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Research on the Application of Virtual Simulation Technology and AI in Modular Teaching of Accounting and Finance Courses

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Abstract. This study investigates the application of virtual simulation technology and artificial intelligence (AI) in modular learning for accounting and finance modules. With new productive forces such as AI and virtual simulation technologies transforming education paradigms, there is growing momentum towards more interactive, modularized, and personalized learning systems. This research evaluates the effectiveness of combining these technologies by conducting an experiment on 60 accounting students from vocational colleges, divided into control and experimental groups. The experimental group was taught modularized course content enhanced with virtual simulations and AI-facilitated individualized learning paths, while the control group was taught through traditional lecture-based instruction. Pre-and post-test measures, engagement data, and student comments were collected and analyzed. Findings indicated that students in the experimental group showed significant improvement in academic performance, interest in learning, and course satisfaction. These findings emphasize the capability of virtual simulation and AI in forming modular, flexible, and learner-centered models in accounting education. Yet, technological infrastructure, curriculum change, and teacher training are areas of concern that should be resolved. There is a call for additional research into the long-term implications of these technologies and their potential use across disciplines.

Keywords: virtual simulation, Artificial Intelligence (AI), modular learning, accounting education, personalized learning, technology-enhanced instruction

1 Introduction

The rapid advancement of digital technologies has profoundly influenced higher education, with virtual simulation technology and artificial intelligence (AI) emerging as critical tools for creating more interactive, adaptive, and personalized learning environments. In the field of accounting and finance education, traditional lecture-based teaching methods, while historically effective, often fall short in promoting student engagement, practical skill development, and individualized learning experiences. Modular teaching, which structures courses into independent, thematically focused units, offers a flexible framework well-suited to the integration of these emerging technologies. Virtual simulations enable students to engage in realistic financial scenarios, facilitating experiential learning, while AI-driven systems support personalized learning paths, real-time feedback, and dynamic content adaptation. Despite the theoretical advantages, the application of virtual simulation and AI in modularized accounting education has received limited empirical investigation, and the actual impact on learning outcomes remains uncertain. Furthermore, challenges related to technological infrastructure, curriculum reconfiguration, and faculty competency represent significant barriers to widespread adoption. Against this background, this study aims to explore the application of virtual simulation technology and AI in modular accounting and finance courses, evaluating their effects on student engagement, knowledge retention, academic performance, and satisfaction. Through a controlled experimental design involving university-level accounting students, this research seeks to provide evidence-based insights into how new productive forces can modernize accounting education, enhance learning effective-ness, and offer potential strategies for cross-disciplinary implementation. In addition, this study explores broader pedagogical implications. In particular, this study explores the benefits of these technologies for self-directed learning; and the critical thinking required for future career success,

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especially in the context of the rapid digitalization of the financial sector. This study will explore issues of access and equity, and whether these technologies can enhance students' learning experience in an accessible way, ultimately promoting inclusive education. The conceptual structure of this study helps analyze the relationship between technology, pedagogy, and learner outcomes in the teaching process. Accurately identifying learner outcomes will help develop future-oriented practical courses that engage future students in accounting education while reaffirming students' commitment to lifelong learning.

2 Virtual Simulation and AI in Accounting Education

This section focuses on the impact of virtual simulation technology and artificial intelligence on accounting and finance education. Virtual simulation provides students with an immersive and interactive space to participate in complex real-life scenarios such as auditing, fraud investigation or financial reporting. This experiential learning experience provides students with an integrated perspective of theory and practice, ensuring that students master the necessary skills and are ready for industry practice. Virtual simulation is also equipped with advanced tools such as 3DMAX software and optimization algorithms, which are particularly suitable for future training, efficiency improvement and human-computer interaction. AI uses intelligent tutoring systems and learning analytics to achieve personalized and modular learning. ITS provides real-time feedback and customizes content according to individual needs, which is a powerful strategy to promote learning outcomes and scalability. Various methods, including Bayesian knowledge tracing for assessing student mastery, can be used to provide customized learning paths with targeted guidance. In all educational contexts and fields, research has explored the efficacy of AI in education, including computer programming for the Australian Accounting and Finance Association (ABSAC) and the financial field where AI provides guided tutoring, such as responding to learners' needs like a human, thereby stimulating learning engagement. The use of virtual simulation and AI is in line with the principles of experiential learning, which aims to create spaces that promote learning and equip students with the theoretical and practical skills to effectively cope with a changing world. It is noteworthy that, at least so far, students have a positive attitude towards their experience with virtual simulation and AI; they clearly feel that it has not only enhanced their practical skills, but also their employment prospects as individuals trying to view accounting and finance practices from a modern perspective. The trend towards AI reinforces the change in pedagogy.

2.1 Virtual Simulation Technology

The introduction of virtual simulation as a teaching aid in the evolving accounting education landscape is a paradigm shift towards applied and interactive learning. These simulation environments offer a virtual learning environment that enables students to learn and explore difficult accounting scenarios, including financial statement preparation, auditing, fraud investigation, budgeting, and cost control. The use of emerging technologies in accounting education is within the overall trend of computerization and increasing reliance on intelligent systems to improve learning outcomes and professional readiness. The importance of practice training was reiterated in Almahameed and Bisharah's [1] study, which aimed at rebuilding the accounting training system according to virtual simulation technology. This not only enabled the cultivation of basic accounting skills, but also aligned education practice with the changing needs of the industry. Specifically, the use of 3DMAX software and particle swarm Optimization (PSO) algorithm for scheduling practical training resources showed innovative methodology in optimizing the learning process and human-computer interaction. In PSO, solutions are adjusted iteratively according to the velocity update formula:

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot (p_i - x_i(t)) + c_2 \cdot r_2 \cdot (g - x_i(t)) \quad \textbf{(1)}$$

Where v_i is the velocity, x_i the position, p_i the individual best position, g the global best, and w, c_1, c_2 are weighting factors.

In forensic accounting education, the adoption of technologies such as data analytics AI, machine learning, and blockchain analysis is revolutionizing the teaching model. These technologies bridge the gap between academic education and industry practice, allowing students to gain practical experience in fraud detection and auditing [2]. This synergy enables students to handle complex financial investigations more efficiently and confidently. The influence of virtual reality (VR) has also extended from traditional classrooms to vocational training in industries. According to a study by Holuša [3], VR can be employed as a sustainable and effective training tool to quickly improve employees' work behavior and habits, and the model is also very promising in the continuous professional development of accounting education. Additionally, artificial intelligence in financial reporting has been gaining growing attention. Almasarwah [4] demonstrated that financial reporting systems based on artificial intelligence can lead to improved reporting quality, compliance, and firm performance, but concerns regarding algorithm transparency, data privacy, and exorbitant implementation costs remain of serious concern. The application of machine learning technology in detecting financial fraud is particularly important, with a specific focus on earnings manipulation detection. New composite models and simulation-based sampling approaches must be developed to handle unbalanced data sets and enhance the robustness of financial audit processes [5]. Briefly, the integration of virtual simulation, artificial intelligence, and other new technologies with accounting practice and education is a revolutionary development for the skill, efficiency, and ethical values of future accountants. Concisely, the literature shows that technology can facilitate experiential, interactive learning experiences in various ways, help students address real-world accounting issues, and advance the continuous development of the accounting sector.

2.2 AI in Modularized Teaching

AI is gaining recognition for its revolutionary power to transform education, particularly in shaping personalized and modular pedagogic architectures. Coupling intelligent tutoring systems (ITS) with learning analytics platforms propels this revolution towards meeting the needs for learning that is personalized based on individual learners' differences in needs, preferences, and learning trajectories. Analysis by Fletcher and Kulik [6] reveals that intelligent tutoring systems are getting as effective as human tutors, with AI potential to augment or replace traditional tutoring and provide scalable and accessible learning support. Lin [7] also mentioned in detail how AI and ITS can be used together, as they referred to the new paradigms supporting sustainable education such as enhancing interactivity and providing real-time feedback, which are essential components of personalized learning environments.

One foundational mechanism in AI-based adaptation is Bayesian Knowledge Tracing (BKT), often used in ITS to estimate a student's mastery of specific skills:

$$P(L_t) = P(L_{t-1}) + (1 - P(L_{t-1})) * P(T) \tag{2}$$

Where $P(L_t)$ is the probability that a student knows a skill at time t, $P(L_{t-1})$ is the previous knowledge state, and $P(T)$ is the probability of learning after one attempt.

Andriushchenko [8] provide a comprehensive overview of the impact of AI, depicting how such technologies not only improve the learning outcome but also revolutionize pedagogical methods, establishing the fact that AI is actually reshaping teaching in various learning settings.

Wang [9] also demonstrated the viability of AI in tailored learning experiences through experimentation with ITS in a live school setting by way of social experiment. Although their research reflected methodological shortcomings and a biased allocation of ITS research, it highlights the long-term incorporation and utilization of ITS across diverse school environments. Ayeni [10] also contributed by evaluating AI personalized learning systems in universities and determined that the age had little influence on learning in AI-infused courses. This suggests the need for research on determinants of effectiveness of AI-based learning systems. Barrera Barrera [11] examined the possibility of AI in fortifying drivers of personalized learning, casting some light on how AI can meet the needs of individual learners and contribute to educational achievement in the context of Education 4.0.

In the specific area of computer programming instruction, Frankford [12] proposed a revolutionary method by integrating GPT-3.5-Turbo as an artificial intelligence tutor for computer programming, showing the advantage of prompt feedback and scalability in personalized learning environments. Finally, Li [13] proposed a design framework for designing next-generation ITS based on large language models (LLMs), demonstrating an improvement in devising tutor-recommended problem-solving strategies in modular education systems. Collectively, these reports present a balanced insight into the status quo and prospects of AI in education, elaborating on how AI-driven platforms can be positioned at the center as part of modular learning through assessing student engagement and modifying content delivery to respond to students' individual needs.

2.3 Virtual Simulation Technology and Artificial Intelligence

The application of virtual simulation and smart learning technologies in accounting and finance teaching is a significant breakthrough in teaching practice. These technologies provide an interactive, experiential learning environment for teaching complex topics, engaging students in authentic situations that reflect professional problems. Burdon and Munro [14] recognize the pedagogic benefits of virtual simulation in financial and accounting instruction, noting its ability to balance theoretical concepts with practical applications, thereby improving students' understanding and readiness for real-world tasks. Similarly, Chen and Zhou [15] indicate the strengths of reinforcement learning approaches to financial teaching, which respond dynamically to student feedback and provide iterative opportunities for building proficiency and improving understanding. Students' perceptions of these technologies also influence their learning capacity. Grabińska [16] compared graduate students' and students' views on the role of new tools in finance classes and concluded that they were generally positive and recognized the relevance of technological proficiency to modern financial practice. Alshamsi [17] extends the research scope to analyze the systemic impact of generative technologies on the teaching of education and suggests that fields such as accounting and finance will be immensely benefited by an evolving digital method, especially by more modularized and personalized content delivery.

Though not precisely focused on automation or simulation, Janssen [18] favor an educational paradigm founded upon practical learning and experience. The practice-based pedagogy and modular course organization that they advocate fit well with the growing inclination of incorporating active technologies into accountancy courses. Overall, these studies indicate the shift in pedagogy in finance and accounting towards more interactive, student-centered learning environments characterized by greater conceptual clarity, greater engagement, and better alignment with professional demands.

3 Using MS Word

This research thoroughly evaluated the effectiveness of virtual simulations and artificial intelligence (AI) based personalized learning experiences on modular learning in accounting. This study employed an quasi-experimental design, 60 accounting students from vocational colleges were randomly assigned to a control group exposed to lectures or an experimental group taught though technology create modular learning. The intervention consisted of use of scenario based virtual simulations and personalized learning pathways based on the interaction with students). The study occurred over a 16 week semester length format and sought to measure knowledge gain, Knowledge retention, motivation, engagement, and overall satisfaction. Data collection utilized a combination of measures (i.e., pretest, post test and student engagement). A pre assessment and post assessment confirmed knowledge gain and learning retention. Student engagement was measured in the students LMS to count the number of logs into the course, the amount of time in the course and the number of times the student interacted with the learning tools and resources. The educational standardization was imposed through educational credit course assignments, culminating personal projects and transcriptions of students final grades. Essentially, each group of students would have equal opportunity to demonstrate similar accomplishments. Final we had constructed an anonymous survey to collect qualitative feedback questions regarding participants experiences, perceptions, and any challenges associated with the development and technology under study. Statistical analyses included Independent and paired t-tests. This was to substantiate the between groups equivalencies at baseline and to compare groups learning improvements both within and between groups. One-way ANOVA was used to further test for overall effectiveness of the experimental treatment. Correlation analysis was also performed to explore various relationships between the engagement metrics and academic outcomes. Final thematic coding was used to code the qualitative response data.

3.1 Design Experimental

Quasi-experimental design was used in this research to analyze the impact of incorporating virtual simulation technology and AI-based personalized learning modules in modular accounting education. The aim was to compare student academic performance, motivation, and learning satisfaction for these technology-supported learning interventions with typical teaching methods. 60 accounting students from vocational colleges were recruited for this study. To reduce selection bias and make the two groups comparable in their baseline characteristics, the students were allocated to either a control group (n = 30) or an experimental group (n = 30) by random assignment.

The control group used traditional lecture-style instruction, i.e., classroom lectures, readings from textbooks, and instructor discussions on accounting. The experimental group used a modular system of learning and deployed two technology-based interventions:

Virtual simulation modules: This module provides scenario-based simulations that engage students in real accounting activities such as financial statement preparation, internal auditing, and decision making under uncertainty. These modules try to offer a simulated, hands-on learning environment.

AI-powered personalized learning pathways: The AI system is used to analyze students' individualized learning and performance patterns. Based on the individual learning requirements of each student, the system provides personalized feed, adaptive quizzes, and tutoring content, thereby providing an individualized learning experience to fill students' learning gaps.

The entire experimental treatment lasted for one semester (16 weeks) and modular design enabled students to focus on learning specific accounting competencies such as financial analysis, auditing, and tax accounting. The design not only aimed at assessing students' knowledge acquisition and retention, but also assessing students' engagement and satisfaction with the technology intervention.

3.2 Data Collection

To evaluate the effectiveness of the experimental treatment, we used a strict data collection plan. We measured the control and experimental groups at multiple points in time during the study.

Pre-test and post-test measurement: Standardized tests of knowledge for key accounting concepts and applications were administered at the beginning (week 1) and end (week 16) of the course. Pre-test was used to determine knowledge baseline equivalence between the two groups of students, and post-test determined students' learning and retention of knowledge. Besides measuring knowledge, the post-test also measured how satisfied students were with the learning method and whether they perceived the effectiveness of virtual simulation and AI-intervention.

Engagement Metrics: Learner engagement was monitored regularly through the university's Learning Management System (LMS). Logged measures were the log-in frequency, time spent learning per module, interaction rate with virtual simulations, and AI-provided feedback event frequency viewed by each student. Such quantitative measures of engagement enable us to examine the intensity and frequency of student interaction with the learning tool and serve as an indicator of student active involvement with the learning content.

Performance Measures: Student academic performance was measured on the basis of a variety of quantitative measures, including post-test scores, assignment scores, project evaluations, and final course grades. The assignments and projects were evaluated using a standardized rubric in order to enable comparability and consistency across the control and experimental groups. The performance measures enabled a full analysis of student outcomes on a variety of dimensions of academic achievement.

Qualitative Feedback: In an attempt to gain deeper insight into the subjective experiences, perceptions, and attitudes of students toward the modular, technology-enabled learning model, students were urged to complete an anonymous survey at the end of the semester. The survey utilized open-ended questions on their learning experience, perceived strengths of the technology-based intervention, and challenges encountered in the course. The qualitative data provided rich insights into students' subjective experiences and attitudes toward the intervention.

3.3 Statistical Analysis

A set of statistical analyses were conducted to measure the quality of the technology-enhanced intervention and compare it with traditional instructional practices. The statistical methods employed were both correlational and inferential.

Baseline Comparability: Independent samples t-tests were conducted to assess whether there was a significant difference in the control and treatment groups for pre-test scores. This was necessary to confirm that the groups are equal prior to the initiation of the study and to exclude any pre-existing difference in academic content that would distort the intervention results.

Comparative Effectiveness: Paired t-tests were performed between each group in order to test pre-test and post-test scores in order to evaluate learning gain. This provided a method by which to quantitatively calculate the improvement in academic performance throughout the duration of the class. Independent samples t-tests and one-way analysis of variance (ANOVA) also compared the magnitude of improvement within the control group and experimental group. The experimental treatment (virtual simulations and AI) was set up to determine if it had any statistically significant impact on learning gain compared to instruction with traditional methods. Statistical significance criteria were $p < 0.05$.

Correlation with Engagement and Performance: Pearson correlation tests were conducted to analyze the correlation between student engagement metrics (e.g., interaction frequency with virtual simulation modules, frequency of AI feedback events accessed) and academic performance measures (e.g., post-test scores, final grade). The goal was to determine whether higher levels of engagement with the technology interventions were correlated with better academic performance.

3.4 Survey Design

Create a survey to collect student feedback on virtual simulation and AI-driven personalized learning modules. The following is a structured survey designed to collect students' subjective evaluation of this technology supported learning experience. The survey questionnaire design is shown in Table 1.

Table 1. Survey questionnaire design on the application of artificial intelligence and virtual simulation technology in the classroom

Question	Answer options
1. How helpful do you think virtual simulations and AI-driven personalized learning modules are to your learning? (Select one)	Very helpful Somewhat helpful Not helpful Not helpful at all
2. After using virtual simulations and AI-driven personalized learning paths, did you find it easier to understand more difficult course concepts? (Select one)	Yes No
3. Which aspects of the technology were most helpful in your learning? (Select all that apply)	Practical applicability of virtual simulations Timeliness of AI feedback AI-driven personalized learning paths Interaction with technology
4. Do you think these technologies helped you apply theoretical concepts to real-world scenarios? (Select one)	Yes No
5. How do you rate the timeliness and quality of AI feedback? (Select one)	Very timely and helpful Sometimes timely, but not very helpful Not timely and not helpful
6. How would you describe your experience interacting with the AI in the course? (Select one)	Very helpful for learning Somewhat helpful Not helpful at all I did not enjoy interacting with the AI
7. Which feature of the virtual simulation did you find most beneficial? (Select one)	Realism of the scenario Task and challenge setting Ability to repeat practice and receive feedback
8. Over the course of the semester, how often did you interact with the course content? (Select one)	Weekly Occasionally Rarely
9. Do you feel that the use of technology has increased your motivation to learn in this course? (Select one)	Yes No
10. After the course, are you interested in continuing to use similar technology-based learning tools? (Select one)	Very interested Interested Not interested

11. What challenges did you encounter while using the virtual simulation and AI learning paths? (Select all that apply)	Technical issues Unfamiliarity with technology Unable to learn at my own pace Additional issues: _____
12. Do you think you need more training or support to better use these technologies? (Select one)	Yes No
13. Are you satisfied with the use of virtual simulations and AI-driven learning interventions in this course? (Select one)	Very satisfied Satisfied Moderately Dissatisfied
14. At the end of the course, how much of an impact did you feel the virtual simulations and AI interventions had on your learning outcomes? (Select one)	Very helpful Somewhat helpful Not helpful Not helpful at all
15. What suggestions or feedback do you have for this technology-driven learning experience? (Open-ended)	
16. How do you think these technologies can be improved in future courses? (Open-ended)	

3.5 Data Validity Analysis

To demonstrate the validity and reliability of the data collected in this study, we implemented several protective designs in the data collection and analysis phase to allow for accurate measurement and encapsulate real learning outcomes. In the first instance, in the validity analysis of the pre-test and post-test, standardized knowledge tests were administered to both the control group and the experimental group at the start of the course (Week 1) and at the completion of the course (Week 16). We evaluated the students' learned knowledge, and the retention of knowledge, by evaluating the students' pre-tests and post-tests. After analysis, the validness of the pre- and post-test analysis was checked with a paired *t*-test to evaluate the learning from the control group to the experimental group; while independent sample *t*-tests were conducted in order to validate mean similarity in academic baseline for, Group 1 (control group) and Group 2 (experimental group) before conducting the experiment in order to reduce selection bias. The paired *t*-test formula is:

$$t = \frac{\overline{d}}{s_d / \sqrt{n}} \tag{3}$$

Where $\overline{d}$ is the mean of the differences between the pre-test and post-test scores, s_d is the standard deviation of the differences, n is the sample size. For baseline comparability, an independent sample *t*-test was used to compare the pre-test scores between the control group and the experimental group. The formula for the independent sample *t*-test is:

$$t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{4}$$

Where $\overline{X_1}$ and $\overline{X_2}$ are the mean pre-test scores of the experimental and control groups, respectively, s_1^2 and s_2^2 are the variances of the two groups, n_1 and n_2 are the sample sizes of the experimental and control groups.

Secondly, valid student engagement was assessed through logs from the Learning Management System (LMS) that tracked log-in frequency, time spent in each module, interactions within virtual simulations, and the frequency of AI feedback events. These quantitative engagement statistics were examined as a measure of student's active engagement with the course content in order to answer the research questions. To address the second research question related to the relationship between engagement and academic success, Pearson correlation analysis was applied. The formula for the Pearson correlation coefficient is:

$$r = \frac{n\sum xy - \sum x \sum y}{(n\sum x^2 - (\sum x)^2)(n\sum y^2 - (\sum y)^2)} \tag{5}$$

Where x represents engagement data, y represents academic performance data, n is the sample size.

The themes and patterns in students' experiences were examined for validity using thematic coding (a procedure in which answers to open-ended questions were categorized and coded). The coding was conducted reliably, as two independent researchers cross-validated the codes provided. Statistical validity of the results was assessed through paired t-tests, independent sample t-tests, and one-way analysis of variance (ANOVA), which allowed for the comparison of learning gains between the control and experimental groups. All tests were conducted at a significance level of $p < 0.05$ to ensure dependable results were obtained. The one-way ANOVA equation used was:

$$F = \frac{Between - group\,variance}{Within - group\,variance} = \frac{\frac{SS_{between}}{df_{between}}}{\frac{SS_{within}}{df_{within}}} \tag{6}$$

Where $SS_{between}$ is the sum of squares between groups, SS_{within} is the sum of squares within groups, $df_{between}$ and df_{within} are the degrees of freedom between and within groups, respectively [19].

4 Results and Discussion

This section will provide an in-depth analysis of the impact of virtual simulation and AI-driven personalized learning modules on accounting education outcomes. The experimental group showed an average improvement in post-test scores compared to the control group (traditional teaching). Statistical analysis based on pre-tests and post-tests further confirmed these results, indicating that active and adaptive learning environments can effectively enhance knowledge retention and concept learning. Data on student engagement in course interaction showed that the experimental group actively engaged with the course materials every week of the course compared to the control group. The experimental group's engagement peaked at the beginning of each assessment period, and since no further assessment periods were set, engagement was higher throughout the course. The frequency of engagement was significantly positively correlated with academic performance. Students in both the experimental and control groups indicated that they performed better when they were actively engaged in learning than when they were not. Qualitative feedback from students also showed that they believed that the simulation was relevant to real work, that AI feedback was timely, and that interacting with AI was conducive to improving interactivity.

4.1 Knowledge Gains and Engagement Outcomes

Fig. 1 shows a chart of comparison of post-test and pre-test results of experimental and control groups, where it is clear how virtual simulation technology and AI-based customized learning modules affected accounting education. The mean pre-test score at the beginning of the semester for both groups was 65.0%, setting a fair starting point and ensuring that random assignment strategy was effective in achieving comparability between the two groups. This comparability is crucial to the internal validity of the study because it results in post-test differences that are reflective of the intervention rather than of differences that may have already existed.

After the 16-week learning period, the control group (instructed with only traditional lecture-mode teaching), however, showed a slight increase, their post-test mean being 72.0%. This 7% gain, while statistically significant within the sample, shows minimal change created by passive, instructor-controlled classrooms. On the other hand, the experimental group, which employed a modular course supplemented with virtual simulation modules and AI-based personalized learning paths, managed to achieve a high mean post-test score of 87.0%, a 22% improvement. Inferential statistical tests such as independent sample t-tests and analysis of variance showed that this was a statistically significant 15 percentage points higher than the control group ($p < 0.05$).

In addition, the experimental group's high posttest score also indicates that technology-based instruction can successfully apply complex accounting scenarios into practice and bridge the gap between theoretical teaching and real practice. The modular structure of the content, coupled with the adaptive facilitation of the AI system, enables students to learn at their own pace, revisit challenging concepts, and receive personalized feedback [20]. All these advantages do not take place in the control group. In conclusion, these findings validate the merit of incorporating advanced digital tools into university instruction, especially in applied subjects such as accounting, where contextual learning and critical thinking are particularly essential.

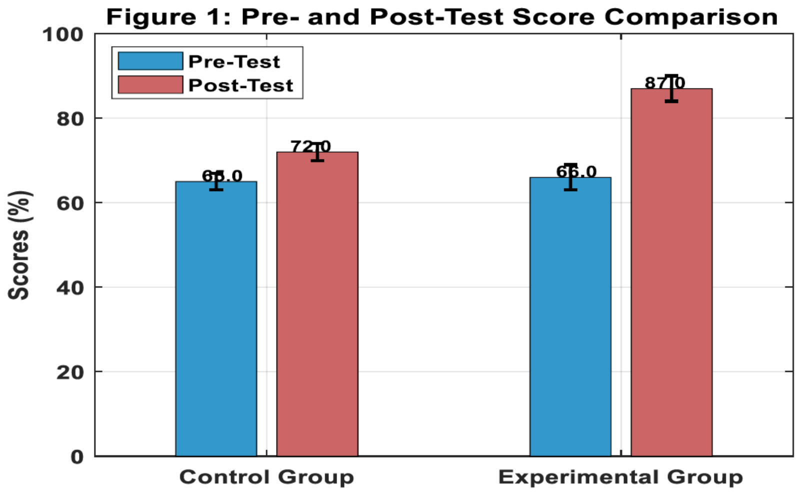

Fig. 1. Pre- and Post-test score comparison

Fig. 2 shows the weekly engagement frequency of students in the experimental and control groups over the 16-week semester, providing a temporal view of students' interactions with course content and technology. Engagement frequency refers to measurable interactions with course elements, such as accessing virtual simulations, receiving AI-generated feedback, and engaging in adaptive learning modules.

From the beginning, the experimental group's engagement was consistently higher than the control group's. The experimental group's engagement rose steadily from an average engagement frequency of 5 times in week 1 to a peak of 10 times in week 16. The plotted data show a steady upward trend with slight fluctuations in between, indicating that students' engagement with the technology-enhanced learning environment was sustained and gradually deepened. Notably, several peaks in engagement, especially around weeks 6, 9, and 13, may correspond to assessments or simulation-based assignments, indicating that students in the experimental group actively responded to course requirements and actively used the tools provided for preparation and practice.

In contrast, the control group's engagement frequency was low at the beginning (around 3) and rose only slightly throughout the semester. Although slight increases were observed around weeks 6 and 10, they were still small and lacked consistency. The overall trend for the control group was relatively flat, suggesting a more passive or less interactive learning experience, which may reflect the traditional lecture-based teaching model.

In addition, the relatively flat and continuous upward curve for the experimental group suggests that the modular structure, combined with adaptive feedback, can foster sustained learning motivation and self-directed learning habits. Students can relearn challenging modules and engage in learning at their own pace, thereby maintaining motivation throughout the course. In contrast, the control group's engagement performance was inconsistent and less pronounced, which may reflect the limitations of static content delivery and the lack of interactive stimulation. The engagement data shown in Fig. 2 provide compelling evidence that virtual simulations and AI-driven personalization can not only improve academic performance, but also create a more proactive and self-directed learning environment. These technologies promote continuous interaction, which is critical to the successful implementation of modular learning in accounting and similar application-driven disciplines.

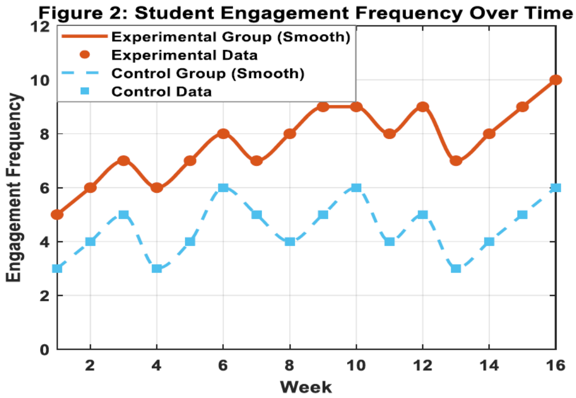

Fig. 2. Student engagement frequency over time

Fig. 3 is a scatter plot with a regression line that illustrates the correlation between student engagement frequency and academic performance scores. Each point on the scatter plot shows a student's total engagement, as measured by frequency of interaction with virtual simulations and AI feedback events, against their respective academic performance, as measured by scores on posttests, assignments, and project grading.

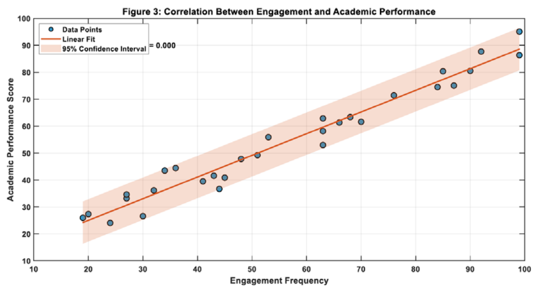

Fig. 3. Correlation between engagement and academic performance

The regression analysis indicated a positive linear relationship between academic performance and engagement with a Pearson correlation coefficient of $r = 0.68$, indicating a moderately strong relationship between academic performance and engagement. The p-value associated (< 0.01) confirmed that the relationship was statistically significant, where the null hypothesis was rejected and it was evident that the relationship was not by chance.

The scatter plot hugs the linear trend line closely, especially in the middle and upper levels of engagement, which further contributes to the strength of the correlation. The gray zone around the line is the 95% confidence interval, which is very narrow, especially in the middle range of the data, indicating that the prediction model is extremely accurate and has minimal variability. As the rate of interaction increased, corresponding academic achievement scores also rose consistently, with the most interactive students (over 90%) scoring near or over 90%.

This finding has instructional significance. It suggests that engagement is not simply a behavioral indicator but a chief determinant of academic success in technology-enhanced learning environments. Active involvement in personalized content, formative assessment, and real-time feedback mechanisms appears to increase cognitive engagement, motivation, and subject matter mastery [21].

Moreover, this correlation is consistent with self-regulated learning theory, which emphasizes active involvement, metacognitive monitoring, and iterative feedback as catalysts for academic success. The results also confirm previous research that adaptive education systems can improve learning outcomes by providing content tailored to individual needs and facilitating timely student engagement.

4.2 Figures and Photographs

Fig. 4 shows student responses to the three features of the virtual simulation modules: interactivity, AI feedback, and applicability to the real world. Most (58.7%) ranked real-world applicability first, reflecting the importance of relating learning to practice. 38.7% selected AI feedback, commenting on the value of timely, targeted feedback in facilitating understanding. Only 19.9% mentioned interactivity, suggesting it was less effective or could be better done. These results accord with the broad overall level of student satisfaction (circa 85%) among the experimental group and reflect original content and receptive AI as significant drivers of top-quality learning experience.

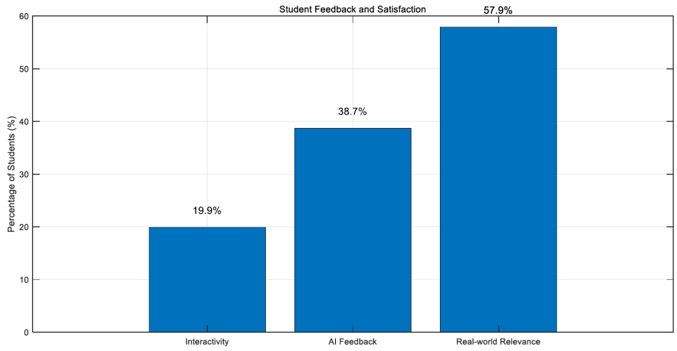

Fig. 4. Student feedback and satisfaction

Many students reported that the ability to receive instant, personalized feedback from the AI system helped clarify complex accounting concepts and improved their overall learning efficiency.

Fig. 5 presents students' needs for support and training participation in the AI-supported learning process. While 48.8% of the students indicated a need for support, largely due to the initial issue of adapting to the personalized, independent nature of the AI learning system, the percentage of students who participated in training increased significantly to 75.9%. This reflects that while issues exist, most students have an active interest in pursuing resources to address them. The findings show that while instant AI feedback can effectively facilitate learning, its potential can only be optimally harnessed alongside an effective support system and proper learner orientation.

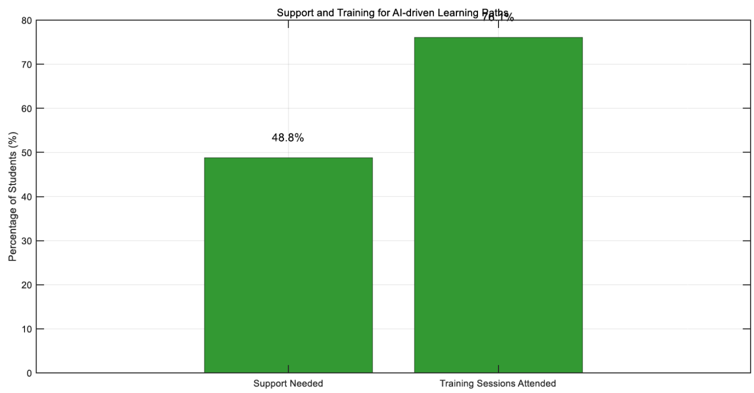

Fig. 5. Support and training for AI-driven learning paths

4.3 Broader Implications

Fig. 6 is a radar chart illustrating students' perceived impacts of learning through AI-facilitated virtual simulations in accounting education. The radar chart highlights three notable outcomes: improved cognitive involvement (19.9%), improved academic performance (38.7%), and other impacts like increased confidence or independent learning (67.9%). Among those, the most significant perceived benefit fell under "other im-pacts," whereby aside from measurable educational gains, students valued broader learning effects like motivation, self-confidence, and autonomy. Improved learning performance was also a significant result, affirming that AI simulations can enhance understanding and application of sophisticated accounting concepts. Cognitive engagement, while the least cited, nevertheless reflects a substantial percentage of the cohort recognizing increased mental engagement in the learning process. These findings agree with current literature in that technology-enhanced learning environments have the potential to provide more productive learning. In addition, the integration of modular course design with adaptive AI systems is a non-constraining, personalized solution in that it can provide for varying learning rates and learning strategies. But effective adoption depends on adequate technology infrastructure, and on training teachers not just in using the systems but also in instructional planning to maximize the best of modular and personalized learning. The chart underlines that although academic and intellectual achievement is most important, students value highly personal development and engagement, too, which must be factored into future course development and evaluation.

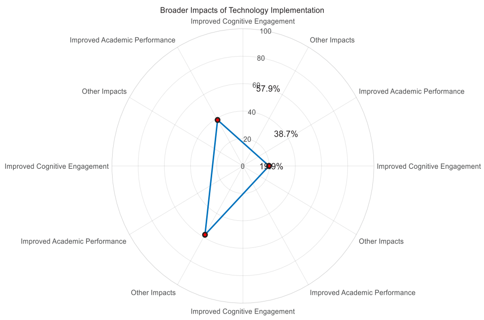

Fig. 6. Broader impacts of technology implementation

5 Curriculum Framework Design for Virtual Simulation and Artificial Intelligence

Based on the above analysis conclusions, virtual simulation platforms and artificial intelligence assisted solutions are introduced into accounting courses in vocational colleges. This article only explores the overall framework design scheme and provides implementation methods [22]. The overall structure of the framework is shown in Fig. 7.

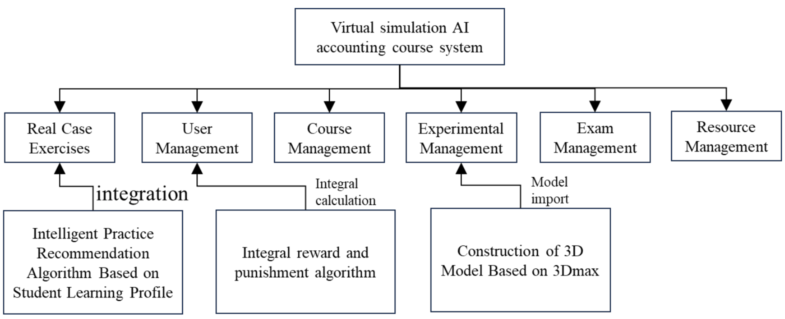

Fig. 7. System architecture design

The virtual simulation teaching platform adopts the B/S architecture and mainly implements the following functions:

1) Cross platform access enables access to virtual simulation teaching platforms such as personal computers, tablets, and mobile phones without the need to install additional client software.

2) Simplify deployment and updates, the virtual simulation teaching platform concentrates the main business logic and data processing on the server side, and the client browser only needs to be responsible for display and interaction.

3) Unified user interface, through the B/S architecture, the platform can provide a unified user interface to ensure that users have a consistent experience on different devices.

4) Flexible system expansion and maintenance, the B/S architecture makes the server-side of the platform the core, which can flexibly expand and adjust the system's capacity and performance to meet the needs of user growth and functional expansion. At the same time, system maintenance is also more convenient, and patch updates, security upgrades, and other operations can be performed through the server-side.

The system architecture diagram is shown in Fig. 8.

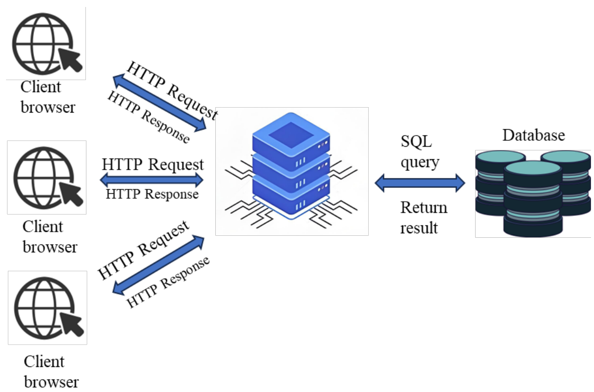

Fig. 8. System architecture diagram

In the system, based on the use of virtual platforms by students, analyze their learning status, obtain a portrait of their current learning content through a model, and then provide targeted examples of financial case exercises in the classroom.

Firstly, students are classified and processed to distinguish their learning level and ability. The learning characteristics of students are labeled, and the processing results are shown in Table 2.

Table 2. Learner profile

Index	Calculation method	Value range	Data type
Learner activity level	The ratio of active days to registration days	$[0,1]$	Float
Quality requirements for learners' courses	Average quality of courses selected by learners	$[0,1]$	Float
Learner's knowledge level	Mean score of learners' practice	$[0,1]$	Float
Learner effort level	The proportion of learners who relearn	$[0,1]$	Float

Based on the learner profile obtained by a single student user, automatically extract exercises of corresponding difficulty. For an exercise, the lower the average score, the longer the exercise time, and the more people participate in the exercise, the greater the difficulty level of the exercise. Therefore, this article selects the following features to model the difficulty level of course exercises, and uses the *K*-Means clustering algorithm to cluster these four features [22]. The clustering feature names are shown in Table 3.

Table 3. Classification of difficulty characteristics of practice questions

Feature name	Feature description	Feature values
Challenge_time_taken	Average practice duration	Non-negative real numbers
Challenge_ score	Average practice score	Non-negative real numbers
Chalenge_retake_user_ratio	Proportion of learners attempting to practice again	$[0,1]$
Answer_open_user_ratio	Proportion of learners viewing answers	$[0,1]$

Based on students' learning situation and the difficulty level of practice questions, this article uses the relational matrix recommendation algorithm to recommend practice questions [23]. The schematic diagram of the algorithm model is shown in Fig. 9.

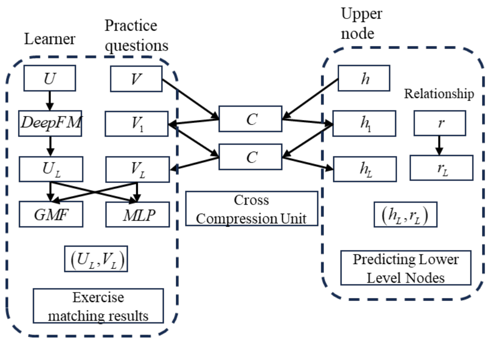

Fig. 9. Recommended algorithm framework

6 Conclusion

This study provides empirical evidence supporting the integration of virtual simulation technology and AI-driven personalization into modularized accounting and finance education. Through a controlled experimental design, it was demonstrated that students exposed to technology-enhanced modular learning environments achieved significantly higher academic performance, exhibited greater engagement, and reported higher levels of learning satisfaction compared to those in traditional lecture-based settings. The incorporation of virtual simulations allowed students to immerse themselves in realistic accounting scenarios, fostering practical skill development, while AI-driven learning paths enabled dynamic adaptation to individual student needs, promoting deeper knowledge retention and learner autonomy.

The findings of this research contribute to the growing body of literature advocating for the modernization of accounting education in response to emerging productive forces. By aligning pedagogical strategies with technological advancements, this study underscores the transformative potential of modular, technology-enhanced learning frameworks in cultivating more competent, adaptable, and future-ready accounting professionals. Moreover, the study identifies critical technological and pedagogical challenges that must be addressed to maximize the benefits of these innovations, emphasizing the necessity of robust infrastructure, faculty training, and curricular redesign.

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