An AI-Empowered Teaching Framework for Accounting Simulation Practice: Design and Implementation Based on Role-Based Collaborative Learning

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Abstract. While artificial intelligence increasingly permeates accounting work, research on integrating AI into accounting education has centered on lecture-format courses, with simulation-based experimental courses receiving far less scrutiny. This paper addresses that imbalance by proposing a teaching framework designed specifically for role-based accounting simulation practice. The framework employs a dual-layer structure: a learning layer in which students rotate through four accounting positions over a 32-hour intensive course, and an AI assistance layer deploying three agent types−Auditor, Analyst, and Mentor−at two strategically chosen intervention points. A design-based research methodology underpins the work. Three design principles−informed by learning theory and refined through the design process−govern the framework: matching AI sophistication to role seniority, requiring independent task completion before AI engagement, and positioning AI feedback at natural task boundaries. Two cases are detailed: an intelligent voucher auditing module in which students must detect deliberately embedded false positives in AI-generated audit reports, and a financial analysis module in which students identify omissions in AI-produced assessments before constructing their own. The framework contributes a replicable design for integrating AI into experiential accounting education while preserving the hands-on character that defines simulation-based learning.

Keywords: AI-Empowered Education, Accounting Simulation Practice, Experimental Teaching Framework

1 Introduction

Artificial intelligence, robotic process automation, and big data analytics are reshaping the accounting profession [1]. Large accounting firms now deploy AI systems for automated data entry, financial forecasting, and audit risk assessment—changes that redefine what competencies new accountants need [2]. For accounting educators, the question is no longer whether AI will affect the profession, but how to equip students to work alongside and critically assess AI tools in daily practice.

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Simulation-based teaching has accumulated a substantial evidence base in accounting education, letting students experience the rhythm and pressure of professional accounting work before entering the workplace[3]. In Chinese universities, Accounting Simulation Practice is typically structured around role rotation: students cycle through four position groups—cashier and AP/AR accountant, asset/cost and operating/profit accountant, tax and general ledger accountant, and accounting supervisor—on an integrated platform such as First. Each role handles a segment of the document trail for a simulated manufacturing business, and together the class produces a complete set of books and statements.

This format, for all its strengths, has clear pain points. The most fundamental is a feedback bottleneck. A single instructor overseeing 40-50 students who together generate several hundred vouchers, dozens of ledgers, and a full set of financial statements within 32 contact hours cannot provide individualized diagnostic commentary at the depth the task requires [3][6]. Students tend to master procedural mechanics—voucher entry, ledger posting while remaining underprepared for higher-order tasks such as financial interpretation and risk assessment[5]. Manual error checking in vouchers and reconciliations is slow and incomplete [4]. Engagement in simulation sessions is often perfunctory. Since procedural completion of the required document flows is sufficient to pass course assessments, students have limited incentive to invest in deeper inquiry. When effort is directed at step completion rather than the formation of professional judgment, participation remains at the surface level, and the higher-order competencies that simulation-based training is intended to develop go largely unrealized. Furthermore, students who train entirely in AI-free simulations enter workplaces where algorithmic tools are embedded in standard workflows, creating a mismatch between educational experience and employment reality [14].

Beyond these pedagogical challenges, day-to-day simulation teaching reveals additional practical difficulties. Feedback typically arrives hours or days after task completion, when its formative value has diminished; students repeat errors without realizing them. Platform-level validation checks basic requirements such as debit-credit balance but cannot detect substantive accounting errors, creating a false sense of mastery. As students gain access to general-purpose AI tools, some submit AI-generated work without verification, undermining the core purpose of hands-on training. These practical constraints motivate a framework that embeds AI to provide timely, contextual feedback at scale while simultaneously requiring students to question and supplement AI-generated content.

Generative AI and large language models (LLMs) offer ways to address these gaps through real-time error flagging, on-demand analytical support, and simulated professional judgment scenarios [7]. Researchers have explored AI-augmented accounting teaching across multiple fronts, from multi-tool teaching platforms [8] and curriculum intelligentization [9] to simulation-based and gamified approaches. However, the literature lacks a design framework purpose-built for role-based simulation—one that maps AI interventions onto specific positions, specifies interaction designs, and ensures AI strengthens rather than weakens experiential learning [10].

2 Methodology

This study employs a design-based research (DBR) methodology [11], suited to complex educational interventions where controlled experiments are impractical at the design stage. The design process followed Lehtonen's [12] framework, which requires simultaneous attention to four dimensions: content (accounting standards, auditing procedures, financial analysis methods), pedagogy (role-based collaborative learning, feedback design, scaffolding), practice (voucher processing, tax calculation, statement preparation), and technology (simulation platform, LLM-based agents, prompt construction). Attending to all four dimensions prevents the common pattern of letting technological capabilities drive pedagogical decisions. This paper reports the first DBR phase analysis, design, and framework development. Classroom implementation and iterative refinement based on empirical evidence constitute the planned next phases.

3 Framework Design

3.1 Design Principles

Three principles govern the framework, each grounded in established learning theory and refined through the design process. Their theoretical foundations draw on situated learning, cognitive apprenticeship, and feedback intervention theory [6].

P1: Role-Based Progressive Integration. The sophistication of AI support rises with the responsibility level of each position. Students in the cashier role encounter AI primarily as a reference tool (AI Mentor); those in the accounting supervisor role engage the AI Analyst, which requires them to evaluate, critique, and supplement machine-generated financial analyses. This arrangement mirrors the cognitive apprenticeship trajectory and reflects the professional reality that junior accountants use AI for efficiency while senior accountants direct and evaluate AI outputs.

P2: Augmentation Over Replacement. Students complete each task independently before any AI tool is introduced. AI agents flag issues, suggest alternatives, and raise questions; they never execute tasks for students. If a student learns that the AI will catch and fix voucher errors, the incentive to develop careful checking habits weakens. The framework treats AI as an intelligent colleague whose outputs require professional scrutiny, not as an automated corrector.

P3: Timely and Contextual Feedback. AI interventions are placed at natural task completion boundaries, where feedback can inform the next block of work rather than arriving after the fact. Feedback is contextualized to the student's current role, the specific transaction data, and the applicable accounting standards.

3.2 Dual-Layer Architecture

Students rotate through four positions over four consecutive days (32 contact hours), as shown in Table 1.

Table 1. Course Structure and Role Rotation

Period	Day	Hours	Role	Key Tasks	AI Support
I	1	4	Cashier & AP/AR Accountant	Cash receipts/payments; supplier and customer transactions	AI Mentor
II	2	4	Asset/Cost Accountant & Operating/Profit Accountant	Fixed asset depreciation, cost allocation; revenue recognition, profit calculation	AI Auditor at IP1
III	3	12	Tax Accountant & General Ledger Accountant	VAT calculation, tax returns; journal summarization, trial balance	AI Mentor
IV	4	12	Accounting Supervisor & Comprehensive Review	Financial statements, financial analysis; full-cycle review	AI Analyst at IP2

The rotation follows the natural accounting document flow: transactions recorded by the cashier feed into the operating accountant's voucher work, which informs the cost accountant's allocations and tax calculations, culminating in the accounting supervisor's review and financial reporting.

The AI assistance layer comprises three agent types. AI Auditor reviews voucher entries against Chinese Accounting Standards (CAS), checking account classification, amounts, element completeness, and unusual patterns. It produces a structured report identifying each issue with a severity rating and CAS reference, but never auto-corrects entries. AI Analyst performs horizontal and vertical financial statement analysis, computes key ratios, benchmarks against manufacturing industry data, flags risk indicators, and generates a preliminary assessment. Certain analyses are deliberately withheld—segment profitability, cash flow quality—to create space where students must generate their own insights. AI Mentor provides on-demand explanations of concepts, step-by-step platform guidance, and CAS references throughout the course. The three agents can be deployed on LLM-based platforms such as Claude or Deepseek, or through structured prompting with general-purpose models.

Two intervention points are defined. IP1: Post-Entry Voucher Verification (end of Day 2). Voucher preparation carries the highest error rate of any simulation activity, and errors propagate through all subsequent processes. The AI Auditor reviews each student's complete voucher set at this checkpoint, delivering individual-level diagnostic feedback at a scale no instructor can match. IP2: Financial Data Analysis (Day 4). The AI Analyst introduces automated analysis that students must verify and supplement, building the habit of treating AI output as input to professional judgment rather than finished work.

4 Implementation

The framework was developed for the Accounting Simulation Practice course (32 hours, 2 credits, approximately 40–50 students per section) at Guangzhou City University of Technology, using the First platform which simulates a medium-sized manufacturing enterprise with roughly 50–150 transactions over one compressed fiscal year.

The platform handles voucher processing, ledger maintenance, tax calculation, and financial statement preparation with basic system-level validation but no intelligent contextual feedback functions the AI agents supplement.

4.1 Case 1: Intelligent Voucher Auditing

This case operates at IP1, targeting the operating accountant role on Day 2. Learning objectives are correctly preparing vouchers for revenue, expense, and period-end adjustment transactions; recognizing common voucher errors; and critically evaluating AI-generated audit findings.

The case unfolds in four phases. In the first phase (approximately three hours), students independently process 25 – 35 transactions covering product sales, service revenue, raw material purchases, manufacturing overhead distribution, and period-end accruals—all without AI assistance, to establish baseline procedural competence. In the second phase, students submit their voucher set to the AI Auditor, which examines each entry against a knowledge base including CAS standards, the standard chart of accounts, and a library of common student error patterns. The output specifies voucher number, issue type, severity rating, applicable CAS provision, and suggested correction; processing a full batch takes 30 – 60 seconds per student. In the third phase, students work through the audit report, correct confirmed errors, consult the AI Mentor for uncertain items, and document disputed findings with accounting rationale, followed by a short reflection.

The fourth phase is a critical evaluation exercise. The AI Auditor is configured to produce two or three false positives in each batch—findings where a correct entry is flagged as erroneous, generated through prompt variations causing overly strict standards interpretation, missed contextual business logic, or rejection of acceptable alternative accounting treatments [13]. Students know some findings may be wrong but not which ones; they must identify suspected false positives, justify their determinations with CAS references, and propose how the AI's prompting could be improved. This develops critical AI evaluation skills essential for modern accounting practice [14].

4.2 Case 2: Financial Analysis and Risk Early Warning

This case operates at IP2, targeting the accounting supervisor role on Day 4. Learning objectives are preparing a complete set of financial statements from an adjusted trial balance; computing and interpreting financial ratios across liquidity, solvency, profitability, and efficiency categories; identifying risk indicators and assessing their severity; and producing an integrated analysis combining AI-generated and independently developed insights.

The first phase (approximately 2.5 hours) requires students to prepare the income statement, balance sheet, and cash flow statement from the adjusted trial balance accumulated over Days 1 – 3, applying CAS presentation formats and ensuring cross-statement consistency. During the second phase, students submit their statements to the AI

Analyst. The agent returns a multi-section report covering horizontal and vertical analysis, 18 financial ratios with industry benchmark comparisons, a risk dashboard flagging indicators that have crossed warning thresholds, and a narrative risk assessment. The report carries an explicit section titled "Analyses Not Performed," listing segment profitability, cash flow quality, and forward-looking projections—analyses the AI deliberately omits to signal where independent student work must begin.

The third phase is a structured collaborative analysis: students verify accuracy by recomputing a random sample of ratios, search for insights the AI did not capture, assess whether risk ratings are appropriate, and produce a final report integrating verified AI findings with independently identified insights. A required subsection, "What the AI Missed," ensures every student develops their own analytical observations. In the final phase, student teams receive a risk scenario—major customer default, key supplier price shock, regulatory change requiring capital expenditure, or foreign exchange movement—and use the AI Analyst to model the financial impact. The AI can project how the scenario would affect ratios and cash flows but cannot weigh strategic trade-offs or anticipate second-order effects; teams must assess what the AI overlooks, develop a response strategy, and write a concise risk response memo.

5 Discussion

5.1 Design Rationale and Implementation

Each design choice in the framework corresponds to a specific problem identified at the outset. The AI Auditor at IP1 addresses the feedback-volume bottleneck: it processes each student's voucher set in under a minute, delivering diagnostic commentary at a granularity no instructor can sustain across an entire class. This arrangement directly applies Hattie and Timperley's [6] central finding that feedback timing is as consequential as feedback content.

The student-AI collaborative analysis in Case 2 splits the analytical work: the AI handles computation, ratio derivation, and benchmark lookup; the student handles verification, gap identification, and risk interpretation. Case 1's exercise pushes this dynamic further by embedding deliberate errors in AI output as training material. Students learn that even a well-configured audit agent can be wrong in systematic ways and practice arguing against AI findings using accounting standards. Bakarich and O'Brien [14] flagged this evaluative orientation toward AI as underdeveloped in current graduates the framework builds it in from the start. The role-progressive design means a student experiences two different relationships with AI within a single four-day course: as a junior accountant relying on AI for accuracy checks, and as a supervisor interrogating AI-generated analysis before signing off.

The AI intervention logic is platform-independent: agents process structured accounting data that any simulation platform produces. Implementation options span from full agent-based deployment on Claude or Deepseek with API integration to structured prompting through general-purpose LLM web interfaces for resource-constrained settings.

5.2 Limitations

The baseline AI literacy assumption remains a structural limitation rooted in differences across Chinese higher education that no course-level intervention can resolve. Three dimensions of institutional stratification are directly relevant. First, infrastructure: institutions range from Double First-Class universities with dedicated computing resources to provincial and vocational colleges dependent on shared public services with intermittent access. Second, faculty AI literacy: a spectrum from instructors already integrating LLMs into research and teaching to those for whom AI remains unfamiliar as a professional tool. Third, student digital readiness: cohorts vary from those routinely interacting with AI applications to those encountering LLMs for the first time in this course. These gradients covary with institutional resource endowments and regional economic contexts.

These gradients carry direct implications for implementation. At well-resourced institutions, the primary adaptation task is pedagogical rather than technical: integrating AI assistance without eroding the independent skill development that the framework's augmentation principle is designed to protect. At resource-constrained institutions, the more immediate bottleneck is faculty AI literacy; institutional partnerships, shared AI teaching resources across campuses, or inter-institutional training consortia may offer interim pathways that individual institutions cannot establish alone. These are pragmatic responses to structural conditions, not remedies for the underlying literacy gap which remains a limitation the framework acknowledges but cannot itself resolve. Future research should empirically examine which adaptation measures prove effective at different positions along the institutional spectrum, and develop AI-augmented tools calibrated to the baseline literacy levels of the settings in which they are most needed.

6 Conclusion

This paper proposed an AI-empowered teaching framework for accounting simulation practice, responding to the gap between traditional role-based pedagogy and an AI-integrated professional environment. The dual-layer architecture keeps hands-on simulation intact while adding AI assistance at the workflow points where it delivers the clearest pedagogical value.

Three contributions distinguish this work. First, the framework provides implementation detail at the task-and-timing level—which AI agent, at which moment, with which interaction design—rather than course-level generalities. Second, the augmentation-over-replacement principle, operationalized through requiring independent task completion before AI engagement, offers a specific answer to the widely acknowledged tension of introducing powerful AI tools into a course whose purpose is developing human professional competence. Third, the deliberate use of AI limitations—false positives requiring detection, intentional analytical omissions requiring completion—treats AI's imperfections as pedagogical assets rather than problems to be eliminated.

Future work should proceed along three lines: quasi-experimental classroom studies measuring the framework's effect on procedural accuracy, analytical quality, and AI evaluation skills; development of additional integration points for tax compliance and internal control assessment; and exploration of adaptive agents that adjust support based on individual student performance patterns. As AI becomes embedded in accounting workflows, the relevant question for educators is not whether to integrate AI into simulation courses, but how to produce graduates who can direct AI tools with professional judgment rather than defer to them uncritically.

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