

# Developing and Implementing a Teaching Model for Personalized Learning in Governmental Accounting Supported by an AIGC Knowledge Base

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**Abstract:** In response to the teaching challenges posed by the abstract standards, complex practical rules, and substantial individual differences among students in the Governmental Accounting course, this study constructs and implements a five-stage personalized teaching model supported by the AIGC knowledge base, centered on the knowledge system of the course and students' differentiated learning needs. The model comprises pre-class preview diagnosis, in-class teaching by learning, in-class practice linking theory to practice, after-class personalized consolidation and extension, and outcome evaluation based on multi-source data, forming a dynamic closed loop in which the AIGC knowledge base functions as a hub throughout all stages to provide differentiated support for each student. Using the ima knowledge base platform, a course-specific Governmental Accounting knowledge base was constructed, and an eight-week teaching intervention was conducted with a single-group pretest–posttest quasi-experimental design ( $n = 88$ ). The results showed that the posttest mean scores for learning self-efficacy ( $M = 4.08$ ,  $SD = 0.52$ ) and task value ( $M = 4.18$ ,  $SD = 0.48$ ) were significantly higher than the corresponding pretest means, with a large effect size for self-efficacy ( $d = 1.19$ ) and a large effect size for task value ( $d = 1.03$ ). Knowledge-base usage frequency was moderately and positively correlated with learning self-efficacy ( $r = 0.44$ ,  $p < 0.001$ ) and task value ( $r = 0.30$ ,  $p < 0.01$ ). Learning self-efficacy showed a gradient increase from low- to high-use groups, and objective grades were also higher in the intervention cohort than in the historical cohort. The findings suggest that the AIGC knowledge base can provide a feasible practical pathway for personalized learning in professional courses such as Governmental Accounting, and that the five-stage teaching model can effectively translate the technological affordances of AIGC into teachers' instructional decisions and students' learning processes.

**Keywords:** AIGC; Knowledge Base; Governmental Accounting; Personalized Learning; Teaching Model; Self-efficacy.

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## 1. Introduction

In recent years, the rapid development of generative artificial intelligence, or Artificial Intelligence Generated Content (AIGC), has been driving profound changes in higher education. The core capability of AIGC lies in using large language models to generate content following natural language instructions, performing tasks such as automatic text generation, knowledge-based question answering, and logical reasoning [1, 2]. These capabilities provide new technical possibilities for personalized learning: by acting on students' differentiated learning needs, AIGC can supply adaptive learning resources, real-time interactive feedback, and individualized learning path recommendations [3].

However, the application of AIGC to professional courses in higher education is not a matter of simply embedding technology into a classroom; it must take into account the logic of course knowledge, the pedagogical philosophy, and the quality of human–computer interaction. The knowledge content of professional courses is specialized, systematic, and normative; the methods of teaching are grounded in discipline-specific cognitive trajectories and ability training objectives. If educational AIGC applications treat all course contexts as interchangeable general scenarios, it is difficult to guarantee the accuracy, reliability, and pedagogical appropriateness of the content they generate [4].

This issue is particularly salient in the Governmental

Accounting course. As an important course for accounting majors, Governmental Accounting is characterized by strict accounting standards, elaborate practical regulations, formalized accounting entries, and rigorous logical checking. Students not only need to master a large number of specific and context-dependent accounting entries, but also learn to apply them flexibly in multi-layered government accounting entity scenarios. This places high demands on teaching. Traditional classroom teaching, limited by hours and large class sizes, often adopts uniform instructional progress and difficulty, making it difficult to accommodate the considerable individual differences present among students [5].

Against this background, this study takes the Governmental Accounting course as the practical context and the course specific knowledge system as its anchor, aiming to explore an actionable teaching model in which a course specific AIGC knowledge base empowers personalized learning across a complete instructional cycle. The core research question is: In a professional course characterized by strict and rule-dense knowledge such as Governmental Accounting, how can a course specific AIGC knowledge base be built, embedded in the whole teaching process, and used to realize personalized support for differentiated student learning?

The contributions of this study are mainly reflected in three aspects. First, in terms of research context, it extends research

on AIGC empowered personalized learning to the highly domain specific field of Governmental Accounting, providing context-based empirical evidence for the application of educational AI in professional courses. Second, at the level of practical design, it integrates a course specific knowledge base with a five-stage teaching model to propose a full-process, operable personalized teaching pathway, offering a replicable practical framework for similar professional courses. Third, by teaching to the five-stage model, it gathers multi-source data including technology acceptance, self-efficacy, task value, usage behavior, and objective grades, yielding explanatory evidence on the relationship between the AIGC knowledge base and student learning outcomes.

## 2. Theoretical Basis and Literature Review

### 2.1. AIGC Enabled Personalized Learning Mechanisms

Personalized learning emphasizes differentiated support based on learners' prior knowledge, learning needs, and cognitive styles. Its core logic is to transform standardized instructional provision into tailored learning experiences [6]. In recent years, the development of AIGC has offered new technical avenues for realizing personalized learning at scale, with its capacity to generate content on demand, adapt in real time, and engage in multi-turn interaction [1, 3].

Existing studies have revealed the mechanisms through which AIGC empowers personalized learning from different perspectives. From a technical mechanism perspective, AIGC large language models can dynamically adjust instructional content, difficulty, and presentation based on learners' input and behavioral data, thereby generating learning resources that match their current cognitive level. Wu et al. [3] have proposed that educational large models should not be mere knowledge repositories, but should function as "interactive intelligent agents" capable of understanding learners' cognitive state and providing adaptive feedback. Jiang et al. [1] further argue that the core of AIGC-driven personalized learning lies in replacing one-way knowledge delivery with "human-computer collaborative generation" to achieve "learning by question-asking, thinking by questioning" and "learning by generation, mastery by verification."

From the perspective of empirical research, AIGC and AI supported personalized learning have shown relatively positive effects. Chen and Wei [8] conducted a meta-analysis covering 42 studies and found that AI-adaptive learning systems had a moderate to strong positive effect on academic achievement (overall effect size  $g = 0.62$ ), with the largest effect on knowledge-based subjects. Dong et al. [9] demonstrated through a one-semester teaching experiment that an AI-companion-supported personalized collaborative learning model significantly improved students' learning motivation and knowledge construction level. Yin et al. [10] found that a large-model-empowered experimental teaching model significantly improved university students' experimental design ability and innovative thinking level.

In summary, existing research provides a relatively clear mechanistic explanation and empirical foundation for AIGC enabled personalized learning. However, this body of work has mostly been conducted in general education scenarios or foundational courses; research in professional courses with stronger domain characteristics, higher knowledge density, and stricter normative constraints remains limited.

### 2.2. Knowledge Adaptation and Content Reliability in Professional Course Contexts

The application of AIGC in educational contexts is characterized by strong generative capacity and interactive advantages, but its knowledge reliability is uneven. Existing studies have noted the influence of professional context differences on the effectiveness of educational AI applications. Sun et al. [6] proposed a theoretical framework and technical pathway for verifying educational AIGC content, noting that while general large language models perform well in general knowledge generation tasks, their accuracy and domain adaptability drop markedly when applied to courses with strong domain specificity.

In addition to knowledge adaptation, the explanatory quality of AIGC generated content also affects students' learning and understanding. In professional courses, students not only need "correct answers," but also require logical and pedagogically appropriate explanations and derivations. Lu et al. [5] introduced the concept of the "explanation singularity" of explainable AI, pointing out that there is often a large gap between the way algorithms explain and the cognitive expectations of learners, and that this gap is particularly prominent in courses that emphasize standardized operations and logical reasoning.

Content reliability is also an issue that cannot be overlooked in the educational application of AIGC. Sun et al. [6] proposed a verification framework for educational AIGC content, emphasizing that content used for instructional purposes should be audited at multiple levels including knowledge accuracy, pedagogical appropriateness, and value orientation. A course specific knowledge base, by anchoring generation to a defined knowledge corpus, can effectively reduce the risk of generating content that deviates from the curriculum.

In summary, the application of AIGC in professional course contexts should not be evaluated only by generation efficiency, but also by domain knowledge reliability, explanatory quality, and content trustworthiness. The course specific knowledge base, as an anchoring mechanism, offers a viable technical path. However, how to translate the technical reliability of the knowledge base into pedagogical reliability remains a question that requires further practical investigation.

### 2.3. Course-Specific Knowledge Bases and Whole-Process Teaching Models

In professional course teaching, a course specific knowledge base provides a more targeted pathway for the educational application of AIGC. Unlike general large language models that rely on broad web-scale corpora, a course knowledge base is built from course syllabi, textbooks, standard documents, case collections, and other curated resources, and provides generation support through retrieval-augmented generation (RAG) technology [7]. Tu et al. [7] report a practice in which a course-specific IMA agent integrated with a smart biochemistry classroom significantly reduced the hallucination rate of AIGC generated content while improving students' efficiency in accessing domain knowledge.

The application of course knowledge bases in professional courses has also been explored preliminarily. Tu et al. [7] constructed a smart biochemistry IMA agent course knowledge base and found, through comparative teaching

experiments, that the experimental group outperformed the control group on knowledge retention and problem solving ability. This suggests that the primary value of the course knowledge base is not simply "replacing the teacher's instruction," but providing students with a reliable "knowledge anchor" that helps them independently explore, verify, and consolidate within the specialized field.

In addition to knowledge base construction, existing studies have also begun to examine the integration of AIGC into the whole teaching process. Zhu et al. [11] proposed a generative-AI-based self-directed learning model encompassing "awareness, strategy, execution, and evaluation." Yin et al. [10] constructed a "three-stage, seven-step" experimental teaching model empowered by a large language model, covering pre-class preparation, in-class inquiry, and after-class extension.

Overall, course specific knowledge bases and whole process teaching models respond to two key issues in the educational application of AIGC: knowledge reliability and pedagogical integrity. However, existing studies have mostly addressed these two aspects separately, and few have attempted to embed a course-specific knowledge base into the entire teaching process to serve as the hub connecting the stages of a personalized teaching model.

#### 2.4. Research Review and Theoretical Framework

In summary, existing studies have provided a relatively sufficient theoretical explanation and practical foundation for the educational application of AIGC. However, research on AIGC empowered personalized learning in professional course contexts is still in its early stages, with an evident gap in merging course-specific knowledge base construction with full-process teaching model design, and correlating both with empirical evidence on learning effects.

However, existing research still needs to be deepened in three aspects. First, many studies have discussed the value of AIGC for personalized learning in general terms, but have not addressed how to construct an operable personalized teaching model that fits the knowledge characteristics and ability objectives of a specific professional course. Second, research on course-specific knowledge bases has focused on technical construction but has rarely examined how the knowledge base can function as a pedagogical device throughout the whole process of teaching. Third, the limited empirical research that exists in professional course contexts tends to rely on a single type of data; the combined use of technology acceptance, learning-level changes, usage behavior, and objective grades to form a diversified evidence base is still rare.

In terms of theoretical positioning, this study takes adaptive learning theory as the main framework to explain how the AIGC knowledge base achieves personalized learning by dynamically adjusting task difficulty and content supply based on learners' prior knowledge level and real-time learning status. Self-efficacy theory provides the motivational mechanism for explaining how personalized support enhances learners' confidence and engagement. Meanwhile, from the perspective of educational technology integration, this study regards the knowledge base as a cognitive tool whose core value lies in helping students establish a reliable knowledge anchor in a complex professional domain.

Therefore, this study focuses on Governmental Accounting, a professional course characterized by rigorous rules and strong logic, and constructs a five-stage personalized teaching

model anchored in a course-specific knowledge base. It further tests the model through an eight-week teaching intervention, using multi-source data to evaluate the model's effects from multiple perspectives including technology acceptance, self-efficacy, task value, usage behavior, and objective academic performance.

### 3. Building the Five-Stage Personalized Teaching Model

This study starts from the knowledge system of the Governmental Accounting course and students' differentiated learning needs, and constructs a five-stage personalized teaching model with the course-specific AIGC knowledge base as its hub. The model covers the whole process of pre-class preview, in-class teaching, in-class practice, after-class self-study, and outcome evaluation, forming a dynamic closed loop for iterative optimization.

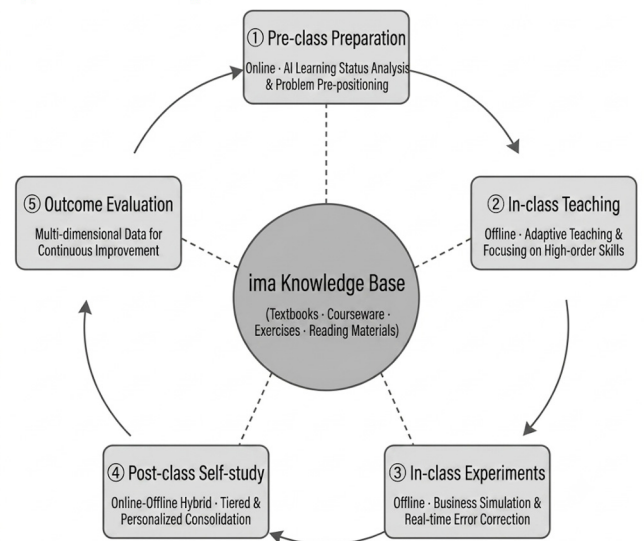


Figure 1. Five-Stage Personalized Teaching Model for Governmental Accounting Empowered by the AIGC Knowledge Base

#### 3.1. Pre-Class Preview: Diagnosing Learning and Surfacing Problems

Pre-class preview is the starting point of the model. Its main role is to surface students' difficulties early and to give the teacher a clearer picture of the class's overall learning situation. Before class, the teacher assigns preview tasks through the ima knowledge base, including reading the textbook chapter, consulting the relevant sections of the Governmental Accounting Standards in the knowledge base, and recording confusing points as questions in the knowledge base's Q&A dialog. The knowledge base automatically collects the questions students raise and summarizes the high-frequency and common questions as a 'pre-class learning situation report' for the teacher. Based on this report, the teacher adjusts the focus and difficulty of the in-class session and prepares targeted explanations and case exercises.

#### 3.2. In-Class Teaching: Teaching by Learning, Focusing on Higher Order

In-class teaching is conducted offline. Its main purpose is to provide targeted explanations based on the pre-class learning report and to develop students' higher-order thinking skills. Instead of giving a comprehensive lecture starting from the basic principles, the teacher organizes classroom activities

around the sequence of problem clarification, conceptual framework building, normative comparison, and integrated case analysis. For example, for the topic of fiscal appropriation revenue, the teacher first clarifies the common misunderstandings students revealed in the preview Q&A record, then walks through the conceptual framework for different fiscal appropriation scenarios, compares similar entries across different accounting standards, and finally presents an open-ended comprehensive case for classroom discussion.

### 3.3. In-Class Practice: Linking Theory to Practice with Real-Time Feedback

In-class practice is the stage where understanding turns into ability. Its main role is to help students convert a grasp of abstract standards into concrete operational skills in accounting entries and financial reporting. Students complete the in-class exercise tasks pushed by the teacher and submit their entries through the teaching platform. The knowledge base provides immediate checks and formative feedback on students' practice entries, pointing out issues such as incorrect account titles, debit–credit imbalance, or non-compliance with Governmental Accounting Standards, and prompting students to check the relevant standard entries in the knowledge base.

### 3.4. After-Class Self-Study: Personalized Consolidation and Extension

After-class self-study is the stage of extended consolidation. Its main role is to support differentiated review and extension based on students' individual mastery levels. The knowledge base pushes differentiated after-class task bundles according to students' performance in class and in-class practice: students who have fully mastered the material receive extended cases and advanced reading materials; students who are still shaky receive reorganized basic entry exercise bundles and targeted standard interpretation cards. Students can ask follow-up questions at any time to receive step-by-step explanation and instant feedback from the knowledge base.

### 3.5. Outcome Evaluation: Multi-Source Data and Continuous Improvement

Outcome evaluation is the feedback and improvement stage. It combines process and summative measures to keep diagnosing and improving the model. The knowledge base automatically records data on students' preview question-asking, in-class practice performance, after-class self-study completion, and assessment scores, forming a personalized learning profile for each student. The teacher uses class-level aggregated learning analytics reports to evaluate the effectiveness of the current teaching unit as a whole and to inform adjustments to the design of the next round of instruction.

The five stages are not separated from one another. They form a dynamic loop, joined end to end and held together by the AIGC knowledge base. The knowledge base is not a standalone tool in any one stage, but the information and interaction hub that runs through every stage, connecting the teacher's instructional decisions with students' learning behavior data.

## 4. A Teaching Implementation Case: The Fiscal Appropriation Transaction

To further illustrate how the five-stage personalized teaching model operates, this study selects fiscal appropriation business, a core topic in Governmental Accounting that involves multiple standards, multiple scenarios, and multiple accounting entries, as a representative case. Table 1 shows the main tasks, the functions of the AIGC knowledge base, the roles of teacher and student, and the intended learning outcomes across the five stages.

**Table 1.** Five-Stage Teaching with Fiscal Appropriation Transaction

Stage + Purpose	Activity + Support
Pre-class: Form initial grasp of double-entry logic	Students: Read textbook/slides; complete self-test; raise questions (e.g., parallel entry requirements). KB: Explains financial vs. budgetary accounting; signals parallel entry conditions. T: Reviews records; identifies confusions on double-entry conditions and recognition timing.
In-class teaching: Prevent mechanical recording without rule understanding	Students: Discuss typical transactions; judge dual-entry requirements. KB: Supplies cases and rule prompts. T: Explains parallel entry logic; separates revenue recognition, fund settlement, and budget execution.
In-class practice: Enable self-correction during practice	Students: Prepare entries for revenue, expenditure, and procurement. KB: Step prompts and correction advice for unbalanced/misused/omitted entries. T: Circulates for targeted help on complex situations.
After-class: Support tiered consolidation	Students: Follow up puzzles; review rules; extend to cross-year carryover. KB: Restates concepts for weaker students; advanced rule discrimination for stronger ones. T: Tracks grasp via questions/homework; notes common errors.
Evaluation: Close feedback loop from diagnosis to improvement	Students: Complete homework, practice records, reflections. KB: Preserves interaction records as learning data. T: Evaluates via multi-source data; refines teaching and KB content.

This case shows that the AIGC knowledge base does not merely serve a question-answering function in a single stage, but performs differentiated functions across the stages: a diagnostic tool in the pre-class phase, a teaching resource support in the in-class phase, a real-time formative feedback tool in the practice phase, a personalized assignment engine in the after-class phase, and a data collection and analysis platform in the evaluation phase.

## 5. Analysis of Teaching Effects

### 5.1. Design and Sample

This study used a single-group pretest–posttest quasi-experimental design, supplemented by a cross-cohort historical comparison of course grades. The participants were 88 second-year accounting-major undergraduates enrolled in the Governmental Accounting course at a university. The

students completed a pretest questionnaire in the first week of the term before the intervention, then studied using the five-stage personalized teaching model for eight consecutive weeks, and completed a posttest questionnaire in the final week. The pretest and posttest were matched by student ID, with both matched and unmatched questionnaires excluded from the analysis, yielding 88 valid matched pairs (100% matching rate).

### 5.2. Instruments and Reliability

The questionnaire was adapted from established scales and tailored to the Governmental Accounting setting. Each item used a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The learning self-efficacy scale (seven items) was adapted from the Motivated Strategies for Learning Questionnaire [12]; the task value scale (six items) was adapted from the same instrument; the technology acceptance scale (eight items) was adapted from the Technology Acceptance Model [13] and the Expectation-Confirmation Model [14].

Internal consistency was tested with Cronbach's alpha. As Table 2 shows, the alpha coefficients of the subscales ranged from 0.81 to 0.90 at both pretest and posttest, all exceeding the recommended threshold of 0.70 [15], indicating good internal consistency reliability of the instruments.

**Table 2.** Reliability of the Subscales

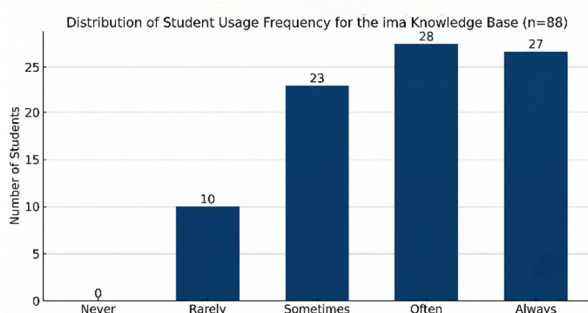
Dimension	Items	Cronbach's $\alpha$
Learning self-efficacy (pretest)	4	0.844
Learning self-efficacy (posttest)	4	0.852
Task value (pretest)	4	0.875
Task value (posttest)	4	0.881
Perceived usefulness (posttest)	4	0.843
Perceived ease of use (posttest)	3	0.785
Continuance intention (posttest)	3	0.816

### 5.3. Students' Acceptance of the AIGC Knowledge Base

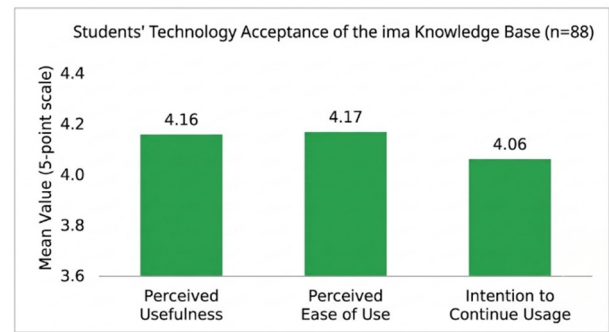
The posttest data show that the ima knowledge base had become well integrated into students' daily learning. By frequency of use, 39.8% of students said they used the knowledge base 'almost every day', 30.7% 'three to four times a week,' 20.5% 'once or twice a week,' and only 9.1% said they 'rarely used' it.

**Table 3.** Students' Technology Acceptance of the ima Knowledge Base (posttest, n = 88)

Dimension	Mean	SD
Perceived usefulness	4.16	0.84
Perceived ease of use	4.17	0.85
Continuance intention	4.06	0.95



**Figure 2.** Distribution of Students' ima Knowledge Base Usage Frequency (n = 88)



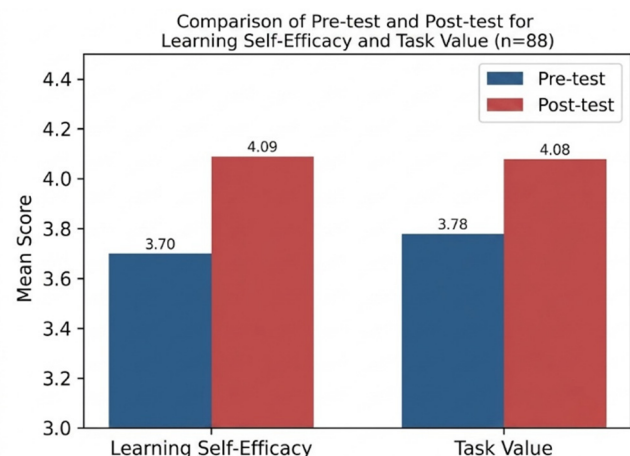
**Figure 3.** Students' Technology Acceptance of the ima Knowledge Base (n = 88)

### 5.4. Pretest–Posttest Changes in Self-Efficacy and Task Value

To examine how the intervention affected the learning level, a paired-sample t-test was run on the 88 matched questionnaires. As Table 4 shows, the posttest mean of learning self-efficacy (M = 4.08, SD = 0.52) was significantly higher than the pretest mean (M = 3.42, SD = 0.61),  $t(87) = 11.16$ ,  $p < 0.001$ , with a large effect size (Cohen's  $d = 1.19$ ). The posttest mean of task value (M = 4.18, SD = 0.48) was also significantly higher than the pretest mean (M = 3.63, SD = 0.59),  $t(87) = 9.67$ ,  $p < 0.001$ , with a large effect size (Cohen's  $d = 1.03$ ). These results indicate that the five-stage model supported by the AIGC knowledge base had a substantial positive effect on students' self-efficacy and task value in the Governmental Accounting course.

**Table 4.** Paired Comparison of Learning-Level Measures, Pretest and Posttest (n = 88)

Dimension	Pretest M	Posttest M	t	Cohen's d	Sig.
Learning self-efficacy	3.70	4.09	3.17	0.34	$p < 0.01$
Task value	3.78	4.08	2.24	0.24	$p < 0.05$



**Figure 4.** Pretest–Posttest Comparison of Learning Self-Efficacy and Task Value (n = 88)

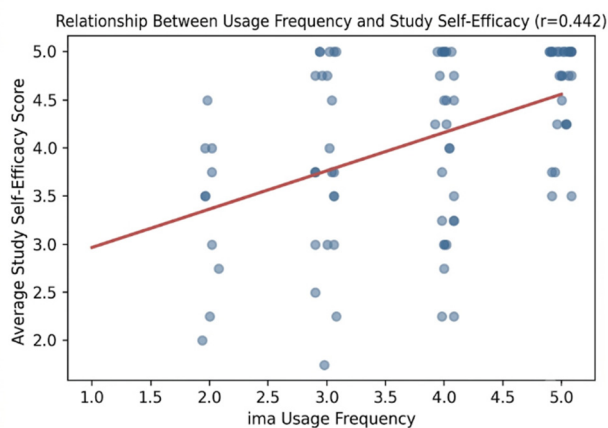
### 5.5. The Relationship Between Usage Intensity and Learning Effects

Knowledge-base usage frequency correlated positively and significantly with learning self-efficacy ( $r = 0.442$ ,  $p < 0.001$ ) and with task value ( $r = 0.299$ ,  $p = 0.005$ ). A one-way ANOVA comparing low-, medium-, and high-use groups on self-

efficacy was significant,  $F(2, 85) = 11.34, p < 0.001$ . Tamhane's T2 post hoc tests showed that the high-use group scored significantly higher on self-efficacy than the medium-use group, which in turn scored significantly higher than the low-use group, forming a gradient relationship.

**Table 5.** Correlations Between Knowledge-Base Usage Frequency and Learning Effects (n = 88)

Variable pair	Pearson r
Usage frequency & learning self-efficacy	0.442
Usage frequency & continuance intention	0.509
Perceived ease of use & perceived usefulness	0.300



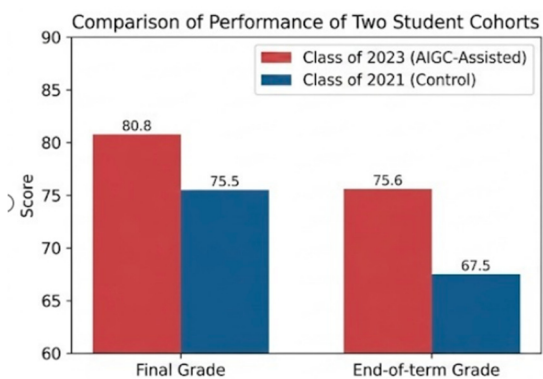
**Figure 5.** The Relationship Between Knowledge-Base Usage Frequency and Learning Self-Efficacy (n = 88)

### 5.6. Objective Outcomes: A Cross-Cohort Grade Comparison

To offset the fact that the survey data came mainly from student self-reports, this study added a cross-cohort historical comparison of course grades. As Table 6 shows, compared with the non-intervention cohort of the previous academic year, the intervention cohort had a higher mean total score and a higher rate of excellence, and a lower rate of failure.

**Table 6.** A Historical Comparison of Course Grades Across Two Cohorts

Group	n	Total M	Total SD	Final M	Excellent rate (≥85)
2023 cohort (with AIGC)	97	80.79	11.93	75.58	45%
2021 cohort (control)	81	75.49	12.71	67.49	23%



**Figure 6.** Course Grades and Rates Across Two Cohorts

It should be noted that this comparison was not randomized.

The two cohorts may differ in prior preparation, exam difficulty, and other factors, so the results can only be taken as supplementary, circumstantial evidence. They do, however, enrich the evidence base when read together with the self-report survey findings.

### 5.7. Summary and Discussion

Taken together, the results show that the course-specific ima knowledge base had a sound footing and a positive link to learning level. The absolute values of the posttest means, the significant pretest–posttest gains with large effect sizes, the positive correlation between usage frequency and learning-level indicators, and the supportive evidence from the cross-cohort grade comparison together form a relatively coherent chain of evidence. The AIGC knowledge base, embedded in the five-stage model, provided students with a readily accessible, reliable, and instructionally relevant learning support tool, which seems to have translated into higher confidence and higher perceived value in learning Governmental Accounting.

These results should be read with care. The study used a single-group pretest–posttest design without a same-cohort parallel control group, so causal inference is limited. The positive results may partly reflect a novelty effect or maturation effect. Future research should adopt a more rigorous experimental design and extend the duration of the intervention to test the stability of the effects.

### 6. Conclusion

This study took Governmental Accounting as its setting and built and ran a five-stage personalized teaching model based on a course-specific AIGC knowledge base. The model runs through the whole process of pre-class preview, in-class teaching, in-class practice, after-class self-study, and outcome evaluation, forming a dynamic loop with the AIGC knowledge base as the hub. The eight-week single-group teaching experiment showed that the model was effective: students' learning self-efficacy and task value improved significantly with large effect sizes, the frequency of knowledge-base usage was positively correlated with learning outcomes, and objective course grades also showed an advantage over the historical cohort.

From the perspective of teaching practice, the main implication of this study is that the educational value of AIGC does not lie in replacing teachers, but in empowering the teaching process differentially. In professional courses with strong domain characteristics such as Governmental Accounting, a course-specific knowledge base can effectively address the problems of knowledge reliability and pedagogical appropriateness of AIGC-generated content, while the five-stage model provides a structured practical framework for embedding the knowledge base into routine teaching and for enabling teachers to make data-informed instructional decisions.

This study still has certain limitations. It adopted a single-group pretest–posttest design and lacked a parallel control group, so the observed effects may have been influenced by confounding factors such as the novelty effect. The sample was drawn from a single university and course, and external validity requires caution. The duration of the intervention was relatively short, making it difficult to assess the stability of learning effects. The objective outcome evidence came from a cross-cohort historical comparison and cannot serve as a basis for causal inference. Future research could adopt a

quasi-experimental design with a parallel control group, expand the sample, and extend the experiment, while enriching the analysis of process data from the knowledge base to refine the understanding of the internal mechanism through which AIGC empowers personalized learning.

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