

# Research on the Construction of Assessment Indicators for College Students'

## Learning Engagement in Blended Learning Environment

Huimin Lyu<sup>1\*</sup>, Yujiao Cheng<sup>2</sup>, Dingding Guo<sup>3</sup>, Yuelin Ding<sup>4</sup>, Li Lan<sup>5</sup>

<sup>1 2 3 4 5</sup>South China Normal University

\* lhmjyjs@163.com

**Abstract:** *With the wide application of blended learning mode in higher education, accurately assessing the degree of college students' input in the blended learning environment has become an important issue in educational research and practice. On the basis of systematically analyzing the current research status of blended learning, learning input and multi-source data integration at home and abroad, this study adopts the comprehensive assignment method, combining hierarchical analysis and entropy value method, to scientifically and reasonably determine the weights of the dimensions and indicators, and effectively avoid the excessive influence of a single indicator on the evaluation results. The establishment of evaluation indicators provides scientific basis and specific guidance for educational practice, assesses students' learning engagement status more accurately, provides powerful support for personalized teaching and learning interventions, and also provides new ideas and methods for the study of learning engagement in a blended learning environment.*

**Keywords:** blended learning, learning engagement, multi-source data, integrated weighting method

### 1. Introduction

With the rapid advancement of educational informatization, blended learning has emerged as a pivotal model in higher education, integrating the strengths of face-to-face and online learning. However, its cross-temporal and cross-modal characteristics pose unprecedented challenges to assessing students' learning engagement—a critical factor in evaluating educational effectiveness. Traditional assessment methods, constrained by singular data sources and subjective biases, often fail to comprehensively capture the multidimensional nature of engagement in blended environments (Dai L. T., 2023). This limitation hinders the optimization of teaching strategies and the realization of blended learning's full potential. Recent developments in multi-source data integration offer innovative solutions (Wang M.-T. et al., 2016). Existing evaluation frameworks are mostly dominated by the three dimensions of learning inputs, with a weak representation of the value of social inputs, and for the few four-dimensional evaluations, there are fewer analytical studies on expressions in the area of affective inputs. By synthesizing diverse datasets from virtual and physical learning spaces, it becomes possible to construct a more holistic and objective evaluation framework (Yin R., & He S., 2023). In this study, through literature analysis and policy research, the evaluation framework of student learning engagement in a blended learning environment was developed, based on which, combined with the comprehensive assignment method, the weighting system of assessment indicators for blended learning engagement was

established. The research results aim to provide actionable insights for personalized instructional interventions and to improve the quality of blended learning practices.

## **2.Literature Review**

### ***2.1. Review of blended learning engagement***

Current scholarship on blended learning engagement, while limited in volume, demonstrates thematic diversity spanning four interrelated domains. Research predominantly confirms a positive correlation between blended learning modalities and enhanced learner engagement (Shen X. et al, 2022), with recent advancements in educational informatization and AI applications further validating engagement as a critical quality metric for blended learning ecosystems (Li Y. & Xu L, 2022). Academic inquiries have progressively shifted from analyzing dimensional constructs of engagement—particularly through learning activity taxonomies and pedagogical innovations—to developing conceptual models that reflect divergent epistemological interpretations of engagement mechanisms (Wang X. & Guo S. , 2022). Parallel investigations into determinants of engagement converge with broader learning engagement studies, identifying tripartite influences encompassing intrinsic learner characteristics, extrinsic instructional interventions, and environmental moderators, thereby providing theoretical scaffolding for variable selection in contemporary research frameworks (Ren Q. , 2021). Methodologically, measurement practices predominantly adapt legacy instruments from traditional classroom or online learning contexts (Zhang H. et al , 2023), relying heavily on self-reported data while increasingly incorporating multi-modal approaches that synthesize classroom observations with digital trace analytics (Gao F. & Lv J. , 2025; Ma F. , 2024). Notably, emerging hybrid assessment frameworks that transcend context-specific limitations offer promising paradigms for operationalizing blended learning engagement, though scholarly consensus regarding standardized metrics remains nascent, underscoring the imperative for context-sensitive measurement innovations in this evolving field.

### ***2.2. Review of multi-source data on learning engagement***

Researchers have defined multi-source data across various domains, with multimedia data analytics encompassing text, images, audio, and video. Current research on multi-source data fusion focuses on three key areas: algorithms and models, processes and techniques, and evaluation models. Multi-source data fusion algorithms range from simple methods to probabilistic, fuzzy inference, and artificial intelligence-based approaches. Fusion can occur at three levels: data-level (original data), feature-level (extracted features), and decision-level (local decisions from evaluation and reasoning).

In education, Zhang Zhi et al. developed a comprehensive quality evaluation model using big data (Zhang Z. & Qi Y.-G., 2017). This model collects student data from both formal and informal learning environments, both online and offline, creating a comprehensive data warehouse (Wang Y. , 2024; Liu Y et al, 2024). The model standardizes multi-source data reflecting student quality, applies mathematical models for big data analysis, and generates digital profiles of individual and group student quality. This study provides valuable insights into data collection and integration processes, particularly for learning engagement research, by clarifying what data to collect and how it reflects specific information.

### 3.Method

#### 3.1. Curriculum and Participants

This chapter establishes a blended learning input evaluation index system by collecting student data and combining the comprehensive assignment method. In order to ensure the representativeness of student data, this study chooses to carry out in a comprehensive university in the first semester of 2024, the whole university elective course "Innovative Thinking", which mainly relies on the Learning Channel platform to carry out blended teaching, covering online independent learning and offline classroom face-to-face teaching two parts. The offline classroom is equipped with multimedia teaching equipment, such as multimedia computers, slide projectors and a stable network environment, which provides strong support for the teacher's knowledge teaching, group cooperative learning and classroom interaction and communication activities. The online course is carried out on the Learning Channel platform and supports the login of cell phones, tablet PCs and other terminal devices, which is convenient for students to participate in learning anytime and anywhere. There are 87 students in the course, coming from different grades and majors. In terms of the distribution of majors, the course covers a wide range of disciplines such as philosophy, economics and law, reflecting the diversity of disciplines. As for the gender composition of the students, there are 38 male students and 49 female students, with a certain gender balance. In summary, the diversity of these students in terms of specialty and gender makes their data better represent the situation of college students in blended learning situations, providing a reliable data base for the study.

#### 3.2. Data analysis

Through the systematic sorting of the evaluation framework construction basis, principles and framework elements analysis, this study divided the blended learning input into four dimensions: behavioral input, cognitive input, emotional input and social input, and further clarified the specific evaluation elements under each dimension with the combination of literature sorting and experts' opinions, and put forward the evaluation framework of the blended learning input of college students with multi-source data as shown in Table 1.

**Table 1.** *Blended learning engagement degree indicator system*

| PI                     | SI                             | TI                                                                                                                                                   |
|------------------------|--------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------|
| Behavioral input<br>A1 | Online behavioral input<br>B1  | Total online platform login time C1<br>Online video completion C2<br>Online test score C3                                                            |
|                        | Offline behavioral input<br>B2 | Offline class attendance C4<br>(Questionnaire) Listening to lectures C5<br>(Questionnaire) Taking notes C6<br>(Questionnaire) Completing homework C7 |
| Cognitive input<br>A2  | Online cognitive input<br>B3   | (Post) Understanding C8<br>(Post) Applying C9<br>(Posts) Analyzing C10<br>(Posts) Creating C11<br>(Posts) Evaluating C12                             |
|                        | Offline cognitive input        | (Questionnaire) Understanding C13                                                                                                                    |

|                         |                             |           |                                                                                                                                                                                                                                           |
|-------------------------|-----------------------------|-----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                         | B4                          |           | (Questionnaire) Applying C14<br>(Questionnaire) Analyze C15<br>(Questionnaire) Creating C16<br>(Questionnaire) Evaluating C17                                                                                                             |
| Emotional engagement A3 | Online engagement B5        | emotional | (Content analysis) positive C18<br>(Content analysis) Neutral C19<br>(Content analysis) Negative C20                                                                                                                                      |
|                         | Offline Engagement B6       | Emotional | (Expression recognition) positive C21<br>(Expression recognition) Neutral C22<br>(Expression recognition) Negative C23<br>(Questionnaire) Positive C24<br>(Questionnaire) Neutral C25<br>(Questionnaire) Negative C26                     |
| Social engagement A4    | Online social engagement B7 |           | Online discussion participation C27<br>Number of questions initiated online C28                                                                                                                                                           |
|                         | Offline social input B8     |           | Number of offline interactions with teachers C29<br>Number of offline interactions with peers C30<br>(Questionnaire) Student-student interaction C31<br>(Questionnaire) Group work C32<br>(Questionnaire) Teacher-student interaction C33 |

In this study, classroom videos, questionnaires, and online platform data were collected according to the blended learning engagement multi-source data measurement. Among them, students' expression recognition was collected through classroom video, the frequency of seven emotions was recorded and converted into positive, negative, and neutral emotion scores according to the emotion scoring formula, and observed student-student interactions and teacher-student interactions; student self-assessment data of offline learning engagement was obtained through student self-reported questionnaires; students' offline attendance, completion of online learning, and interactions were collected through online platforms, and the textual data was crawled to get the scores according to the student comment text; the above collected data were summarized to get the raw data of students' blended learning engagement dimensions. Then, the weights of the blended learning input evaluation indexes are determined using a combination of subjective and objective weighting methods. Specifically, the subjective assignment part adopts the hierarchical analysis method, and the objective assignment part adopts the entropy value assignment method. This method ensures the scientificity and rationality of weight allocation. The specific weight calculation process is shown in Figure 1 below.

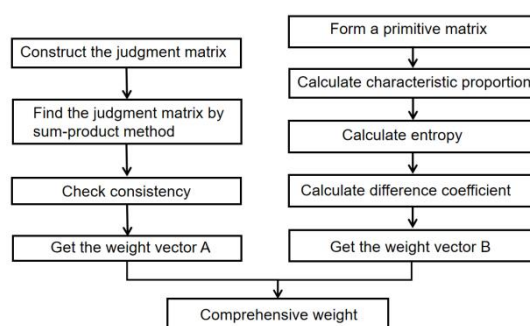


Fig. 1.Comprehensive weighting method weight calculation process

### 3.2.1. Hierarchical analysis

Hierarchical analysis, as a classical subjective weight calculation method, assigns weights to the elements of each level by decomposing the elements related to decision-making into hierarchical structures such as objectives, guidelines and programs, and then combining qualitative and quantitative analysis. Its core lies in constructing a hierarchical structure model and determining the relative importance of each element through expert scoring or two-by-two comparison, so as to provide a scientific basis for decision-making. In this study, 23 teachers and doctors were invited to assign values to the importance degree of each index according to the 1-9 scale method, so as to construct the judgment matrix for two-by-two comparison, and the evaluation result of one of the teachers was used as an example to construct the judgment matrix and carry out calculations, so as to obtain the judgment matrix of the indexes of guideline level, as shown in Fig. 2.

$$A = \begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{3} & 2 \\ 2 & 1 & \frac{1}{2} & 3 \\ 3 & 2 & 1 & 4 \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{4} & 1 \end{bmatrix}$$

Fig. 2. Judgment matrix A

According to the judgment matrix A, the maximum eigenvalue method is used to solve the indicator weights, and the consistency test is performed on the evaluation results. After calculation, the consistency ratio is obtained less than 0.1, which indicates that the consistency of this judgment matrix is acceptable and the weight vector is valid.

The weights of the indicators for the remaining 22 experts and PhDs were determined and a consistency test was conducted. Given that the judgment matrix is the result of a fuzzy quantification of human experience, full consistency could not be achieved. After the test, five of the judgment matrices failed the consistency test, and the total number of valid results was 17.

The process of calculating the secondary and tertiary indicators is the same as that of the primary indicators.

### 3.2.2. Entropy method

The entropy assignment method is a data-based objective weight calculation method. This study uses the entropy value method, which first preprocesses the data, transforms the data into dimensionless values through indicator positive or negative (e.g., negative emotions), standardization or normalization, and then proceeds sequentially with the calculation of indicator weights, indicator entropy value, coefficient of variance, and the determination of indicator weights to ultimately calculate the composite scores of the samples, according to which the composite scores can be ordered and evaluated so as to get the weights of indicators. According to the comprehensive score, the samples can be sorted and evaluated, so as to get the indicator weights, and then determine the indicator weight system of blended learning input degree.

### 3.2.3. Comprehensive empowerment method

In this study, the comprehensive assignment method combining hierarchical analysis method and entropy value method is adopted to ensure the objectivity of the indexes through the

combination of subjectivity and objectivity. Firstly, the weight of hierarchical analysis method and the weight of entropy value method are determined, and then two coefficients  $\alpha$  and  $\beta$  are introduced to indicate the importance degree of hierarchical analysis method and entropy value method in the comprehensive assignment respectively, and satisfy. In this study, 0.5 is taken for each, indicating that subjective and objective factors are equally important.

For the  $i$ th indicator ( $i=1,2,\dots,n$ ), the formula for its composite weight  $W_{Combined}(i)$  is as follows:

$$W_{Combined}(i) = \alpha \times w_i^{AHP} + \beta \times w_i^{Entropy}$$

According to this formula, the composite weight of each indicator is calculated in turn, and finally the composite weight vector is obtained:

$$W_{Combined} = (W_{Combined}(1), W_{Combined}(2), \dots, W_{Combined}(n))$$

### 3.3. Results

According to the first-level index weights of blended learning input degree derived from the above comprehensive assignment method, in order to present the index weights more intuitively and centrally, the index weights derived from hierarchical analysis method, entropy value method, and comprehensive assignment method are integrated, and the first-level index weights are shown in Table 2, the second-level index weights are shown in Table 3, and the third-level index weights are shown in Table 4.

Table 2. Blended learning engagement degree primary indicator weight

|                                          | A1     | A2     | A3     | A4     |
|------------------------------------------|--------|--------|--------|--------|
| Weight (hierarchical analysis)           | 0.2372 | 0.2635 | 0.3217 | 0.1776 |
| Weight (entropy method)                  | 0.1111 | 0.2906 | 0.3668 | 0.2316 |
| Weight(Comprehensive empowerment method) | 0.1742 | 0.2770 | 0.3443 | 0.2046 |

Table 3. Blended learning engagement degree secondary indicator weight

|                                          | B1     | B2     | B3     | B4     | B5     | B6     | B7     | B8     |
|------------------------------------------|--------|--------|--------|--------|--------|--------|--------|--------|
| Weight (hierarchical analysis)           | 0.1425 | 0.0947 | 0.1863 | 0.0772 | 0.1194 | 0.2023 | 0.0711 | 0.1065 |
| Weight(entropy method)                   | 0.0523 | 0.0588 | 0.211  | 0.0796 | 0.15   | 0.2168 | 0.0717 | 0.1599 |
| Weight(Comprehensive empowerment method) | 0.0974 | 0.0768 | 0.1987 | 0.0783 | 0.1347 | 0.2096 | 0.0714 | 0.1332 |

Table 4. Blended learning engagement degree tertiary indicator weight

|                                          | C1     | C2     | C3     | C4     | C5     | C6     | C7     | C8     | C9     | C10    | C11    |
|------------------------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Weight (hierarchical analysis)           | 0.0732 | 0.0348 | 0.0345 | 0.0062 | 0.0218 | 0.0231 | 0.0436 | 0.0373 | 0.0365 | 0.0366 | 0.0377 |
| Weight(entropy method)                   | 0.0334 | 0.0086 | 0.0103 | 0.0066 | 0.0151 | 0.0153 | 0.0218 | 0.0429 | 0.0417 | 0.0423 | 0.0412 |
| Weight(Comprehensive empowerment method) | 0.0533 | 0.0217 | 0.0224 | 0.0064 | 0.0185 | 0.0192 | 0.0327 | 0.0401 | 0.0391 | 0.0395 | 0.0395 |

|                                                    | C12        | C13        | C14        | C15        | C16        | C17        | C18        | C19        | C20        | C21        | C22        |
|----------------------------------------------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|
| Weight<br>(hierarchical<br>analysis)               | 0.03<br>82 | 0.01<br>54 | 0.01<br>42 | 0.01<br>51 | 0.01<br>41 | 0.01<br>84 | 0.03<br>85 | 0.03<br>68 | 0.04<br>41 | 0.05<br>12 | 0.04<br>23 |
| Weight(entropy<br>method)                          | 0.04<br>29 | 0.01<br>79 | 0.01<br>80 | 0.01<br>29 | 0.01<br>77 | 0.01<br>31 | 0.04<br>98 | 0.05<br>03 | 0.04<br>99 | 0.05<br>38 | 0.06<br>86 |
| Weight(Compreh<br>ensive<br>empowerment<br>method) | 0.04<br>06 | 0.01<br>67 | 0.01<br>60 | 0.01<br>40 | 0.01<br>59 | 0.01<br>58 | 0.04<br>42 | 0.04<br>36 | 0.04<br>70 | 0.05<br>25 | 0.05<br>55 |
|                                                    | C23        | C24        | C25        | C26        | C27        | C28        | C29        | C30        | C31        | C32        | C33        |
| Weight<br>(hierarchical<br>analysis)               | 0.02<br>25 | 0.03<br>83 | 0.02<br>18 | 0.02<br>62 | 0.03<br>75 | 0.03<br>36 | 0.02<br>66 | 0.03<br>25 | 0.01<br>65 | 0.01<br>53 | 0.01<br>56 |
| Weight(entropy<br>method)                          | 0.02<br>43 | 0.01<br>73 | 0.02<br>03 | 0.03<br>25 | 0.03<br>33 | 0.03<br>84 | 0.04<br>38 | 0.04<br>14 | 0.02<br>72 | 0.02<br>83 | 0.01<br>92 |
| Weight(Compreh<br>ensive<br>empowerment<br>method) | 0.02<br>34 | 0.02<br>78 | 0.02<br>11 | 0.02<br>94 | 0.03<br>54 | 0.03<br>60 | 0.03<br>52 | 0.03<br>70 | 0.02<br>19 | 0.02<br>18 | 0.01<br>74 |

## 4. Discussion

### 4.1. Introduction and Expansion of Social Input Dimensions

In this study, social input is included in the evaluation dimension of blended learning input, and the social dimension is comprehensively evaluated from both online and offline aspects. Specifically, online social input is quantified by analyzing students' interactive behaviors on the learning platform (e.g., the number of times they participated in discussions, the number of times they initiated questions, etc.); and offline social input is assessed by observing students' interactive behaviors in the classroom (e.g., the number of times they interacted with the teacher and their peers, the number of times they interacted with each other, etc.). This way of evaluating social input from multiple perspectives not only enriches the scope of learning input evaluation, but also provides a more comprehensive perspective for understanding students' interactive behaviors in a blended learning environment.

### 4.2. Establishment of weights for evaluation indicators for multi-source data

This study constructed a comprehensive multidimensional evaluation model with four dimensions: behavioral, cognitive, emotional and social, which provides a scientific basis for the comprehensive assessment of blended learning input. By integrating data from multiple sources (e.g., platform login time, video completion, quiz scores, classroom attendance, group cooperation performance, etc.), the model can more comprehensively reflect the state of students' learning engagement, and the weights of the indicators for evaluating the degree of students' learning engagement in a blended learning environment are established through the synthesis of hierarchical analysis and entropy value method.

## 5. Discussion

On the basis of constructing the evaluation framework, this study further determines the weights of indicators by carrying out empirical research. The stage of determining the weights of indicators adopts the comprehensive assignment method, combining the hierarchical analysis method with the entropy value method, to scientifically and reasonably determine the weights of the dimensions and indicators, which effectively avoids the excessive influence of a single indicator on the evaluation results. It more accurately assesses students' learning engagement status, provides strong support for personalized teaching and learning intervention, and promotes the effective implementation and development of blended learning mode in higher education. However, there are still some shortcomings in the current study, first, it fails to analyze students' offline social engagement from a more in-depth perspective. Second, the data collection method of student-student interaction and teacher-student interaction is cumbersome and lacks intelligence and automation. This manual collection method is not only time-consuming and labor-intensive, but also may lead to incomplete data and subjective bias. In view of the above research shortcomings, future research on blended learning inputs can be expanded and deepened in terms of combining the evaluation model with stage experiments and optimizing data collection and analysis methods. With the rapid development of generative artificial intelligence technology, subsequent studies can further explore its application in learning input data collection.

## Reference

- Wang, M.-T., Fredricks, J. A., Ye, F., et al. (2016). The math and science engagement scales: Scale development, validation, and psychometric properties. *Learning and Instruction*, 43, 16–26.
- Dai, L. T. (2023). Target orientation, guiding principles and practical path of digital transformation of education driven by design intelligence. *Journal of East China Normal University (Education Science Edition)*, 41(3), 12-24.
- Yin, R., & He, S. (2023). Evaluation of blended learning inputs from the perspective of evidence-based teaching evaluation. *Research on Electrochemical Education*, 44(5), 120-128.
- Shen, X., Yuan, D., & Chen, H. (2022). From "hybrid" to "integration": The design and practice of integrated teaching. *Modern Educational Technology*, 32(4), 40-49.
- Li, Y., & Xu, L. (2022). Teaching power model construction of university teachers in blended learning environment - Based on the analysis of rooted theory. *Education Development Research*, 42(9), 71-79.
- Ren, Q. (2021). A study of the effect of motivational regulation on learning engagement in college English classroom under blended teaching environment. *Foreign Language E-Learning*, 45(1), 44-50, 60, 7.
- Wang, X., & Guo, S. (2022). Practice and inspiration of online-offline integrated teaching at Tsinghua University. *Modern Education Technology*, 32(4), 106-112.
- Zhang, H., Liu, Y., & He, S. (2023). The construction of blended teaching quality evaluation index system for sports professional motor skills courses. *Education Theory and Practice*, 43(21), 57-61.
- Gao, F., & Lv, J. (2025). Research on factors influencing students' online learning satisfaction in blended teaching. *Jiangsu Higher Education*, 41(2), 78-85.

- Ma, F. (2024). An experimental study on the impact of blended learning approach on learning effect in secondary school mathematics based on digital platform. *Shanghai Educational Research*, 44(11), 56-66.
- Li, M., Qi, X., & Zhang, L. (2024). A study on the developmental trajectory of college students' engagement in blended academic English learning. *Foreign Language E-Learning*, 46(5), 60-68, 113.
- Zhang, Z., & Qi, Y.-G. (2017). Construction of multi-source and multi-dimensional comprehensive quality evaluation model based on big data. *\*China Electrochemical Education\**, \*(09)\*, 69–77+97.
- Wang, Y. (2024). The construction and practice of blended learning community in English language theory courses - Taking "English Pragmatics" course as an example. *Foreign Language Society*, 45(3), 90-96.
- Liu, Y., Jai, R., & Ren, Z. (2024). Research on the impact of blended learning on college students' higher-order thinking ability in the digital era. *Modern University Education*, 40(6), 92-100.
- Zhang, S., Gao, L., & Yang, Y. (2023). Dilemmas and improvement strategies of blended teaching of Civics and Politics in higher education programmes. *Educational Theory and Practice*, 43(3), 57-60.