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Practice of Hierarchical Teaching for Advanced Mathematics Based on AI Knowledge Graph

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Abstract: *The quality of higher education has attracted global attention, and foundational courses shoulder the critical mission of core knowledge imparting. Therefore, improving the quality of higher education must start with enhancing the teaching quality of foundational courses. Currently, the teaching of foundational disciplines faces dilemmas including a single teaching method, excessively large class sizes, and a lack of hierarchical educational objectives. These issues hinder students' learning initiative and effective interaction between teachers and students, resulting in insufficient momentum for improving teaching quality. To address the aforementioned problems, this paper introduces AI knowledge graph technology and proposes a hierarchical teaching model, taking Advanced Mathematics as an example, to achieve precise learning situation diagnosis, dynamic stratification, and intelligent resource matching. A controlled experiment was carried out with 100 undergraduates from two parallel engineering classes as research subjects. The experimental group adopted the AI knowledge graph-driven hierarchical teaching model, while the control group used the traditional teaching model. Results indicate that the experimental group achieved a final average score of 81.96 (compared to 76.72 in the control group, p=0.018**), a pass rate as high as over 94%, and was significantly superior to the control group in self-directed learning time (8 hours/week vs. 7 hours/week in the control group).The research confirms that this model can effectively enhance teaching precision and learning effectiveness, offering practical references for the intelligent reform of foundational discipline teaching in universities.*

Keywords: *AI Knowledge Graph; Advanced Mathematics; Foundational Disciplines; Hierarchical Teaching; Intelligent Teaching; Empirical Study*

1. Introduction

Foundational discipline courses are public compulsory courses offered by all undergraduate universities. They serve as a key bridge connecting secondary education and undergraduate professional learning, and play a vital role in the construction of college students' knowledge systems, the cultivation of their thinking abilities, and even their future career development.

However, the current teaching of foundational disciplines in universities still faces numerous practical dilemmas. On one hand, public foundational courses have long been in the "peripheral position" of undergraduate talent cultivation. Some universities tend to prioritize majors over foundational disciplines, and insufficient attention is paid to the teaching quality of foundational disciplines. On the other hand, the traditional teaching model for foundational disciplines has obvious shortcomings. Taking Advanced Mathematics as an example, most universities still adopt a "one-size-fits-all" uniform teaching model: there is high homogeneity in teaching content, progress, and assessment criteria. This model can neither meet the in-depth exploration needs of students with a solid foundation and extra learning capacity, nor adapt to the personalized needs for strengthening weak areas of students with a weak foundation and slow learning pace. Eventually, it leads to the phenomenon of polarization where "high-achieving students cannot meet their learning needs (lit. 'cannot get enough to eat') and low-achieving students struggle to keep up," which seriously undermines students' learning enthusiasm and the effectiveness of course teaching.

With the advent of the "Internet + Education" era, the in-depth integration of technologies such as AI with education has provided new possibilities for teaching reform, and the demand of contemporary college students for personalized and precise teaching has also become increasingly prominent. However, the problems of the disconnection between traditional teaching models and technology empowerment, and the mismatch between teaching supply and student needs remain unsolved, and there is an urgent need for new teaching models to break the deadlock.

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Against this backdrop, AI Knowledge Graph, with its core advantages of being structured, visualized, and intelligent, provides a new approach to addressing the challenges in foundational discipline teaching. AI Knowledge Graph can systematically organize and visually present knowledge points, logical connections, and key and difficult points of foundational disciplines such as Advanced Mathematics, accurately mapping the knowledge network and students' cognitive paths; while Hierarchical Teaching takes students' individual differences as its starting point. By accurately identifying students' knowledge foundations and learning abilities, it formulates differentiated teaching objectives, content, and evaluation systems to achieve the goal of "teaching students in accordance with their aptitude". This paper organically integrates the two, constructing a hierarchical teaching model for foundational disciplines based on AI Knowledge Graph. This model not only leverages technological means to break through the bottlenecks of "inaccurate learning situation diagnosis, unscientific hierarchical standards, and untimely teaching adjustments" in traditional hierarchical teaching but also fully meets students' personalized learning needs through hierarchical design. Based on this, this paper takes the Advanced Mathematics course as the empirical research object, systematically conducting research on the construction and application of the hierarchical teaching model for foundational disciplines based on AI Knowledge Graph. It aims to provide replicable and promotable practical pathways for improving the teaching quality of foundational disciplines and advancing undergraduate foundational teaching reform, thereby laying a solid foundation for the cultivation of first-class undergraduate talents.

2. Related Works

In recent years, the application of digital technologies and intelligent means in foundational discipline education has continued to expand. Many scholars have explored the impact of AI, gamification, curriculum reform, and teacher professional development on teaching effectiveness, and summarized some representative research results.

Xu Li et al. discussed the pain points in Python programming teaching, such as teacher "monologues" and over-reliance on quantitative evaluation. Taking undergraduate students from the School of Computer Science as the research objects, they leveraged mathematical models to mine the characteristics of learning process data, constructed a multi-dimensional learning effectiveness evaluation system, conducted an empirical study, and proposed curriculum optimization suggestions. Their core idea of data-driven and precision-oriented teaching optimization provides a direction for this paper to construct a precision teaching model for foundational disciplines based on AI Knowledge Graph[1]. Pingshan Wang pointed out that AI technology has driven education to urgently need transformation. He analyzed the inevitability of reform from multiple dimensions, explored AI applications such as intelligent tutoring and classroom management as well as the multi-dimensional reconstruction of teaching models, mentioned challenges including ethics and data privacy and proposed corresponding response strategies, and emphasized human-machine collaboration and the cultivation of core competencies[2]. Aiming at problems such as inefficient utilization of teaching resources in traditional Advanced Mathematics instruction, Suxiang Zhang introduced AI and big data technologies to construct an online-offline hybrid teaching model. Through an empirical study on undergraduate engineering students, the scores and pass rate of the experimental group were significantly higher than those of the control group, validating the effectiveness of AI-empowered Advanced Mathematics teaching[3]. Taking university interactive classrooms as cases, Hao J et al. explored the correlation between teachers' questioning strategies, students' AI usage tendencies, and academic performance. They found that higher-order thinking questions are correlated with AI usage, but AI usage has limited impact on academic performance[4]. Taking undergraduate students as the research subjects, Shomotova, A. et al. explored the relationships between digital competence, generative AI usage, personal backgrounds, and AI literacy. Through multiple statistical methods, they found that all of these factors show a strong positive correlation with AI literacy, and proposed curriculum optimization suggestions that integrate AI ethics and practical operation experience[5]. Biehler, R. et al. point out the current state of research on university mathematics education, focus on the learning challenges of skills such as formal reasoning and proofs in higher-order mathematics courses, and synthesize the trends in three core areas: innovation in the teaching and learning of higher-order mathematics, transition between educational stages, and the role of proofs[6]. Focusing on the disconnection between content courses and pedagogy courses in pre-service secondary mathematics teacher education, Marshman, M. interviewed hybrid mathematics teacher educators from Australia and the Czech Republic to explore their identity formation across cross-disciplinary boundaries, and advocates for strengthening collaboration between mathematicians and mathematics educators[7]. Taking 748 undergraduate mathematics students as research subjects, Gonzalez-DeHass et al. explored and found that fixed mindset and parents' attitudes towards helping with mathematics influence students' math anxiety through paths such as avoidance goals, and female students had higher anxiety scores[8]. Taking 90 freshmen taking College English as research subjects, Hu L et al. explored the impact of diversified evaluation on students' sense of learning achievement through multiple methods. They found that learning behaviors, teachers' teaching behaviors, and learning environment all show a significant positive correlation with the sense of learning achievement, and proposed to conduct multi-dimensional and multi-level evaluations by leveraging learning situation data from knowledge graphs[9]. Taking master's students as research subjects, Wiitavaara B. et al. explored through methods such as interviews and phenomenological analysis and found that online learning requires higher levels of students' self-leadership, digital competence, and other capabilities[10]. They emphasized the need to strengthen support for students' self-regulation and the construction of teachers' sense of community. Current studies tend to concentrate on a single aspect of teaching models or instructor professional growth, and they are generally deficient in thorough empirical examination of the targeted intervention mechanisms of intelligent technology and the individualized learning achievements of students.

3. Teaching Steps for a Tiered Instructional Model in Higher Mathematics Based on AI Knowledge Graphs

Taking Advanced Mathematics as an example, this section implements teaching in accordance with the "before class - during class - after class" process based on the hierarchical teaching model supported by AI Knowledge Graph. Before class, the Advanced Mathematics knowledge graph is first constructed; students are divided into three levels (basic level, improvement level, and advanced level) based on learning situation data, and personalized preview resources are pushed to them. During class, differentiated teaching objectives and content are set for the three levels; knowledge graph visualization is used to support interaction, and real-time feedback is captured to adjust teaching. After class, hierarchical assignments and resources are pushed, data is tracked to dynamically optimize hierarchical strategies, and personalized reports including knowledge mastery status are generated. Finally, through grouped experiments (the experimental group adopts this model while the control group uses the traditional model), learning outcomes, behaviors, and subjective perception data are compared to verify the effectiveness of the model.

3.1. Pre-class Preparation Stage

First, systematically sort out the core knowledge system of Advanced Mathematics. Through AI technology, structurally present knowledge points, logical connections, key and difficult points, error-prone points, adaptation relationships with question types, and other elements to form a visual knowledge network, clarifying the hierarchical progressive relationships among various knowledge points. This constructs the Advanced Mathematics AI Knowledge Graph.

Second, release a pre-test (including 30% basic questions, 50% intermediate questions, and 20% difficult questions) through Xuexi Tong, collect students' answer data to initially identify their knowledge weaknesses, and divide students into three levels based on their test scores and error question types: basic level (below 60 points, weak in core concepts), improvement level (60-80 points, solid foundation but needs skill enhancement), and advanced level (above 80 points, requiring application expansion). Synchronize the student list to the class groups in Rain Classroom.

Finally, based on the hierarchical results, dynamically match preview resources using the AI Knowledge Graph: for students at the basic level, push visual explanation videos of the knowledge graph, microlectures on basic knowledge points, and simple example explanations, focusing on filling knowledge gaps; for students at the improvement level, push microlectures on the associated applications of knowledge points and tutorials on the breakdown of typical question types to strengthen their knowledge transfer ability; for students at the advanced level, push extended knowledge points and interdisciplinary cases (such as introductory mathematical modeling) to guide them in independent inquiry.

3.2. In-class Teaching Stage

First, classroom teaching sets different objectives for students at the three levels: students at the basic level are required to master the definitions, formulas, and basic applications of core knowledge points and complete drills on basic examples; students at the improvement level are required to proficiently

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apply knowledge points to solve problems, overcome error-prone points, and finish intermediate-level comprehensive questions; students at the advanced level are required to deepen their understanding of the logical essence of knowledge points, solve complex comprehensive questions and inquiry-based problems, and attempt applications of mathematical modeling.

Second, teachers deliver in-depth lectures on core knowledge points using PPT (taking into account all students), and use knowledge graph visualization to show the position of the current teaching knowledge points in the overall knowledge network as well as associated examination points, helping students establish systematic cognition. Then, teachers release practice questions for the three levels through Rain Classroom: 5 basic questions (e.g., direct application of formulas) for the basic level, 3 intermediate questions (integration of multiple knowledge points) + 2 basic questions for the improvement level, and 2 intermediate questions + 3 extended questions for the advanced level, with students required to complete the questions within a time limit. During this process, teachers should capture real-time classroom feedback, view answer data in real time through Rain Classroom, quickly review and recap knowledge points with concentrated errors for the basic level using PPT, and organize cross-group discussions for common problems among the improvement and advanced levels while conducting roving guidance to ensure that students at all levels "gain meaningful learning outcomes."

Finally, teachers summarize the core points of the lesson using PPT, sort out the knowledge context by combining with the AI Knowledge Graph, and emphasize the key content that students at all levels need to master. Xuexi Tong releases hierarchical assignments: for the basic level, complete basic exercises in the textbook and error question review and recap; for the improvement level, finish intermediate-level comprehensive questions and sorting out problem-solving ideas; for the advanced level, complete extended questions and case analysis reports, with the submission deadline clearly specified.

3.3. Post-class Consolidation and Enhancement Stage

Objective questions are batch-graded by Xuexi Tong, while teachers manually grade subjective questions and label error types. Data such as students' assignment completion rate, accuracy rate, and quality of preview notes are collected and combined with in-class answer data. With the help of the AI Knowledge Graph, dynamic changes in students' knowledge gaps are analyzed, and learning outcomes are fed back to both students and teachers in the form of knowledge graph visualization: marking mastered knowledge points (green nodes), knowledge points to be consolidated (yellow nodes), and unmastered knowledge points (red nodes). This forms students' personal learning profiles, clarifies subsequent improvement paths, and recommends targeted remediation resources. For unmastered knowledge points of students at the basic level, Xuexi Tong pushes PPT supplementary lecture videos and special practice exercises; for students at the improvement and advanced levels, it pushes variant exercises of error questions and extended resources. The difficulty of hierarchical practice questions for the next class is dynamically adjusted, forming a closed loop of "diagnosis-learning-feedback-remediation.".

4. Results and Discussion

4.1. Cluster Design

This study takes 2025-cohort engineering students from an undergraduate institution as the research subjects, selecting 100 students from two parallel classes and adopting a controlled experimental design: the experimental group (50 students) employs the hierarchical teaching model supported by AI Knowledge Graph; the control group (50 students) adopts the traditional teaching model, i.e., PowerPoint presentations + blackboard lectures + a fixed question bank. Students in both groups are instructed by the same teacher, and the textbook and basic course content are consistent to ensure fair comparison.

4.2. Experimental Implementation

The experimental period lasted for a complete semester (17 weeks), and the teaching modules covered core Advanced Mathematics topics such as limits, derivatives, integrals, series, and functions of several variables. Learning data of students in both groups was recorded throughout the entire process, and statistical analysis was conducted around two dimensions: "learning outcomes - learning behaviors." See Table 1 for variable definitions.

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Table 1: Variable Definitions and Descriptions

Variable Type	Variable Name	Variable Definition & Example	Function
Grouping Variable	Group	1 = Experimental Group (AI-based hierarchical teaching), 2 = Control Group (traditional teaching)	Distinguish and compare the two groups
Learning Outcome Indicators	final_score	Students' final Advanced Mathematics scores (e.g., 0-100 points)	Compare the final learning effects of the two groups
	pass_flag	1 = Pass (e.g., ≥60 points), 0 = Fail	Compare the learning initiative of the two groups
Learning Behavior Indicators	self_study_hour	Weekly self-study hours for Advanced Mathematics (e.g., hours)	Compare the learning initiative of the two groups

4.3. Data Analysis Methods

First, the evaluation process verifies data applicability through normality tests and homogeneity of variance tests. Then, for continuous indicators—final average scores and weekly self-study hours—independent samples t-tests are adopted to compare the quantitative differences between the experimental group and the control group, with the effect size Cohen' s d used to quantify the magnitude of the differences. For the categorical indicator (pass rate), Pearson chi-square tests are employed to analyze the association between the pass rates of the two groups. The specific experimental results are as follows:

Table 2 Results of Normality Test for Scores

Variable Name	Sample Size	Median	Mean	Standard Deviation	Skewness	Kurtosis	S-W Test
scores	100	80	79.34	11.171	-0.53	0.105	0.975(0.050*)

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Table 2 presents the results of descriptive statistics and normality test for the quantitative variable (Scores), including the median, mean, and other metrics, which is intended to verify the normality of the data. The Shapiro-Wilk (S-W) test was applied to the Scores variable, yielding a significance p-value of 0.05. Since the result is not significant at this level, the null hypothesis cannot be rejected, and thus the data satisfies the normal distribution.

Table 3: Homogeneity of Variance Test for Scores

Variable Name	Standard Deviation		F	P
	Experimental Group	Control Group		
score	9.75	11.961	2.06	0.154

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Table 3 presents the results of homogeneity of variance, including standard deviations, F-test results, and significance p-values. The results indicate that for the Scores variable, the test yielded a significance p-value of 0.154, which is not significant at the 0.05 significance level. Thus, the null hypothesis cannot be rejected, and the data satisfies homogeneity of variance.

Table 4: Independent Samples t-test Analysis Results for Scores

Variable Name	Variable	Sample Size	Mean	Standard Deviation	t-test	Welch' s T test	Mean Difference	Cohen' s d
scores	Experimental Group	50	81.96	9.75	T=2.401 P=0.018**	T=2.401 P=0.018**	5.24	0.48
	Control Group	50	76.72	11.961				

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Table 4 presents the results of the independent samples t-test, including mean ± standard deviations, t-test statistics, significance p-values, and effect size Cohen' s d. Class 1 and Class 2 had a mean score

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of 81.96 and 76.72, respectively. Since homogeneity of variance was satisfied, the independent samples t-test was employed, yielding a significance p-value of 0.018**, indicating a statistically significant result. This demonstrates that there was a statistically significant difference in scores between Class 1 and Class 2; the magnitude of the difference, as measured by Cohen' s d, was 0.48, representing a small effect size.

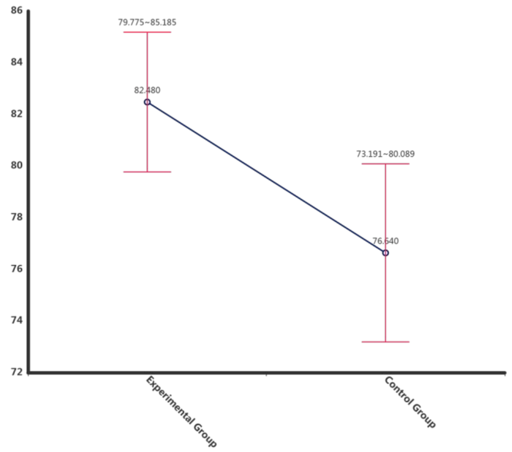

Figure 1: Error Curve Chart for Scores

Figure 1 intuitively shows that the mean score of the experimental group adopting AI knowledge graph-based hierarchical teaching (82.480) is significantly higher than that of the control group using traditional teaching (76.640). Additionally, the error ranges of the two groups basically do not overlap, confirming the statistical significance of the experimental group' s superior performance.

Table 5: Results of Normality Test for Self-Study Hours

Variable Name	Sample Size	Median	Mean	Standard Deviation	Skewness	Kurtosis	S-W Test	YTEWQ
self_study_hour	100	7.578	7.533	1.363	-0.227	-0.882	0.954 (0.001***)	0.086 (0.066*)

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Table 5 presents the results of descriptive statistics and normality test for the quantitative variable (Self-Study Hours), including the median, mean, and other metrics, which is intended to verify the normality of the data. The Shapiro-Wilk (S-W) test was applied to the Self-Study Hours variable, yielding a significance p-value of 0.001. Since the result is statistically significant at the 0.05 significance level, the null hypothesis is rejected, and thus the data does not satisfy the normal distribution. The absolute value of Kurtosis (-0.882) is less than 10, and the absolute value of Skewness (-0.227) is less than 3; further analysis was conducted in conjunction with the normal distribution histogram.

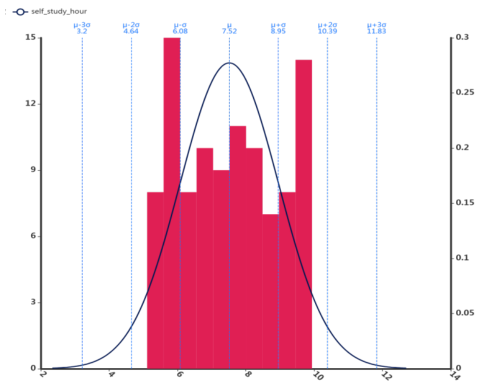

Figure 2: Normality Test Histogram

Figure 2 presents the results of the normality test for the Self-Study Hours variable. If the histogram basically exhibits a bell shape (high in the middle and low at both ends), this indicates that although the

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data is not absolutely normally distributed, it is generally acceptable as a normal distribution.

Table 6: Homogeneity of Variance Test for self_study_hour

Variable Name	Standard Deviation		F	P
	Experimental Group	Control Group		
self_study_hour	1.185	1.41	2.034	0.157

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Table 6 presents the results of homogeneity of variance, including standard deviations, F-test statistics, and significance p-values. The results indicate that for the Self-Study Hours variable, the test yielded a significance p-value of 0.157, which is not statistically significant at the 0.05 significance level. Thus, the null hypothesis cannot be rejected, and the data satisfies homogeneity of variance.

Table 7: Independent Samples t-test Analysis Results for self-study hour

Variable Name	Variable	Sample Size	Mean	Standard Deviation	t-test	Welch' s T test	Mean Difference	Cohen' s d
self_study_hour	Experimental Group	50	7.954	1.185	T=3.229 P=0.002***	T=3.229 P=0.002***	0.842	0.646
	Control Group	50	7.112	1.41				

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Table 7 presents the results of the independent samples t-test, including mean ± standard deviations, t-test statistics, significance p-values, and effect size Cohen' s d. Class 1 and Class 2 had a mean self-study hour of 7.954 and 7.112, respectively. Since homogeneity of variance was satisfied, the independent samples t-test was employed, yielding a significance p-value of 0.002***, which indicates a statistically significant result. This demonstrates that there was a statistically significant difference in self-study hours between Class 1 and Class 2; the magnitude of the difference, as measured by Cohen' s d, was 0.646, representing a medium effect size (with critical values of 0.20, 0.50, and 0.80 corresponding to small, medium, and large effect sizes, respectively).

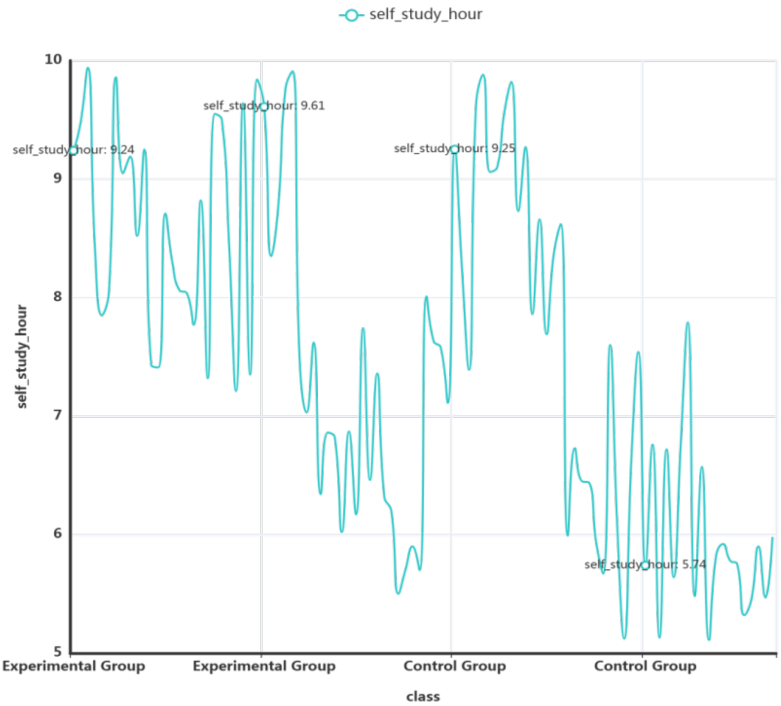

Figure 3: Line Chart for Self-Study Hours

Figure 3 illustrates the distribution of self-study hours among students in the experimental group and the control group: the self-study hours of the experimental group are generally significantly higher (mostly concentrated in the range of 7-9.64 hours), while those of the control group show a significant downward trend in the later stage (mostly dropping to around 5-6 hours). This intuitively reflects that the

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AI knowledge graph-based hierarchical teaching model can enhance students' engagement in independent learning.

Table 8: Chi-square Test Analysis Results for Pass Rate

Variable Name	Name	Class		Total	Test Method	X^2	P
		Experimental Group	Control Group				
Pass Status	Pass	48	47	95	Pearson chi-square test	0.211	0.646
	Fail	2	3	5			

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Table 8 presents the results of the model test, including data frequencies, chi-square values, and significance p-values. The results of the Pearson chi-square test indicate that the significance p-value is 0.646. Although $p>0.05$, indicating no statistically significant difference, the pass rates of both groups are as high as 94%+. This demonstrates that AI-based hierarchical teaching does not reduce the pass rate and is slightly higher than that of the control group. Combined with the statistically significant improvement in the average score, it is confirmed that the model "not only improves scores but also ensures passing rates."

5. Conclusions

This study systematically verified the effectiveness of the hierarchical teaching model for advanced mathematics based on an AI knowledge graph through controlled experiments and multi-dimensional statistical analysis. The core conclusions are as follows: First, in terms of learning outcomes, the final average score of the experimental group (81.96 points) was significantly higher than that of the control group (76.72 points), with an independent samples t-test result of $P=0.018<0.05$. Additionally, the pass rates of both groups exceeded 94%, indicating that the model can not only effectively improve students' overall academic performance but also ensure the basic passing rate and avoid polarization. Second, in terms of learning behaviors, the weekly self-study hours of the experimental group (7.954 hours) were significantly longer than those of the control group (7.112 hours), with a t-test result of $P=0.002<0.01$ and a medium effect size (Cohen' s d=0.646). This proves that the model can effectively stimulate students' initiative in independent learning and improve their learning engagement.

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