https://doi.org/10.62836/jissh.v3i3.0025
Global Science Publishing
JISSH
Journal of Integrated Social Sciences and Humanities
https://ojs.sgsci.org/journals/jissh
Article

Reconfiguring Financial Technology Education through AI Algorithms and Large Language Models: An Industry-Responsive Framework for Innovation Capacity Development

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Abstract: The Financial institutions are now being influenced by the introduction of artificial intelligence (AI) algorithms and large language models (LLMs) to perform risk management, investment analysis, compliance checks, and customer service. The new generation of financial technology experts is expected to have a different knowledge and skill set as well as the ability to work with the current technological advancements. This will be done through the application of educational ecology, which focuses on the development of competencies, the integration of education in industry, and the role of financial technology talent. It identifies enterprise needs and student capabilities, curriculum design based on scenarios, and feedback on the governance of the situation. In this way it can be considered that the AI algorithms and LLMs are not just tools of learning but also means of acquiring interdisciplinary problem solving, engineering skills, and financial literacy and responsible use of AI. The research thus offers a step-by-step procedure towards the creation of an expert in financial technology who is ready to serve the industry with the help of reliable AI in financial services.

Keywords: financial technology talent development; AI algorithms; large language models; curriculum reform; industry-education integration; student capability; innovation capacity; responsible AI governance

1. Introduction

The financial sector has reached a new level of digitization: the digital tools are not only used to provide the supporting role in the business processes, but also to be an active part of the core decision-making process. The main financial activities including credit analysis, fraud risk control, transaction monitoring, user portraits, asset portfolio development, investment analysis and submission of regulatory documents are now conducted on the basis of data processing and modeling algorithms. Meanwhile, generative AI and artificial intelligence as large language models (LLMs) are being applied to reshape how organizations can deal with unstructured information, serve customers and manage knowledge [1].

This change is also a question of education in the sense that as financial institutions start to use AI-based

Received: 5 July 2026; Accepted: 20 July 2026.
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systems, what should be the approach to training students on the basis of professional graduate programs with regard to the companies where the work in finance is being supported by AI algorithms and big language models? It has also been revealed that governance, testing, data quality, controls and transparency are needed in AI and machine learning in financial organizations [2]. NIST AI Risk Management Framework is another framework that makes it clear that the management of trustworthy AI needs to be mapped, measured and managed at every stage of its life cycle [3]. The conventional courses of financial engineering tend to concentrate on the mathematical modeling and pricing of derivatives, whereas the conventional computer science course tends to focus on general algorithms or software or standard datasets. This difference does not lie in the technologies but in the synthesis of cross disciplinary skills. Students will need to have an understanding of how they can relate business logic of financial businesses, data management, algorithmic modeling, LLM design, engineering processes and regulatory responsibilities in order to practice enterprise AI. An undergraduate student is required to interpret a problem of the enterprise into the task of learning, create a prototype that is responsible, describe the results of the model to the stakeholders who are not technical, record the risk of the model, and analyze the social and business implications of implementing AI.

The emergence of the financial language model is a good example of the necessity to be trained in such an interdisciplinary way. The BloombergGPT demonstrates the use of large-scale financial corpora as the basis of domain-specific language modeling [4]. FinGPT presents the possibility of an open source system of financial LLMs [5]. PIXIU offers training information and assessment criteria of the financial language task [6]. Such researches indicate that the value of the LLMs in the financial field will not be determined by the size of the model, but also on the quality of data, tasks, evaluation and governance of the domain.

Three limitations of the current curriculum are still in place. To begin with, there is a gap between the knowledge and technology development that students can be trained to know about the isolated machine learning algorithms, but they do not realize how the retrieval augmented generation, agent-based activities, or model validation and engineering activities affect the requirements of the enterprise capability. Second, it is possible to separate financial situations and learn tasks. The students might improve their performance on classification scores based on open datasets without having any idea of credit policy, suitability control, anti-money laundering procedures, market-abuse detection or compliance reports. Thirdly, academically focused evaluation systems. The student work is usually determined by accuracy of the models used or writing of the report, whereas the financial AI facing enterprises has to have proof of its robustness, explainability, fairness, auditability, data lineage, teamwork and human interaction.

This article suggests a curriculum change in the financial technology education with an industry-based approach. The model is based on the principle of enterprise demand analysis, student mapping and the capacity to be able to learn, modular curriculum planning, project learning and feedbacking. It will be written in the same manner as an applied research paper in education: Introduction, Methods, Results, Discussion and Conclusions. The fundamental assumption is that AI algorithms and big language models are not some background technologies, but rather, they are the new driving force behind the financial services, work flows in enterprises and even the skills required by professionals. The objective of the introduction of AI algorithms and large language models does not involve instructing people how to use new technologies, but it involves training them to become financial technology experts who can address real life issues in the business world using interdisciplinary knowledge and engineering skills and responsible application of AI.

2. Methods

The approach is the design of methodology, as AI has become popular among financial institutions. The study does not take the starting point in the traditional course categories but rather it starts with the implementation of artificial intelligence to the field of finance, including risk decisioning, investment research, compliance review, customer and enterprise operations automation, and so on, which are then converted into courses that can be trained.

2.1. Industry Demand Identification

The first methodological step is to determine the ways in which financial institutions are utilizing AI and how these applications alter the expectations of graduate students. The analysis will include four common institutional groups: commercial banks, securities and fund companies, insurance firms and financial technology enterprises. In all these organizations, AI implementations can be divided into five scenario clusters that each represent a specific source of curriculum demand as opposed to a general trend in technology.

The first one is the cluster of risk decisioning. It encompasses credit ratings, loan applications, early-warning systems and fraud detection, insurance claim analysis and portfolio management. The second group is that of market and investment intelligence. It entails the extraction of events, news sentiment, creation of research reports, financial question answering and portfolio attribution. The third category is compliance and regulatory technology. This comprises anti-money laundering tracking, suspicious transactions triage, policy search, document review and regulatory reporting help. Customer and wealth operations are the fourth cluster. This involves intelligent service, profiling of customers, recommending products and giving advice in a specific manner. The fifth cluster is productivity of enterprise. This consists of knowledge-base searching, drafting documents, code support, automation of processes and workflow agents within the organization.

These scenario clusters suggest that the development of financial AI talent cannot be structured by technology. Algorithms need to be linked with business processes, learning activities and governance responsibilities in a curriculum. The suggested framework does not copy enterprise AI systems but converts enterprise AI applications into part of the curriculum to learn by students. The proposed framework is a summary of the translation between enterprise demand and curriculum design and student outcomes (as seen in Figure 1). Scenarios in banking, securities, insurance and wealth-management establish capability needs; case resources and data sandboxes are used to support curriculum translation; and student portfolios illustrate financial reasoning, engineering practice, responsible AI literacy and innovation capacity.

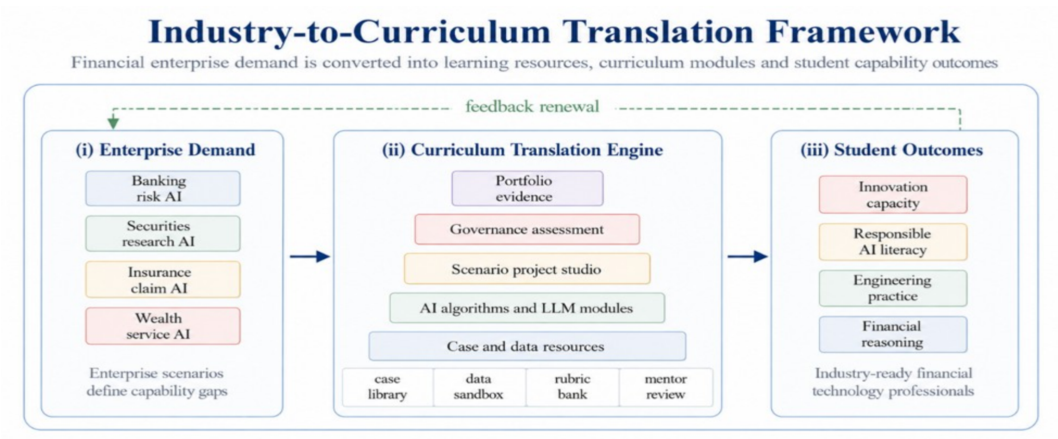

Figure 1. Industry-to-curriculum translation framework linking financial enterprise demand, curriculum translation mechanisms and student capability outcomes.

2.2. Capability Mapping

The second one is the process of transforming AI financial scenarios into units of capability to be learned. The competency-based education does not focus on a course completion but rather focuses on performance that can be observed. To train the students in financial AI, it is necessary to have at least six dimensions of core competencies: reasoning in the field of finance, data engineering, algorithmic modeling, LLM application design, practice and risk management of the engineering. All these dimensions may be trained by the use of scenario-based exercises based on the actual applications of financial AI.

As an example, a credit risk project must have students create the features and determine the stability of the model, explain the factors that led to the decision, create the thresholds of manual reviews and write the report on the validation of the model. The assistant of investment research is expected to ingest documents, test quality of retrieval, generate answers based on the facts, check citations, hallucinate. A rule-base building compliance assistant needs sensitive information management, audit logging and escalation design.

The curriculum competency map is a combination of scenario intensity matrix and T-shaped ability ladder, which demonstrates the breadth in financial AI scenarios as well as depth in core professional competencies (Figure 2). The scores are indicative planning values instead of empirical measures.

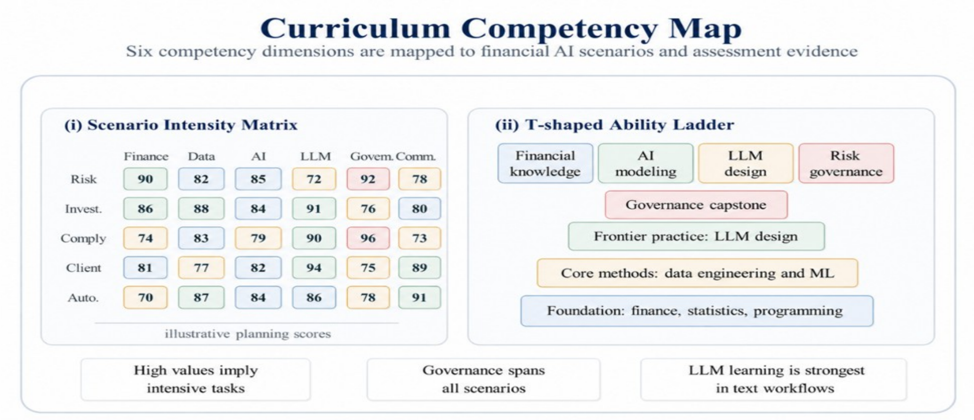

Figure 2. Curriculum competency map combining scenario intensity, T-shaped ability development and curriculum planning notes for financial AI education.

2.3. Scenario-Driven Learning Design

The third step of the methodology is to learn the AI-based financial situations as opposed to a single tool. Scenario learning involves problem statement, data processing, model development, validation and reflection and feedback. It can be integrated with CDIO—based engineering education since students need to make up their mind, design, implement, and test a learning prototype in an actual setting. More importantly, the scenario will carry out curriculum activities: it has linked theory, laboratory exercises, enterprise case study, group work and evidence of evaluation.

The scenario in an AI algorithm course could be fraud detection or credit risk early warning. Students initially study feature construction, model selection and stability evaluation before they present a model explanation and risk-control note. The scenario of an investment research assistant or compliance document reviewer can be presented in an LLM application course. Document parsing, retrieval design, prompt engineering, grounded answer generation and hallucination testing are learned by students but these skills are assessed as elements of a financial workflow instead of being demonstrated independently. The same scenario may also be applied to model validation, fairness assessment, audit logging and incident response in a governance course.

It is thus necessary to repeat the same enterprise situation in different courses at various levels of complexity. A first year student can be able to do a guided experiment based on either public or synthetic data. The second phase project can include designing a prototype, with the team, and an enterprise mentor will assess it as well as produce a report of validation. An end capstone might entail the students incorporating business needs, algorithmic effectiveness, compliance issues and user interaction. The spiral learning process transforms the demand of the enterprise into the development of student capabilities.

2.4. Governance-Oriented Feedback

The fourth step is to develop a feedback mechanism. Financial AI education should not consider governance as an after-class ethical subject but as a requirement in the model lifecycle. Studies on the governance of AI models in financial services have indicated that self-regulation, monitoring and institutional control mechanisms are key to responsible deployment [7]. The recent literature on financial regulatory interpretation also indicates that LLMs can change how students learn policy retrieval, rule reasoning and compliance explanation [8]. The generative AI profile of the AI Risk Management Framework further supports the need to teach hallucination control, information integrity, misuse prevention and human oversight in LLM-based financial applications [9].

The results of learning analytics, the review of enterprise mentors, the model validation process and the business simulation and compliance checklists are all to be fed back. The feedback must cause curriculum adjustment in case a course project is not successful because of data leakage, erratic behavior, low citation accuracy or lack of explanation of the decisions made by the students.

3. Results

The results can be interpreted as a product of the curriculum design that is related to the financial AI. They do not present an enterprise in terms of how it should implement the use of an AI system, but rather demonstrate how one can reconstruct the work of financial activity by AI as a learning process for graduates and its assessment, as well as joint education processes.

3.1. Student Learning Pipeline for Financial AI Projects

The suggested curriculum structure will lead to a pipeline of students learning, which is related to the financial AI in enterprise. The pipeline does not represent an enterprise system as the end point of research but it demonstrates how one can turn an enterprise financial AI scenario into a sequence of stages of learning (see Figure 3). It also involves case analysis and problem solving, data preparation and training of AI and LLMs, validation and reflection, assessment and portfolio building. There is a learning objective, a practice assignment and an evaluation artifact at each step.

This process of learning can be converted into curriculum based projects. The student is first going to study the case of an enterprise, identify the problem in terms of finances, make the data and documents ready, select the right AI or LLM tools, go through the stages of the gate review, validate the results and finally present a portfolio. This does not constitute a working prototype but rather a learning artifact that is documented and auditable as well as a requirement brief, description of data, validation report, reflection note and presentation to the mentors of the enterprise.

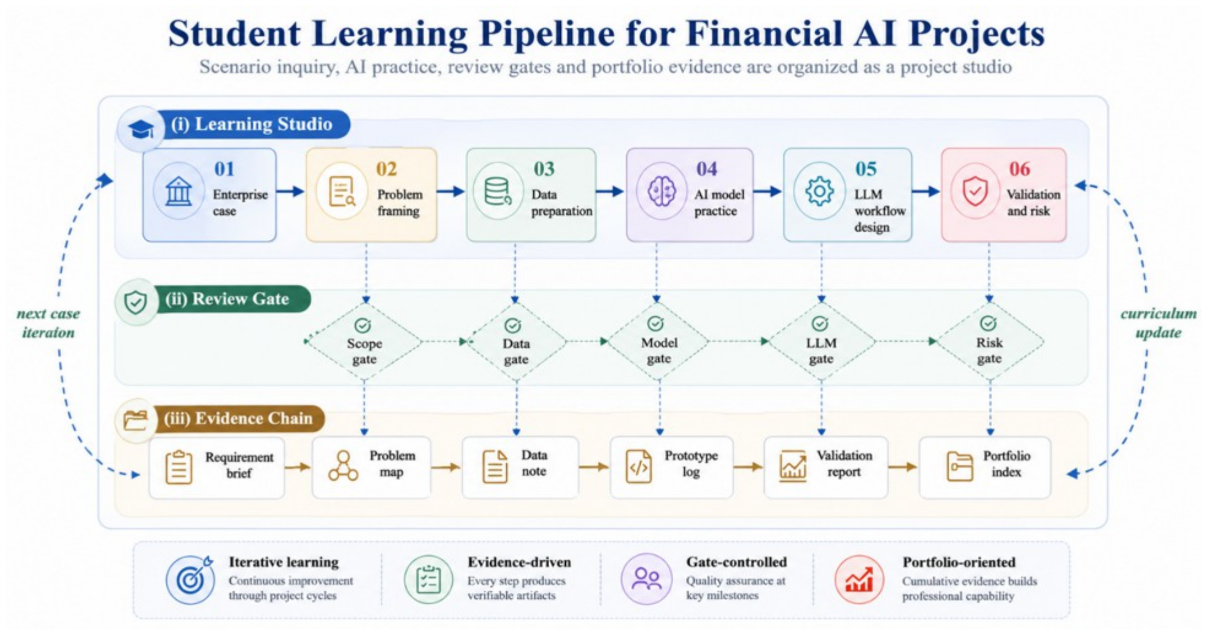

Figure 3. Student learning pipeline for financial AI project courses linking enterprise cases, review gates, assessment evidence and portfolio outcomes.

3.2. Trustworthy Financial AI Lifecycle

The model of the trustworthy life cycle is not to be taught as an activity that can be done in a single step of the financial AI education but instead should be integrated throughout the entire process since it is impossible to separate the use of AI in the field of finance and its risks, compliance duties and operational responsibility. It starts with framing of business problem which includes the students defining what they want to achieve financially, how much risk will be taken on board, and who will be responsible to take the actions. It then passes through data design, training the model, independent validation, controlled implementation, monitoring and incident review. The student evidence at every level of governance should include: the history of the data lineage, privacy analysis, stability of features, comparison of benchmarks, explainability test, fairness analysis, approval documentation and rollback plan. In the loop, the point of the model deployment is not the end; the students have to know that the financial AI systems are under constant observation and control by drift, bias, misuse and regulatory alteration.

This lifecycle facilitates an alteration in the assessment. The students must be assessed by model cards, validation reports, data lineage documentation, monitoring dashboards and incident-response design besides the final prediction metrics.

3.3. Industry-Education Integration Ecosystem

The third part of the framework is a system of education. The universities can not be able to achieve all the aspects of developing Financial AI talent as it requires the learning materials such as real-world applications of the AI, practice of model governance, compliance issues and feedback on production of financial institutions. This ecosystem will have its center at the Financial AI Joint Learning Lab where the universities are connected with the financial institutions, regulatory environments and technological platforms that share the cases in reusable ways, data sandboxes, rubrics and joint supervision (Figure 4).

The ecosystem explains the division of responsibilities. Theoretical coherence, curriculum organization and research training are offered by universities. Financial institutions offer scenarios, mentors and evaluation comments. Technology platforms offer tools and sandboxes to teaching laboratories. Regulatory context offers compliance boundaries and governance rubrics. The shared outputs facilitate repeated case renewal, student assessment and enterprise-facing practice.

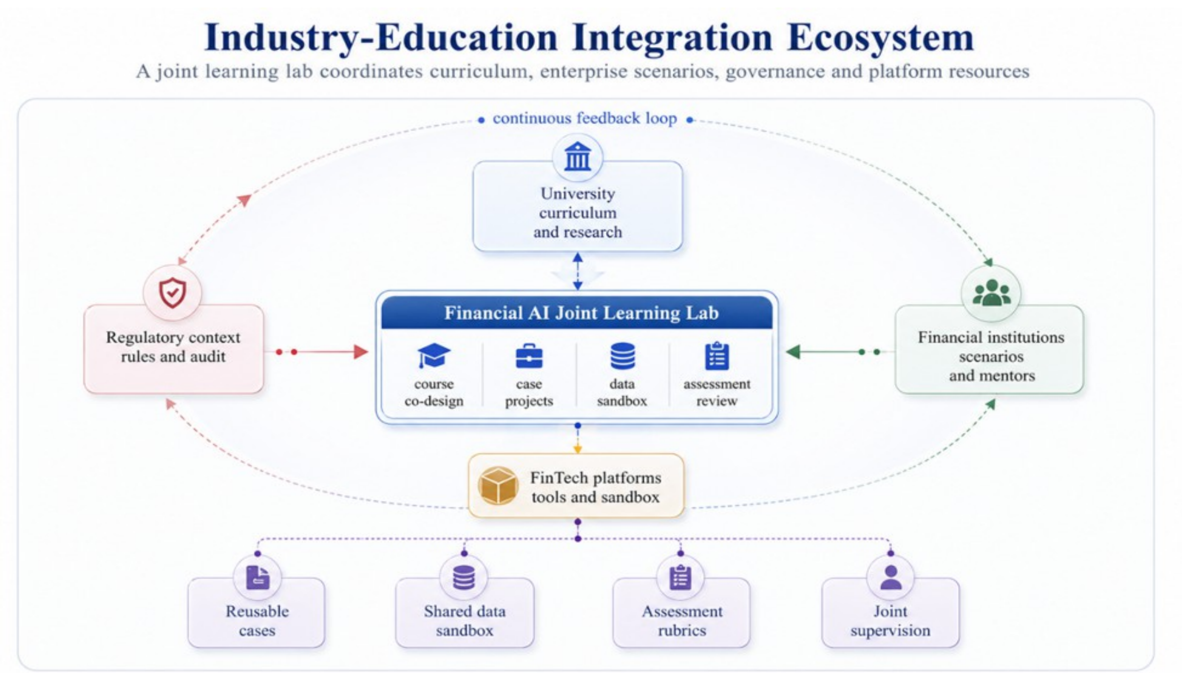

Figure 4. Industry-education integration ecosystem centered on a Financial AI Joint Learning Lab for co-training financial technology professionals.

4. Discussion

The proposed framework has three educational implications. Since these curriculum designs are inspired by actual financial AI applications, the educational argument is inextricable from the transition to AI-powered financial services.

First, financial AI curriculum reform should be shifted to system reconstruction. It is not enough to introduce a course called large model applications when the rest of the curriculum continues to separate finance, algorithms, engineering and governance. The translation framework in Figure 1 between industry and curriculum implies that programs should start with enterprise demand created by AI adoption in banks, securities firms, insurance companies and FinTech enterprises, transform it into learning resources and curriculum modules, and finally assess whether students have developed transferable professional capabilities. This translation process, instead of a single algorithm, is the actual object of professional training.

Second, the curriculum of the financial LLM education should be based on the groundedness and responsibility. It is not advisable to learn RAG, agent planning, prompt injection defense, citation check and hallucination testing as trendy pieces of technology. They must be taught in the curriculum since they are used to teach students how to integrate information search, economic reasoning, verification of facts, risk management and business communication with the users of the business. The technologies are brought up not as a subject of technical nature but as a part of enterprise skills that are needed in the contemporary world of financial services. Figure 3 can then be considered as a learning process of the student: the stages will be tasks, the tasks will lead to evidence and the evidence will enable the teacher to assess the capabilities of the student.

Third, the innovation capability is to be determined in the form of learning artifacts that are similar to production. In a good student project there should not only be a model but also a business requirement document, data dictionary, validation report, model card, monitoring plan, compliance note, reflection record and demonstration system. These things educate students on how to interact with business managers, risk officers, engineers and regulators. They can even be quantified, assessed and compared with other groups. It also makes the graduate education and enterprise expectations more consistent.

There is also the issue of implementation. The financial information is delicate and cannot be used in the classroom. The best way to do this would be a mixture of open data, fake data, desensitized institutional examples, and simulated work processes in order to allow students to have realistic experiences without any need to break the rules of data protection. There is another problem that of teacher competence. It has been observed that most university lecturers are well versed in algorithms but they are not as experienced in practical use of finance systems; on the other hand, teachers who have worked in the field of finance are not necessarily skilled in engineering large language model applications. In order to correct this situation, there should be a two level mentorship program among universities. Academic advisors protect the integrity of the theories and the standard research methods, and industry practitioners will provide the students with an opportunity to experience the limits of business operations. One of the more significant barriers is the speed of AI technology change. The curriculum must also set triggers on updates: whenever new tools or regulations are needed, the cases of projects and rubrics of evaluation must be updated.

The social aspect of the system is also more global. The AI in financial sector has an impact on the credit access, information about investments, consumer and systemic risk. Thus, students should not be educated by the financial AI to enhance the efficiency of automation. It needs to be able to create professionals who are responsible and know how to find harm, protect against it, explain why the model acts as it does to the non-technical people and make a sensible decision when the results of the model are not aligned with what they would expect of it according to the rules or values. The suggested framework can be applied to banks, securities firms, insurance providers, asset management companies, wealth management services and FinTech companies that may have various approaches to the use of AI.

5. Conclusions

The paper is based on the assumption of a financial technology talent development system that can be responsive to the industry by the use of AI algorithms and large language models. The framework has its foundation in the change in the AI-based financial services, and it integrates the needs of the enterprise, mapping of competencies, learning with scenarios, feedbacks on governance and collaboration between industries and education into a curriculum reform process. Its significant role is that it would make financial AI training not an enhancement but a reformation of the system, where the AI algorithms and the large language model will serve as tools of learning to develop industry-ready graduates who are equipped with knowledge in financial reasoning, engineering practice, responsible AI management and innovation.

Funding

This work was supported by Postgraduate Education Reform and Quality Improvement Project of Henan Province (Grant No. YJS2025XQLH10), the Henan Provincial Key Science and Technology Research Program (Grant No. 262102211082) and Postgraduate Education Reform and Quality Improvement Project of Henan Province (Grant No. YJS2026ZYJC12).

Author Contributions

The study was conceived and supervised by S.Z. J.G. was responsible for the implementation of the proposed method, experimental design, data analysis, and manuscript preparation. Y.Z. contributed to the experimental validation, result analysis, and refinement of the manuscript. Y.T. provided guidance on the research framework and contributed to the revision of the manuscript. P.Q., Y.X. and Z.H. contributed to methodology discussion, experimental verification, and manuscript improvement. G. Z. and H. L. provided technical support and contributed to the discussion and refinement of the research. Q.Z. contributed to literature review, visualization, and manuscript organization. M.X. participated in manuscript review and provided constructive suggestions. All authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

The research was conducted with the written consent of all participants. All the participants were also told about the details of the study, the process and the confidentiality as well as the right to withdraw at any time.

Data Availability Statement

Not applicable.

Conflicts of Interest

The authors declare no conflicts of interest.

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