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From Fragmentation to Coherence: A Knowledge Graph-Driven Integration Framework for Blended Learning

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Abstract
Cross-platform resource fragmentation increases not only the cognitive load of students but also the workload of teachers. It is a problem that has long plagued teachers and students in blended teaching. In response to this problem, this study proposed a knowledge graph-driven integration framework. This framework first organized the core concepts of a course into a hierarchical knowledge graph, and then associated the corresponding micro-lectures, digital textbook segments, and virtual simulation exercises. On the basis of this framework, the research further constructed a knowledge graph-driven teaching model to solve the low efficiency of resource integration in blended teaching. A quasi-experimental study was conducted with 180 sophomores from six intact classes. The results showed that the final exam scores of the experimental group were higher (82.1 vs. 76.2, $p < 0.001$), their perception of resource coherence was stronger (4.0/5.0 vs. 3.2/5.0, $p < 0.001$), and their cognitive load was significantly lower (4.9/10 vs. 6.1/10, $p < 0.001$). Besides, the weekly workload of teachers decreased by 37.8%. These results demonstrated that the knowledge graph-driven teaching model can not only create a coherent learning environment for students, but also significantly improve students' learning outcomes and teachers' teaching efficiency. It is recommended that courses relying on cross-platform resources for blended teaching adopt this model. Future research could further test this model in different disciplines and over a longer period to see how it works in different scenarios.

Keywords: blended learning, cognitive load, instructional efficiency, knowledge graph-driven integration, learning outcomes, resource coherence

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Introduction

The rapid development of digital learning tools has greatly broadened learners' access to learning resources and profoundly changed the form of education (Alharbi & Basiouni, 2025). However, such rapid development has also brought a prominent problem of resource fragmentation. When learning resources are scattered on multiple disconnected platforms, both students and teachers have to suffer from high cognitive costs (Graham, 2013). It is just like putting jigsaw pieces in different rooms. A fragmented layout like this will seriously hinder learners from forming a coherent and systematic knowledge structure.

This problem is particularly prominent for courses that require in-depth understanding, and *Introduction to Linguistics* is a typical example. Taking the knowledge point of "vowels" as an example, if students want to master it, they need to integrate relevant knowledge such as acoustic physics, pronunciation mechanism and regional accent variations. However, these resources are often scattered on different platforms. Learners have to switch back and forth between various platforms, watching micro-lectures on one platform, reading a digital textbook on another platform, and then changing to a third platform to complete simulation exercises (Wang & Li, 2021). As students spend a lot of cognitive energy on integrating scattered resources, it is difficult to concentrate on core learning tasks (Huang et al., 2021).

In response to this problem, this study proposes a knowledge graph-driven integration (KGDI) framework to solve the problems of resource fragmentation and low integration efficiency in blended teaching. Different from most existing knowledge graphs that focus on the hierarchical presentation of knowledge points (Ji et al., 2021), the KGDI framework uses a knowledge graph to integrate learning resources from different platforms. The design idea is consistent with the core principle of Sweller's (2010) cognitive load theory. If students spend too much energy on scattered learning resources, learning efficiency will naturally decline. Based on this, this paper proposes three research questions.

RQ1: Compared with the traditional blended learning model, what is the impact of the KGDI model on students' learning outcomes?

RQ2: How does the model affect students' learning experience?

RQ3: What is its effect on teachers' teaching efficiency?

At the theoretical level, this study applies the cognitive load theory to the construction of the KGDI framework, and thus expands the application scope of the theory. At the practical level, the research provides a solution to the long-standing problems of resource fragmentation and low efficiency in blended teaching. Therefore, the study proposes the following three hypotheses.

Hypothesis 1: Students who learn with the KGDI model will perform better than those who use the traditional blended learning model.

Hypothesis 2: Students using the KGDI model will have lower cognitive load and a stronger sense of resource coherence.

Hypothesis 3: Teachers who use the KGDI model will have higher teaching efficiency.

Literature Review

Blended teaching combines the advantages of offline classroom teaching and online autonomous learning. It is now a mainstream teaching model in higher education. It is generally believed that "effective blended learning can make education more flexible and efficient" (Aljuaid, 2024, p. 45). Garrison and Kanuka (2004) highlighted the positive role of blended learning in building active learning communities. Alsalihi (2025) and Mir et al. (2023) believed that well-designed blended learning can continuously improve learning outcomes compared with

pure online teaching or traditional offline classes.

Since the design of blended learning is more in line with the natural laws of cognitive development (Tambunan et al., 2021), it is more advantageous in situations such as complex problem solving (Tabassum & Mohd Saad, 2025). Such tasks always pose a challenge to students' theoretical knowledge application ability.

Blended learning cannot be carried out without the support of various factors (Bernard et al., 2014). At the institutional level, administrative support such as technology investment and platform construction is essential (Abirami et al., 2023). At the teaching level, teacher training for blended teaching is also indispensable (Ni & He, 2024). For China, thanks to the implementation of the national "Internet + education" policy, blended teaching platforms such as XuetangX and Zhihuishu have developed rapidly.

However, with the rapid development of blended learning, increasing workload has become one of the primary concerns in blended learning (Al Hajri et al., 2025). Some teachers mentioned that nearly one-third of their lesson preparation time was spent on dealing with various technical problems of multiple platforms, so it was difficult for them to concentrate on personalized teaching (Denbel, 2023). In addition, students also complained that switching back and forth between different learning platforms made them physically and mentally tired (Skulmowski & Xu, 2022).

The research on cognitive science provided empirical evidence for this cognitive load caused by resource fragmentation. Brain activity-related experiments found that frequent switching of learning platforms significantly increased students' cognitive load and squeezed out cognitive resources originally used for deep learning (Shaya et al., 2025). The research of Wang et al. (2024) showed that when students repeatedly switched between micro-lectures, digital textbooks and simulation tools, the working memory capacity for conceptual integration decreased by about 30%. As working memory shrinks, the cognitive space for deep processing of knowledge is naturally compressed. These findings not only explain why students feel physically and mentally exhausted, but also show that resource fragmentation has become a key shortcoming that hinders the development of blended teaching.

Although scholars have tried many methods to integrate resources, most of them failed to establish an effective knowledge association system and could not meet the personalized learning needs (Zawacki-Richter et al., 2019). In this context, knowledge graphs have gradually become an effective way to solve this problem. One of its core advantages is that it can link scattered knowledge points into a complete knowledge network. In this way, it can not only intuitively show the dynamic relationship between concepts, but also organically integrate various learning resources.

Studies have confirmed the ability of knowledge graphs to solve complex integration problems in different fields. In the construction industry, a knowledge graph can integrate regulations, industry standards, equipment manuals and training materials to help reduce the occurrence of safety accidents (Xiang et al., 2025). In manufacturing, the application of knowledge graphs has increased production efficiency by 31% (Su et al., 2025).

However, knowledge graphs have not achieved the same effect in education as they have shown in other industries, and related research is still relatively scattered (Fan, 2024). Most of the existing research is limited to a single scenario, such as how to organize course resources or how to track personalized learning paths (Fedorenko & Kravchenko, 2023; Guo et al., 2025). In addition, this kind of research is mainly based on qualitative methods. There are few studies that have realized the comprehensive integration of multiple types of learning resources, and even

fewer studies on the evaluation of the actual effect of knowledge graphs on teaching.

In general, there are two main shortcomings in the existing research. First, most research on knowledge graphs in education is still limited to independent modules. No research has attempted to achieve the comprehensive goals of resource integration, efficiency improvement and personalized learning through knowledge graphs. Second, most existing research is based on case analysis and theoretical discussion, lacking the support of empirical experiments.

To make up for the above research deficiencies, this study proposes a knowledge graph-driven integration (KGDI) framework and a corresponding KGDI teaching model based on relevant educational theories. A quasi-experiment will be carried out to test the rationality of the framework and the overall effect of this model.

KGDI Model Construction

Knowledge Graph-Driven Integration Framework

The KGDI framework is designed to solve the problem of resource fragmentation in blended teaching. As shown in Figure 1 (original design of this study), this framework takes the knowledge graph as the carrier, uses core knowledge points as the associated nodes, and then integrates three core teaching resources, namely, micro-lectures, digital textbooks, and virtual simulation exercises. In this way, an integrated learning ecosystem is formed, which can realize the dynamic integration of cross-platform teaching resources. In addition, this framework also uses large language models (LLMs) and neural network verification technology to complete the automatic tagging and linking of resources.

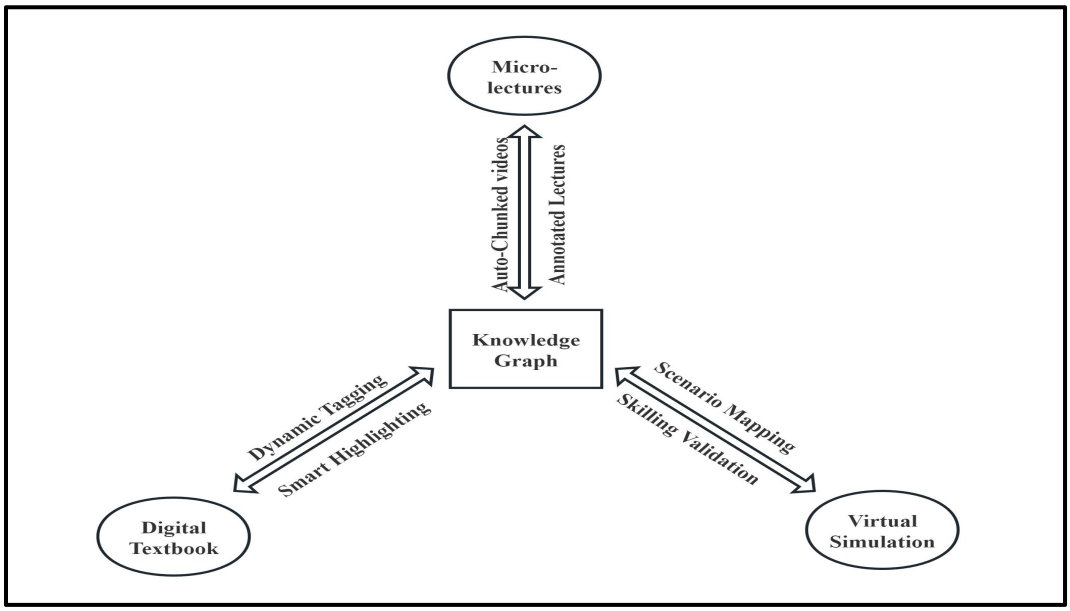


Figure 1. Knowledge graph-driven integration framework

Introduction to Linguistics has a total of 47 micro-lectures, all of which are hosted on the Zhihuishu Platform. Each video is divided into several labeled knowledge modules, which correspond to the concepts in the knowledge graph. The generation of tags is mainly completed automatically using large language models and named entity recognition technology, so that students can quickly locate the corresponding video clips when learning a specific knowledge point. In addition to these micro-lectures, there are 1,235 other learning resources on the

platform, such as extended reading materials, quizzes and discussions. They are also connected to the knowledge graph, so as to realize the seamless connection and collaborative linkage of various resources.

The digital textbook *Introduction to Linguistics* has a total of six chapters, and the full text is about 60,000 words. The textbook also embeds 56 supplementary videos, 136 charts and 118 interactive exercises. Each section has an exclusive label that can be directly associated with the knowledge graph.

In order to meet the practical training needs of the pragmatics chapter, a virtual simulation project was also designed. It is divided into three progressive stages, namely, warm-up, cross-cultural simulation and practical application. With the help of 3D models and panoramic scenes, a simulated learning environment is built. Each simulation module is accurately matched with the corresponding knowledge point in the knowledge graph.

The KGDI framework integrates the three core learning resources through the intelligent coordination mechanism, and labels them with concept tags and positioning tags. This design is expected to reduce the cognitive load of learners switching between different platforms from the root. For example, when students learn "speech act theory", the knowledge graph will automatically aggregate the relevant resources of multiple platforms and then present them in an orderly manner according to the teaching logic. The theoretical explanation from the textbook is presented first, then the supporting micro-lecture is shown, and finally the virtual simulation task is provided. This model not only retains the original advantages of various resources, but also realizes the seamless connection of cross-platform resources, and ensures the coherence of the learning process.

Three-Phase Teaching Model Based on Knowledge Graph-Driven Integration

Based on the KGDI framework, the study further constructs the KGDI model. The model consists of three interlocking teaching stages, namely, pre-class preview, in-class teaching and post-class consolidation. The overall operation process is shown in Figure 2 (original design of this study).

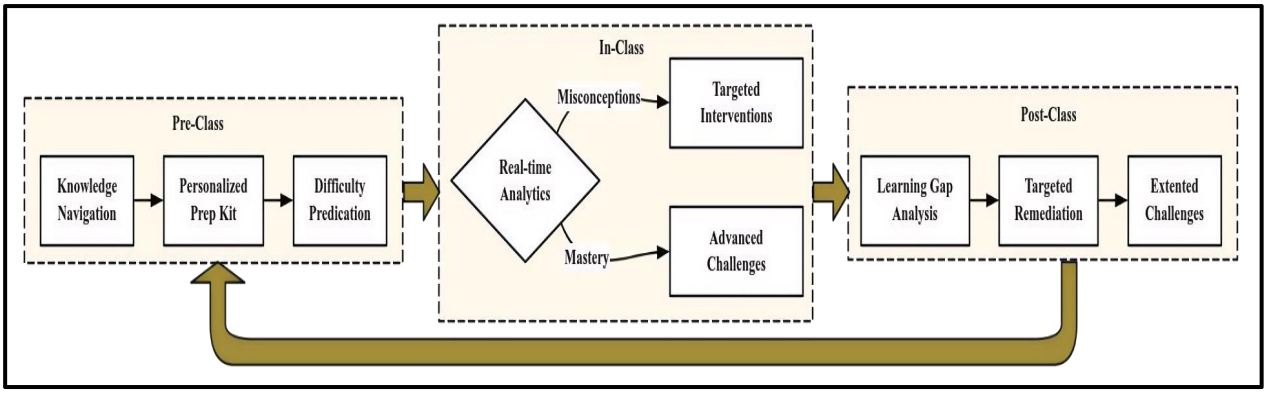


Figure 2. KGDI three-phase teaching model

In the pre-class stage, students can learn by themselves with the help of the KGDI framework. This framework will intuitively show the hierarchical relationship between knowledge points and help students quickly grasp the key points and difficulties. Then, according to the actual learning level of students, the framework will recommend some resources suitable for them, such as micro-lectures, relevant chapters of textbooks, and pre-class exercises. The targeted preview will enable students to prepare more fully for offline classroom learning. At

the same time, this framework will also generate a learning report for teachers to help them prepare lessons more efficiently.

In the classroom teaching stage, the KGDI framework mainly serves as a practical teaching assistant. Teachers use it to intuitively review the core knowledge points and summarize the common learning problems of students. For the content that students have mastered, the system will assign some slightly more difficult tasks to help them go further; in the face of learning difficulties, the framework will offer corresponding exercises for students. During the whole process, the interaction between teachers and students is recorded, which can be used as an effective basis for academic evaluation.

After class, students use the KGDI framework to consolidate what they have learned. The framework can accurately find out the weak points of each student and customize a personalized review plan for them. For students with outstanding learning ability, it will also arrange advanced tasks for them. With the gradual advancement of learning activities, the teaching objectives will be achieved.

As the coordination center of the whole framework, the knowledge graph organically integrates the originally separated learning resources, and makes intelligent recommendations according to students' learning progress, so as to improve students' learning experience and outcomes.

The innovation of this model is mainly reflected in four aspects. First, it constructs a dynamic resource integration mechanism, so that different learning resources can be organically linked. Second, a two-layer adaptive system is built, which can not only meet the needs of the group, but also take into account the individual's learning progress. Third, relying on automated data analysis, the system is expected to improve the accuracy of learning feedback while reducing the workload of teachers. Fourth, with the help of a unified navigation interface provided by the knowledge graph, the learning experience is kept coherent, which is of great importance for both students and teachers.

Methodology

This section introduces the research methodology used to verify the effectiveness of the KGDI model.

Research Participants

The subjects of this study were 180 sophomores majoring in English from six intact classes at Zhejiang Yuexiu University. There were 102 female and 78 male students, aged between 19 and 21. The research was carried out in the compulsory course *Introduction to Linguistics* during the spring semester of 2024. The six intact classes were randomly divided into an experimental group and a control group, with three classes and 90 students in each group. The experimental group adopted the KGDI teaching model, while the control group adopted the traditional blended teaching model. The pre-test results of the course showed that there was no significant difference in their initial knowledge base and demographic characteristics ($p > 0.05$).

Research Instruments

Tests

Both groups participated in the same final exam under standardized test conditions, so as to compare their learning outcomes. The test paper was designed by the teacher and consisted of five types of questions to comprehensively examine students' theoretical understanding and

practical application ability. The full score was 100 points, and validity was ensured through a pre-test. The overall reliability was satisfactory (Cronbach's $\alpha = 0.87$).

Questionnaires

This study used a questionnaire to evaluate students' learning experience from three dimensions, namely perceived coherence of resource integration, cognitive load and overall satisfaction. A five-point Likert scale was used to measure the perceived coherence of resource integration. One point represented "very poor" and five points meant "very good". The cognitive load was measured by a 10-point scale, with 1 point representing the lowest load and 10 the highest. In the data analysis stage, this dimension was reverse-scored. The overall satisfaction was also measured by a 5-point Likert scale, with 1 point indicating "very dissatisfied" and 5 points "very satisfied". Before conducting the formal investigation, the questionnaire was pre-tested to ensure its clarity and reliability.

Time Logs

The teacher recorded the working hours she spent under the two teaching models with standardized weekly working time logs. The statistical scope was limited to three tasks, which were assignment grading, resource coordination, and personalized feedback. The verification of the time logs was carried out in two ways. One was to randomly check 20% of the timestamp entries in the three tasks to see whether the time recorded by the system was equivalent to the actual operation time. The other was to cross-check the accuracy of the recorded time for assignment grading and personalized feedback with screen recordings.

Interviews

In order to investigate the experiences of the teacher and students after using the KGDI model, semi-structured interviews were conducted after the intervention. The student interviews employed purposive sampling to ensure that the sample covered learners of different academic levels. All interviews were recorded (about 25 minutes per interview), and then the recordings were converted into text for thematic analysis.

Research Procedures

During the 16-week semester, both groups used the same learning resources but adopted different teaching models. The experimental group used the KGDI model, while the control group followed the traditional blended teaching model. The same instructor taught both groups. All students took identical pre- and post-tests, and the test scores were used to assess their learning outcomes. At the end of the teaching intervention, all students completed a questionnaire covering cognitive load, perceived resource coherence and overall learning satisfaction. This study also conducted semi-structured interviews with the teacher and purposively sampled students. In addition, the instructor kept weekly time logs to record instructional activities.

In data analysis, independent-samples *t*-tests were used to compare the post-test scores and questionnaire results of the two groups, after having confirmed no significant pre-test differences between them; paired-samples *t*-tests were used to analyze teaching efficiency based on 16-week time logs. This study calculated Cohen's *d* and reported a 95% confidence interval. For categorical indicators such as the excellent rate, the chi-square (χ^2) test was used to compare the differences between groups. The qualitative data obtained from the interviews were coded

and analyzed with reference to the six-phase analysis framework proposed by Braun and Clarke (2006). All statistical tests were performed at a two-tailed significance level of 0.05. For multiple comparisons, the Bonferroni method was used for correction.

Results

This chapter presents the results of the quasi-experimental study, including data on academic performance, cognitive load, resource coherence, learning satisfaction and teaching efficiency.

Academic Performance

The standardized final exam was the main evaluation tool to measure the impact of the KGDI model on learning outcomes. Table 1 shows that the performance of the experimental group was better than that of the control group across all dimensions, and the differences were statistically significant.

Table 1. *Final examination performance comparison*

Assessment Metric	KGDI Group (*SD*)	Control Group (*SD*)	Statistical Significance (95% CI)
Mean Total Score	82.1 (6.9)	76.2 (8.1)	$t(178) = 4.37$, $p < 0.001$, $d = 0.78$ [0.45, 1.11]
Excellence Rate (≥80)	68%	41%	$\chi^2(1) = 15.3$, $p < 0.01$
Essay Questions	82.3% (9.1)	71.9% (12.1)	$t(178) = 4.88$, $p < 0.001$, $d = 0.85$ [0.51, 1.19]
Syntactic Analysis	74.5% (11.3)	67.5% (13.4)	$t(178) = 3.98$, $p < 0.001$, $d = 0.62$ [0.29, 0.95]

In the final exam, the experimental group achieved a mean total score of 82.1 ± 6.9, which was 5.9 points higher than that of the control group (76.2 ± 8.1). And the difference was also substantial in terms of the excellence rate. 68% of the students in the experimental group achieved a score of 80 or above; however, this proportion dropped to 41% in the control group ($\chi^2(1) = 15.3$, $p < 0.01$).

There were also significant differences in the scores of different types of questions between the two groups. In terms of essay questions, the correct rate of the experimental group was 82.3 ± 9.1%, significantly higher than that of the control group (71.9 ± 12.1%). Similarly, the correct rate of the experimental group reached 74.5 ± 11.3% on syntactic analysis, while the control group's accuracy rate was only 67.5 ± 13.4%. These results showed that this new teaching model has a significant positive effect on students' academic performance, especially on their theoretical understanding and knowledge application ability.

Learning Experience

At the end of this teaching intervention, 180 subjects participated in a questionnaire survey. The questionnaire consisted of 15 items, which were further divided into three dimensions, with 5 items in each dimension. The first dimension was resource coherence perception (Cronbach's $\alpha = 0.88$); the second was about cognitive load assessment (Cronbach's $\alpha = 0.82$); and the third one was learning satisfaction (Cronbach's $\alpha = 0.85$). As shown in Table 2, the results of the survey further confirmed the effectiveness of the KGDI model.

Table 2. *Learning experience survey results*

Evaluation Dimension	KGDI Group (*SD*)	Control Group (*SD*)	Statistical Test
Resource Coherence	4.0 (0.7)	3.2 (0.9)	$t(178) = 7.2, p < 0.001$
Cognitive Load	4.9 (1.4)	6.1 (1.6)	$t(178) = -5.1, p < 0.001$
Learning Satisfaction	4.1 (0.7)	3.2 (1.1)	$t(178) = 6.8, p < 0.001$

Note:
Resource Coherence/ Learning Satisfaction: 1 = Very poor, 5 = Excellent
Cognitive Load: 1 = Low load, 10 = High load (reverse-scored)

Analysis of resource coherence showed that students using the KGDI system perceived a significantly higher degree of resource integration. The five-point scale was used in the study. The results showed that the average score of the experimental group was 4.0, and that of the control group was only 3.2. The difference between the two groups was statistically significant ($t(178) = 7.2$, $p < 0.001$), indicating that the KGDI model can indeed create a more coherent learning environment for students.

There was also a significant difference in the level of cognitive load between the two groups ($t(178) = -5.1$, $p < 0.001$). The cognitive load of the students in the experimental group was lower, with an average score of 4.9 and a standard deviation of 1.4. In contrast, students in the control group generally had a much higher cognitive load ($M = 6.1$, $SD = 1.6$).

In the dimension of learning satisfaction, although the effect size between groups was slightly smaller than that of cognitive load and resource coherence, the difference was still statistically significant ($t(178) = 6.8$, $p < 0.001$). The mean score of the KGDI group was 4.1 ($SD = 0.7$), which was significantly higher than 3.2 ($SD = 1.1$) of the control group. This shows that the students in the experimental group were more satisfied with their blended learning model.

The positive results of the above three dimensions jointly verified the effectiveness of the new model, which could not only improve students' objective academic performance, but also enhance their subjective learning experience.

Instructional Efficiency

The teacher's time log showed that the KGDI model significantly improved teaching efficiency. The details are presented in Table 3.

Table 3. *Instructional efficiency comparison*

Task Category	KGDI Group (*SD*)	Control Group (*SD*)	Time Difference (95% CI)	Time Reduction	Statistical Significance
Grading	3.5 (0.9)	5.4 (1.2)	-1.9 ± 0.3 [-2.2, -1.6]	↓35.2%	$t(15) = -9.7, p < 0.001, d = 1.25$
Resource Coordination	2.1 (0.6)	3.8 (1.1)	-1.7 ± 0.4 [-2.0, -1.4]	↓44.7%	$t(15) = -7.8, p < 0.001, d = 1.05$
Personalized Feedback	2.3 (0.7)	3.5 (0.9)	-1.2 ± 0.3 [-1.5, -0.9]	↓34.3%	$t(15) = -6.2, p < 0.001, d = 0.85$
Total	7.9 (1.5)	12.7 (2.3)	-4.8 ± 0.6 [-5.4, -4.2]	↓37.8%	$t(15) = -12.1, p < 0.001, d = 1.4$

Notes:

Time units = hours/week (M ± SD)
n = 16 paired observations (same instructor over 16 weeks)
Time Difference = KGDI group time - Control group time
d = Cohen's effect size for paired samples

Table 3 shows that automated grading significantly reduced the teacher's time spent on assignment grading by 35.2%, from 5.4 hours per week (*SD* = 1.2) to 3.5 hours (*SD* = 0.9). This reduction was mainly due to two core functions of the KGDI framework. One was the use of automatic scoring technology (AST). Most objective questions could thus be graded automatically. The other was the use of an AI agent in the evaluation of subjective questions. The agent evaluated students' assignments according to the reference answer preset by the teacher, and the teacher only needed to conduct a sampling review, which greatly improved teaching efficiency. This framework could also automatically generate a personalized comprehensive learning report for each student, which was convenient for the teacher to grasp the students' learning situation more accurately.

With the use of various modern technologies, the teacher's time spent on routine tasks was greatly reduced. With the help of large-scale online optimal matching (LOOM) metadata auto-labeling technology, the teacher's weekly time spent on resource coordination was decreased from 3.8 hours (*SD* = 1.1) to 2.1 hours (*SD* = 0.6), a decrease of 44.7%. The AI agent also acted as a teaching assistant to help students answer questions at any time. In this way, the teacher's personalized feedback time was reduced from 3.5 hours per week to 2.3 hours per week.

On the whole, the KGDI model reduced the weekly workload of the teacher by 37.8%. Teachers could thus focus more on personalized teaching design, laying a good foundation for the long-term development of blended teaching.

Interview Findings

In this study, semi-structured interviews were conducted with 12 students (6 in each group) and their teacher. Each interview lasted about 25 minutes, and the total time was 310 minutes. In order to systematically analyze the content of the interview and extract common themes, two coders conducted independent coding analysis of the interview transcripts. The results showed that the inter-coder reliability was high (κ=0.82). The following are the three major findings from the analysis.

Integrated Resources Enhancing Learning Efficiency

Students in the KGDI group generally felt that the integrated interface of the knowledge graph did improve learning efficiency. One student said: "I used to spend a lot of time looking for learning resources on different platforms, and now the system can automatically associate everything." In contrast, students in the control group mentioned that they had to take some compensatory measures. One student mentioned: "I have to spend extra time to put together the learning resources scattered on different platforms." The teacher also confirmed this change: "Students no longer ask where to find resources and can focus more on deep learning." These findings were consistent with the cognitive load reduction reported in the questionnaire, indicating that the integrated interface could effectively reduce students' cognitive consumption.

Personalized Learning Supporting Diverse Learner Needs

The adaptive function of the KGDI framework took the needs of learners of different

academic levels into account. A student with a relatively weak foundation mentioned that when encountering difficulties, the system recommended some easy-to-understand examples to help him. Students with good grades also felt rewarded because the challenging exercises provided by the system could help them improve themselves. The teacher also said that with the help of the personalized learning reports generated by the system, she had a clearer understanding of students' individual differences, so that she could adjust the teaching arrangement more precisely. The feedback from the teacher and students explained why the overall academic performance of the KGDI group was better.

Automated Workflow Boosting Teaching Efficiency

The teacher's teaching efficiency was significantly improved, and the teacher summarized two possible reasons in the interview. First, the automatic classification of resources saved a lot of time for manual collection and classification. The teacher remarked: "I used to spend hours looking for teaching resources on various platforms, and now these can be done automatically by the framework." In addition, intelligent scoring improved the efficiency of academic feedback. The AI agent could grade most of the students' assignments and accurately identify their common errors.

In general, the results of qualitative research were complementary to the conclusions of the previous quantitative research, which clearly explained why this teaching model had such obvious advantages in improving academic performance, reducing cognitive load and improving teaching efficiency.

Discussion

Based on the empirical results, this chapter further discusses the theoretical advancements, practical innovations as well as the evolving role of technology in blended learning.

Theoretical Advancements in Blended Learning

This study used the cognitive load theory proposed by Sweller (2010) to explain the mechanism of the KGDI framework in reducing unnecessary cognitive consumption. Since the framework integrates various learning resources in advance, students do not need to waste time on resource integration any more. So the students in the experimental group generally had a much lower cognitive load. This finding is also consistent with Mayer's (2020) cognitive theory of multimedia learning, which mentions that the coherence of information presentation is important for students' learning efficiency.

In addition, the design idea of the KGDI model is also consistent with the constructivism proposed by Piaget (1977). This model matches the learning content suitable for students according to their actual learning level, plans personalized learning paths, and helps them build their own knowledge graphs step by step. From this point of view, the design of this framework is an effective integration of traditional constructivism and modern adaptive teaching.

More importantly, this study redefines what role the learning platform should play in blended learning. Previously, most platforms were only used to store learning resources and provide basic exercises (Balyshev et al., 2024). The KGDI framework integrates the functions of multiple platforms together, and uses the knowledge graph to make these functions work together. In this way, it can not only solve the problem of resource fragmentation in blended teaching, but also meet the personalized learning needs in different teaching scenarios.

Practical Innovations in Blended Learning

It has always been a difficult problem to effectively reduce the workload of teachers while improving the effectiveness of teaching. The KGDI model solves this problem by means of intelligent resource management and automatic tracking of learning progress. The data recorded in the time log showed that after using this model, the teacher's workload decreased by 37.8% ($p < 0.001$).

This result is consistent with the research findings of Dörrenbächer-Ulrich et al. (2024), who pointed out that resource integration can reduce the administrative burden of teachers by 30% to 60%. It is worth emphasizing that the improvement of efficiency was not at the expense of teaching quality. The better academic performance of KGDI students was strong proof.

The model also makes up for the shortcomings of traditional blended learning in personalized teaching (OECD, 2023). The framework can dynamically adjust the difficulty of learning content by providing more easy-to-understand cases for students with weak foundation and offering more challenging tasks for high-level learners. This approach is in line with the precise scaffolding teaching concept proposed by Wong et al. (2019), and also echoes the idea of educational equity advocated by UNESCO (2024).

In summary, the model not only resolves the contradiction between teaching efficiency and learning outcomes in blended teaching, but also realizes personalized learning to a certain extent. Therefore, it is expected to become an important direction for the future development of blended learning.

Evolving Role of Technology in Blended Learning

The emergence of the KGDI model also marks a deep change in the role of technology in blended teaching. Most of the traditional digital tools only serve as a resource library or a carrier of communication, and rarely actively intervene in the learning process of students. The KGDI framework, which integrates various intelligent tools, can assume the function of teaching assistant. For students, it can continuously analyze learning behavior, predict learning needs, accurately recommend appropriate resources and give timely feedback about learning situation; for teachers, it can assist in instructional design, generate real-time class and individual learning reports, and warn students who are lagging behind in their studies.

From this point of view, the KGDI model has the core characteristics of the new generation of educational technology. It is no longer just a simple teaching tool, but an active participant in teaching activities. This is consistent with the concept of human-machine collaboration in education proposed by EDUCAUSE (2024), which advocated the respective advantages and complementary collaboration of human beings and machines. In the educational scenario, this means that machines undertake structured and transactional work, while teachers focus on in-depth teaching, innovative thinking training and interpersonal interaction. With the continuous development of blended learning, technology's role as either a tool or a partner may become increasingly blurred. The KGDI framework provides a leading example of effective human-machine collaboration.

Conclusion

The study constructed a knowledge graph-driven integration (KGDI) framework and a supporting KGDI teaching model to solve the problem of resource fragmentation in blended teaching. The results of empirical research showed that this model could significantly improve teachers' teaching efficiency, optimize students' learning experience, and effectively improve

students' academic performance.

The above results demonstrate that this study has both theoretical and practical value. For one thing, it proves that the KGDI framework can effectively reduce students' cognitive overload and thus broaden the application scope of cognitive load theory. For another, it also verifies that this model can simultaneously improve teachers' teaching efficiency and students' learning outcomes, which points out a new direction for the development of blended teaching. In addition, the research also proves that it is feasible to integrate cross-platform resources with the help of knowledge graphs, so as to provide an operable solution to the problem of resource fragmentation.

It should be noted that the conclusion of this study is only based on a single discipline, and the effectiveness of this model in other disciplines remains to be further verified. In addition, this teaching intervention has only been carried out for one semester, and its long-term application effect is still unclear. Follow-up studies can consider lengthening the experimental time and covering more disciplines to see whether the effect of this model can remain stable.

In general, the KGDI framework has outstanding advantages in improving learning effectiveness and teaching quality. This study aims to provide useful reference for the long-term development of blended teaching in higher education.

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References

Abirami, A. M., Pudumalar, S., & Pandeeswari, S. T. (2023). Designing an effective teaching learning environment for an undergraduate software engineering course. *International Journal of Adult Education and Technology*, *14*(1), 1–21. https://doi.org/10.4018/IJAET.321655

Al Hajri, M., Bani Orabah, S., Domalaon, D., & Bijani, H. (2025). Evaluating the quality of blended learning in higher education: Teachers' and students' perceptions in an Omani EFL context. *Arab World English Journal*, Special Issue on CALL, (11), 20-42. https://doi.org/10.24093/awej/call11.2

Alharbi, W., & Basiouni, A. (2025). The impact of blended learning on EFL student satisfaction and retention: A customer satisfaction model approach. *Arab World English Journal*, *16*(1),

179–206. https://doi.org/10.24093/awej/vol16no1.11
Aljuaid, H. (2024). The impact of artificial intelligence tools on academic writing instruction in higher education: A systematic review. *Arab World English Journal* (Special Issue on ChatGPT), 26-55. https://doi.org/10.24093/awej/ChatGPT.2
Alsalihi, H. D. A. (2025). The Effect of a Blended Approach in Enhancing Paraphrasing and Summarization Skills among EFL Female Students in Academic Writing. *Arab World English Journal,* Special Issue on CALL (11), 177-191. https://doi.org/10.24093/awej/call11.11
Balyshev, P., Darinskaia, L., Molodtsova, G., & Oskina, A. (2024). Organizing students' online teamwork for sustainable development. *International Journal of Online Pedagogy and Course Design*, *14*(1), 1–16. https://doi.org/10.4018/IJOPCD.353300
Bernard, R. M., Borokhovski, E., Schmid, R. F., Tamim, R. M., & Abrami, P. C. (2014). A meta-analysis of blended learning and technology use in higher education: From the general to the applied. *Journal of Computing in Higher Education*, *26*(1), 87–122. https://doi.org/10.1007/s12528-013-9077-3
Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa
Denbel, D. G. (2023). Challenges of Teaching and Learning Mathematics Courses on Online Platforms. *International Journal of Online Pedagogy and Course Design*, *13*(1), 1–15. https://doi.org/10.4018/IJOPCD.321155
Dörrenbächer-Ulrich, L., Sparfeldt, J. R., & Perels, F. (2024). Knowing how to learn: Development and validation of the strategy knowledge test for self-regulated learning (SKT-SRL) for college students. *Metacognition and Learning*, *19*, 1–45. https://doi.org/10.1007/s11409-024-09379-w
EDUCAUSE. (2024). *2024 EDUCAUSE Horizon Report: Teaching and Learning Edition*. EDUCAUSE.
Fan, J. (2024). A big data and neural networks-driven approach to designing a student management system. *Soft Computing*, *28*(2), 1255–1276. https://doi.org/10.1007/s00500-023-09524-8
Fedorenko, S., & Kravchenko, T. (2023). Multimodal resources and students' motivation in English for specific purposes. *Arab World English Journal*, *14*(1), 59–70. https://doi.org/10.24093/awej/vol14no1.4
Garrison, D. R., & Kanuka, H. (2004). Blended learning: Uncovering its transformative potential in higher education. *The Internet and Higher Education*, *7*(2), 95–105. https://doi.org/10.1016/j.iheduc.2004.02.001
Graham, C. R. (2013). Emerging practice and research in blended learning. In M. G. Moore (Ed.), *Handbook of distance education* (3rd ed., pp. 333–350). Routledge.
Guo, Z., Guan, H., He, C., Xu, Y., & Liu, R. (2025). Knowledge graph-enhanced interleaved multi-head attention knowledge tracing. *International Journal of Data Warehousing and Mining*, *21*(1), 1–20. https://doi.org/10.4018/IJDWM.377619
Huang, R., Spector, J. M., & Yang, J. (2021). *Educational technology: A primer for the 21st century* (2nd ed.). Springer.
Ji, S., Pan, S., Cambria, E., Marttinen, P., & Philip, S. Y. (2021). A survey on knowledge graphs: Representation, acquisition, and applications. *IEEE Transactions on Neural Networks and Learning Systems*, *33*(2), 494–514. https://doi.org/10.1109/TNNLS.2021.3070843
Mayer, R. E. (2020). Cognitive theory of multimedia learning. In R. E. Mayer (Ed.), *The*

Cambridge handbook of multimedia learning (3rd ed., pp. 57–72). Cambridge University Press. https://doi.org/10.1017/9781108894333.008

Mir, N. A., Fathima, A., & Suppala, S. (2023). A new paradigm for blended learning: Leveraging inverted pedagogy and digital communication to foster effective learning. *International Journal of Adult Education and Technology*, *14*(1), 1–10. https://doi.org/10.4018/IJAET.321654

Ni, N., & He, Z. (2024). The application of blended learning in animation majors at colleges and universities in the era of "Internet +" *International Journal of Web-Based Learning and Teaching Technologies*, *19*(1), 1–12. https://doi.org/10.4018/IJWLTT.336835

OECD. (2023). *OECD digital education outlook 2023: Towards an effective digital education ecosystem*. OECD Publishing. https://doi.org/10.1787/c74f03de-en

Piaget, J. (1977). *The development of thought: Equilibration of cognitive structures*. Viking.

Shaya, N., AbuKhait, R., Madani, R., & Ahmed, V. (2025). Conceptualizing blended learning models as a sustainable and inclusive educational approach. *International Journal of Sustainability in Higher Education*, *26*(9), 90–111. https://doi.org/10.1108/IJSHE-03-2024-0167

Skulmowski, A., & Xu, K. (2022). Understanding cognitive load in digital and online learning: A new perspective. *Educational Psychology Review*, *34*(1), 171-196. https://doi.org/10.1007/s10648-021-09624-7

Su, C., Jiang, Q., Han, Y., Wang, T., & He, Q. (2025). Knowledge graph-driven decision support for manufacturing process: A graph neural network-based knowledge reasoning approach. *Advanced Engineering Informatics*, *64*, 103098. https://doi.org/10.1016/j.aei.2024.103098

Sweller, J. (2010). Element interactivity and intrinsic, extraneous, and germane cognitive load. *Educational Psychology Review*, *22*(2), 123–138. https://doi.org/10.1007/s10648-010-9128-5

Tabassum, Z. A., & Mohd Saad, M. R. (2025). A decadal examination of community of inquiry and blended learning in EFL/ESL development: A systematic review. *Arab World English Journal*, *16*(1), 179–206. https://doi.org/10.24093/awej/vol16no1.11

Tambunan, H., Silitonga, M., & Sidabutar, U. B. (2021). Blended learning in teaching technical teacher candidates with various types of learning styles. *International Journal of Mobile and Blended Learning*, *13*(3), 1-13. https://doi.org/10.4018/IJMBL.2021070104

UNESCO. (2024). *Global education monitoring report 2024: Education leadership.* UNESCO.

Wang, H., & Li, A. (2021). A systematic approach for an English education model based on the neural network algorithm. *Journal of Intelligent & Fuzzy Systems*, *40*(2), 3455-3466. https://doi.org/10.3233/JIFS-189383

Wang, K., Chai, C. S., Liang, J. C., & Sang, G. (2024). Exploring teachers' behavioural intentions to design artificial intelligence-assisted learning in Chinese K–12 education. *Technology, Pedagogy and Education*, *33*(5), 629–645. https://doi.org/10.1080/1475939X.2024.2369241

Wong, W., Chao, T., Chang, C., & Chen, K. (2019). Online scaffolding for data modeling in low-cost physical labs. *International Journal of Distance Education Technologies*, *17*(4), 1–20. https://doi.org/10.4018/IJDET.2019100101

Xiang, Y., Luo, Y., Ning, Z., Liu, Y., Yang, Z., Li, Z., & Lin, P. (2025). Construction method of multimodal knowledge graph for safety management in hydropower underground engineering. *Journal of Tsinghua University (Science and Technology)*, *65*(3), 433-445. https://doi.org/10.16511/j.cnki.qhdxxb.2025.26.014

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education - where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0