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Analysis of factors influencing student learning experience in the blended online-offline smart education model

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Abstract: Research on the influencing factors of students' learning experience in the blended online-offline smart education model is significant for optimising the allocation of educational resources and improving teaching effectiveness. In this study, first, 14 key factors were identified across five dimensions, including course environment, platform, and course design. Through expert inquiry, logical connections between factors were analysed, and an adjacency matrix was established. Next, the reachable matrix was calculated to reveal the hierarchical structure, defining the reachable set and antecedent set to extract factors hierarchically. Finally, an interpretive structural model was constructed to demonstrate the hierarchy and interactions among factors. Test results indicate that the proposed method maintains over 95% accuracy in analysing learning experience factors, with a factor weight stability index ranging between 0.97 and 0.99 and a fluctuation amplitude of only 0.02.

Keywords: blended online and offline; smart education model; learning experience; analysis of influencing factors.

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Juan Hu received her PhD in Teaching and Technology from Assumption University in Thailand in 2022. She is currently teaching at the School of Music, Henan Vocational and Technical College. Her research interests include local music and teaching and technology. She has hosted one national level high-quality online open course and one provincial-level ideological and political demonstration course; and won one second prize and one third prize in a national teaching competition. In recent years, she has published a total of 27

papers and led or participated in 28 provincial-level projects; participated in the compilation of eight textbooks; three national invention patents and four computer software copyrights.

1 Introduction

With the rapid development of information technology, the blended online-offline smart education model has gradually emerged as an important trend in the field of education (Khan and Goli, 2023). This model integrates traditional classroom teaching with digital learning resources to provide students with a more flexible and personalised learning experience (Yao et al., 2024). However, under this novel educational model, students' learning experience is influenced by a multitude of factors, including technological conditions, teacher guidance, curriculum design, and students' self-directed learning ability (Harada et al., 2022; Liu et al., 2024; Cox et al., 2024). Especially in the post-pandemic era, the widespread application of blended online-offline education models has made it particularly important to explore their impact mechanisms on students' learning experiences. Current research on smart education by domestic and foreign scholars primarily focuses on technology applications, while systematic analysis of students' learning experience remains insufficient (Tao, 2024). Therefore, this study aims to explore the key factors affecting students' learning experience under the blended online-offline smart education model, thus providing a theoretical basis and practical guidance for optimising the education model and improving learning outcomes.

Chen and Gu (2021) proposed an analysis of the factors influencing online course user experience from the perspective of the two-factor theory. By referring to the user experience analysis framework within the product and service scope, multiple research methods were comprehensively used, such as surveys and interviews with numerous online course learners, in-depth analysis of key events, questionnaire surveys and data statistics, exploratory factor analysis and confirmatory factor analysis, etc. Finally, an evaluation scale covering three core dimensions of usability, support services, and visual presentation was constructed. In addition, based on the two-factor theory, the health and incentive factors affecting the user experience of online courses were deeply explored, and corresponding optimisation strategies and paths were proposed. However, this method adopts a static evaluation framework and fails to incorporate real-time interactive data and dynamic learning behaviour, making its two-factor model difficult to adapt to new teaching modes such as AI-driven adaptive learning, indicating a significant theoretical lag. Wu et al. (2022) proposed a study on students' learning experience and its influencing factors under the expansion of enrolment. Students who enter the learning stage through the expansion of enrolment have gained a relatively positive learning experience during academic advancement, including satisfaction with learning achievements, ability to adapt to future career positions, mastery of theoretical essence in professional fields, and accumulation of practical operation skills related to the profession. Moreover, a close and obvious correlation exists between the quality of this learning experience and the effectiveness of management services and professional cognitive enlightenment education for the expanded enrolment group. However, this method only focuses on the self-evaluation of expanded enrolment students and fails to establish a control group analysis (such as longitudinal comparison with non-expanded

enrolment students), resulting in the inability to distinguish between the ‘effect of expanded enrolment policies’ and the ‘impact of general teaching quality’. Its conclusion may confuse group specificity and educational universality factors. Zhu and Duan (2021) proposed a key element analysis method for online classroom learning experience based on the Kano model. Based on the core principle framework of the Kano model, the constituent factors of the learning experience in the context of online classroom were identified. Through a series of scientific processes such as Kano exclusive questionnaire architecture design, large-scale distribution survey, deep data analysis, and optimised element extraction and identification, the core key factors of online classroom learning experience were accurately identified. However, this method only uses the static classification method of traditional Kano questionnaires, and fails to integrate the backend behaviour data of online learning platforms, resulting in a deviation between the classification results of elements and the actual user experience. This is especially evident in the identification of ‘reverse needs’ and ‘hidden pain points’, where accuracy is insufficient.

This study innovatively applies the explanatory structural model to the field of blended smart education, systematically identifying multidimensional key factors that affect the learning experience. Through rigorous expert inquiry and matrix operation methods, a clear hierarchical influencing factor system model was established for the first time, revealing the inherent logical relationships between various factors. This study provides a scientific decision-making framework for educational practitioners, enabling them to accurately identify core influencing factors and optimise online and offline educational resource allocation strategies. The research results have deepened the understanding of blended learning models from a systems theory perspective, providing new theoretical basis and methodological support for improving the quality of smart education. The detailed technical route of this method is as follows:

- 1 Based on the blended online-offline smart education model, the system extracts five core dimensions: curriculum environment and platform, curriculum design, teacher characteristics, learner characteristics, and social interaction, totalling 14 specific influencing factors. Through multi-dimensional structured analysis, a complete system of influencing factors from technical support to social interaction is clearly defined, and an experiential evaluation framework covering all teaching elements is established, thereby providing scientific classification standards and operational definitions for optimising blended learning environments. The research results present a complex interactive relationship among technology, teaching methods, and learner characteristics in blended education.
- 2 Through two rounds of expert consultation, a consensus is reached to transform the logical relationships between 14 influencing factors of learning experience into adjacency matrices. The binary representation method is used to accurately depict the influence path between factors with 0 and 1, thereby forming a complete causal relationship network. This method effectively avoids subjective judgment bias while presenting the interaction mechanism of various elements in the blended education system through a structured matrix, laying a data foundation for subsequent hierarchical analysis.

- 3 By using matrix operations, the adjacency matrix is converted into a reachable matrix, which fully presents the direct and indirect influence paths between various factors. With MATLAB software for Boolean operations, the system identifies all potential impact relationships, breaking through the limitations of only analysing direct correlations. By revealing the complex multi-level transmission mechanism in blended education systems, this matrix not only provides data support for constructing explanatory structural models, but also clarifies implicit hierarchical relationships and facilitates a comprehensive mapping of the learning experience impact network.
- 4 A five-layer explanatory structure model is constructed based on the reachability matrix for hierarchical extraction. Learning outcomes occupy the top level, forming a goal-oriented approach; the middle layer contains elements of teaching interaction and learner characteristics; the bottom layer is underpinned by course content and resources. This model elucidates the transmission paths and hierarchical dependencies between elements in blended education, presenting a systematic impact chain from bottom-level resources to top-level outcomes. Through structured analysis, the multi-level mechanism of learning experience formation is clearly demonstrated.

2 Analysis of factors influencing student learning experience in the blended online-offline smart education model

2.1 Determination of influencing factors

The influencing factors of students' learning experience in the blended online-offline smart education model are mainly manifested in five aspects: curriculum environment and platform, curriculum design, teachers, learners, and social interaction (Torunlar and Engn, 2024). Based on these five aspects, this study summarises the factors affecting students' learning experience in online courses into the five dimensions shown in Table 1.

2.2 Adjacency matrix building

The study first conducted a preliminary analysis of the logical connections among 14 key factors, engaging two experts specialising in blended learning course design and two educational technology PhDs with relevant learning experience to participate in the inquiry. After two rounds of discussion and revision, the research team reached a consensus and clarified the relationships among various factors affecting students' learning experience in the smart education model integrating online and offline approaches. These relationships were converted into an adjacency matrix 'A', with specific results shown in Table 2. The value 0 indicates that the row factor has no effect on the column factor, while 1 denotes an influence relationship.

Table 1 Factors influencing students' learning experience and corresponding meanings

<i>Dimension</i>	<i>Influencing factor</i>	<i>Description</i>
Course environment and technology	Platform and technical support (F1)	The course platform is simple, easy to use, stable, fully functional, and rich, with comprehensive and effective technical support.
	Learning atmosphere (F2)	The atmosphere of discussion in online courses and the active participation of other students.
Course design	Content and resources (F3)	The richness and quality of learning content and resources.
	Course flexibility (F4)	The flexibility of the course in terms of time, space, and methods, such as allowing students to learn the course through mobile means, can provide relatively flexible learning time, and can support collaborative learning in various aspects.
	Learning activity design (F5)	Different teaching methods and activity designs for online courses, such as behaviourist teaching method emphasising the distribution and consumption of knowledge, while connectivist teaching method focuses on creating knowledge through the connection of knowledge.
Teacher	Evaluation design (F6)	Course assignments, posting requirements, quizzes in course videos, peer evaluations, course exams, etc.
	Assistance situation (F7)	Teachers' attitudes towards the curriculum, their enthusiasm for participating in the course, and their ability to inspire students' motivation and enthusiasm.
Student	Computer preferences (F8)	Learners prefer learning methods in the online environment and are able to adapt to this learning environment.
	Learning motivation (F9)	Learners' motivation, interest, willingness, etc. towards the course.
	Learning style (F10)	The ways in which learners possess or prefer during the learning process.
	Self-directed learning ability (F11)	Students' ability to self-manage and automatically adjust their learning process.
	Learning harvest (F12)	Improvement in certificate acquisition, knowledge acquisition, problem-solving skills, social skills, and other aspects.
Social interaction	Teacher student interaction (F13)	The communication and interaction between teachers and students in the course, such as problem discussion and exchange, feedback on assignments.
	Peer interaction (F14)	Discussion, communication, and social connections among students.

2.3 Analysis of the hierarchical relationship of influencing factors

The adjacency matrix only reveals the direct correlation between various elements. To gain a deeper understanding of its hierarchical structure, it is necessary to calculate the reachability matrix. The calculation method involves using the identity matrix as the

basis. In the case of $(A + I)K - 1 \neq (A + I)K + 1 = R(A)(K \geq 2)$, the obtained result is the reachable matrix, which depicts the possible relationship network between each element (Sprecher, 2023). By applying MatrixLaboratory software, the reachable matrix $R(A)$ is calculated and obtained, and its specific values and structure are presented in Table 3.

Table 2 Adjacency matrix

<i>Influence factor</i>	<i>F1</i>	<i>F2</i>	<i>F3</i>	<i>F4</i>	<i>F5</i>	<i>F6</i>	<i>F7</i>	<i>F8</i>	<i>F9</i>	<i>F10</i>	<i>F11</i>	<i>F12</i>	<i>F13</i>	<i>F14</i>
F1	0	0	0	1	0	0	0	0	1	0	0	0	0	0
F2	0	0	0	0	0	0	0	0	1	0	0	1	0	0
F3	0	0	0	1	1	0	0	0	1	0	0	1	0	0
F4	0	0	0	0	0	0	0	0	1	0	0	0	1	1
F5	0	1	0	1	0	1	1	0	1	0	0	1	1	1
F6	0	1	0	0	0	0	1	0	1	0	0	1	1	1
F7	0	1	0	0	1	1	0	0	1	0	0	1	1	1
F8	0	0	0	0	0	0	0	0	0	0	0	1	0	0
F9	0	0	0	0	0	0	0	0	0	0	0	1	1	1
F10	0	0	0	0	0	0	0	1	0	0	0	0	0	0
F11	0	0	0	0	0	0	0	0	0	0	0	1	0	0
F12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F13	0	0	0	0	0	0	0	0	1	0	0	1	0	0
F14	0	1	0	0	0	0	0	0	1	0	0	1	0	0

Table 3 Reachable matrix

<i>Influence factor</i>	<i>F1</i>	<i>F2</i>	<i>F3</i>	<i>F4</i>	<i>F5</i>	<i>F6</i>	<i>F7</i>	<i>F8</i>	<i>F9</i>	<i>F10</i>	<i>F11</i>	<i>F12</i>	<i>F13</i>	<i>F14</i>
F1	1	1	0	1	0	0	0	0	1	0	0	1	1	1
F2	0	1	0	0	0	0	0	0	1	0	0	1	1	1
F3	0	1	1	1	1	1	1	0	1	0	0	1	1	1
F4	0	1	0	1	0	0	0	0	1	0	0	1	1	1
F5	0	1	0	1	1	1	1	0	1	0	0	1	1	1
F6	0	1	0	1	1	1	1	0	1	0	0	1	1	1
F7	0	1	0	1	1	1	1	0	1	0	0	1	1	1
F8	0	0	0	0	0	0	0	1	0	0	0	1	0	0
F9	0	1	0	0	0	0	0	0	0	0	0	1	1	1
F10	0	0	0	0	0	0	0	1	0	1	0	1	0	0
F11	0	0	0	0	0	0	0	0	0	0	1	1	0	0
F12	0	0	0	0	0	0	0	0	0	0	0	1	0	0
F13	0	1	0	0	0	0	0	0	1	0	0	1	1	1
F14	0	1	0	0	0	0	0	0	1	0	0	1	1	1

2.4 Establishment of hierarchical analysis and interpretation structure model

Based on the calculation results of the reachable matrix $R(A)$, a hierarchical analysis was conducted. In analytic hierarchy process, two sets need to be defined first:

- 1 Reachable set $R(S_i)$, which refers to the set of all factors that element S_i can reach in the reachable matrix (i.e., all factors containing '1' in the row corresponding to S_i).
- 2 The leading set T , which refers to the set of all factors in the reachable matrix that can reach S_i by other factors (i.e., all factors containing '1' in the column corresponding to S_i).

The basic method for conducting hierarchical analysis is as follows: first, the hierarchy is extracted based on the condition of $R(S_i) \cap Q(S_i) = R(S_i)$, and the first factor extracted is the topmost factor; then, the corresponding rows and columns are removed from the reachable matrix, and the factors meeting this condition are extracted again (Wang and Zhang, 2023); similarly, all factors are extracted in a descending order of hierarchy, thereby forming a hierarchical relationship between them, as shown in Table 4.

Table 4 Hierarchical relationship of factors influencing learning experience

<i>Level</i>	<i>Factors included</i>
1	F12
2	F2, F8, F9, F11, F13, F14
3	F4, F10
4	F1, F5, F6, F7
5	F3

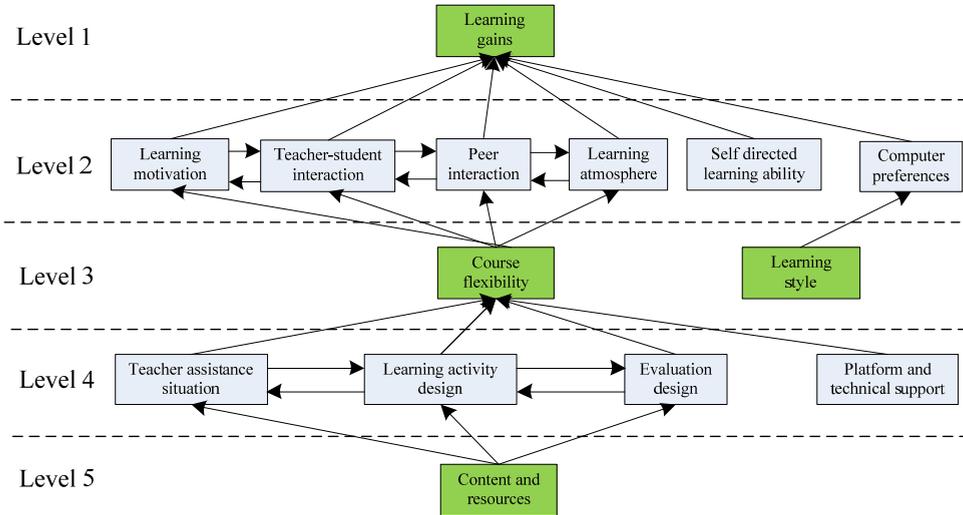
In the five-level architecture, learning outcomes (F12) rank at the top as dominant elements driving the learning experience. The six elements located at the lower level are directly influenced by the acquisition of painting skills, with their close relationships revealed through reachability matrix analysis – including but not limited to learning paths (F2), motivation stimulation (F9), teacher-student interaction (F13), and peer communication (F14) – forming a highly interconnected network. The third-level curriculum adaptability (F4) directly impacts the upper-level F2, F9, F13, and F14. The four key fourth-level elements directly affect curriculum adaptability while demonstrating significant interactions, exemplified by learning activity planning (F5), evaluation mechanism design (F6), and auxiliary support (F7), which forms tightly coupled relationships. Bottom-level content and resources (F3) directly impact upper-level F5, F6, and F7, which collectively constructs a bottom-up learning ecosystem.

Based on the analytic hierarchy process results, this study constructed an explanatory structural model reflecting the impact mechanism of students' learning experience in blended online-offline smart education using the interpretive structural modelling method, with specific results presented in Figure 1.

This study identified 14 key elements significantly affecting student learning experiences in online-offline smart education contexts: technological platform support capabilities, created learning environments, teaching content/resource richness, course arrangement flexibility, learning activity designs, evaluation system constructions, teacher assistance provisions, student computer preferences, learning motivation,

adaptability to diverse learning styles, self-directed learning skills, obtained learning outcomes, teacher-student interactions, and peer communications (Zeng et al., 2024).

Figure 1 Explanation structure model of factors influencing learning experience (see online version for colours)



Using the interpretive structural modelling method, a systematic framework was constructed to analyse influencing factors of learning experience. Fourteen key elements were analysed and categorised in detail, with their hierarchical structure and interactions clearly depicted. In this model architecture, learning effectiveness occupies the top level and directly influences other hierarchical elements. The foundational level, content and resources, form the basis of all influencing factors, demonstrating self-evident importance. While middle-layer factors affect the learning experience indirectly rather than directly, they remain indispensable components. Collectively, these elements form a complex system working synergistically toward final learning outcomes.

3 Test experiment

3.1 Test data

Data were collected from 300 students who participated in the blended online-offline smart education model for a period of 16 weeks. According to online learning behaviour data, students log in to the platform 2.3 times a day, with an average learning time of 37 minutes per session. The completion rate of course video viewing reaches 85.6%, with a replay rate of 42.3%. Offline classroom attendance records show an average attendance rate of 91.2% for compulsory courses and 68.7% for elective courses. In terms of teacher-student interaction, each student initiates an average of 3.1 online questions per week and receives an average response time of 4 hours and 15 minutes from the teacher. The evaluation of learning effectiveness shows that the average improvement in mid-term to final exam scores is 12.8 points, with a 9.4-point improvement in theoretical courses and a 16.2-point improvement in practical courses.

According to the monitoring data of the technical environment, the average response time of the teaching platform is 1.2 seconds, and the success rate of video buffering is 98.4%. Analysis of learning behaviour reveals that 78.5% of students tend to engage in online learning between 19:00–22:00 in the evening. The resource utilisation shows that the average download rate of PPT courseware is 23.7 times per chapter, and the opening rate of expanded reading materials is 61.9%. According to device usage statistics, smartphones account for 54.3%, tablets 21.8%, and laptops 23.9%. According to the tracking of learning effectiveness, the average final grade of students who completed their assignments on time reaches 86.4 points, which is 14.7 points higher than the group who did not complete their assignments on time. In the satisfaction survey, 82.6% of students expressed their approval of the blended learning mode, with the highest satisfaction rate of 88.3% towards the online Q&A system.

3.2 Test plan and indicators

The method proposed in this paper was compared and tested with the methods in Wu et al. (2022) and Zhu and Duan (2021) in terms of the factor analysis accuracy and factor weight stability index based on learning experience.

Accuracy of analysis of factors influencing learning experience: accuracy refers to the ability of analytical methods to accurately identify and quantify the degree of impact of various factors on students' learning experience. It reflects the degree of agreement between the model output results and the true impact relationship, including correct identification of key influencing factors, accurate estimation of the direction and intensity of the impact, and so on. High precision means that the analysis results can reliably reflect the causal relationships between various factors and student experiences in actual educational scenarios, providing a reliable basis for educational decision-making.

Factor weight stability index: the factor weight stability index is an important indicator for evaluating the reliability of the analysis method for factors affecting students' learning experience. It is used to quantify the stability of the importance ranking of different factors in the analysis model under different conditions.

3.3 Analysis of test results

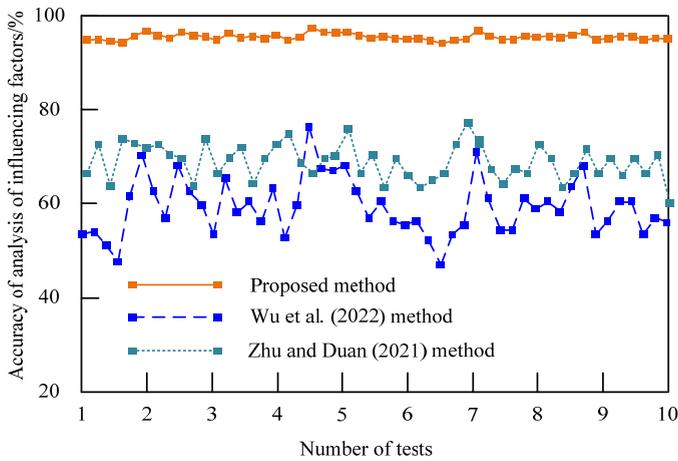
3.3.1 Analysis accuracy of factors influencing learning experience

Under the blended online-offline smart education model, students' learning experience is influenced by multiple factors including technological tool adaptability, teacher-student interaction quality, and course design rationality. Accuracy tests for learning experience factor analysis enables quantitative evaluation of each factor's specific impact on learning outcomes, thereby eliminating subjective speculation. High-precision analysis identifies key variables and provides data-supported evidence for educational optimisation. The accuracy analysis results of the three-learning experience factor evaluation methods are presented in Figure 2.

As shown in the figure, the accuracy of our proposed method in analysing factors affecting the learning experience remains above 95% in ten tests, showing extremely stable performance. In contrast, the method in Wu et al. (2022) exhibits significant fluctuations, reaching approximately 55% at one test, nearly 70% at four tests, but mostly below 60% at other test times. Similarly, the method in Zhu and Duan (2021) is also

unstable: it reaches about 75% at 2 testing times, but only about 60% at six testing times. The method proposed in this article not only exhibits much higher accuracy than the other two methods, but also demonstrates no significant fluctuations. It can more stably and accurately quantify the impact of various factors on students' learning outcomes, thus providing more reliable data support for educational optimisation. This is because this proposed method adopts rigorous matrix operations and hierarchical analysis techniques. It accurately characterises factor correlations through adjacency matrices, reveals multi-level transmission paths using reachability matrices, and constructs an explanatory structure model system to present hierarchical relationships. As a result, it achieves precise quantification and stable evaluation of the influencing factors of blended education.

Figure 2 Analysis accuracy of factors affecting learning experience (see online version for colours)



3.3.2 Factor weight stability index

Educational data exhibits characteristics including high sample heterogeneity and strong contextual dependency. Should factor weights fluctuate excessively across samples, analytical results would lose their guiding significance. Testing weight stability through systematic methods identifies genuinely universal core factors, eliminates spurious correlation interference, and thus ensures analytical conclusion comparability across universities, grades, and cultural backgrounds. This evaluation also reveals method sensitivity to small samples and missing data, providing stability assessment benchmarks for educational policymakers while preventing resource misallocation due to weight drift. The weight stability index results for learning experience factors across three analytical methods are presented in Table 5.

As shown in Table 5, the factor weight stability index of our proposed method has always remained in the range of 0.97–0.99, with a fluctuation amplitude of only 0.02. In contrast, the index of the method in Wu et al. (2022) fluctuates between 0.62–0.69, with an amplitude of 0.07; The index of the method in Zhu and Duan (2021) fluctuates between 0.68–0.73, with an amplitude of 0.05. In 10 tests, our proposed method achieves the highest stability of 0.99 four times, while the other two methods have the highest

stability of only 0.72 and 0.73, respectively. The stable high index performance of our propose method indicates that it can effectively overcome the influence of sample heterogeneity, thus ensuring consistency of analysis conclusions in different educational contexts and providing reliable basis for educational decision-making. This is because this method adopts a combination of expert consensus and matrix operations. It ensures the accuracy of factor correlation through two rounds of expert inquiry, establishes a rigorous hierarchical structure using reachable matrix analysis, and verifies the weight allocation logic based on explanatory structure models. As a result, it achieves a stable evaluation of the weights of factors affecting mixed education.

Table 5 Factor weight stability index

Number of tests	Factor weight stability index		
	Proposed method	Wu et al. (2022) method	Zhu and Duan (2021) method
1	0.98	0.65	0.72
2	0.97	0.68	0.70
3	0.99	0.63	0.69
4	0.98	0.67	0.71
5	0.97	0.64	0.73
6	0.99	0.66	0.68
7	0.98	0.62	0.70
8	0.97	0.69	0.72
9	0.99	0.65	0.71
10	0.98	0.67	0.69

The method of analysing the influencing factors of blended education proposed in this study demonstrates significant originality and scientific contribution. It innovatively integrates expert wisdom and mathematical modelling, employing adjacency matrices to accurately quantifies factor correlations, and reachability matrices to reveal deep transmission mechanisms. Furthermore, a five-layer explanatory structure model is constructed to fully present the impact path. Its scientific value is reflected in the establishment of a research paradigm that integrates qualitative judgment and quantitative analysis, achieving analysis accuracy of over 95% and weight stability of 0.97–0.99, which breaks through the limitations of traditional methods affected by sample fluctuations. This method provides a new analytical framework for blended education research that combines theoretical depth and practical reliability, enabling measurable and verifiable accurate evaluation of the multi-factor interaction effects of complex education systems.

4 Conclusions

Through systematic analysis of learning experience influencing factors in the blended online-offline smart education model, this study has identified 14 key factors spanning five dimensions: instructional environment, curriculum design, teacher factors, learner characteristics, and social interaction. Furthermore, it employs rigorous modelling and data analysis to reveal complex inter-factor relationships and hierarchical structures. The proposed methodology demonstrates superior performance in both analytical accuracy

and factor weight stability, ensuring research outcomes with high reliability and strong generalisability. These achievements establish a theoretical foundation for optimising blended smart education while providing practical improvement directions for educators, emphasising targeted regulation of key factors to enhance learning experience and outcomes. Future advances in educational technology should encourage broader research efforts to promote the development of blended smart education toward greater personalisation and efficiency.

Declarations

All authors declare that they have no conflicts of interest.

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