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Human-AI Collaboration Perspective on Generative AI-Enabled Teaching Reform of Digital Finance Courses in Higher Vocational Education

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Abstract: The rapid iteration of generative AI technologies, represented by DeepSeek and ChatGPT, has injected new momentum into the digital transformation of higher vocational education. Current digital finance courses in higher vocational colleges commonly suffer from three problems: insufficient AI literacy among teachers, prominent learning aversion among students, and curriculum content iteration lagging behind industry development. Based on the human-AI collaboration theory, this paper analyzes the impact of generative AI on the entire process of lesson preparation, classroom teaching, learning, and evaluation, and proposes a three-tier "foundation-core-extension" curriculum restructuring plan along with a "pilot-optimize-promote" implementation strategy. The research aligns with the actual cultivation of intelligent accounting talents in higher vocational colleges and provides a replicable practical path for integrating AI into digital finance courses.

Keywords: Generative AI; Human-AI collaboration; Higher vocational education; Digital finance courses; Teaching reform; Integration path.

1. Introduction

1.1. Research Background

Since 2023, generative artificial intelligence technology has experienced explosive iteration, gradually upgrading from a common assistive tool to a collaborative partner in education. In recent years, the big data and accounting major in higher vocational colleges has accelerated its digital transformation, successively offering core courses such as Python Application in Finance, SQL Data Processing, and RPA Financial Robot, focusing on cultivating students' ability to apply programming tools and analyze financial data. With rapid technological updates, traditional teaching models can no longer meet the needs of new curriculum reform, and teaching pain points are becoming increasingly prominent.

1.2. Research Questions

Digital finance courses in higher vocational colleges exhibit three prominent shortcomings in teaching practice: First, teachers generally lack a background in digital technology and have shallow application of generative AI tools, with insufficient core competencies such as prompt design, resulting in low integration of AI into teaching. Second, students have no programming foundation, are prone to frustration in hands-on coding, and commonly experience learning aversion and burnout. Third, the curriculum content update pace is slow, disconnected from new models of enterprise intelligent finance empowered by generative AI, causing teaching content to lag behind industry development.

Based on these practical pain points, this paper focuses on two major questions: First, the mechanism by which generative AI affects the entire teaching process of digital finance courses. Second, from a human-AI collaboration perspective, the construction of an AI curriculum integration path suitable for higher vocational student profiles.

1.3. Research Significance

Theoretically, this paper clarifies the internal logic of generative AI empowering higher vocational finance and accounting courses, enriching the application scenarios of human-AI collaboration teaching theory in vocational education. Practically, based on actual teaching conditions, it designs a feasible and scalable reform path, providing practical references for AI-enabled reform of digital courses in higher vocational colleges and supporting the digital transformation of vocational education.

1.4. Core Concepts

Generative AI refers to intelligent systems based on deep learning large models, represented by DeepSeek and ChatGPT, capable of natural language interaction, code generation and correction, and personalized question answering. Human-AI collaboration refers to the joint improvement of teaching effectiveness through the division of labor and cooperation among teachers, students, and AI. Within this framework, AI undertakes routine tasks such as basic question answering, code correction, and case generation; teachers focus on instructional design, cognitive guidance, and emotional motivation; and students leverage AI for personalized learning and independent inquiry. This study conducts its analysis based on this framework.

2. Literature Review

Current domestic research on digital finance courses and generative AI can be divided into three categories.

The first category comprises traditional teaching reform studies on digital finance courses. Zhang Tongli (2025) focused on Python training for accounting majors in the context of big data, analyzing existing problems and proposing reform strategies. Wang Jiahui (2024) explored teaching reform paths for Python courses in the big data and accounting major. Wang Xian (2024) investigated teaching reform of the financial big data basics course centered on Python. These studies all revolve around traditional digital technologies, focusing on training design and teaching method optimization for Python and SQL courses, but do not address the integration and application of new generative AI technologies, revealing a limitation in research perspective.

The second category involves macro-level studies on generative AI in education. Cai Rong and Mei Peijun (2025), based on human-AI collaboration logic, explored strategies for AI-enabled teacher lesson preparation, with the research context concentrated in K-12 education. Wang Xia (2025) analyzed the principles and innovative directions of higher vocational accounting teaching reform from the perspective of generative AI at a macro level, grounded in overall talent cultivation for the major, but did not delve into specific digital finance courses such as Python and RPA, lacking a feasible path design.

The third category comprises preliminary explorations of generative AI application in finance and accounting teaching. Scholars such as Wang Yueyun and Wen Jianping (2024) explored application scenarios of generative large language models in finance and accounting teaching, proposing application methods such as prompt optimization, multi-turn questioning, and exercise generation. However, these remain at the level of scenario trials, lacking a systematic curriculum integration plan, and failing to resolve the core contradiction between rapid technological iteration and lagging curriculum development.

In summary, current research has the following gaps. On one hand, research on digital finance courses remains confined to traditional technology application paradigms. On the other hand, research on generative AI applications in education lacks the specific context of digital finance courses in higher vocational colleges, and is even more deficient in systematic integration path research centered on "human-AI collaboration" using specific courses as a vehicle.

This study takes digital courses of the big data and accounting major in higher vocational colleges as the practical vehicle, proposes a feasible integration path from the perspective of human-AI collaboration, and preliminarily validates its effectiveness through teaching practice, offering solutions for digital finance courses in higher vocational colleges to meet the challenges of the AI era.

3. Three Major Problems Facing Digital Finance Course Teaching in Higher Vocational Colleges

During the process of advancing digital finance course construction in the big data and accounting major of higher vocational colleges, prominent difficulties exist across three dimensions—teachers, students, and curriculum—which are interwoven and mutually causal, collectively forming a complex predicament constraining teaching quality improvement.

3.1. Insufficient AI Literacy and Application Ability of Teachers

Currently, accounting teachers in higher vocational colleges generally lack AI literacy. First, most teachers lack a computer science background, with their understanding of generative AI tools remaining superficial, stopping at the level of "having heard of" or "having tried" them. The proportion of teachers who can skillfully use this technology for teaching design and resource development is low. Second, teachers have an incomplete understanding of AI tool functions, mainly focusing on basic functions such as text generation and information retrieval, lacking application ability in education-specific scenarios such as code generation, code explanation, and error diagnosis. Third, regarding the key skill of prompt engineering, the vast majority of teachers have not yet mastered basic techniques and cannot obtain ideal AI output through high-quality prompts.

The main reasons for the above problems include the following four aspects. First, the speed of technological iteration exceeds the normal update rhythm of teachers. Generative AI technology has major version updates or new tools emerging almost every month, with new functions and usages constantly appearing; however, teachers' teaching content and methods are often adjusted by semester or even academic year, making it difficult to keep pace with technological development. Second, there is a lack of targeted hands-on training. Most AI application training currently provided by higher vocational colleges for teachers stops at conceptual introductions and function descriptions, lacking step-by-step operational guidance combined with specific courses (such as Python for financial analysis). Third, teachers' daily workload is heavy. Tasks such as lesson preparation, lecturing, grading assignments, guiding student competitions, and participating in program development occupy a significant amount of teachers' time, leaving very limited time for systematic self-study of new technologies. Fourth, some teachers have a fear of new AI technologies or lack intrinsic motivation. Faced with an unfamiliar technological field, some teachers tend to stick to familiar teaching methods, with low willingness to actively learn and try new approaches.

The insufficient AI literacy of teachers directly leads to the following consequences: the actual utilization rate of AI tools in teaching is extremely low, with most classrooms still following traditional teaching models; the efficiency of teaching resource development is low, with teachers still manually compiling cases and designing exercises, which is time-consuming and yields variable case quality; teachers cannot provide reasonable guidance on student use of AI, and some students who try to use AI on their own may experience over-reliance or improper use due to lack of proper guidance.

3.2. High Cognitive Load and Severe Learning Aversion Among Students

Higher vocational accounting students face significant learning difficulties in digital courses. First, they have weak programming foundations. The vast majority of students have not systematically learned programming and are completely unfamiliar with concepts such as Python syntax, data structures, and algorithm logic. Second, cognitive load is too high. Learning programming itself requires simultaneously understanding grammatical rules, mastering logical structures, and memorizing function methods, which is burdensome for accounting students without a computer science background. Third, learning aversion is severe. According to classroom observations, most students are prone to frustration after multiple program errors, with some directly giving up hands-on practice and waiting for teacher assistance; in the classroom, students' coping behaviors when encountering code errors show clear stratification, with notable differences in autonomous debugging, online searching, and passive help-seeking behaviors.

The reasons for this include: first, a gap between course content and students' prior knowledge, with a lack of effective articulation between mathematics and information technology education at the high school level and the computational thinking required for programming; second, the traditional "teacher demonstration → student imitation" teaching model cannot meet personalized learning needs, as different students encounter different obstacles, making it difficult for teachers to attend to all students simultaneously; third, a lack of immediate feedback mechanisms, where students often wait more than a day for feedback after submitting assignments, errors are not corrected promptly, and problems accumulate, affecting subsequent learning efficiency.

3.3. Curriculum Content Iteration Speed Lagging Behind Technological Development

Although digital finance courses are newly established, their content update speed still lags far behind the latest technological developments. Taking Python Application in Finance as an example, current course content mainly covers basic syntax, Pandas data analysis, data visualization, and similar frameworks. However, the emergence of generative AI has profoundly changed how Python programming works. Code that previously had to be written manually can now be automatically generated with AI assistance; function parameters that previously had to be memorized can now be queried through natural language. Nevertheless, existing curriculum systems have not yet incorporated these changes into teaching content.

The lag in curriculum content iteration is multifaceted. First, training cases are outdated. The financial analysis cases in courses are mostly simplified teaching cases designed by teachers, which differ from the complexity of actual enterprise applications. Second, technology application methods are outdated. Courses still emphasize the traditional programming teaching model of "writing code from scratch," failing to introduce the new paradigm of "human-computer collaboration." Third, the response to new industry trends is slow. When enterprises begin to widely adopt certain new tools or methods in financial data analysis, it often takes one to two years for course content to be updated.

The main reasons for the lag in curriculum content are as follows. First, there is a time delay in the curriculum content update mechanism. Syllabus revision requires multiple procedures such as teaching and research section discussion, departmental review, and academic affairs office filing, making rapid iteration difficult. Second, teachers have limited energy. Developing high-quality training cases requires significant time investment, and teachers' regular teaching tasks are already quite heavy. Third, school-enterprise cooperation is insufficiently deep. Teachers lack timely and comprehensive understanding of real business scenarios and the current state of technology application in enterprises.

3.4. Interrelationships Among the Three Major Problems

The problems across the three dimensions of teachers, students, and curriculum are not isolated but interact and mutually reinforce each other, forming a dynamic cycle. Specifically, insufficient AI literacy among teachers directly constrains the efficiency and quality of curriculum content updates, because teachers are the main force behind curriculum development. The lag in curriculum content leads to a gap between the knowledge and skills students learn and actual enterprise needs, thereby weakening students' learning motivation and self-efficacy. Increased learning difficulties and heightened learning aversion among students, in turn, increase teachers' tutoring burden and teaching pressure, making it even harder for teachers to find time and energy to learn and master new AI technologies. To break this negative cycle, an intervention point that can simultaneously act on multiple links is needed. This study suggests that generative AI technology itself, with its capabilities of automated content generation, personalized tutoring, and immediate feedback, holds the promise of becoming a key breakthrough to break this cycle.

4. Impact of Generative AI on the Entire Teaching Process of Digital Finance Courses from a Human-AI Collaboration Perspective

This study systematically analyzes the impact mechanism of generative AI across four links: teacher lesson preparation, classroom teaching, student learning, and teaching evaluation.

4.1. Teacher Lesson Preparation: From "Developer" to "Designer"

Under the human-AI collaboration teaching model, generative AI restructures the logic of teacher lesson preparation, shifting from "manual development" to a new model of "intelligent generation + teacher optimization."

First, intelligent generation of comprehensive teaching resources. By designing precise prompts, teachers can have AI generate Python financial analysis cases, SQL query training banks, RPA process design task sheets, etc., covering the complete teaching chain of data collection, cleaning, analysis, and visualization, significantly reducing the time teachers spend on writing documentation and creating cases. Taking the "Pandas data cleaning" module as an example, traditional lesson preparation takes 4-6 hours, which is reduced to 1-2 hours with AI use, greatly improving lesson preparation efficiency.

Second, intelligent matching of cutting-edge teaching materials. Generative AI can capture the latest tax policies and industry intelligent finance cases in real time, automatically linking them to course knowledge points, effectively solving the problems of outdated teaching content and policy lags. For example, when preparing a case on "the impact of tax policies on financial statements," AI can automatically associate the latest value-added tax reform policies and generate corresponding accounting treatment examples, enhancing the timeliness and professionalism of teaching content.

Third, precise adaptation to student profiles. AI can intelligently assess the learning characteristics of the current class based on previous students' frequent errors and knowledge weaknesses, designing differentiated teaching difficulty levels and training tasks for different classes, achieving precise lesson preparation and tiered design, changing the previous "one-size-fits-all" lesson preparation model. Additionally, AI can automatically generate differentiated exercises based on difficulty levels set by teachers, meeting the learning needs of students at different levels.

Fourth, promoting teacher role transformation. AI takes over routine, repetitive lesson preparation work, and teachers transition from content developers to curriculum designers, student profile assessors, and learning guides, focusing their energy on instructional design, key and difficult point management, and educational guidance, greatly enhancing teaching professionalism.

4.2. Classroom Teaching: "AI Dual-Teacher" System of Human-AI Collaboration

Under the human-AI collaboration teaching model, generative AI is embedded in the classroom as an "AI teaching assistant," forming a "dual-teacher" collaborative teaching pattern with the human teacher, transforming traditional classroom interaction models.

First, pre-class of foundational knowledge. Teachers can move the explanation of basic knowledge points such as Python basic syntax and SQL query types to the pre-class preparation stage, with AI acting as a "preparation assistant." Students interact with AI through natural language to understand concepts and complete pre-class quizzes. Classroom time is then freed up for in-depth discussions, case analysis, and solving higher-order problems, effectively improving classroom time utilization efficiency.

Second, real-time code error diagnosis and correction. During hands-on training, when students encounter code errors (e.g., "NameError: name 'pd' is not defined"), in traditional classrooms they wait an average of 3-5 minutes for teacher assistance. With AI introduction, students paste the error message directly to AI, which quickly explains the cause of the error and provides correction suggestions, effectively reducing students' waiting time for answers to hands-on questions. Personalized learning support effectively reduces programming cognitive load and enhances students' learning confidence.

Third, supporting real-time tiered teaching implementation. In the same classroom, different students have different learning paces and mastery levels. AI can push variant exercises of different difficulty levels based on each student's real-time performance. Faster learners receive extended tasks, while slower learners receive basic consolidation exercises, enabling within-class tiered teaching without requiring teachers to prepare multiple lesson plans simultaneously.

Fourth, reshaping the teacher's classroom role. In the human-AI collaboration classroom, teachers transform from "answer machines" to "learning organizers" and "deep thinking guides." Teachers can patrol the classroom, focusing attention on students with learning difficulties, providing concentrated explanations for complex problems that AI cannot handle, and organizing students to share their experiences using AI to solve problems, fostering students' metacognitive abilities and critical thinking.

4.3. Student Learning: Personalized Support and Cognitive Load Reduction

The student learning link is the most directly and profoundly affected area by generative AI. Under the human-AI collaboration model, this technology positively impacts students' learning paths, cognitive load, and learning behaviors.

First, providing personalized learning path planning. Each student has significantly different programming foundations and learning paces. Traditional classrooms use a uniform pace, leading to some students "not getting enough" while others "cannot keep up." Generative AI can dynamically adjust the difficulty and pace of recommended content based on students' learning histories, answer records, and interaction behaviors. Students with weaker foundations receive more detailed syntax explanations and more basic exercises, while advanced learners receive challenging tasks (e.g., "try using groupby with apply to implement more complex aggregation operations"), truly enabling teaching according to aptitude.

Second, effectively reducing the cognitive load of programming learning. The cognitive load of programming learning primarily comes from two dimensions: explicit memory of grammatical rules and function methods, and logical reasoning of problem-solving paths. Generative AI helps students complete substantive programming tasks without memorizing all grammatical details by providing code hints and error explanations, effectively reducing explicit memory load, allowing students to focus their limited cognitive resources on higher-order abilities such as problem decomposition, algorithm design, and result validation. Classroom observations show that with AI assistance, the average number of "stuck moments" per programming task for students decreases from 4-5 to 1-2, students' programming aversion is effectively alleviated, and active classroom participation significantly increases.

Third, promoting the formation of autonomous learning behaviors. Under AI-assisted mode, students' behavior sequence when encountering problems shifts from the traditional "try once → fail → wait for teacher → give up or solve" to "try → fail → consult AI → understand and correct → try and iterate → succeed or advance." This shift cultivates students' habits of actively seeking help and solving problems independently. Notably, in later stages, the quality of students' questions posed to AI significantly improves: from low-level questions like "How do I write code?" initially, gradually transforming into high-quality questions with critical thinking and exploratory spirit, such as "The code generated by AI uses a loop; can we use vectorized operations to optimize efficiency?"

Fourth, supporting the continuous accumulation of learning confidence. Because AI responds immediately, patiently, and without any judgmental pressure, students find it easier to experiment and explore in a "non-threatening" environment. In interviews, many students indicated that AI made them "no longer afraid of making mistakes," and their learning initiative and self-confidence significantly increased. The proportion of students voluntarily answering questions in class rose from approximately 15% to approximately 30%.

4.4. Deep Impact of Generative AI on the Teaching Evaluation Link

Generative AI provides technical support for the transformation of teaching evaluation from "outcome-oriented" to "process-oriented," making process-oriented evaluation truly feasible.

First, automatic collection and organization of learning profile data. AI can automatically record and analyze students' learning behavior data, including code submission frequency, common error types, dialogue logs with AI, task completion time, help-seeking frequency, etc. This data is presented in a structured manner, forming visualizable learning profile reports, providing teachers with rich process information that is difficult to obtain in traditional classrooms.

Second, assisting teachers in precise diagnosis and intervention. Based on learning profile reports, teachers can quickly identify common knowledge blind spots in the class (e.g., "more than 60% of students made the same error in the 'handling missing values' step"), allowing for focused review and targeted exercise design. At the same time, teachers can promptly identify students with learning difficulties (e.g., "a student has repeatedly failed simple tasks and has abnormally low AI interaction frequency") and proactively provide individual intervention, preventing problem accumulation.

Third, improving the efficiency and depth of assignment grading. In programming assignment grading, AI can assist teachers with automatic syntax checking and logic verification, outputting preliminary scores and error classifications, leaving teachers only with the need for review and qualitative evaluation. This approach significantly improves grading efficiency while reducing the time teachers spend on repetitive labor, allowing them to devote more energy to in-depth analysis of student assignments, personalized feedback, and problem summarization.

Fourth, supporting quantitative assessment of teaching effectiveness and continuous improvement. By comparing learning behavior data and performance results of different classes and different semesters with AI assistance, teachers can quantitatively evaluate the effectiveness of teaching reforms, identify effective teaching strategies, provide data support for continuous curriculum iteration, and promote a spiral increase in teaching quality.

4.5. Long-term Impact of Generative AI on Curriculum Development and Iteration

Generative AI can track new developments in industry Python libraries, RPA applications, and financial big data technologies in real time, automatically generating curriculum update suggestions, compressing the traditional update cycle of several months to short-term iteration. Simultaneously, it can batch-develop diverse training cases and exercise resources, quickly building dynamic teaching case libraries, solving the persistent problems of outdated resources and low development efficiency, promoting the transformation of curricula from static textbooks to dynamic capability cultivation platforms.

5. Integration Path of Generative AI and Digital Finance Courses

Based on the above analysis, this section proposes a systematic integration path from three dimensions: curriculum content restructuring, teaching resource construction, and implementation strategy.

5.1. Curriculum Content Restructuring: "Foundation-Core-Extension" Three-Tier Module

In terms of curriculum content, traditional digital finance courses are usually organized in a linear sequence of "Python basics → Pandas data processing → data visualization → comprehensive project." With generative AI integration, the curriculum content should be adjusted to a "foundation-core-extension" three-tier module, reflecting the progressive logic from "AI-assisted" to "AI-empowered."

5.1.1. Foundation Module: AI-Assisted Basic Skills Training

This module targets introductory content such as Python basic syntax and Pandas basic operations. Students use AI to understand basic concepts, complete simple programming exercises, and initially learn how to ask AI questions and verify whether the code provided by AI is correct. A typical activity is the "AI Collaboration Challenge": the teacher assigns a specific small task, such as "use Python to open an Excel file named 'sales.xlsx' and calculate the sum of the 'Sales' column." Students can use AI to generate code, but after completion, they must explain the meaning of each line of code to the teacher or peers. This design aims to ensure that while using AI tools, students truly understand the logic behind the code, avoiding mere "copy-paste."

5.1.2. Core Module: AI-Empowered Typical Financial Business Scenario Applications

This module targets common data analysis tasks in financial work. For example, the teacher provides an "expense reimbursement details sheet" (Excel file) for a small enterprise over a quarter, containing fields such as department, reimbursement date, expense category, and amount. Task requirements: use Python to read the data, calculate the total reimbursement amount for each department, identify the expense category with the highest reimbursement amount, and finally generate a simple bar chart. Students need to independently complete the entire process from data reading, cleaning, calculation, to visualization, with AI providing assistance throughout: automatically generating code to read Excel, suggesting groupby for grouping aggregation, helping interpret error messages in the results. A typical activity adopts project-based learning: the teacher provides a more comprehensive case, such as "monthly income statements (revenue, cost, expenses) for various stores of a company, use Python to calculate the net profit of each store, analyze which store has the strongest profitability, and propose two improvement suggestions." Students complete the analysis report in groups, can use AI to assist with code writing, but the final analysis conclusions and suggestions must be made by the group themselves. The teacher guides students to compare different analysis plans provided by AI (e.g., different grouping methods, different chart types), cultivating their ability to judge information quality and make sound business decisions.

5.1.3. Extension Module: AI-Simulated Enterprise Real Financial Automation Projects

In this module, generative AI plays the core role of a "real business environment generator." The teacher only needs to set the task objective, and AI automatically generates a complete set of enterprise simulation datasets, naturally implanting various anomalies and complex situations commonly encountered in real financial work.

Taking the "consolidation and reconciliation of multi-subsidiary revenue statements" task as an example. The teacher sets the task objective (e.g., "consolidate the monthly revenue statements of three subsidiaries, identify records with amount discrepancies or time mismatches"), and AI automatically generates three sets of Excel data files with similar structures but different formats, naturally implanting common enterprise problems (inconsistent column names, missing amounts, duplicate entries, cross-period records, etc.). Different students receive randomly generated data versions, preventing plagiarism. Students need to write Python programs to complete column name mapping, data cleaning, cross-table matching, and anomaly marking.

Through such AI-driven simulation training, students not only master the core skills of Python data processing and automated reconciliation but also develop professional competencies in analyzing complex business logic and handling real data environments, closely aligning with the actual requirements of enterprise financial digitalization positions.

5.2. Teaching Resource Construction: "AI + Teacher" Dual-Engine Driven Resource System

Curriculum integration requires supporting resources. This study proposes building three types of resources, forming an "AI + teacher" dual-engine driven resource construction model.

First, building an AI teaching case library. Systematically collect and categorize high-quality teaching cases generated or optimized by teachers with AI assistance. Each case includes: task description, teaching objectives, difficulty level, AI-generated sample code, teacher's optimized version, common error prompts, and extended task suggestions. The case library is categorized by module (Python basics, Python advanced syntax, Pandas data analysis, data visualization, web scraping, etc.) and continuously updated. The construction method adopts a closed-loop process of "teacher assigns task → students attempt using AI → teacher selects excellent cases → optimizes and adds to library," which both accumulates teaching resources and promotes teacher and student understanding and mastery of AI tools.

Second, building a prompt template library. Teaching practice demonstrates that high-quality input (prompts) is the key to obtaining useful AI output. During the teaching process, a set of prompt templates for digital finance courses is accumulated and organized, covering typical scenarios such as teaching case generation, code correction, tiered exercise generation, and learning profile analysis. For example, a template for generating teaching cases: "Please generate a case for higher vocational accounting students to practice [Pandas data cleaning], including data description, task requirements, sample code, with difficulty level [intermediate]." A template for code correction: "The following Python code reports an error [paste code and error message], please explain the cause of the error and provide corrected code." These templates lower the technical threshold for teachers to use AI, improving the efficiency and output quality of human-AI collaboration.

Third, establishing a dynamic curriculum content update mechanism. One of the core advantages of generative AI is the timeliness of its knowledge. A dual "monthly update + event-driven" mechanism can be established in teaching: once a month, teachers use AI to capture new technologies, new tools, and new cases in the field of digital finance, screening them for inclusion in the curriculum resource pool; when important policy releases or major industry events occur (such as new accounting standards implementation, typical intelligent finance implementation cases), a rapid update channel is activated immediately. This mechanism significantly shortens the curriculum content update cycle from the traditional several months or even a year to just a few weeks, effectively solving the core contradiction of teaching content lagging behind enterprise applications.

5.3. Implementation Strategy: Three-Stage "Pilot-Optimize-Promote" Approach

Teaching reform needs to proceed gradually. This study proposes a three-stage "pilot-optimize-promote" approach to ensure the reform is implemented steadily and iteratively.

First, pilot stage (1-2 months). Select one digital course (e.g., "Application of Big Data Technology in Finance") and conduct the teaching reform pilot in one class (approximately 50 students). Main tasks include: training the pilot class teacher in AI tool use, designing AI integration plans for 1-2 teaching units, implementing them in classroom teaching, and collecting student feedback and process data. The goal of this stage is to verify the feasibility of the AI integration plan, identify major problems and risks, and accumulate first-hand experience for subsequent optimization.

Second, optimization stage (2-3 months). Systematically optimize based on feedback from the pilot stage. Specific tasks include: revising teaching plans, adding AI usage guidelines (e.g., "students must think independently before consulting AI," "AI-generated code must be manually verified"); supplementing the case library and prompt template library to enrich teaching resources; adjusting course evaluation methods to include "human-AI collaboration ability" as an assessment indicator, guiding students to use AI appropriately. After optimization, select another class in the same grade for small-scale promotion and validation to test the transferability of the optimization effects.

Third, promotion stage (one semester). Fully implement the reform plan in all classes offering digital courses within the big data and accounting major. Establish a regular exchange mechanism for the teaching and research group, where teachers regularly share practical experiences, successful cases, and lessons learned from AI-integrated teaching, forming a teaching research culture of collaborative lesson preparation, peer observation, and collective reflection. Simultaneously, summarize replicable implementation guidelines and standard operating procedures (SOPs), including AI tool selection recommendations, prompt design specifications, classroom AI usage rules, learning profile data analysis templates, etc., for reference by other majors within the institution and similar institutions outside.

6. Conclusion

From the perspective of human-AI collaboration, this study systematically analyzed the impact of generative AI on the entire teaching process of digital finance courses in higher vocational colleges and proposed a corresponding integration path. The main conclusions are as follows.

First, generative AI has a significant positive impact on the entire teaching process. In lesson preparation, AI significantly improves case development efficiency, with the teacher's role shifting from content developer to instructional designer. In classroom teaching, AI acts as an immediate answering assistant, greatly shortening students' code debugging waiting time, forming an "AI dual-teacher" collaborative teaching model. In student learning, AI provides personalized learning paths, effectively reducing students' programming cognitive load and enhancing their learning confidence. In teaching evaluation, AI supports process data collection and analysis, enabling process-oriented learning profile diagnosis, and significantly improving the efficiency of assignment grading and learning profile analysis.

Second, the human-AI collaboration model effectively alleviates the three prominent problems. Regarding insufficient AI literacy among teachers, this study proposes a new lesson preparation model of "intelligent generation + teacher optimization" and an approach to building a prompt template library. Regarding students' high cognitive load and learning aversion, an "AI teaching assistant + tiered tasks" support system is constructed. Regarding the lag in curriculum content iteration, an AI-driven dynamic update mechanism is established, shortening the curriculum update cycle from the traditional one to two years to just a few weeks.

Third, the three-tier "foundation-core-extension" module and the three-stage "pilot-optimize-promote" strategy are operationally feasible and replicable. The foundation module emphasizes basic skills training with AI assistance, the core module focuses on AI-empowered typical financial scenarios, and the extension module uses AI to simulate real enterprise project environments. The three-stage promotion strategy ensures steady implementation of teaching reform and provides a replicable implementation framework for similar institutions.

This study is primarily based on the author's institutional teaching practice and theoretical analysis, with a relatively limited research sample scope, lacking large-scale quantitative empirical comparison, and focuses only on core digital finance courses, leaving the research coverage to be broadened. Supporting mechanisms such as the cultivation of AI literacy for teachers and students and the human-AI collaboration evaluation system still need further refinement in subsequent teaching practice.

Future research will expand the sample scope, conduct controlled teaching experiments to further verify the effectiveness of AI integration in teaching; expand course application scenarios; and improve the human-AI collaboration teaching evaluation and AI capability cultivation system for teachers and students. Simultaneously, as generative AI continues to iterate, the curriculum integration path and teaching resource construction will be continuously optimized, gradually forming a scalable AI teaching paradigm for higher vocational finance and accounting courses.

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