Data-Driven Construction and Practice of the AI + Pharmaceutics Course: An Empirical Analysis Based on the Chaoxing Platform

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Abstract Taking the AI + Pharmaceutics course at Zhaoqing University as a case, this research conducts a quantitative analysis based on operational data accumulated on the Chaoxing Platform during the 2024 – 2025 academic year, examining multiple dimensions including learning engagement, resource development, interaction quality, and AI application. The findings reveal that: the course recorded 134 656 page views and 27 643 activities, indicating active student participation in online learning; resource development formed a support system comprising 107 chapter-based resources and 293 test bank items, with 2 164 discussion forum interactions involving 91 participants; however, the depth of AI tool application remains insufficient (only 3 sessions of AI tutoring and 1 instance of AI-assisted test generation), exposing a typical dilemma of "constructed but underutilized" resources. Based on the data analysis, this paper proposes improvement strategies centered on establishing a closed-loop operational mechanism of "data collection → learning diagnosis → instructional intervention → effect evaluation", providing empirical evidence for the digital and intelligent transformation of pharmaceutical sciences courses.

Key words Artificial intelligence (AI), Pharmaceutics, Data-driven, Chaoxing Platform, Course construction

1 Introduction

Artificial intelligence (AI) is profoundly reshaping the landscape of higher education instruction. The *Opinions on Accelerating the Digitalization of Education*, jointly issued by the Ministry of Education and eight other departments, explicitly advocates for deepening the integration of large language models with education and teaching, and exploring new paradigms for "AI + education" application scenarios. Against this backdrop, effectively integrating AI technologies into the development of core professional courses has become a critical issue in university teaching reform[1].

As a core course in pharmaceutical engineering, Pharmaceutics faces three major challenges: (i) its theoretical knowledge system is highly complex, encompassing multiple dimensions such as formulation principles, preparation processes, and quality control, which renders comprehension difficult for students; (ii) practical teaching demands substantial equipment and facilities, making it challenging for traditional instructional models to meet personalized training needs; (iii) teaching evaluation predominantly relies on summative assessments, lacking precise diagnosis and timely intervention regarding students' learning processes[2].

Existing studies have explored the application of AI in pharmaceutical sciences education. Deng *et al.*[1] developed an intelligent-assisted instructional model covering the full cycle of "pre-class, in-class, and post-class" phases, with empirical findings demonstrating significant improvements in students' academic performance and experimental skills. Su *et al.*[3] integrated knowledge graphs and AI teaching assistants into the Pharmacy Administration course, finding that students held positive attitudes toward AI integration and showed improved academic outcomes.

Tsinghua University's "AI Teaching AI" innovative teaching model, leveraging a multi-agent learning platform, achieved an increase in learning test accuracy from 45.7% to 75.3%, revealing the effectiveness of data-driven instruction[4]. However, most existing studies remain at the descriptive level of construction models, with quantitative analyses based on authentic course operational data being relatively scarce. While some research has found that domain-specific AI chatbots can significantly enhance pharmacy students' trust and learning comfort, it also indicates that the depth and effectiveness of AI tool application vary considerably across contexts, underscoring the need for greater attention to the actual application depth of AI tools in real teaching settings, grounded in local operational data[5].

This study takes the construction and practice of the AI + Pharmaceutics course at Zhaoqing University as an example. Based on authentic operational data accumulated on the Chaoxing Platform, it systematically analyzes the current implementation status and existing problems of AI-empowered Pharmaceutics instruction, aiming to provide empirical evidence for the digital and intelligent transformation of similar courses.

2 Research design

2.1 Case background The AI + Pharmaceutics course, offered by the School of Food and Pharmaceutical Engineering at Zhaoqing University, was officially launched in the 2024 – 2025 academic year on the Chaoxing Fanya Smart Course Platform (Fig. 1). The course team consists of five members, including both full-time university instructors and industry mentors, who have systematically advanced AI-empowered course development across multiple dimensions, including teaching content restructu-

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ring, instructional method innovation, and assessment system reform.

2.2 Data sources and analytical methods The data for this study were derived from the course operational data on the Chaoxing Platform during the 2024 – 2025 academic year, encompassing six dimensions: (i) basic course information (enrollment numbers and class count); (ii) learning engagement (page views, activity counts, and participation frequency); (iii) resource development (chapter-based resources, test bank, and knowledge base); (iv) teaching implementation (assignments, quizzes, discussions, and classroom activities); (v) AI application (access statistics for AI tools such as AI tutoring and AI-assisted test generation); and (vi) learning behavior distribution (heatmaps and active time periods). The analytical approach primarily employs descriptive statistics, supplemented by comparative analysis.

To clearly articulate the complete logical chain of data collection, analysis, and teaching optimization, we construct a data-driven closed-loop operational framework for course implementation (Fig. 2). This framework incorporates the above six categories of platform data into the core "multi-dimensional data collection" component. With the course resource repository serving as the underlying support, statistical analysis is conducted to diagnose learning status and AI application patterns. Based on these diagnostic results, targeted human-AI collaborative instructional intervention strategies are designed. Teaching effectiveness is then evaluated through multi-dimensional indicators on the platform, and the results are fed back to iteratively optimize course resources and instructional design, thereby forming a continuous improvement loop for teaching. The original Chaoxing platform interface screenshots presented in Fig. 3 through Fig. 7 are empirical quantitative data corresponding to each stage of this framework.

3 Results of data analysis

3.1 Learning engagement analysis The course covered three classes with a total of 92 enrolled students. Platform data showed that the course accumulated 134 656 page views (PV) and 27 643 learning activities, with an average of approximately 300 activities per student. Over the past month, the number of active students remained at 92 (full attendance), with 5 807 teacher-student activities and two active classes (Fig. 3).

The learning heatmap revealed a distinct temporal concentration in students' online learning patterns (Fig. 4): evening hours from 20:00 to 24:00 constituted the peak learning period, with significantly higher activity levels on Saturdays and Sundays compared to weekdays. This distribution suggests that: (i) students tend to utilize fragmented evening and weekend time for online learning, which aligns with the general pattern of "fragmented and embedded learning"; and (ii) the stronger willingness for autonomous learning on weekends provides data-driven support for implementing flipped classroom strategies and pre-class preparation.

3.2 Course resource development analysis In terms of resource development, a total of 107 chapter-based resources were created (including 100 video resources, accounting for 93.5%, and 7 other resources), along with 25 supplementary materials and 293 test bank items. Besides, 160 resources were uploaded to the AI knowledge base (44 documents and 116 videos), generating 3 249 knowledge slices (Fig. 5).

The predominance of video resources (93.5%) indicates that the course content is primarily video-based, while other resource formats such as audio, documents, images, and animations have not yet been fully developed. The scale of the test bank (293 items) and the knowledge base (3 249 slices) lays a foundation for subsequent AI-assisted test generation, intelligent item development, and personalized recommendation. As noted in previous research, the core value of AI-assisted instruction lies in its capacity to provide students with adaptive, personalized learning pathways and resource recommendations, and the richness of resource development directly affects the realization of this goal.

3.3 Teaching implementation and interaction quality analysis Teaching implementation data revealed that 13 assignments and 4 test papers were created; 7 chapter quizzes were released, with 622 completions (an average of 6.76 quizzes per student); a total of 2 164 discussion forum posts were generated, with 91 students participating (a participation rate of 98.9%); and 20 classroom activities were launched (Fig. 6).

The 98.9% participation rate in the discussion forum represents a notable strength of course interaction. Research has shown that the "question-response-follow-up inquiry-extension" deep dialogue chain serves as an important indicator for measuring learning depth, and the high participation rate in the Pharmaceutics course discussions provides a promising foundation for fostering such deep interactions. However, the "zero release" of assignments and examination modules warrants attention, while instructors created these resources, they have not yet been officially deployed for use, revealing a gap between instructional design and platform functionality implementation.

3.4 AI application status analysis The AI application data constitute a core finding of this analysis. The results showed that AI tutoring was accessed 3 times (all by students), while AI-assisted test generation was accessed once, and access to both the resource assistant and AI research assistant tools was zero. These findings reveal the following issues. First, the overall utilization rate of AI tools is extremely low, highlighting a typical dilemma of "constructed but underutilized", despite 160 resources being uploaded to the knowledge base and 3 249 slices being generated, AI-driven intelligent retrieval and personalized recommendation functions have rarely been invoked. Second, teacher-side AI usage is zero, indicating that instructors have not yet leveraged AI-assisted test generation or intelligent item development to enhance efficiency during the lesson preparation phase. Although the AI workstation provided on the Chaoxing Platform can assist instructors in rapidly generating courseware, lesson plans, and practice items, thereby reducing repetitive work, the data suggest that instruc-



Fig. 1 Homepage of the Pharmaceutics course on the Chaoxing Fanya Smart Course Platform

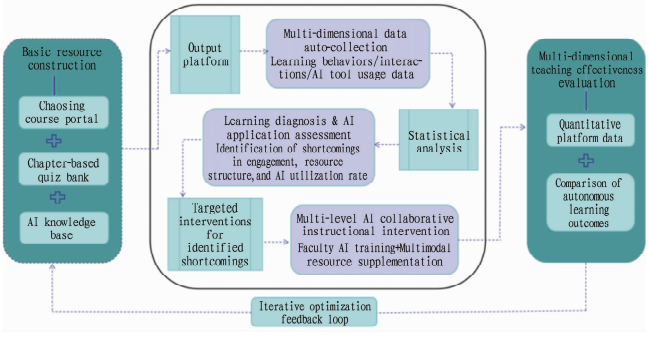


Fig. 2 Data-driven closed-loop operational framework for the AI + Pharmaceutics course



Fig. 3 Overview of basic course operation data (number of classes, enrolled students, activities, and page views)

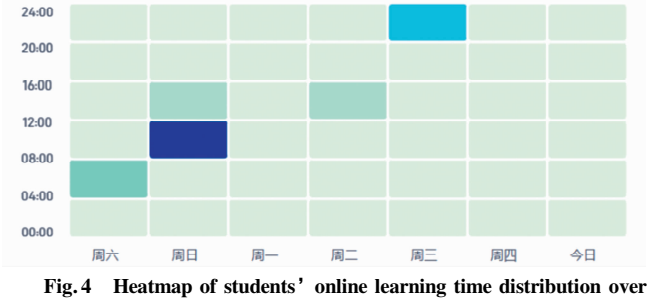


Fig. 4 Heatmap of students' online learning time distribution over the past 7 days



NOTE A. Composition of chapter resources; B. Composition of AI knowledge base resources.

Fig. 5 Distribution of course resources and AI knowledge base resources

tors have not yet developed the habit of utilizing these tools. Third, student-side AI usage remains at an "exploratory" level (3 sessions of AI tutoring), and students have not yet developed the learning habit of employing AI tools for targeted reinforcement (Fig. 7).



NOTE Data include assignments, examinations, quizzes, discussions, and classroom activities.

Fig. 6 Core data of teaching operation



NOTE AI tools include (AI tutoring, AI test paper generation, material assistant, and AI research assistant.

Fig. 7 Access statistics of AI application tools

This finding is consistent with the conclusions of systematic reviews: although AI tools can theoretically enhance cognitive knowledge acquisition and affective learning outcomes, their effectiveness and depth of use vary considerably across different contexts. Han *et al.* [6], in a meta-analysis of 68 experimental studies, found significant heterogeneity in AI effectiveness across educational stages, subject areas, and intervention durations (I^2 = 95%). Lipnevich *et al.* [7], in a scoping review of 104 studies on AI-based feedback, further revealed that the effectiveness of AI feedback is strongly dependent on implementation contexts and task characteristics, and that the mere deployment of AI tools does not automatically lead to instructional improvement, teacher intervention and human supervision remain critical to ensuring efficacy. These lines of evidence indicate that promoting the transition of AI tools from "construction" to "effective utilization" is a pressing practical issue that requires urgent attention.

4 Discussion

4.1 Prerequisites for realizing the "data-driven" paradigm shift A core finding of this study is that the course has accumulated considerable operational data (134 656 page views and 27 643 activities), establishing a foundation for transitioning from an "experience-driven" to a "data-driven" approach. However, data accumulation does not automatically translate into instructional optimization. Maier and Krämer[8], in their updated framework for data-driven decision-making (DDDM), explicitly assert that effective DDDM requires the integration of quantitative technical data with qualitative pedagogical insights and contextual factors; mere data collection is insufficient to improve teaching effectiveness. The Chaoxing Smart Course Platform advocates a "teacher-student-machine" tripartite collaborative logic, teachers leverage data to provide precise guidance, students obtain personalized support through data, and machines accurately match the needs of both parties via AI and platform functionalities[9]. In this regard, Li Zhiyong, Vice President of Xiamen University[10], points out that classrooms in the intelligent era are transforming into "learning communities" characterized by deep "teacher-student-machine" interaction and collaborative exploration, and that universities must construct novel instructional models based on this tripartite synergy. To achieve this goal, it is necessary to establish a closed-loop operational mechanism of "data collection → learning diagnosis → instructional intervention → effect evaluation", thereby transforming platform data into evidence-based pedagogical decision-making.

4.2 Strategies for enhancing the depth of AI tool application To address the low utilization rate of AI tools, a phased approach is recommended: (i) teacher-side piloting: conduct specialized training on the AI Workbench to encourage instructors to utilize AI-assisted test generation and intelligent item development functions, thereby activating the existing 293-item test bank and 3 249 knowledge slices as teachable resources; (ii) student-side integration: incorporate AI tutoring and error collection functions into the formative assessment system, establishing incentive mechanisms for usage[11]; and (iii) contextualized embedding: design AI tool application tasks within specific scenarios such as pre-class preparation, review, and quizzes, avoiding the pitfall of "use for use's sake"[12]. Practical experience from Zhengzhou University of Light Industry demonstrates that combining AI-based learning analytics with teaching early warning systems can effectively identify at-risk students and enable timely intervention. By integrating multi-source information including class attendance rates, learning completion rates, and library usage data, the institution constructed an academic risk profile for students, achieving a transition from "experience-based management" to "data-driven precision intervention"[13].

4.3 Diversification and precision of resource formats The current predominance of video resources (93.5%) indicates that other formats such as audio, documents, and animations remain underdeveloped. Different learning scenarios require different resource modalities: short videos and documents are suited for pre-

class preparation; test banks and knowledge slices support consolidation; and case studies and frontier literature facilitate advanced learning. Lu Mingzhu[14], in constructing a multimodal smart learning space, noted that unimodal resources cannot satisfy diverse learning needs, and that resource development should follow a multi-layer framework of "course teaching→data acquisition→intelligent analytics→application services". Further practical evidence from the School of Pharmaceutical Sciences at Capital Medical University demonstrates that virtual simulation experiment platforms can serve as complementary tools for physical experiments and as autonomous learning platforms, forming a "virtual-actual combination" multimodal teaching model that effectively enhances students' learning outcomes and employment competitiveness[15]. It is recommended that subsequent development efforts focus on supplementing document-based resources (*e. g.*, case analyses, process documents) and interactive resources (*e. g.*, virtual simulation tasks) to construct a multimodal resource matrix.

4.4 Research limitations This study is based on operational data from a single semester and a single course, employing a descriptive analytical approach. It has not yet conducted correlational or regression analyses linking platform behavioral data with academic performance, and thus possesses inherent limitations in causal inference. A more rigorous evaluation of the effectiveness of AI tool usage warrants validation through quasi-experimental designs in future research[16]. In the field of pharmacy education, Halford and Heitz[5] have employed a multi-cohort quasi-experimental design to assess the instructional efficacy of AI chatbots, validating AI tool acceptance and effectiveness through pre- and post-intervention surveys across two consecutive student cohorts. Their methodological framework provides a referable paradigm for the present study to adopt more rigorous designs in the future, such as introducing control groups, implementing pre- and post-test interventions, and conducting multi-cohort cross-semester validation. Furthermore, the analytical dimensions of this study are primarily confined to descriptive statistics, without employing regression analysis, learning behavior sequence analysis, or other methods to explore correlational mechanisms and causal pathways among variables, which is an area that also merits further investigation in future research.

5 Conclusions

This study systematically analyzes the current state of the AI + Pharmaceutics course development based on authentic operational data from the Chaoxing Platform. The findings reveal that: (i) the course has achieved notable success in resource development and student engagement, laying a foundation for data-driven instruction; (ii) the high-quality interaction in the discussion forum (participation rate of 98.9%) represents a major strength of the course implementation; and (iii) the depth of AI tool application remains insufficient, with both instructors and students exhibiting a "constructed but underutilized" dilemma. It is recommended that future efforts focus on activating AI tool utilization, refining the formative assessment system, and establishing a data-driven closed-loop mechanism for instructional improvement, thereby advancing the course from "construction" to "effective utilization" and providing a transferable practical paradigm for the digital and intelligent transformation of pharmaceutical sciences courses.

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