International Journal of Innovative Research and Scientific Studies, 8(5) 2025, pages: 2010-2021

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Effects of self-directed learning model based on AI-driven adaptive learning system on learning achievement of teacher qualification examination

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Abstract

University students increasingly pursued professional qualifications such as the Teacher Qualification Examination (TQE) to improve employability. However, they faced challenges in self-directed learning (SDL) due to difficulties in monitoring progress and identifying resources. This study aimed to examine the effects of an SDL model based on an Artificial Intelligence (AI)-driven Adaptive Learning System (ALS) on TQE learning achievement among students majoring outside of teaching fields. The research employed an experimental design with 80 TQE candidates selected through simple random sampling. Validated instruments included SDL-ALS lesson plans and a 50-item Educational Teaching Knowledge and Competence Test. Data analysis was conducted using Repeated-measures ANOVA. The results indicated significant achievement gains from pre-test ($M = 51.40$, $SD = 13.44$) to post-test ($M = 92.10$, $SD = 11.07$) and retention-test ($M = 92.83$, $SD = 10.82$) ($p < 0.001$, $\eta^2 = 0.988$). There was no significant difference between the post-test and retention test ($p > 0.05$). Additionally, lower scores in the SD retention test suggested greater gains among students with initially lower performance. The findings concluded that the SDL-ALS model significantly improved TQE knowledge mastery and retention. Its design effectively addressed individual learning gaps through adaptive scaffolding and structured self-direction. This equity-enhancing SDL-ALS model provided undergraduate students with an effective self-directed learning tool, transformed teachers into diagnostic mentors, and offered researchers a validated framework for integrating adaptive AI with structured pedagogy.

Keywords: Adaptive learning system, Artificial intelligence, Learning achievement, Self-directed learning, Teacher qualification examination.

DOI: 10.53894/ijirss.v8i5.9330
Funding: This study received no specific financial support.
History: Received: 9 July 2025 / **Revised:** 11 August 2025 / **Accepted:** 12 August 2025 / **Published:** 15 August 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Institutional Review Board Statement: The Ethical Committee of Hanshan Normal University, China has granted approval for this study on 3 January 2025 (Ref. No. 2025010308).
Publisher: Innovative Research Publishing

1. Introduction

A group of higher education teaching and learning experts from diverse institutions noted in the *2022 EDUCAUSE Horizon Action Plan: Hybrid Learning* that over the next decade, "Higher education is available on demand. Institutions provide on-demand training and micro-credentials for cross-institutional degree programs, professional and workforce development, and technical career training." [1]. In fact, this trend was becoming more and more evident in China, where the pressure of employment was increasing. It was difficult for university students to find a satisfactory job with just a college degree when they graduated. Therefore, in order to increase their competitive capital, many university students chose to obtain several qualifications during their school years. These qualification exams were not mandatory; the type of certificate chosen by each student varies, and the school did not create courses specifically for these qualifications. Therefore, the preparation process was self-directed learning (SDL). Students who had stronger SDL skills were more likely to pass the various professional qualification exams and be qualified to practice, and had more and better opportunities for advancement. For non-teaching major students, the teacher qualification examination (TQE) was just that.

The Law of the People's Republic of China on Teachers stipulates that China has a teacher qualification system, and that anyone who does not possess the qualifications recognized as a teacher under the law must pass the national Teacher Qualification Examination (TQE) to apply for a teaching qualification. Simultaneously, the Regulations on Teacher Qualification and the Measures for the Implementation of the Regulations on Teacher Qualification were formulated in accordance with this law. The primary and secondary TQE have been piloted in Zhejiang and Hubei provinces since 2011. In 2015, the reform of the TQE was officially implemented, breaking the teacher lifelong system and the five-yearly examination. The reform resulted in the implementation of a unified national examination with increased content and difficulty. By 2021, full coverage of the unified examination had been achieved in 31 provinces in mainland China [2]. The Examination Center of the Ministry of Education developed the syllabus of each subject according to the standards of the primary and secondary school TQE. The syllabus of the Primary and Secondary School TQE specified the content and requirements of the examination, the structure of the examination paper, and examples of question types.

However, students frequently encountered challenges during self-directed learning, including an inability to accurately assess their own learning progress. They required external cues, such as questions or activities, to help them effectively compare their perceived understanding with their actual knowledge [3]. Moreover, the vast amount of information available online has made it particularly hard for learners to find suitable learning resources for specific topics of interest [4, 5]. When presented with such a large quantity of learning materials, learners had to spend significant time and effort sifting through them to locate the resources they needed. Xiong [6] conducted research on the online self-directed learning of Chinese college students. She found that students lacked clarity in planning their study time, setting learning goals, and determining their study direction, which indicated a substantial need for subsequent guidance. Simultaneously, students also required teacher guidance during the knowledge acquisition process. Without this, they struggled to verify the quality of online materials and efficiently identify effective learning resources.

Artificial Intelligence (AI)-driven Adaptive Learning System (ALS) demonstrated substantial potential in supporting SDL by enabling personalized educational experiences tailored to individual needs. Ajani et al. [7] argued that ALS emerged as a critical AI technology in higher education, analyzing student data (e.g., test performance, interaction patterns) to dynamically adjust content difficulty and pacing, thereby empowering learners to take control of their learning processes and reducing reliance on instructors. Dabingaya [8] further validated this claim through a study on mathematics education, where AI-powered adaptive platforms significantly increased student engagement and post-assessment scores, confirming their efficacy in fostering personalized learning pathways. Costa et al. [9] reinforced these findings by comparing adaptive learning with traditional methods, highlighting its effectiveness while acknowledging challenges such as algorithmic optimization and scalability. Kem [10] reviewed emerging adaptive platforms and concluded that they support individualized pacing and skill mastery, enhancing engagement across diverse educational contexts. Kabudi et al. [11] emphasized the potential of AI-enabled ALS in facilitating personalized learning experiences and improving student outcomes. Finally, Dutta et al. [12] revealed that ALS could individualize learning paths, deliver tailored feedback, and dynamically adapt to diverse needs, thereby aligning with SDL principles of autonomy and self-regulation.

Collectively, these studies underscored AI-driven ALS as a transformative tool for SDL, enabling learners to improve their learning achievement.

The challenge of SDL in ALS stemmed from insufficient control over the planning and assessment strategies provided to students. Excessive strategies could lead to arbitrary and inadequate decision-making, which might negatively impact learning outcomes [13]. To address this, developing a model that combined SDL theory with AI-driven ALS became essential.

2. Research Objective

The research objective of the study was to examine the effect of the SDL-ALS model on the learning achievement of non-teaching major students in the pre-test, post-test, and retention test.

3. Research Hypothesis

The non-teaching major students learning through the SDL-ALS model have significantly higher learning achievement in both post-test and retention test phases than pre-test scores, at a significance level of 0.05.

4. Literature Review

4.1. Self-Directed Learning

SDL refers to a process in which individuals take the initiative, with or without the help of others, to formulate learning goals, develop a learning plan, identify learning resources, implement learning activities, and evaluate their learning level [14-16]. The researchers analyzed the components of SDL [15, 17-19] as follows:

- Formulating learning goals: the initial stage of Self-Directed Learning (SDL). A learning goal is an outcome that a student sets for themselves. The student is confident that they can achieve this outcome in the future through personal effort.
- Developing a learning plan: a series of specific steps or arrangements for learning. Its purpose is to help the student reach their learning goals.
- Identifying learning resources: the process of recognizing and selecting materials, tools, or strategies that are relevant and effective for achieving specific learning goals.
- Implementing learning activities: the execution of the designed learning plan to achieve the learning goals.
- Evaluating learning outcomes: the systematic process of assessing and measuring the extent to which learners have achieved the learning goals.

4.2. AI-Driven Adaptive Learning System

AI-Driven adaptive learning was a learning system built upon the integration of adaptive learning theory, AI technology, and big data analysis technology. Its purpose was to offer learners personalized learning support and guidance. This system continuously adapted the way learning content was presented. These adjustments were based on each individual student's performance, learning speed, and preferences. Furthermore, the system also adapts to the students' learning strategies, the difficulty levels of tasks, the timing of feedback, and interactions happening in real-time. By leveraging AI and machine learning, the system minimized frustration, optimized understanding, and ultimately improved academic outcomes through tailored pacing and individualized training pathways [8, 11, 20, 21].

The components of ALS include the Domain Model, User Model, Pedagogical Model, and Adaptive Engine. The user-perceivable results for each model are distinct. For the Domain Model, it is the list of knowledge that the learner acquires. The User Model's results encompass records and analysis of the learner's knowledge level, learning behaviors, and other personality traits. Regarding the Pedagogical Model, its results include the teaching strategies or learning strategies provided by the adaptive learning system and the tests. Adaptive Engine acts as the bridge and link between the Domain Model, User Model, and Pedagogical Model. Its user-perceivable result is the recommendation of adaptive learning resources, learning paths, and learning strategies [12, 22, 23]. The ALS used in this study was *Lianmi AI*, which was developed by Beijing Lianmi Microcourse Artificial Intelligence Technology Company (as shown in Figure 1-5). *It was a professional platform for studying for vocational examinations* in China that focuses on teacher qualification examinations [24].

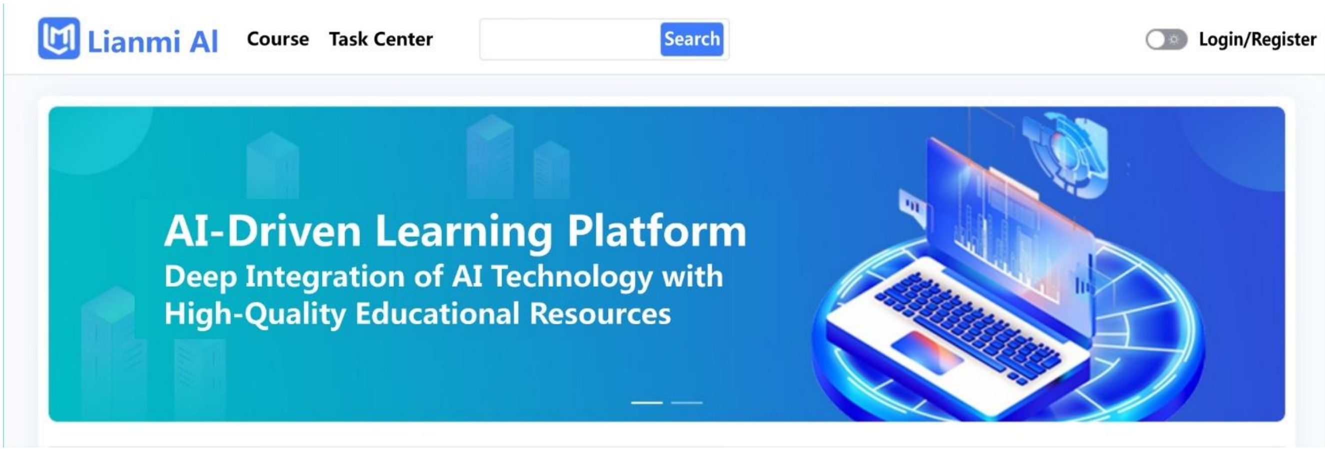

Figure 1.
Home of Lianmi AI Adaptive Learning.

Figure 1 presents the homepage of Lianmi AI Adaptive Learning, displaying the interface where users access and navigate to their enrolled courses.

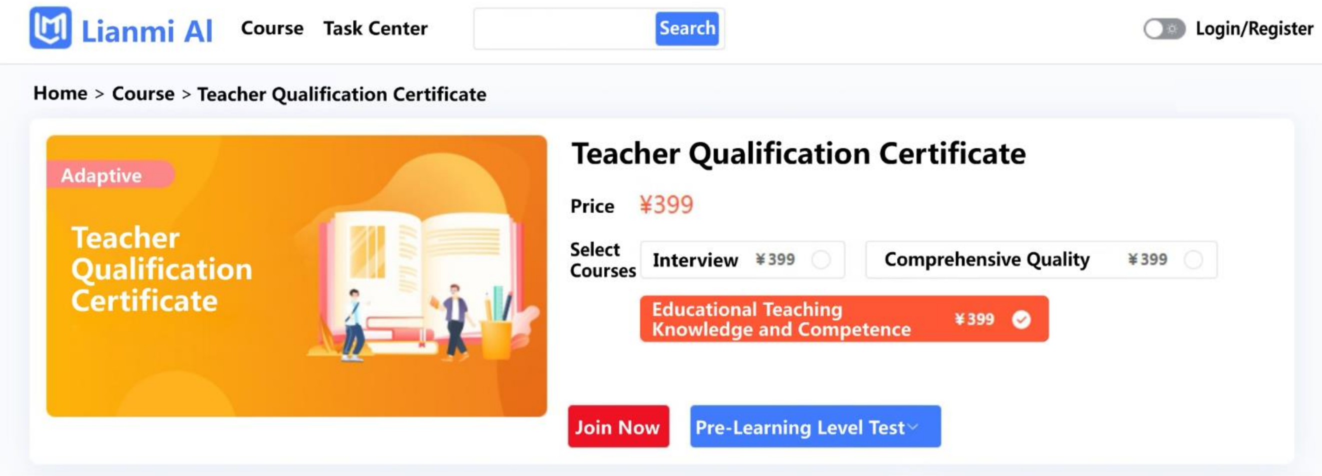

Figure 2.
Entrance to the Pre-Learning Level Test in Lianmi AI Adaptive Learning.

Figure 2 depicts the main page of Educational Teaching Knowledge and Competence, one of the TQE courses within Lianmi AI Adaptive Learning. It clearly shows the entry button labeled "Pre-Learning Level Test" that students use to initiate the adaptive assessment.

Figure 3.
The Adaptive Learning Resources in Lianmi AI Adaptive Learning.

Figure 3 illustrates the adaptive learning resources section of Lianmi AI Adaptive Learning. It shows the resources dynamically provided to students based on their needs, including instructional videos and a list of relevant knowledge points targeted for learning. (Only a portion of the knowledge points was shown.)

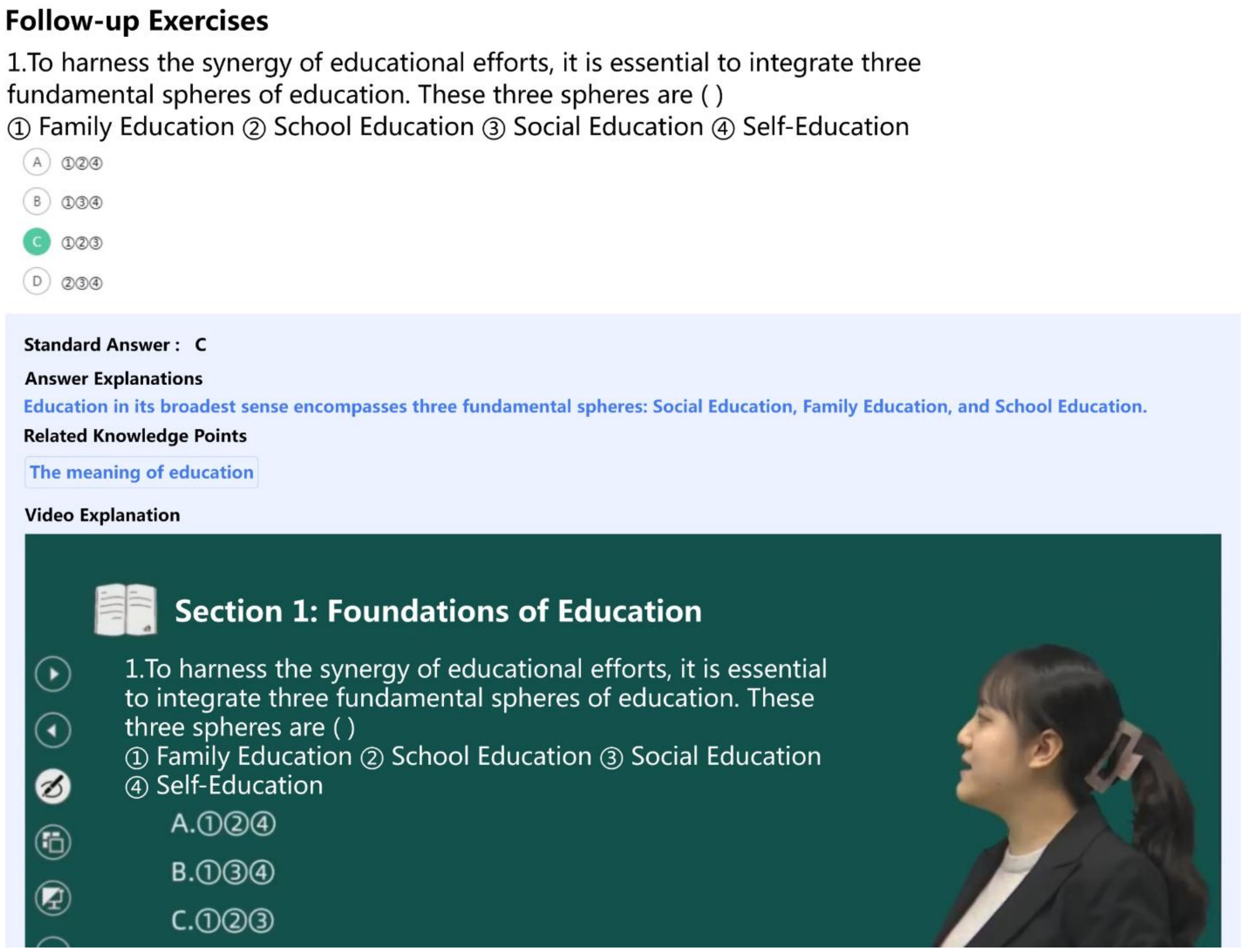

Figure 4.
The Follow-up Exercises and Their Explanations.

Figure 4 captures the follow-up exercises interface on Lianmi AI Adaptive Learning. It displays a sample exercise question, the corresponding standard answer, and a detailed explanation of that answer. The explanation includes the specific knowledge points involved and a video tutorial explaining the solution.

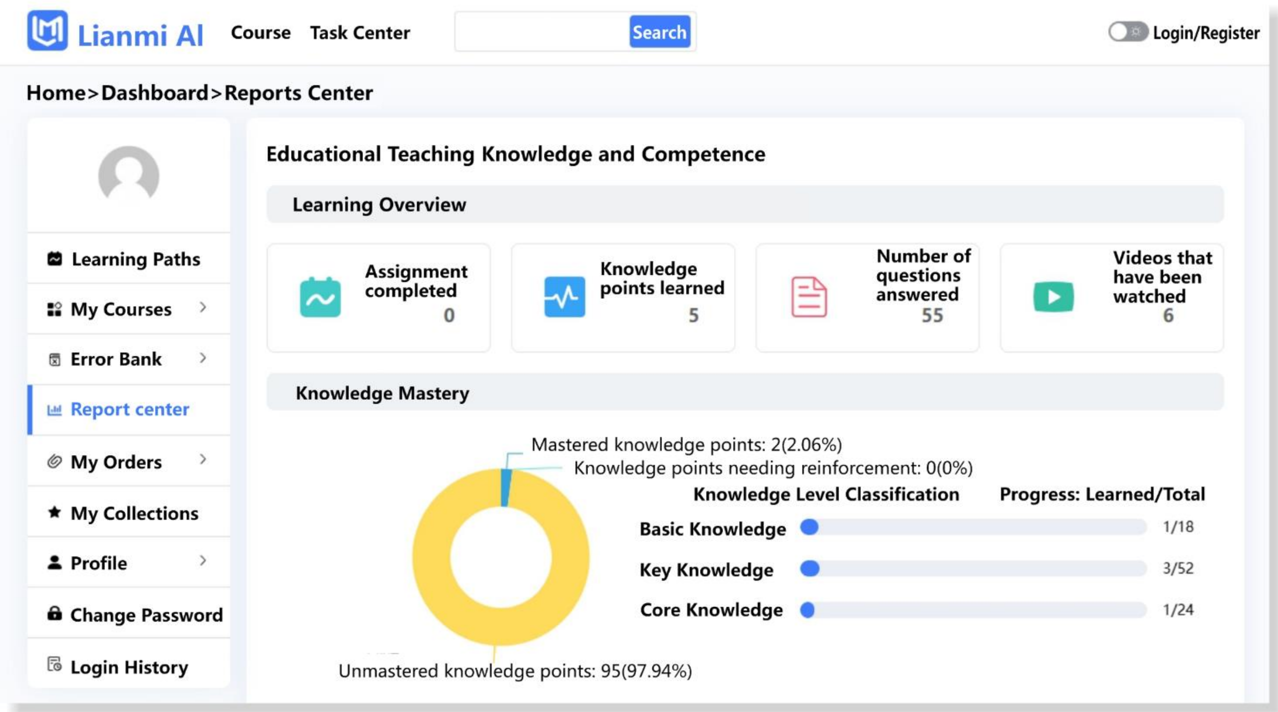

Figure 5.
Report on students' Learning Processes and Knowledge Levels.

Figure 5 shows the Report Center dashboard within Lianmi AI Adaptive Learning. It visualizes the platform's tracking and recording of individual student learning progress, performance data, and the learning trajectory (sequence of activities and resources accessed).

5. SDL-ALS Model

Combining the components of SDL and AI-Driven ALS yielded the SDL-ALS Model, as shown in Figure 6. The learning steps of the SDL-ALS Model were described in detail in Table 1.

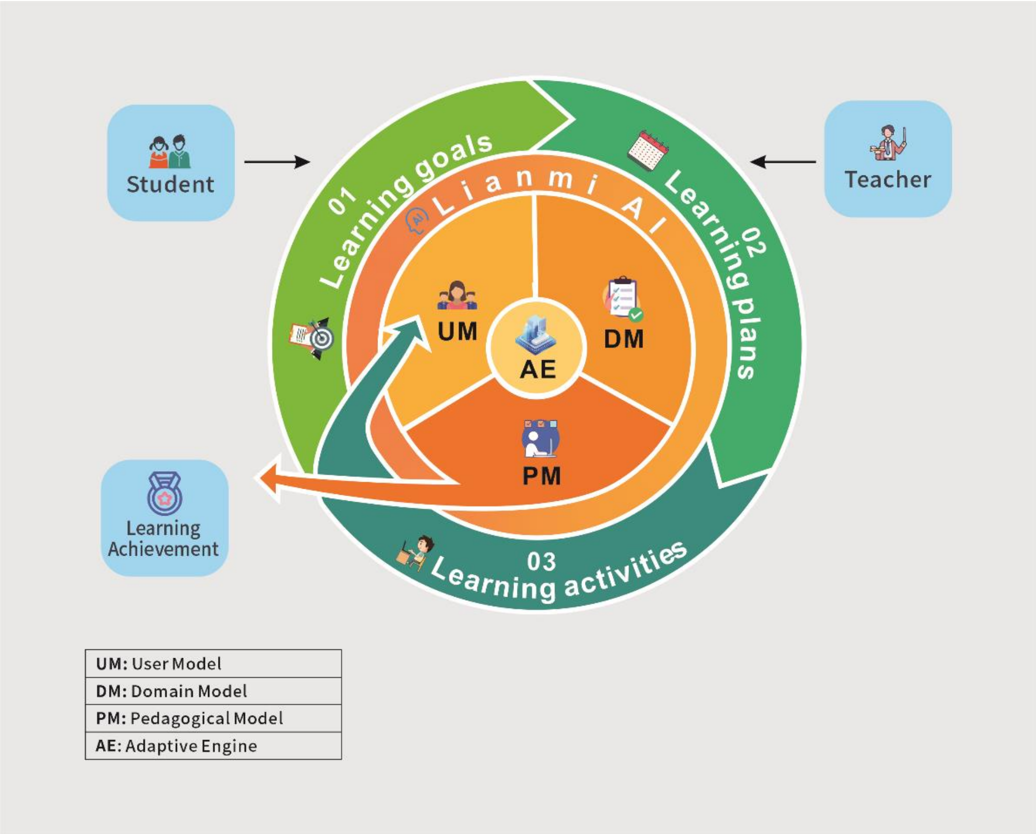

Figure 6.
The SDL-ALS model**.**

Table 1.
Learning Steps of the SDL-ALS Model.

Learning Step	Student's Activities	Teacher's Activities	System	Components
Step 1: Formulating learning goals				
	Students establish their learning goals on their own.		Provide the knowledge list	1. Learning Goals 5. Domain Model
Step 2: Developing a learning plan				
Sub-step 1: Lesson Plan Explanation & Personal Planning Guidance		The teacher describes the lesson plan to students and also guides them in creating their personal learning plans.		2. Learning Plan
Sub-step 2: Personalized Learning Plan Development	All students design their own learning plans.			2. Learning Plan
Sub-step 3: Personalized Learning Plan Review & Feedback		The teacher examines the students' learning plans and provides suggestions.		2. Learning Plan
Step 3: Learning activities				
Sub-step 1: Advance evaluation	Taking tests before staring learning		Provide tests and analyze students' knowledge levels.	6. Pedagogical Model

Table 1 (Continued).
Learning Steps of the SDL-ALS Model.

Learning Step	Student's Activities	Teacher's Activities	System	Components
Sub-step 2: Self- learning	Self- learning in ALS		Deliver adaptive learning materials, customized learning routes, and tailored learning approaches.	3. Learning Activities 7. Adaptive Engine
Sub-step 3: Student evaluation	Taking tests after each part of study		Provide tests and continually updates the report of students' learning	4. User Model 6. Pedagogical Model
Sub-step 4: Targeted guidance		Pay attention to students' learning progress, provide the targeted guidance when it is necessary		4. User Model

6. Methodology

6.1. Population and Sample

The population in this study consisted of 166 students who were non-teaching major students preparing for TQE at Hanshan Normal University, China.

The sample of this study was 80 non-teaching major students who are preparing for TQE at Hanshan Normal University, selected by using simple random sampling method. (See Table 2).

Table 2.
Demographics for Experiment.

Location	**Chaozhou City, Guangdong Province, China**
University	Hanshan Normal University
Level	Undergraduate, the 2nd year
Ages	19-20
Sampling technique	Simple random sampling
Experimental group	n = 80

6.2. Research Framework

The research framework of this study was visually depicted in Figure 7.

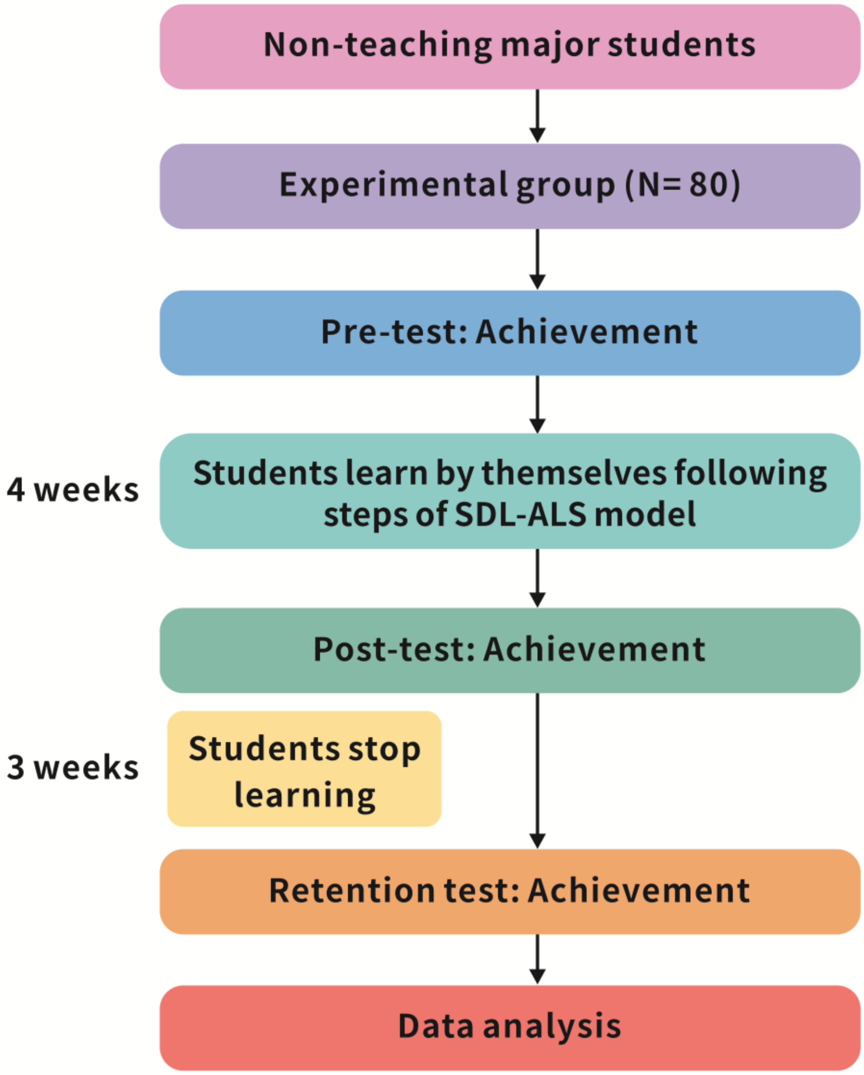

Figure 7.
The Research Framework.

6.3. Research Design

This research employed a longitudinal experimental design, with the study structure outlined in Table 3. Three rounds of achievement tests were conducted: pre-test, post-test, and retention test. The intervention commenced following the pre-test, with subsequent assessments administered immediately after the intervention (post-test) and three weeks later (retention test).

Table 3.
Experimental Design.

O_1	X	O_2	3 weeks later	O_3

Note:
X is learning based on the SDL & ALS model.
O_1 O_2 O_3 are the measurements of the students' achievement.

6.4. Research Instruments

The research instruments in the study included lesson plans developed based on the SDL-ALS model and tests on Educational Teaching Knowledge and Competence.

6.4.1. Lesson Plans

The first treatment instrument for the experiment in this study was the lesson plans developed based on the SDL-ALS model, which had 5 steps of SDL and 4 components.

The lesson plans were validated by five experts using the completed lesson plan evaluation form (see Appendix). The four lesson plans were validated by five experts using a completed lesson plan evaluation form. The mean scores for the lesson plans were 4.54, 4.67, 4.58, and 4.79 (on a scale where 4.51-5.00 = Very High). All lesson plans achieved a "Very High" rating. This result demonstrated that the lesson plans were well-suited and appropriate for use in this study.

6.4.2. Tests on Educational Teaching Knowledge and Competence

In this study, the Educational Teaching Knowledge and Competency test consists of the following four major sections: Educational Fundamentals and Basic Principles, Secondary School Curriculum, Secondary School Teaching, and Psychology of Learning for Secondary School Students.

The Educational Teaching Knowledge and Competency test scores were used as the data for Learning Achievement. The test consisted of 50 multiple-choice questions, each worth 2 points, for a total of 100 points.

The content validity of the test was assessed using the Item-Objective Congruence (IOC) method. Five content experts were invited to evaluate the alignment between each test item and its corresponding learning objective. All 50 items demonstrated IOC values ranging from 0.6 to 1.0, exceeding the minimum acceptable threshold of 0.5. Consequently, all items were retained for measuring students' learning achievement. The internal consistency reliability of the assessment instrument was evaluated using the Kuder-Richardson Formula 20 (KR-20). The computed KR-20 coefficient of 0.79 exceeded the conventional acceptability threshold of 0.70 [25], demonstrating satisfactory reliability for the dichotomously scored test items.

6.3. Data Collection

Prior to data collection, informed consent was obtained from all participating students. Participants received comprehensive details regarding the study's objectives, procedures, potential risks and benefits, and participants' rights, including the right to withdraw. Ethical approval for this research was granted by the Research Ethics Committee of Hanshan Normal University (No: 2025010308).

The experimental procedure was implemented as follows.

In the first stage, students took a pre-test, and their pre-test scores were obtained.

In the second stage, students underwent a four-week learning process in the ALS based on the SDL-ALS model. Initially, students formulated their own learning goals and developed their own learning plans. Teachers reviewed these plans and provided feedback and suggestions. Subsequently, students proceeded with learning activities on the ALS according to their individual plans. The ALS provided learning materials tailored to students' proficiency levels based on pre-test results, continuously assessed their learning progress, and adjusted adaptive learning materials, routes, and approaches delivered to them. The ALS also recorded students' learning trajectories and progress. Teachers used this information from the ALS to offer targeted guidance when necessary.

In the third stage, students who had completed four weeks of study were given a post-test, and their post-test scores were recorded.

In the fourth stage, learning was suspended for all students for three weeks.

In the fifth stage, students were tested again and received their retention test scores.

6.4. Data Analysis

Repeated measures ANOVA was used to determine whether there was a significant difference among pre-test scores, post-test scores, and retention test scores.

7. Results

The statistical analysis of learning achievement across the three testing phases yielded significant findings.

Table 4.
Mauchly's Test of Sphericity

Within Subjects Effect	Mauchly's W	χ^2	df	Sig.
Over the three tests	0.288	97.144	2	<0.001**

Note: **P<0.01.

Before performing the repeated measures ANOVA test, the assumption of sphericity should be check by Mauchly's test. As detailed in Table 4 Mauchly's test indicated that the assumption of sphericity was violated for the within-subjects factor (the three test times), $W = 0.288$, $\chi^2 (2) = 97.144$, $p < 0.01$. This violation necessitated the use of a correction (Greenhouse-Geisser) for interpreting the subsequent ANOVA results.

Table 5.
Repeated Measures ANOVA.

Source of Variance	SS	df	MS	F	p	Partial Eta-Squared
Times	89947.90	1.168	77003.765	472.840	<0.001**	0.988
Error	15028.10	92.280	162.584			

Note: ***P<0.01.*

After confirming the assumption of sphericity, the repeated measures ANOVA test determined the significant differences between the pre-test, post-test, and retention test scores. Table 5 presents the results of the Repeated Measures ANOVA using the Greenhouse-Geisser correction ($\varepsilon = 1.168$). This analysis revealed a statistically significant main effect of time (pre-test, post-test, retention test) on learning achievement, $F(1.168, 92.280) = 472.840$, $p < 0.001$. The extremely large partial eta-squared value ($\eta^2 = 0.988$) indicated that the time factor accounted for a very substantial proportion (98.8%) of the variance observed in learning achievement scores. $p < 0.001$ confirmed that these differences were not due to chance.

Table 6.
Significant Difference of Learning Achievement.

		Numbers of Tests		
Means		**Pre-test**	**Post-test**	**Retention test**
Learning Achievement	Pre-test (M=51.40, SD=13.44)		40.700**	41.43**
	Post-test (M=92.10, SD=11.07)	-40.70**		0.73
	Retention test (M=92.83, SD=10.82)	-41.43**	-0.73	

Note: **P<0.01.

To find the specific differences between the test times identified by the significant main effect, pairwise comparisons with Bonferroni adjustment were performed. Table 6 presents data includes the mean scores (with standard deviations) and the results of pairwise comparisons. The mean learning achievement score was $M = 51.40$ ($SD = 13.44$) for the pre-test, $M = 92.10$ ($SD = 11.07$) for the post-test, and $M = 92.83$ ($SD = 10.82$) for the retention test. The pairwise comparisons demonstrated that both the post-test mean score and the retention test mean score were significantly higher than the pre-test mean score, with mean differences of 40.70 and 41.43 points, respectively, and $p < 0.01$ for both. Furthermore, the lack of a statistically significant difference between the post-test and retention test mean scores, with a mean difference of 0.73 points and $p > .05$, indicates sustained learning achievement three weeks after the intervention concluded. Notably, the standard deviations decreased from the pre-test phase to the post-intervention phase.

8. Conclusion and Discussion

The results of this study provided robust empirical support for the effect of the SDL-ALS Model. First and foremost, the highly significant improvement in learning achievement from pre-test ($M = 51.40$) to both post-test ($M = 92.10$) and retention test ($M = 92.83$) phases ($p < 0.001$, $\eta^2 = 0.988$) confirmed the primary research hypothesis. This dramatic increase, exceeding 40 points on average, demonstrated that the SDL-ALS model enhanced students' mastery of educational knowledge and competency.

This finding aligned with conclusions from previous research. Conducted by Dabingaya [8] at the University of Papua New Guinea (PNG), a quantitative study demonstrated that AI-powered adaptive learning platforms significantly enhance mathematics learning outcomes by delivering personalized, adaptive content tailored to individual needs. Similarly, Wang et al. [26] documented efficacy in two studies of Squirrel AI Learning, one of China's pioneering adaptive learning systems. Their study showed that eighth-grade students from two provinces, randomly placed in the adaptive learning group, demonstrated greater improvement in mathematics compared to classmates receiving instruction from expert teachers in whole-class or small-group settings. In the study conducted by Sari et al. [27] , pre-tests and post-tests were used to measure student performance before and after using adaptive learning systems. The pre-test determined students' starting level of material comprehension, while the post-test measured results after system implementation. Analysis showed significant learning outcome gains directly linked to AI technology, reflected by higher assessment scores. This method allowed researchers to confirm the effectiveness of adaptive learning systems, proving their ability to improve educational results.

Importantly, the non-significant difference between post-test and retention test scores (mean difference = 0.73, $p > 0.05$) indicated that knowledge gains were not transient but remained stable three weeks after intervention cessation, suggesting that students' retention and effective knowledge consolidation occurred through the model's implementation.

Equally noteworthy was the observed reduction in score variability across testing phases, as evidenced by progressively decreasing standard deviations (pre-test SD=13.44 → post-test SD=11.07 → retention test SD=10.82). This pattern implied that the SDL-ALS model functioned as an equity-enhancing intervention. While all students benefited substantially reflected in the soaring group mean, the narrowing score distribution suggested that initially lower-performing students made proportionally greater gains. This "closing the gap" effect aligned with the model's core design: the ALS component provided personalized scaffolding calibrated to individual proficiency levels, while the SDL framework

empowered students to direct their learning. Teacher-guided refinement of learning plans and targeted support further ensured struggling learners received timely assistance, collectively fostering more uniform high achievement.
These outcomes highlighted two synergistic strengths of the AI-Driven ALS within the SDL framework:

(1) AI-Driven ALS's capacity to diagnose and address individual knowledge gaps precisely through continuous assessment and adaptation;

(2) SDL's role in enabling differentiated learning trajectories while maintaining high expectations for all.

The success of the model in sustaining learning gains also emphasized the importance of structured self-direction, where students formulate goals, develop plans (checked by teachers), and engage in self-paced learning in promoting long-term knowledge retention. Future research could explore how specific adaptive strategies (e.g., personalized feedback types) contribute to these effects.

9. Limitations

Two primary limitations warrant consideration. First, the participants were drawn exclusively from a single institution; consequently, this sampling approach restricted the generalizability of findings to populations with diverse educational backgrounds or technological infrastructures. Additionally, learning achievement was evaluated solely through a 50-item multiple-choice test; this narrow assessment scope failed to measure higher-order competencies such as critical thinking or knowledge application.

To address these constraints, future research should prioritize two directions. Specifically, studies should be conducted across multiple institutions (e.g., schools in varied socioeconomic regions) to establish cross-context validity. Concurrently, researchers must incorporate multidimensional assessment tools, including open-ended problem-solving tasks and project-based evaluations to capture advanced cognitive and practical capabilities comprehensively.

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Appendix

Example of A Lesson Plan
1. Course: Educational Knowledge and Competence
2. Topic: Educational Fundamentals and Basic Principles
3. Time: The learning in this lesson will be completed in a total of 7 days, with each day's learning being 60 minutes.

Because students learn using the Adaptive Learning System, the exact amount of time for each student will vary depending on their level of knowledge, comprehension, and state of learning. However, regardless of whether students increase or decrease the amount of time they spend studying each day, they should complete the chapter within seven days.

4. Objectives:
(1) State the emergence and development of education, the emergence and development of pedagogy, the relationship between education and social development, the relationship between education and human development.
(2) Distinguish between different types of education systems.
(3) Interpret aims of education.
(3) Make use of educational research methods
5. Content:
(1) The emergence and development of education
(2) The emergence and development of pedagogy
(3) Relationship between education and social development
(4) Relationship between education and human development
(5) Educational system
(6) Aims of education
(7) Methods of educational research
6. Teaching Steps:
Step 1: Formulating learning goals
Students establish their learning goals on their own according to the knowledge list provided by ALS.
Step 2: Developing a learning plan
Sub-step 1: The teacher describes the lesson plan to students and guides them in creating their personal learning plans.
Sub-step 2: Each student designs his or her own learning plan of "Educational Fundamentals and Basic Principles".
Sub-step 3: The teacher examines the students' learning plans and gives some suggestions.
Step 3: Learning activities
Sub-step 1: Students take the advanced test in ALS. The ALS analyzes students' knowledge levels.
Sub-step 2: ALS provides students with adaptive learning resources based on the results of evaluation and analysis. Students learn on their own in ALS. Different students get different learning materials and exercise items due to different evaluation results.
Sub-step 3: ALS provides tests for each student after each part of the study, as well as continually updates the report of the analysis of students' learning based on students' learning behaviors and results of the tests.
Sub-step 4: Teacher reviews the report of the analysis of students' learning to follow up on student learning and provides targeted guidance or instruction to students when needed.

7. Learning resources:

Learning resources provided by the "Lianmi AI Adaptive Learning" will be used.

8. Evaluation criteria:

8.1 Instrument

Ten questions on Multiple choice with 4-choice selection. The correct answer will give 1 score. The total is 10 scores.

8.2 Method

Testing

8.3 Criteria.

Scores	**Comment**
10-8	Excellent
7-6	Good
5-0	Not pass