characterize the learning experience of secondary school students.

4.2. Experimental status

Recent experimental research has made significant strides in identifying and understanding the mental states of secondary school students. These studies typically engage in a comprehensive analysis incorporating diverse data sources, including learning behavior data, physiological indices, and affective data. By employing various experimental tasks and stimuli, researchers have been able to observe and assess students' responses and performance across different psychological states. Key areas of focus include learning motivation, attentional focus, and emotional experiences. Despite these advancements, current experimental studies face several challenges and limitations:

(1) Sample Size and Representativeness: Many experiments are constrained by the size and diversity of their samples, which can limit the generalizability of the findings.

(2) Variability in Experimental Design: Differences in the design of experiments and the selection of stimulus materials can lead to inconsistencies and affect the comparability of research outcomes across different studies.

(3) Subjectivity and Quantification Issues: Identifying and quantifying secondary school students' psychological states can be subjective. This subjectivity, coupled with limitations in current methodologies, necessitates further refinement and enhancement of research techniques.

4.3. Future directions of the study

To enhance the identification and understanding of secondary school students' psychological states, future research should focus on the following areas:

(1) Data Collection and Feature Extraction: Expand the range of data sources to include more diverse types, such as eye-movement data, EEG data, and social media interactions. These varied sources can provide a richer understanding of students' psychological states; Develop effective features and indicators to construct an accurate mental state identification model. This involves refining data processing techniques to extract meaningful insights from complex datasets.

(2) Model Fusion and Comprehensive Analysis: Develop models that merge different data sources and psychological state characteristics for a more holistic analysis. This integration can offer a nuanced view of students' mental states; Utilize technologies like machine learning and artificial intelligence to enhance the precision and dependability of psychological state identification and predictions.

(3) Long-term Tracking and Evaluation: Establish a mechanism for long-term tracking of secondary school students' psychological states, monitoring their evolution and development over time; Evaluate the effectiveness of psychological state identification methods and educational reforms. This long-term perspective is crucial for understanding the sustained impact of educational interventions and for providing empirical evidence to refine teaching strategies and educational policies.

In conclusion, while significant progress has been made in characterizing secondary school students' psychological states and conducting experimental research, challenges and limitations still persist. Future studies should emphasize strengthening data collection and feature extraction, synthesizing diverse data sources and features, and implementing long-term tracking and evaluation. Such advancements aims to be instrumental in furthering the research into secondary school students' psychological states and enhancing educational practices.

5. Exploration of educational reform model based on quality function deployment theory: For multimodal data identification

5.1. Framework for designing the structure of educational reform based on quality function deployment theory

The structural model for the QFD-based identification of multimodal mental states and educational reform in secondary school students is represented in **Figure 4**:

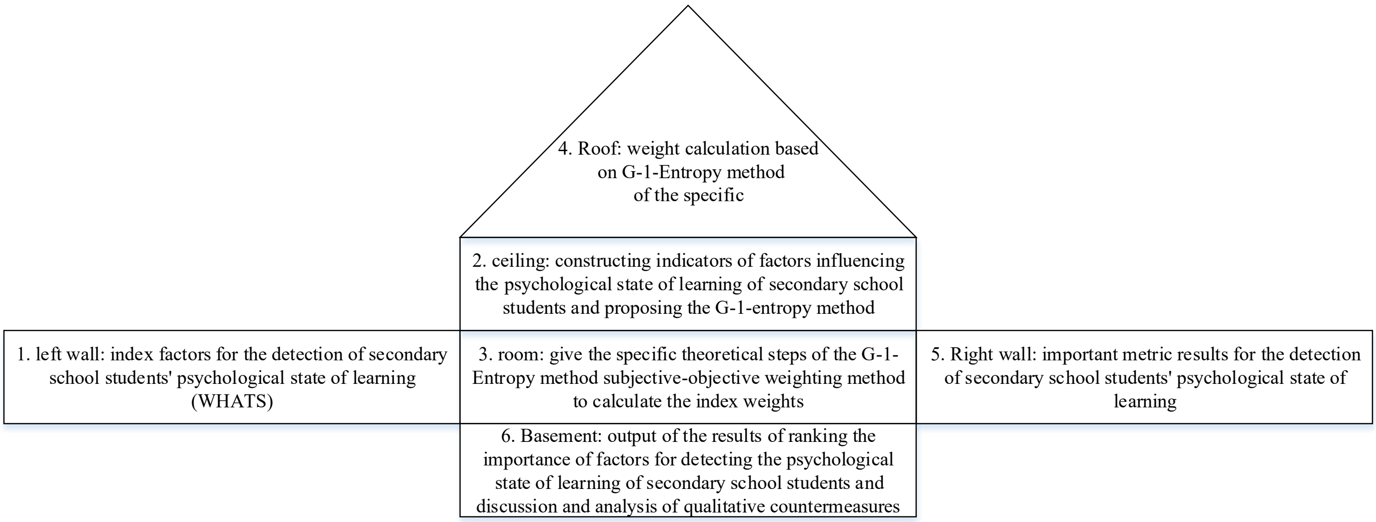


Figure 4. Schematic design of the structure of QFD-based multimodal psychological state identification and quality house of education and education reform for secondary school students

5.2. Research on educational reform issues considering multimodal data identification

5.2.1. Construction of education reform impact indicator system with multimodal data identification

1) Principles of constructing the indicator system.

The construction of an evaluation indicator system is essential for transforming complex evaluations into quantifiable data analysis tasks. A scientifically designed evaluation index system is key to conducting reasonable and effective comprehensive evaluations. Generally, the construction of evaluation indices should adhere to the principles of developmentality, comprehensiveness, and dominance.

(1) Developmental principle: This involves constructing indicators from a developmental perspective. As the nature of things evolves, the index system must be dynamically adjusted. In the context of education and teaching reform, especially

when considering students' psychological state identification through multimodal data, it's crucial to account for potential changes in data identification characteristics and students' psychological states. The principle of developmentality serves as a guide for selecting indices that promote the enhancement of education and teaching quality.

(2) Comprehensiveness principle: When building the evaluation index system, it should encompass multiple perspectives and levels, ensuring the system comprehensively reflects the overall performance and characteristics of the subject under evaluation. In this study, the education and teaching reform should be viewed as a complete, complex system. The identification index of students' psychological state, therefore, should be employed as a key factor in designing the evaluation index system, ensuring a comprehensive understanding of students' psychological states and supporting the improvement of education and teaching quality.

(3) Dominance principle: This principle emphasizes retaining key indicators in the comprehensive index system while eliminating less significant ones. Representative indicators that directly reflect the quality characteristics of education and teaching reform issues and the indices of students' mental health status should be prioritized. Non-representative indicators should be discarded to maintain focus and clarity.

These principles guide the construction of an effective and representative evaluation index system for educational reform, integrating multimodal data identification of students' psychological states to optimize and enhance the educational process.

2) Methodology of constructing the multimodal learning integration technology index system.

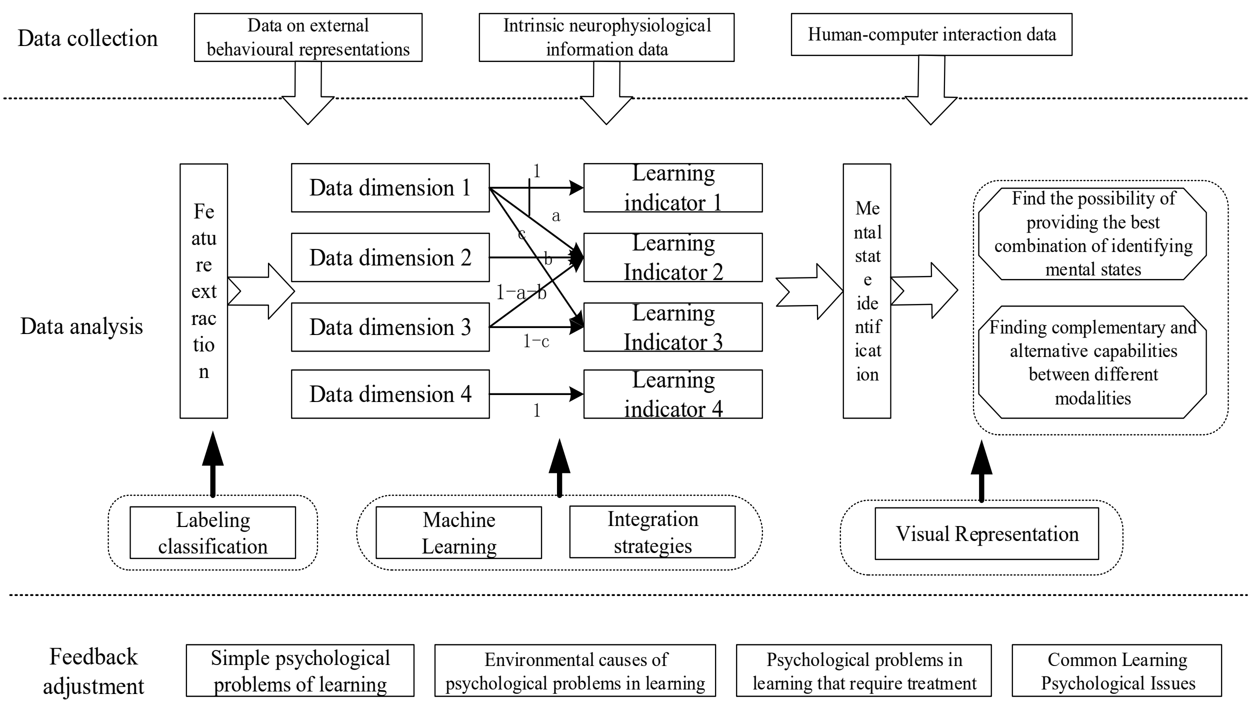


Figure 5. Methodology for identifying multimodal psychological states of secondary school students and constructing an index system for education and educational reform.

In constructing the index system for this study, we have extensively reviewed literature encompassing traditional learning analysis theory (Schwendimann et al., 2017), multimodal learning analysis theory (Blikstein, 2013; Di Mitri et al., 2018), and multimodal fusion technology in deep learning. Research indicates that multimodal learning analysis has emerged as a novel branch in the field of learning analytics. This approach aims to comprehensively and accurately model learning characteristics and patterns by acquiring and integrating multimodal data in complex learning processes (Worsley, 2018). Our study seeks to synthesize indicators and data from existing empirical studies and questionnaires, extracting and summarizing evaluation indicators. The specific methodology is illustrated in **Figure 5**.

Multimodal Learning Fusion Technology: The process begins with breaking down student learning psychology into identifiable indicators: emotional, cognitive, and behavioral indicators, along with multimodal data fusion indicators. The student learning process data is categorized into:

(1) Extrinsic Behavioral Representation Data: Including text, voice, video, facial expressions, and body gestures.

(2) Intrinsic Neurophysiological Information Data: Covering breathing, heartbeat, pulse, eye movement, skin electricity, brain electricity, blood oxygen, and hormone secretion levels.

(3) Human-Computer Interaction Data: Encompassing clicks, fingerprints, touch, pressure sense, handwriting, gestures, text input, voice interaction, and facial expression data.

The correspondence between data and indicators can be one-to-one, many-to-one, or one-to-many. "One-to-one" implies that a single data type measures one learning metric, while "many-to-one" indicates that multiple data types can assess the same metric. "One-to-many" denotes that one type of data can evaluate multiple learning indicators.

The method integrates different modal data through a five-step practical approach: data collection, processing and filtering, representation fusion, data analysis, and data modeling with machine learning models. This is followed by a visual interpretation of data representations and feedback moderation. This approach aims to find the optimal combination of data sources to accurately identify mental states. Additionally, it leverages the complementary and alternative capabilities of modalities to address real-world educational settings where certain modalities might be unavailable, thereby increasing the probability and pathways for teachers to accurately identify students' mental states under limited conditions. Ultimately, the multimodal learning integration technology offers feedback results and suggests educational teaching and learning strategies. This comprehensive approach provides a more nuanced understanding of students' mental states, supporting the development of targeted and effective educational interventions.

3) Construction of multimodal learning fusion technology index system.

The multimodal learning fusion technology index system is constructed based on the principles of index system construction, multimodal data identification methods, and Quality Function Deployment (QFD) theory. The system is structured into two main parts as shown in **Tables 2** and **3** below:

Table 2. Multimodal identification index system of learning mental state.

Tier 1 Indicators (Target level)	**Secondary indicators (Guideline level)**	**Three-level indicators (Program level)**	**Description**
Secondary School Students Learning psychological state identification method A_1	Emotion Recognition B_{11}	Positive emotion recognition accuracy C_{111}	Happy, happy emotions
		Negative emotion recognition accuracy C_{112}	Anger, stressful emotions
		Neutral Emotion Recognition Accuracy C_{113}	Calm and collected emotions
		Emotional change detection accuracy C_{114}	Change from negative to positive, from positive to negative emotions
	Cognitive state recognition B_{12}	Concentration force recognition accuracy C_{121}	Attention, attention duration and attention shifting
		Learn to recognize accuracy with enthusiasm C_{122}	Positive, negative or neutral
		Learning motivation recognition accuracy C_{123}	Learning purpose, motivation, self-regulation, interest and involvement in learning tasks
		Accuracy of cognitive state change detection C_{124}	Attention, concentration, depth and breadth of thought, memory, and the ability to make adaptive adjustments to change
	Behavioral profile recognition B_{13}	Learning attitude recognition accuracy C_{131}	Changes in attitudes and attitude toward learning, such as positive, negative, enthusiastic, indifferent, etc.
		Interactive behavior recognition accuracy C_{132}	Interactive behaviors in the classroom with the instructor and classmates, such as asking questions, answering, and communicating
		Expressive behavior recognition accuracy C_{133}	Express their thoughts and emotions through words, body movements, facial expressions, etc.
		Accuracy of behavior change detection C_{134}	Changes in behavioral status, such as attention span, frequency of interactive behaviors, etc.
	Multimodal data fusion B_{14}	A multimodal approach to the fusion of emotional, cognitive and behavioral traits C_{141}	Obtain information about learners' mental states from various perspectives such as voice, facial expressions, and behavior, and integrate them together for comprehensive analysis
		Accuracy assessment of learning mental state recognition after multimodal data fusion C_{142}	An evaluation of the accuracy of learning mental state identification using multimodal data fusion methods
		Analysis of the effect of multimodal data fusion on the effect of learning mental state recognition C_{143}	Compare and analyze the effects of different multimodal data fusion methods on the recognition of learning mental states, and find the best multimodal data fusion method

Table 3. Multimodal identification of education and educational reform index system based on secondary school students' mental state.

Tier 1 Indicators (Target level)	**Secondary indicators (Guideline level)**	**Three-level indicators (Program level)**
Education Reform Research A_2	A study of the relationship between identification results and academic performance B_{21}	A study on the relationship between the identification results of different learning psychological states and test scores C_{211}
		A study on the relationship between the results of identifying students' learning psychological state and teachers' evaluation C_{212}
		A study of the relationship between changes in students' psychological state of learning and factors such as academic performance, interest in learning, and self-confidence C_{213}
		A study of the relationship between individualized instructional programs and academic performance C_{214}
	Teaching program design and implementation study B_{22}	Feasibility study on developing individualized teaching programs based on the results of learning psychological state identification C_{221}
		A study comparing the effects of traditional teaching methods and teaching methods based on the identification of learning psychological states C_{222}
		Analyzing teachers' strategies and behavior patterns in response to different psychological states of learning C_{223}
	Research on educational reform strategies B_{23}	Propose educational and pedagogical reform strategies based on the identification of students' psychological states of learning C_{231}
		Analyzing students' acceptance of different educational reform strategies under different psychological states of learning C_{232}
		Analyze the differences in students' psychological states of learning in different subjects, grades and regions, and develop corresponding educational C_{233}
		Analyzing the impact of educational reform strategies on students' psychological state of learning C_{234}

This multimodal learning fusion technology index system serves as a comprehensive framework for identifying and analyzing secondary school students' psychological states and applying these insights to educational reform. It integrates various aspects of students' learning experiences and mental states, offering a multidimensional approach to understanding and improving educational practices.

5.2.2. Quantitative calculation of education and educational reform impact indicators based on the G-1-entropy value method

1) Expert identity information weighting calculation method.

The G-1-entropy value method utilizes expert scoring to obtain original data. The credibility of experts is assessed based on criteria such as years of service, education, profession, experience, and title. The weighting criteria for these factors are detailed in **Table 4**.

Table 4. Expert rating weights.

Indicators	Weight r_i	Level	Scores S
Working years	3	>30	0.8
		15–30	0.6
		<15	0.4
Education	2	PhD	0.8
		Master	0.6
		Bachelor	0.4
Major	2	Educational psychology	0.8
		Educational technology	0.6
		Psychology	0.4
Experience	2	There are studies of student psychology and identification techniques	0.8
		There are studies of student psychology and identification techniques	0.4
Title	1	Professor	0.8
		Associate professor	0.6
		Lecture	0.4

The expert credibility is calculated using Equation (7):

$$R_e = \frac{\sum_{i=1}^{5} r_i s}{10} \tag{7}$$

The calculation of weights as per Equation (8):

$$w_e = \frac{R_e}{\sum_{e=1}^{n} R_e} \tag{8}$$

2) Calculation process of the four weights.

(1) Calculating identity information weights of experts:

We invited five experts from the Institute of Education, Chinese Academy of Social Sciences, to score the importance of 10 indicators following the G-1 method. The identity information of these experts is provided in **Table 5**.

Table 5. Identification information of the 5 experts.

No.	Working years	Education	Major	Experience	Title
1	37	Ph.d	Educational Technology	There are studies of student psychology and identification techniques	Associate professor
2	30	Ph.d	Psychology	There are studies of student psychology and identification techniques	professor
3	26	Ph.d	Psychology	There are studies of student psychology and identification techniques	professor
4	15	Ph.d	Educational Psychology	None studies of student psychology and identification techniques	lecture
5	32	Ph.d	Educational Psychology	None studies of student psychology and identification techniques	Associate professor

Based on **Table 5**, the credibility and weights of the experts' identity information are calculated, as shown in **Table 6**.

Table 6. Trustworthiness and weight values of experts' identification information.

No.	Credibility	Weight
1	0.74	0.218935
2	0.66	0.195266
3	0.62	0.183432
4	0.74	0.218935
5	0.62	0.183432

(2) Weight calculation based on the G-1 method:

The raw scoring data obtained through the G-1 method are compiled in Appendix. Using the G-1 method's calculation steps, the results of the experts' weights are shown in **Table 7**.

Table 7. Relative weights of indicator system *i* for 5 experts under G-1 method.

	1	2	3	4	5
C_{111}	0.019487	0.073834	0.041037	0.051709	0.049122
C_{112}	0.048716	0.052738	0.034198	0.032318	0.035087
C_{113}	0.032478	0.061528	0.029312	0.028727	0.040935
C_{114}	0.097433	0.061528	0.051297	0.043091	0.030701
C_{121}	0.018458	0.026556	0.038011	0.050272	0.077187
C_{122}	0.046144	0.018969	0.031676	0.083787	0.064322
C_{123}	0.046144	0.066391	0.095027	0.06284	0.055134
C_{124}	0.030763	0.066391	0.095027	0.06284	0.192967
C_{131}	0.025729	0.053895	0.082023	0.075408	0.025548
C_{132}	0.064322	0.033684	0.051265	0.125681	0.04258
C_{131}	0.042882	0.038497	0.051265	0.094261	0.063871
C_{134}	0.032161	0.029942	0.205058	0.094261	0.127741
C_{141}	0.073766	0.048947	0.079243	0.079243	0.079243
C_{142}	0.05269	0.244734	0.066036	0.049527	0.049527
C_{143}	0.368828	0.122367	0.049527	0.066036	0.066036

Based on the identity weight values of the five experts in **Table 6,** the weighted sum of all indicators in **Table 7** was performed to obtain the subjective weighting results of the G-1 method, as shown in **Table 8** below.

Table 8. Results of subjective assignment of indicator system I under G-1 method.

Tier 1 Indicators (Target level)	Secondary indicators (Guideline level)	Three-level indicators (Program level)	G-1 value
A_1	B_{11}	C_{111}	0.046542
		C_{112}	0.040748
		C_{113}	0.0383
		C_{114}	0.057821
	B_{12}	C_{121}	0.041364
		C_{122}	0.04976
		C_{123}	0.064369
		C_{124}	0.086284
	B_{13}	C_{131}	0.052398
		C_{132}	0.06539
		C_{131}	0.058662
		C_{134}	0.094571
	B_{14}	C_{141}	0.072128
		C_{142}	0.091365
		C_{143}	0.140299

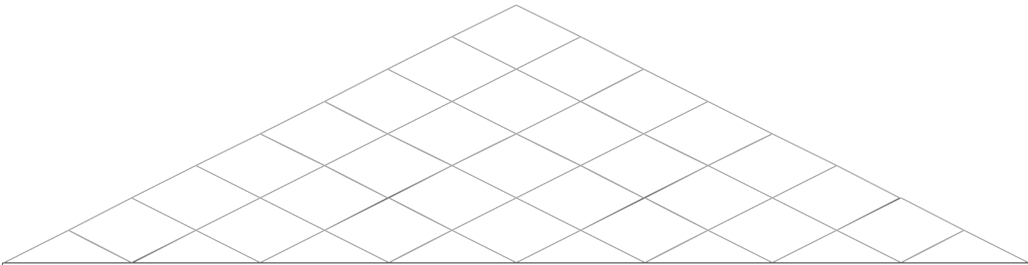
3) Results of weight calculation based on the entropy value method.

Table 9. Objective weight values of indicator system *i* under entropy method.

Indicators	Information entropy	Information utility value	Weighting value
C_{111}	0.747008	0.252992	0.063185
C_{112}	0.664096	0.335904	0.083893
C_{113}	0.594024	0.405976	0.101394
C_{114}	0.799178	0.200822	0.050156
C_{121}	0.740752	0.259248	0.064748
C_{122}	0.81635	0.18365	0.045867
C_{123}	0.80312	0.19688	0.049171
C_{124}	0.659147	0.340853	0.085129
C_{131}	0.821995	0.178005	0.044457
C_{132}	0.713951	0.286049	0.071441
C_{133}	0.71686	0.28314	0.070715
C_{134}	0.787613	0.212387	0.053044
C_{141}	0.839911	0.160089	0.039983
C_{142}	0.646015	0.353985	0.088409
C_{143}	0.646015	0.353985	0.088409

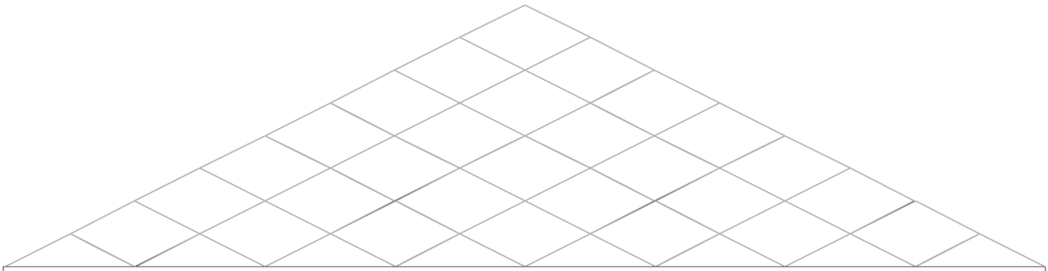
The application of the entropy value method for objective weighting of indicators involves several steps. After standardizing the indicators as per Equation (4) and excluding the influence of physical quantities, the entropy value for each indicator is calculated using Equation (6). Subsequently, the weight value of each indicator is determined using Equation (8). The outcomes of this process are detailed in **Table 9**.

Upon obtaining the objective weight values, the combined weights are calculated based on the G-1-Entropy method within the Quality Function Deployment (QFD) framework. These combined weights for the first and second indicator systems are illustrated in **Figure 6a,b** respectively:



	Ceilings: G-1 entropy method										
	G-1 method weighted results						Entropy method weighting results			Portfolio weighted results	
Psychometric indicators	Expert I	Expert II	Expert III	Expert IV	Expert V	Weighting	Information entropy	Effectiveness value	Weighting values	Portfolio weights	Ranking
C_{111}	0.019	0.074	0.041	0.052	0.049	0.047	0.748	0.253	0.063	0.055	C_{143}
C_{112}	0.049	0.053	0.034	0.032	0.035	0.041	0.664	0.336	0.084	0.062	C_{142}
C_{113}	0.032	0.062	0.029	0.029	0.041	0.038	0.594	0.406	0.101	0.070	C_{124}
C_{114}	0.097	0.062	0.051	0.043	0.031	0.058	0.799	0.201	0.050	0.054	C_{134}
C_{121}	0.018	0.027	0.038	0.050	0.077	0.041	0.741	0.259	0.065	0.053	C_{113}
C_{122}	0.046	0.019	0.032	0.084	0.064	0.050	0.816	0.184	0.046	0.048	C_{132}
C_{123}	0.046	0.067	0.095	0.063	0.055	0.064	0.803	0.197	0.049	0.057	C_{133}
C_{124}	0.031	0.067	0.095	0.063	0.193	0.086	0.659	0.341	0.085	0.086	C_{112}
C_{131}	0.026	0.054	0.082	0.075	0.026	0.052	0.822	0.178	0.044	0.048	C_{123}
C_{132}	0.064	0.034	0.051	0.126	0.043	0.065	0.714	0.286	0.071	0.068	C_{141}
C_{133}	0.043	0.038	0.051	0.094	0.064	0.059	0.717	0.283	0.071	0.065	C_{111}
C_{134}	0.032	0.030	0.205	0.094	0.128	0.095	0.788	0.212	0.053	0.074	C_{114}
C_{141}	0.074	0.049	0.079	0.079	0.080	0.072	0.840	0.160	0.040	0.056	C_{121}
C_{142}	0.053	0.245	0.066	0.050	0.050	0.091	0.646	0.354	0.088	0.090	C_{131}
C_{143}	0.031	0.122	0.050	0.066	0.066	0.140	0.646	0.354	0.088	0.114	C_{122}
	Basement: Proposing educational reform responses in order of importance of indicators										

(a)



Ceilings: G-1 entropy method											
	G-1 method weighted results						Entropy method weighting results			Portfolio weighted results	
Psychometric indicators	Expert I	Expert II	Expert III	Expert IV	Expert V	Weighting	Information entropy	Effectiveness value	Weighting values	Portfolio weights	Ranking
C_{111}	0.019	0.074	0.041	0.052	0.049	0.047	0.748	0.253	0.063	0.055	C_{143}
C_{112}	0.049	0.053	0.034	0.032	0.035	0.041	0.664	0.336	0.084	0.062	C_{142}
C_{113}	0.032	0.062	0.029	0.029	0.041	0.038	0.594	0.406	0.101	0.070	C_{124}
C_{114}	0.097	0.062	0.051	0.043	0.031	0.058	0.799	0.201	0.050	0.054	C_{134}
C_{121}	0.018	0.027	0.038	0.050	0.077	0.041	0.741	0.259	0.065	0.053	C_{113}
C_{122}	0.046	0.019	0.032	0.084	0.064	0.050	0.816	0.184	0.046	0.048	C_{132}
C_{123}	0.046	0.067	0.095	0.063	0.055	0.064	0.803	0.197	0.049	0.057	C_{133}
C_{124}	0.031	0.067	0.095	0.063	0.193	0.086	0.659	0.341	0.085	0.086	C_{112}
C_{131}	0.026	0.054	0.082	0.075	0.026	0.052	0.822	0.178	0.044	0.048	C_{123}
C_{132}	0.064	0.034	0.051	0.126	0.043	0.065	0.714	0.286	0.071	0.068	C_{141}
C_{133}	0.043	0.038	0.051	0.094	0.064	0.059	0.717	0.283	0.071	0.065	C_{111}
C_{134}	0.032	0.030	0.205	0.094	0.128	0.095	0.788	0.212	0.053	0.074	C_{114}
C_{141}	0.074	0.049	0.079	0.079	0.080	0.072	0.840	0.160	0.040	0.056	C_{121}
C_{142}	0.053	0.245	0.066	0.050	0.050	0.091	0.646	0.354	0.088	0.090	C_{131}
C_{143}	0.031	0.122	0.050	0.066	0.066	0.140	0.646	0.354	0.088	0.114	C_{122}
	Basement: Proposing educational reform responses in order of importance of indicators										

(b)

Figure 6. (a) Combined weights for the G-1-entropy method based on the QFD framework—indicator system I; **(b)** combined weights for the G-1-entropy method based on the QFD framework—indicator system II.

We ranked the results of the 15 indicators of the first indicator system from largest to smallest, i.e.,

$$C_{143} \succ C_{142} \succ C_{124} \succ C_{134} \succ C_{113} \succ C_{132} \succ C_{133} \succ C_{112} \succ C_{123} \succ C_{141} \succ C_{111} \succ C_{114} \succ C_{121} \succ C_{131} \succ C_{122}$$

The results of the 11 indicators of the second index system were ranked from largest to smallest, namely.

$$C_{233} \succ C_{222} \succ C_{213} \succ C_{214} \succ C_{223} \succ C_{232} \succ C_{234} \succ C_{221} \succ C_{211} \succ C_{231} \succ C_{212}$$

5.3. Exploration of education and teaching reform models and countermeasures

In this section, we delve into the impact of multimodal data-based learning mental state identification methods on educational teaching reform and propose corresponding countermeasures. By examining the top five ranked indicators from our analysis, we derive the following conclusions and recommendations:

1) Impact of multimodal data fusion on learning psychological state identification:

The integration of multimodal data offers a more comprehensive and accurate understanding of students' learning psychological states, crucial for grasping their emotions, motivations, and attention levels; Educational teaching reforms should encourage the application of multimodal data. The development of advanced data fusion techniques is necessary to enhance the effectiveness of learning mental state recognition.

2) Assessment of learning mental state recognition accuracy post multimodal data fusion:

Assessing the accuracy of learning mental state recognition is vital for gauging its effectiveness and feasibility; Implementing an evaluation mechanism in educational reform is essential for continually monitoring and improving the accuracy of learning mental state recognition. This will also provide benchmarks for the optimization of algorithms and models in practical applications.

3) Detection accuracy of cognitive and behavioral state changes:

Accurate detection and analysis of changes in cognitive states and behaviors are crucial for influencing the learning process and teaching effectiveness; Providing teachers with insights into students' cognitive and behavioral changes expect to enable them to tailor their teaching strategies, thereby optimizing the learning process and enhancing overall educational outcomes.

4) Accuracy of neutral emotion and interactive behavior recognition:

Recognizing neutral emotions and interactive behaviors accurately is key for understanding students' emotional states and social interaction patterns; Improving the accuracy in these areas can aid teachers in fostering a positive learning environment and promote cooperative learning among students. It helps in creating support systems that cater to the emotional and social needs of students, thereby enhancing the overall educational experience.

Based on the above analysis and results, we propose the following models and countermeasures for educational and teaching reform:

1) Personalized Teaching Model: Tailoring learning paths and contents to individual students' needs based on their psychological states identified through multimodal data. This involves adapting teaching strategies and resources in response to students' learning preferences, cognitive abilities, and emotional states, supported by adaptive learning systems and intelligent tools.

2) Teacher Training Model: Integrating multimodal data recognition technology into teacher training to provide personalized guidance and support for teachers' professional development. This includes designing teaching strategies for various psychological states to enhance teachers' understanding and response to students' needs.

3) Curriculum Design Model: Developing a curriculum that adapts to students' psychological states using multimodal data recognition technology. Adjusting course content and interaction methods based on students' emotions, cognitive abilities, and progress, and using multimodal data to refine assessment methods and evaluations.

4) Education Policy Making Model: Formulating more precise and effective education policies based on learning psychological states identified through multimodal data. Utilizing data analysis and prediction models to understand student group characteristics and needs, thereby informing policy formulation and resource allocation.

In summary, the multimodal data-based learning psychological state identification method holds significant implications for education and teaching reform.

By examining the influence and correlation of various indicators, targeted educational strategies and reform models can be developed to improve student learning outcomes and enhance the overall quality of school education. This study is of paramount importance to students, educators, educational administrators, and policymakers, and it contributes positively to the advancement and progress in the field of education.

6. Rationale for conducting the study

The rationale for conducting this study is rooted in the significant impact that students' psychological states of learning have on various aspects of education. These psychological states are intricately linked to students' learning outcomes, motivation, and overall experiences in their educational journey. For educators and administrators, the accurate identification and comprehension of these states are crucial for the development of effective teaching strategies and the implementation of targeted educational interventions. Traditional methods for assessing students' psychological states often encounter issues of subjectivity and limitations, leading to a lack of a full and objective understanding of students' actual states. This study was initiated to investigate a method that utilizes multimodal data for the identification of students' psychological states of learning. The aim is to enhance the accuracy and validity of assessments, moving beyond the constraints of traditional approaches. The outcomes of this research, including the findings and proposed countermeasures, are intended to serve as a scientific foundation and guidance for educational reform. By improving the effectiveness of teaching methods and contributing to the enhancement of educational quality, this study holds significant value for a wide range of stakeholders in the educational sector, including students, teachers, educational administrators, and policy makers. Its development represents a substantial contribution to the progress and evolution of the educational field, highlighting the importance of adapting to innovative methodologies in understanding and supporting students' learning experiences.

In light of our findings, the imperative for international collaboration in educational reform becomes increasingly apparent. By sharing methodologies, data, and insights across borders, educators and policymakers can more effectively address the diverse psychological needs of students worldwide. Our study, while rooted in [specific country/region's] context, reveals universal themes and challenges in understanding and enhancing students' learning experiences. Hence, we advocate for a global dialogue and partnership to leverage the strengths of varied educational systems, fostering innovative solutions that are culturally sensitive and universally effective. Such collaboration not only enriches our collective understanding but also accelerates the implementation of educational reforms that are responsive to the nuanced needs of students across different socio-cultural environments.

7. Conclusion

Our study has made significant theoretical and practical contributions to the field of education. Theoretically, we have introduced a novel method for identifying the psychological states of secondary school students' learning. This method innovatively employs Quality Function Deployment (QFD) as a guiding framework, integrates a multimodal learning fusion technology index system, and utilizes diverse data sources. This approach, unique in its application and composition, has not been previously explored by other researchers. Additionally, we have employed quantitative methods to analyze and interpret data, offering a more objective and quantifiable assessment of students' psychological states, thus providing substantial theoretical support for education and educational reform.

Practically, our study offers a new, comprehensive macroscopic perspective for educational reform. By accurately identifying students' psychological states of learning, educators are better equipped to understand students' learning needs and challenges. This understanding enables the development of targeted teaching strategies and educational reform programs. The application of our findings has the potential to significantly enhance the quality of education, improve student learning outcomes, and foster the sustainable development of educational reform initiatives.

Overall, our research enriches existing knowledge by theoretically advancing the understanding of students' psychological states of learning in the context of multimodal data and practically applying this innovative approach in educational settings. The results of our study provide tangible countermeasures and recommendations, contributing deeper insights into the fields of learning psychological state identification and educational reform. Specifically, our research:

(1) Our study emphasizes the identification methods of secondary school students' learning psychological states and their implications for educational reform, incorporating the use of multimodal data. This approach provides a solid foundation for both theoretical refinement and practical innovation. By conducting an in-depth exploration of secondary school students' learning psychological states and through comprehensive analysis of multimodal data, we achieve a more accurate understanding of students' learning states and psychological needs. This innovative research perspective offers a novel method to comprehend and enhance students' psychological states in learning, thereby facilitating educational and pedagogical reform.

(2) Merging the study of secondary students' psychological states of learning with the current trends in education and educational reform, we have developed a set of indicators encompassing emotion, cognition, behavior, and multimodal integration. These also include the relationship between identification results and learning achievement, as well as the design and implementation of teaching programs and educational reform strategies. These unique multimodal indicators, tailored for the new curriculum reform, provide a more comprehensive approach than traditional single evaluation systems and questionnaire scales. The use of the G1-entropy method for indicator weighting enables a comprehensive assessment and ranking. This method helps circumvent the subjectivity inherent in manual weighting and the mechanistic nature of objective indicator screening, leading to a more reasonable and effective overall evaluation system. It minimizes information loss and ensures that weighted results closely reflect actual outcomes.

(3) In our study of the identification method for secondary school students' learning psychological states and educational reform, considering the application of multimodal data, we align closely with the current context of educational reform in China. We conduct a comprehensive analysis from multiple perspectives, including

emotional, cognitive, behavioral, and multimodal data fusion aspects. This deep dive into the identification methods of students' psychological states, coupled with the integration of multimodal data, allows us to thoroughly understand students' learning states and psychological needs. By considering these varied dimensions, we can more accurately assess the psychological state of learning among secondary school students and offer targeted measures and strategies for education and educational reform.

The primary limitation identified in this study is the potential inadequacy in the precision of the G-1-entropy method. To address this, future research could incorporate advanced technological approaches such as big data analytics, machine learning, deep learning, and other sophisticated artificial intelligence methods. These approaches can digitally measure the factors influencing students' psychological states, thereby proposing an optimal combination of methods to enhance the theoretical depth and reliability of the study's assessment results. Moreover, while acknowledging the constructive efforts in developing the index system, we recognize there are areas for improvement. Future research initiatives should aim to expand and refine the index system, ensuring it encompasses a broader spectrum of factors related to secondary school students' psychological states of learning. By constructing a more comprehensive and detailed indicator system, we can gather more precise and in-depth data. This expansion shall facilitate a more thorough understanding of the diverse psychological states experienced by students in learning environments. Through these advancements, future studies can significantly improve upon the current research, offering more nuanced insights and effective strategies for educational reform. This progression aims to enable a deeper exploration into the complexities of students' learning psychology, paving the way for more targeted and impactful educational interventions and policies.

Author contributions: Conceptualization, XN and BY; methodology, XN; software, XN; validation, XN and BY; formal analysis, XN; investigation, XN; resources, XN; data curation, XN; writing—original draft preparation, XN; writing—review and editing, XN; visualization, XN; supervision, XN; project administration, XN; funding acquisition, BY. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

References

Anderson, J. K., Ford, T., Soneson, E., et al. (2018). A systematic review of effectiveness and cost-effectiveness of school-based identification of children and young people at risk of, or currently experiencing mental health difficulties. Psychological Medicine, 49(1), 9–19. https://doi.org/10.1017/s0033291718002490

Anniko, M. K., Boersma, K., & Tillfors, M. (2018). Sources of stress and worry in the development of stress-related mental health problems: A longitudinal investigation from early- to mid-adolescence. Anxiety, Stress, & Coping, 32(2), 155–167. https://doi.org/10.1080/10615806.2018.1549657

Baghdadi, Y., Harfouche, A. (2019). Using QFD Method for Assessing Higher Education Programs: An Examination of Key Stakeholders' Visions. Switzerland: Springer International Publishing AG, 30, 83-98.

Bakhru, K. M. (2018). Aligning teaching methods for learning outcomes: a need for educational change in management education using quality function deployment approach. International Journal of Learning and Change, 10(1), 54. https://doi.org/10.1504/ijlc.2018.089533

Brann, K. L., Naser, S. C., Splett, J. W., et al. (2021). A mixed-method analysis of the implementation process of universal screening in a tiered mental health system. Psychology in the Schools, 58(11), 2089–2113. https://doi.org/10.1002/pits.22579

Broglia, E., Millings, A., & Barkham, M. (2017). Challenges to addressing student mental health in embedded counselling services: a survey of UK higher and further education institutions. British Journal of Guidance & Counselling, 46(4), 441–455. https://doi.org/10.1080/03069885.2017.1370695

Broglia, E., Millings, A., & Barkham, M. (2017). The Counseling Center Assessment of Psychological Symptoms (CCAPS-62): Acceptance, feasibility, and initial psychometric properties in a UK student population. Clinical Psychology & Psychotherapy, 24(5), 1178–1188. https://doi.org/10.1002/cpp.2070

Chen, I. H., Ahorsu, D. K., Pakpour, A. H., et al. (2020). Psychometric Properties of Three Simplified Chinese Online-Related Addictive Behavior Instruments Among Mainland Chinese Primary School Students. Frontiers in Psychiatry, 11. https://doi.org/10.3389/fpsyt.2020.00875

Chen, S. P., Chang, W. P., & Stuart, H. (2020). Self-reflection and screening mental health on Canadian campuses: validation of the mental health continuum model. BMC Psychology, 8(1). https://doi.org/10.1186/s40359-020-00446-w

Cheon, S. H., Reeve, J., Lee, Y., et al. (2019). Expanding autonomy psychological need states from two (satisfaction, frustration) to three (dissatisfaction): A classroom-based intervention study. Journal of Educational Psychology, 111(4), 685–702. https://doi.org/10.1037/edu0000306

Chong, W. H., Liem, G. A. D., Huan, V. S., et al. (2018). Student perceptions of self-efficacy and teacher support for learning in fostering youth competencies: Roles of affective and cognitive engagement. Journal of Adolescence, 68(1), 1–11. https://doi.org/10.1016/j.adolescence.2018.07.002

Conner, J., Posner, M., & Nsowaa, B. (2022). The Relationship Between Student Voice and Student Engagement in Urban High Schools. The Urban Review, 54(5), 755–774. https://doi.org/10.1007/s11256-022-00637-2

Fisher, H. L. (2022). Editorial: The near ubiquity of comorbidity—what are the implications for children's mental health research and practice? Journal of Child Psychology and Psychiatry, 63(5), 505–506. https://doi.org/10.1111/jcpp.13612

Herman, K. C., Reinke, W. M., Huang, F. L., et al. (2021). An investigation of the psychometric properties of the early identification system–student report in a middle school sample. School Psychology, 36(1), 34–46. https://doi.org/10.1037/spq0000414

Huang, X., Zhang, J., & Hudson, L. (2018). Impact of math self-efficacy, math anxiety, and growth mindset on math and science career interest for middle school students: the gender moderating effect. European Journal of Psychology of Education, 34(3), 621–640. https://doi.org/10.1007/s10212-018-0403-z

Huhtiniemi M, Saakslahti A, Watt A, et al. (2019). Associations among Basic Psychological Needs, Motivation and Enjoyment within Finnish Physical Education Students. J Sports Sci Med., 218(2), 239-247.

Kim, H., Park, K. H., & Park, S. (2021). Gender Differences in Lifestyle and Mental Health among Senior High School Students in South Korea. International Journal of Environmental Research and Public Health, 18(20), 10746. https://doi.org/10.3390/ijerph182010746

Kinker, P., Swarnakar, V., Singh, A. R., et al. (2022). A fuzzy Kano-QFD approach for prioritising NBA quality parameters for service quality enhancement: a case of Indian PEIs. International Journal of Quality Engineering and Technology, 8(4), 406. https://doi.org/10.1504/ijqet.2022.123498

Korpershoek, H., Canrinus, E. T., Fokkens-Bruinsma, M., Boer H. (2019). The relationships between school belonging and students 'motivational, social-emotional, behavioural, and academic outcomes in secondary education: a meta-analytic review. Research Papers in Education, 35(1), 1-40.

Lei, H., Cui, Y., & Chiu, M. M. (2018). The Relationship between Teacher Support and Students' Academic Emotions: A Meta-Analysis. Frontiers in Psychology, 8. https://doi.org/10.3389/fpsyg.2017.02288

Lei, X., Liu, C., & Jiang, H. (2021). Mental health of college students and associated factors in Hubei of China. PLOS ONE, 16(7). https://doi.org/10.1371/journal.pone.0254183

Lustig, S., Kaess, M., Schnyder, N., et al. (2022). The impact of school-based screening on service use in adolescents at risk for mental health problems and risk-behaviour. European Child & Adolescent Psychiatry, 32(9), 1745–1754. https://doi.org/10.1007/s00787-022-01990-z

Ma, Z., Idris, S., Zhang, Y., et al. (2021). The impact of COVID-19 pandemic outbreak on education and mental health of Chinese children aged 7–15 years: an online survey. BMC Pediatrics, 21(1). https://doi.org/10.1186/s12887-021-02550-1

Magson, N. R., Freeman, J. Y. A., Rapee, R. M., et al. (2020). Risk and Protective Factors for Prospective Changes in Adolescent

Mental Health during the COVID-19 Pandemic. Journal of Youth and Adolescence, 50(1), 44–57. https://doi.org/10.1007/s10964-020-01332-9

McIntyre, J. C., Worsley, J., Corcoran, R., et al. (2018). Academic and non-academic predictors of student psychological distress: the role of social identity and loneliness. Journal of Mental Health, 27(3), 230–239. https://doi.org/10.1080/09638237.2018.1437608

Molinari, L., & Mameli, C. (2017). Basic psychological needs and school engagement: a focus on justice and agency. Social Psychology of Education, 21(1), 157–172. https://doi.org/10.1007/s11218-017-9410-1

Moore, S., Long, A. C. J., Coyle, S., et al. (2023). A roadmap to equitable school mental health screening. Journal of School Psychology, 96, 57–74. https://doi.org/10.1016/j.jsp.2022.11.001

Nishio, A., Kakimoto, M., Bermardo, T. Ma. S., et al. (2020). Current situation and comparison of school mental health in ASEAN countries. Pediatrics International, 62(4), 438–443. https://doi.org/10.1111/ped.14137

Oberle, E., Ji, X. R., Guhn, M., et al. (2019). Benefits of Extracurricular Participation in Early Adolescence: Associations with Peer Belonging and Mental Health. Journal of Youth and Adolescence, 48(11), 2255–2270. https://doi.org/10.1007/s10964-019-01110-2

Reardon, T., Harvey, K., Baranowska, M., et al. (2017). What do parents perceive are the barriers and facilitators to accessing psychological treatment for mental health problems in children and adolescents? A systematic review of qualitative and quantitative studies. European Child & Adolescent Psychiatry, 26(6), 623–647. https://doi.org/10.1007/s00787-016-0930-6

Roberts, A. C., Yeap, Y. W., Seah, H. S., et al. (2019). Assessing the suitability of virtual reality for psychological testing. Psychological Assessment, 31(3), 318–328. https://doi.org/10.1037/pas0000663

Scherrer, V., & Preckel, F. (2018). Development of Motivational Variables and Self-Esteem During the School Career: A Meta-Analysis of Longitudinal Studies. Review of Educational Research, 89(2), 211–258. https://doi.org/10.3102/0034654318819127

Schwartz, K. D., Exner-Cortens, D., McMorris, C. A., et al. (2021). COVID-19 and Student Well-Being: Stress and Mental Health during Return-to-School. Canadian Journal of School Psychology, 36(2), 166–185. https://doi.org/10.1177/08295735211001653

Simms, L. J., Zelazny, K., Williams, T. F., et al. (2019). Does the number of response options matter? Psychometric perspectives using personality questionnaire data. Psychological Assessment, 31(4), 557–566. https://doi.org/10.1037/pas0000648

Singh, A. K., & Rawani, A. M. (2021). Industry oriented quality management of engineering education: an integrated QFD-TOPSIS approach. International Journal of System Assurance Engineering and Management, 13(2), 904–922. https://doi.org/10.1007/s13198-021-01360-z

Tang, Y., Wei, J., Xin, Y., et al. (2022). Curriculum design for vocational industrial robotics: the quality function deployment (QFD) approach used in China for vocational course design. SN Social Sciences, 2(5). https://doi.org/10.1007/s43545-022-00366-z

Venta, A., Cuervo, M., Bautista, A., et al. (2022). A strong contender for mental health screening in Latinx immigrant youth: Psychometric properties of the Strengths and Difficulties Questionnaire. Psychiatry Research, 316, 114780. https://doi.org/10.1016/j.psychres.2022.114780

Xiong, T., Kaltenbach, E., Yakovenko, I., et al. (2022). How to measure barriers in accessing mental healthcare? Psychometric evaluation of a screening tool in parents of children with intellectual and developmental disabilities. BMC Health Services Research, 22(1). https://doi.org/10.1186/s12913-022-08762-0

Yahia-Berrouiguet, A., Belabid, Y. (2022). Improving the Quality of Higher Education Service by Using the Quality Function Deployment: A Case Study. Management and economics review, 7(2), 173–181. https://doi.org/10.24818/mer/2022.06-05

Zhang, C., Ye, M., Fu, Y., et al. (2020). The Psychological Impact of the COVID-19 Pandemic on Teenagers in China. Journal of Adolescent Health, 67(6), 747–755. https://doi.org/10.1016/j.jadohealth.2020.08.026

Zhou, S. J., Zhang, L. G., Wang, L. L., et al. (2020). Prevalence and socio-demographic correlates of psychological health problems in Chinese adolescents during the outbreak of COVID-19. European Child & Adolescent Psychiatry, 29(6), 749–758. https://doi.org/10.1007/s00787-020-01541-4

Appendix

Table A1. Original evaluation information of G-1 method experts M1.

	C_{142}	C_{141}	C_{143}	C_{114}	C_{134}	C_{124}	C_{112}	C_{111}	C_{113}	C_{131}	C_{133}	C_{132}	C_{123}	C_{122}	C_{121}
C_{142}	1.0	1.3													
C_{141}	1/1.3	1.0	1.3												
C_{143}		1/1.3	1.0	1.7											
C_{114}			1/1.7	1.0	1.2										
C_{134}				1/1.2	1.0	1.2									
C_{124}					1/1.2	1.0	1.7								
C_{112}						1/1.7	1.0	1.2							
C_{111}							1/1.2	1.0	1.2						
C_{113}								1/1.2	1.0	1.3					
C_{131}									1/1.3	1.0	1.2				
C_{133}										1/1.2	1.0	1.2			
C_{132}											1/1.2	1.0	1.4		
C_{123}												1/1.4	1.0	1.2	
C_{122}													1/1.2	1.0	1.2
C_{121}														1/1.2	1.0

Table A2. Original evaluation information of G-1 method experts M1.

	C_{233}	C_{231}	C_{234}	C_{233}	C_{222}	C_{221}	C_{223}	C_{213}	C_{214}	C_{211}	C_{212}
C_{233}	1.0	1.3									
C_{231}	1/1.3	1.0	1.3								
C_{234}		1/1.3	1.0	1.5							
C_{233}			1/1.5	1.0	1.4						
C_{222}				1/1.4	1.0	1.2					
C_{221}					1/1.2	1.0	1.4				
C_{223}						1/1.4	1.0	1.5			
C_{213}							1/1.5	1.0	1.8		
C_{214}								1/1.8	1.0	1.6	
C_{211}									1/1.6	1.0	1.5
C_{212}										1/1.5	1.0

Table A3. Original evaluation information of G-1 method experts M2.

	C_{143}	C_{142}	C_{141}	C_{111}	C_{114}	C_{113}	C_{112}	C_{124}	C_{123}	C_{122}	C_{121}	C_{131}	C_{133}	C_{132}	C_{134}
C_{143}	1.0	1.2													
C_{142}	1/1.2	1.0	1.3												
C_{141}		1/1.3	1.0	1.6											
C_{111}			1/1.6	1.0	1.2										
C_{114}				1/1.2	1.0	1.2									
C_{113}					1/1.2	1.0	1.3								
C_{112}						1/1.3	1.0	1.4							
C_{124}							1/1.4	1.0	1.3						
C_{123}								1/1.3	1.0	1.2					
C_{122}									1/1.2	1.0	1.2				
C_{121}										1/1.2	1.0	1.5			
C_{131}											1/1.5	1.0	1.5		
C_{133}												1/1.5	1.0	1.3	
C_{132}													1/1.3	1.0	1.2
C_{134}														1/1.2	1.0

Table A4. Original evaluation information of G-1 method experts M2.

	C_{233}	C_{234}	C_{231}	C_{232}	C_{214}	C_{213}	C_{211}	C_{212}	C_{221}	C_{222}	C_{223}
C_{233}	1.0	1.2									
C_{234}	1/1.2	1.0	1.3								
C_{231}		1/1.3	1.0	1.4							
C_{232}			1/1.4	1.0	1.6						
C_{214}				1/1.6	1.0	1.6					
C_{213}					1/1.6	1.0	1.3				
C_{211}						1/1.3	1.0	1.3			
C_{212}							1/1.3	1.0	1.4		
C_{221}								1/1.4	1.0	1.3	
C_{222}									1/1.3	1.0	1.2
C_{223}										1/1.2	1.0

Table A5. Original evaluation information of G-1 method experts M3.

	C_{141}	C_{142}	C_{143}	C_{123}	C_{124}	C_{121}	C_{122}	C_{134}	C_{131}	C_{132}	C_{133}	C_{114}	C_{111}	C_{112}	C_{113}
C_{141}	1.0	1.2													
C_{142}	1/1.2	1.0	1.2												
C_{143}		1/1.2	1.0	1.5											
C_{123}			1/1.5	1.0	1.4										
C_{124}				1/1.4	1.0	1.4									
C_{121}					1/1.4	1.0	1.3								
C_{122}						1/1.3	1.0	1.4							
C_{134}							1/1.4	1.0	1.6						
C_{131}								1/1.6	1.0	1.3					
C_{132}									1/1.3	1.0	1.3				
C_{133}										1/1.3	1.0	1.7			
C_{114}											1/1.7	1.0	1.8		
C_{111}												1/1.8	1.0	1.2	
C_{112}													1/1.2	1.0	1.2
C_{113}														1/1.2	1.0

Table A6. Original evaluation information of G-1 method experts M3.

	C_{234}	C_{232}	C_{231}	C_{233}	C_{223}	C_{222}	C_{221}	C_{213}	C_{212}	C_{214}	C_{211}
C_{234}	1.0	1.8									
C_{232}	1/1.8	1.0	1.2								
C_{231}		1/1.2	1.0	1.3							
C_{233}			1/1.3	1.0	1.6						
C_{223}				1/1.6	1.0	1.5					
C_{222}					1/1.5	1.0	1.2				
C_{221}						1/1.2	1.0	1.3			
C_{213}							1/1.3	1.0	1.3		
C_{212}								1/1.3	1.0	1.2	
C_{214}									1/1.2	1.0	1.2
C_{211}										1/1.2	1.0

Table A7. Original evaluation information of G-1 method experts M4.

	C_{141}	C_{143}	C_{142}	C_{124}	C_{123}	C_{122}	C_{131}	C_{111}	C_{114}	C_{112}	C_{133}	C_{132}	C_{134}	C_{121}	C_{113}
C_{141}	1.0	1.2													
C_{143}	1/1.2	1.0	1.3												
C_{142}		1/1.3	10	1.2											
C_{124}			1/1.2	1.0	1.2										
C_{123}				1/1.2	1.0	1.2									
C_{122}					1/1.2	1.0	1.2								
C_{131}						1/1.2	1.0	1.2							
C_{111}							1/1.2	1.0	1.2						
C_{114}								1/1.2	1.0	1.3					
C_{112}									1/1.3	1.0	1.4				
C_{133}										1/1.4	1.0	1.3			
C_{132}											1/1.3	1.0	1.3		
C_{134}												1/1.3	1.0	1.2	
C_{121}													1/1.2	1.0	1.2
C_{113}														1/1.2	1.0

Table A8. Original evaluation information of G-1 method experts M4.

	C_{213}	C_{214}	C_{211}	C_{233}	C_{234}	C_{221}	C_{232}	C_{222}	C_{231}	C_{212}	C_{223}
C_{213}	1.0	1.2									
C_{214}	1/1.2	1.0	1.2								
C_{211}		1/1.2	1.0	1.3							
C_{233}			1/1.3	1.0	1.4						
C_{234}				1/1.4	1.0	1.6					
C_{221}					1/1.6	1.0	1.7				
C_{232}						1/1.7	1.0	1.3			
C_{222}							1/1.3	1.0	1.2		
C_{231}								1/1.2	1.0	1.4	
C_{212}									1/1.4	1.0	1.3
C_{223}										1/1.3	1.0

Table A9. Original evaluation information of G-1 method experts M5.

	C_{141}	C_{143}	C_{142}	C_{132}	C_{133}	C_{134}	C_{131}	C_{124}	C_{121}	C_{123}	C_{122}	C_{111}	C_{113}	C_{112}	C_{114}
C_{141}	1.0	1.2													
C_{143}	1/1.2	1.0	1.3												
C_{142}		1/1.3	1.0	1.2											
C_{132}			1/1.2	1.0	1.2										
C_{133}				1/1.2	1.0	1.2									
C_{134}					1/1.2	1.0	1.3								
C_{131}						1/1.3	1.0	1.4							
C_{124}							1/1.4	1.0	1.2						
C_{121}								1/1.2	1.0	1.4					
C_{123}									1/1.4	1.0	1.3				
C_{122}										1/1.3	1.0	1.4			
C_{111}											1/1.4	1.0	1.3		
C_{113}												1/1.3	1.0	1.3	
C_{112}													1/1.3	1.0	1.3
C_{114}														1/1.3	1.0

Table A10. Original evaluation information of G-1 method experts M5.

	C_{231}	C_{234}	C_{233}	C_{221}	C_{222}	C_{211}	C_{213}	C_{212}	C_{214}	C_{223}	C_{232}
C_{231}	1.0	1.2									
C_{234}	1/1.2	1.0	1.3								
C_{233}		1/1.3	1.0	1.7							
C_{221}			1/1.7	1.0	1.7						
C_{222}				1/1.7	1.0	1.4					
C_{211}					1/1.4	1.0	1.2				
C_{213}						1/1.2	1.0	1.3			
C_{212}							1/1.3	1.0	1.3		
C_{214}								1/1.3	1.0	1.5	
C_{223}									1/1.5	1.0	1.7
C_{232}										1/1.7	1.0