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Integrating Evidence-Based Medicine and Artificial Intelligence in Ophthalmology Education: A Teaching Reform Study

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Abstract: *Purpose:* This research sets out to explore the practical application value of an innovative teaching mode that organically combines evidence-based medicine (EBM) with artificial intelligence (AI), and analyze its application effect on undergraduate medical students during their ophthalmology internship. *Methods:* This research team independently built a multi-functional online teaching platform integrating EBM and AI technologies, which incorporates specialized evidence resource libraries, AI auxiliary diagnosis tools, and simulated clinical case modules. A total of 30 fifth-year clinical undergraduates receiving ophthalmology internship training were enrolled as research subjects and randomly assigned into two groups with 15 participants each. The experimental group adopted the newly developed EBM-AI integrated teaching method, while the control group received the conventional offline teaching mode. Multiple indicators were adopted to evaluate the teaching effect, covering students' professional theoretical reserves, EBM and AI-related comprehensive abilities, clinical decision-making level, autonomous learning enthusiasm, and subjective evaluation of teaching quality. *Results:* Before the intervention, there was no statistical difference in the basic ophthalmology knowledge reserve between the two groups ($P > 0.05$). After the implementation of different teaching schemes, the experimental group outperformed the control group in all evaluation indicators. To be specific, the experimental group obtained higher scores in overall theoretical assessment (86.12 ± 4.05 vs. 74.93 ± 5.62, $P < 0.001$) and EBM/AI specialized knowledge test (36.25 ± 2.31 vs. 26.80 ± 3.17, $P < 0.001$). Meanwhile, the group also achieved better results in the Script Concordance Test (SCT) for clinical decision-making ability (81.60 ± 5.24 vs. 63.87 ± 6.08, $P < 0.001$). In terms of learning initiative, the weekly self-study duration of students in the experimental group was obviously longer than that of the control group (4.02 ± 0.71 vs. 1.68 ± 0.44, $P < 0.001$). Additionally, the student satisfaction rate of the new teaching model reached 93.3%, which was notably higher than 73.3% of the traditional teaching group ($P = 0.031$). *Conclusion:* The integrated teaching model combining EBM and AI can effectively help interns consolidate EBM and AI professional knowledge, optimize clinical case analysis and decision-making capabilities, and stimulate their enthusiasm for independent learning. Importantly, the new teaching method will not affect students' mastery of basic ophthalmology knowledge. This optimized teaching scheme can serve as a reliable reference for promoting the innovative reform of modern ophthalmology higher education.

Keywords: Evidence-based medicine; Artificial intelligence; Ophthalmology education; Clinical decision-making; Teaching reform

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1. Introduction

Ophthalmology is a distinctive clinical discipline with strong visualization characteristics and high dependence on advanced medical technologies. The daily diagnosis and treatment of various ophthalmic diseases cannot do without auxiliary imaging detection means, including optical coherence tomography, fundus photography, and visual field testing. In the past decade, artificial intelligence technology has achieved explosive development in the field of ophthalmology clinical diagnosis. Deep learning-based intelligent diagnostic systems have been verified to reach the professional level of attending physicians in screening and diagnosing common refractory eye diseases, such as diabetic retinopathy, glaucoma, and age-related macular degeneration [1,2].

As a standardized clinical medical thinking and working mode, evidence-based medicine has become the core guiding principle for global clinical diagnosis and treatment activities. It requires clinical practitioners to integrate high-quality latest medical research achievements, professional clinical experience, and personalized needs of patients to formulate the most scientific and reasonable diagnosis and treatment plans [3].

Despite the dual maturity of evidence-based medicine (EBM) theory and artificial intelligence (AI) clinical application technology, the integration of the two into the daily teaching system of ophthalmology is still in the exploratory stage worldwide, especially in domestic medical colleges. At present, most medical schools in China still take the traditional teacher-centered lecture teaching as the main teaching form of ophthalmology courses. Under this passive learning mode, students mainly receive rigid textbook knowledge, and the teaching content cannot be updated synchronously with the latest industry research progress. As a result, a large number of clinical interns fail to master the method of screening and evaluating high-quality medical evidence, and lack the ability to apply intelligent diagnostic tools to solve practical clinical problems after graduation [4,5].

In order to make up for the deficiencies of traditional teaching, many medical educators have tried to introduce EBM or AI technology into ophthalmology training courses separately. Relevant research results show that EBM-oriented case discussion training can effectively cultivate students' critical thinking ability [6]; AI auxiliary teaching systems can enrich classroom teaching forms and significantly raise students' learning participation [7]. Some scholars have also put forward the theoretical framework of integrating EBM and AI for ophthalmology teaching [8], but relevant research still has obvious limitations: there is no randomized controlled trial to verify the combined teaching effect of the two technologies and confirm their synergistic value in teaching practice. Based on the above research gaps, this study develops a complete set of EBM-AI integrated teaching systems and further analyzes the influence of this teaching mode on undergraduates' clinical ability, knowledge absorption, and learning motivation through controlled experiments, so as to provide a practical basis for the reform of ophthalmology teaching.

2. Materials and methods

2.1. Study design

This research adopted a prospective single-center randomized controlled trial design, and the research cycle spanned from March 2024 to March 2025. The research subjects were ophthalmology interns from the Affiliated Hospital of North Sichuan Medical College. Before the formal start of the research, all participants were fully informed of the research content, teaching arrangement, and related risks, and signed written informed consent voluntarily.

2.2. Participants

Thirty fifth-year undergraduate students majoring in clinical medicine who participated in ophthalmology rotation internship were selected as research subjects. The inclusion criteria for participants were as follows: students who had completed basic ophthalmology and internal medicine theoretical courses; students with no previous ophthalmology internship experience; students who voluntarily participated in this research and cooperated with all teaching arrangements and achievement assessments. The exclusion criteria included: students who accumulated more than three days of absence during the internship rotation; students who had received systematic EBM or AI professional training outside the regular curriculum before the research.

The research team used a computer random number generator to divide all enrolled students into an experimental group and a control group equally, with 15 people in each group. Statistical analysis was conducted on the basic information of the two groups including age, gender proportion, and academic performance of previous courses. The results showed that the baseline data of the two groups were basically consistent, and the difference was not statistically significant (all $P > 0.05$), which met the conditions for controlled research.

2.3. Development of the EBM-AI integrated teaching platform

A cross-terminal web-based teaching platform compatible with computers and mobile devices was specially developed for the experimental group in this research. The platform is divided into four independent and interconnected functional modules to cover the whole process of pre-class preview, in-class training, and post-class assessment:

Module 1: EBM Evidence Resource Database. This module integrates multiple mainstream medical evidence databases at home and abroad, including PubMed, Cochrane Library, and core Chinese medical journals. To lower the learning threshold for interns, the research team sorted out and summarized high-quality clinical evidence aiming at frequently occurring ophthalmic diseases, and compiled detailed operational guidelines to help students master the standardized construction method of PICO (Population, Intervention, Comparison, Outcome) clinical research questions.

Module 2: AI Auxiliary Diagnosis Training Module. Three kinds of mature and verified intelligent diagnosis models were embedded in the platform, covering diabetic retinopathy grading (sensitivity: 0.96, specificity: 0.93), glaucomatous optic nerve damage detection, and children's myopia progression trend prediction. The module adopts a dual-diagnosis learning mode: students need to complete the interpretation of ophthalmic imaging images independently at first, then compare their diagnosis results with AI intelligent analysis feedback. The system will automatically mark the inconsistent parts between manual diagnosis and

AI results to facilitate students in carrying out error analysis.

Module 3: Virtual Simulation Case Base. A total of 20 high-simulation virtual clinical cases were created, covering corneal diseases, glaucoma, retinal diseases, and optometry-related common clinical scenarios. Each case was set with multiple decision nodes. Students need to retrieve relevant medical evidence through the platform and write down a detailed decision-making basis before giving diagnosis and treatment suggestions. The system will automatically record students' resource retrieval paths, cited literature, and the rationality of final clinical decisions.

Module 4: Learning Data Statistics Module. This module can automatically collect and count students' learning behavior data on the platform, including login frequency, learning duration of each functional module, completion rate of virtual cases, and scores of embedded daily quizzes. Teachers can view the learning data of all students in real time, accurately identify students with weak learning effects and difficulties in mastering key knowledge, and formulate targeted personalized tutoring plans.

2.4. Teaching intervention

The internship rotation cycle of all students was 4 weeks, with a total of 24 hours of professional teaching time. The teaching hours of the two groups were kept consistent, but the teaching modes and contents were completely different.

The control group adopted the traditional ophthalmology internship teaching mode: teachers arranged 2 hours of professional knowledge lectures every week to explain the core knowledge of common ophthalmic diseases; organized 2 hours of case discussion and bedside teaching activities every week; arranged students to observe outpatient diagnosis and treatment work under the guidance of instructors. The whole teaching process did not involve targeted EBM and AI professional training.

The experimental group took the self-developed EBM-AI integrated platform as the core carrier, and completed the staged teaching training in three phases within 4 weeks:

Phase 1 (the first week): Basic learning and pre-job training. All students in the experimental group completed two online special training courses on the platform, which respectively focused on the standardized formulation method of PICO clinical questions and the functional characteristics and application limitations of ophthalmic AI diagnostic tools. After the training, a baseline knowledge test was arranged to clarify students' initial mastery of relevant knowledge points.

Phase 2 (the second to third week): Immersive interactive training. Two fixed teaching activities were arranged every week: First, a 3-hour virtual case simulation training. Students formed two-person groups to analyze typical cases (such as sudden vision loss in elderly diabetic patients). The training links included putting forward standardized PICO questions, retrieving supporting evidence through the EBM database, using AI tools to analyze fundus images, comparing the differences between manual diagnosis and AI results, and finally forming a complete diagnosis and treatment scheme with sufficient evidence. Second, a 2-hour small-group flipped classroom discussion. Students took turns to share their case diagnosis ideas and decision-making processes. Teachers guided students to discuss the causes of differences between manual judgment, AI diagnosis results, and authoritative medical evidence, and focused on analyzing the applicable scenarios and defects of AI tools (such as poor image quality leading to diagnostic errors and inaccurate identification of atypical cases).

Phase 3 (the fourth week): Knowledge consolidation and comprehensive assessment. Students were required to independently complete the analysis and decision-making of three complex virtual clinical cases without any step-by-step guidance from teachers and platforms. The completion quality of the cases was included in the final internship performance assessment.

2.5. Outcome measures

Primary outcome indicator: Students' clinical decision-making ability, which was evaluated by the Script Concordance Test (SCT). The test paper contained 15 real ophthalmology clinical scenarios, and each scenario was equipped with 3–4 diagnostic and treatment-related evaluation items. Students needed to score the feasibility of corresponding operation schemes according to the actual clinical situation. The total score of the test ranged from 0 to 100 points. In order to ensure the objectivity of scoring results, two evaluators who did not know the grouping situation scored all test papers separately.

Secondary outcome indicators: (1) Theoretical knowledge level: a closed-book written test with a full score of 100 points was adopted. The test questions were divided into two parts, including 60 points of basic ophthalmology knowledge and 40 points of EBM and AI-related applied knowledge (covering PICO question formulation, AI result interpretation, and clinical evidence application). (2) Learning initiative: the platform automatically counted the average weekly independent learning time of students and the number of voluntarily completed virtual simulation cases. (3) Student satisfaction: an anonymous satisfaction questionnaire was issued after the internship. The questionnaire included five Likert five-scale scoring items and an overall satisfaction evaluation option, and students could independently evaluate the teaching quality. (4) Teacher feedback: semi-structured interviews were conducted with three internship instructors to collect their objective evaluation of the EBM-AI teaching model, as well as the difficulties encountered in the teaching process and suggestions for optimization.

2.6. Statistical analysis

SPSS 26.0 statistical software was used to process all research data in this study. The measured data conforming to normal distribution were expressed by mean ± standard deviation (SD), and independent-samples t-test was used for inter-group comparison; data that did not meet the normal distribution characteristics were analyzed by Mann-Whitney U test. Count data were compared by chi-square test or Fisher's exact test according to the sample size. In all statistical tests, $P < 0.05$ was defined as the threshold for statistically significant differences.

2.7. Ethical considerations

The whole research process strictly abided by the relevant provisions of the Declaration of Helsinki. All participants had the right to withdraw from the research at any stage without any negative impact on their internship performance and academic scores. All data collected in the research were anonymized and desensitized to protect the personal privacy of students and teachers.

3. Results

3.1. Participant flow and baseline characteristics

All 30 enrolled students successfully completed the 4-week internship rotation and all assessment items, with a 100% participation completion rate. The baseline information of the two groups is shown in **Table 1**.

There was no significant difference between the experimental group and the control group in terms of age composition, gender ratio, and previous academic performance (all $P > 0.05$), indicating that the research samples were comparable.

Table 1. Baseline characteristics of participants

Characteristic	Control group (n = 15)	Experimental group (n = 15)	P value
Age (years, mean ± SD)	22.4 ± 0.8	22.6 ± 0.7	0.472
Gender (male/female)	8/7	7/8	0.713
Previous course grade (100-point scale)	79.2 ± 5.1	80.1 ± 4.8	0.625

3.2. Theoretical knowledge

The scores of the post-intervention theoretical knowledge test of the two groups are listed in **Table 2**. The overall theoretical score of the experimental group was obviously higher than that of the control group, and the difference was extremely significant ($t = 6.342$, $P < 0.001$). In terms of basic ophthalmology knowledge, the scores of the two groups were relatively close, and there was no statistical difference ($t = 1.785$, $P = 0.085$). This result verifies that the EBM-AI integrated teaching will not crowd out the learning time of basic professional knowledge and damage students' basic discipline literacy. In terms of EBM and AI specialized knowledge, the experimental group had an absolute advantage in scores, and the gap between groups was prominent ($t = 9.316$, $P < 0.001$).

Table 2. Comparison of theoretical examination scores between the two groups (points, mean ± SD)

Outcome measure	Control group (n = 15)	Experimental group (n = 15)	t value	P value
Total theoretical knowledge (100)	74.93 ± 5.62	86.12 ± 4.05	6.342	<0.001
Basic ophthalmology (60)	48.13 ± 3.08	49.87 ± 2.13	1.785	0.085
EBM+AI knowledge (40)	26.80 ± 3.17	36.25 ± 2.31	9.316	<0.001

3.3. Clinical decision-making ability

The SCT test results showed that the average score of clinical decision-making ability of students in the experimental group reached 81.60 ± 5.24, while that of the control group was only 63.87 ± 6.08. The inter-group difference was extremely significant ($t = 8.602$, $P < 0.001$). It can be concluded that the immersive training based on EBM and AI can effectively help students sort out clinical diagnosis ideas and improve their problem-solving ability when facing ambiguous and complex real clinical cases.

3.4. Learning initiative

According to the statistical data of the teaching platform, the weekly average independent learning time of students in the experimental group was 4.02 ± 0.71 hours, which was far longer than the 1.68 ± 0.44 hours of the control group ($t = 10.793$, $P < 0.001$). In addition, in terms of voluntary learning tasks, students in the experimental group actively completed 12.3 virtual cases on average, while the average number of voluntary completed cases in the control group was only 4.1. The above data fully prove that the new teaching mode can effectively stimulate students' autonomous learning motivation.

3.5. Student satisfaction

After collecting and sorting out the anonymous satisfaction questionnaires, the research team found that 14 out of 15 students in the experimental group held a positive attitude towards the EBM-AI integrated teaching mode, with an overall satisfaction rate of 93.3%; the satisfaction rate of the control group for traditional teaching was 73.3% (11/15). The chi-square test confirmed that the satisfaction gap between the two groups was statistically significant ($\chi^2 = 4.658$, $P = 0.031$). From the open-ended feedback of students in the experimental group, most interns indicated that the new teaching mode helped them get rid of rote memorization learning methods, master the method of screening and evaluating clinical evidence independently, and realize that AI diagnostic tools have inherent limitations, so critical thinking is indispensable in clinical diagnosis.

3.6. Teacher feedback

The three interviewed internship instructors all stated that the initial launch of the EBM-AI integrated teaching mode required teachers to spend extra time learning platform operation methods and designing targeted teaching cases, which increased the early preparation workload. However, long-term teaching practice showed that this teaching mode also promoted teachers to continuously update their EBM evidence retrieval ability and AI tool application level. Meanwhile, the learning data statistics module of the platform can help teachers accurately locate students' weak points in learning, so as to carry out one-to-one targeted tutoring and improve the overall teaching efficiency.

4. Discussion

4.1. Synergistic effects of EBM and AI integration

Based on the comprehensive research data, this study confirms that EBM and AI have obvious synergistic effects in ophthalmology teaching, rather than simply superposing two independent teaching contents. The embedded AI diagnostic module provides students with instant personalized learning feedback, simplifies the complex process of clinical evidence retrieval, and reduces the learning difficulty for interns who are new to clinical work. On the other hand, the EBM theoretical system makes up for the defect of blind dependence on intelligent tools caused by over-reliance on AI technology. It teaches students to evaluate the rationality of AI diagnosis results from multiple dimensions such as evidence level and patient applicability.

For example, when the AI system recommends panretinal photocoagulation for patients with diabetic retinopathy, students trained by EBM can take the initiative to think about the evidence basis of the recommended scheme and whether the scheme is applicable to patients with mild proliferative retinopathy. This dual-dimensional training mode can help students avoid two extreme wrong attitudes in the face of emerging intelligent medical technologies: blind superstition and complete rejection [9,10].

4.2. Comparison with previous studies

The research conclusions of this paper are consistent with the existing related research results: EBM training can cultivate students' critical thinking quality [6], and AI auxiliary teaching can effectively activate students' learning enthusiasm [7]. However, most of the previous related studies only carried out single-variable intervention research, separately analyzing the teaching value of EBM or AI. Related literature reviews pointed out that most of the current AI medical education researches have defects such as imperfect evaluation indicators and lack of control groups, which reduce the credibility of research conclusions [11].

Different from previous studies, this research adopts a rigorous randomized controlled trial design and takes multiple authoritative indicators such as SCT score and theoretical test score as evaluation criteria. The effect size of each core research indicator is larger than that of the single-mode teaching intervention scheme mentioned in previous literature, which further verifies the synergistic teaching advantage of integrating EBM and AI.

4.3. Why basic knowledge was not compromised

In the process of designing the research scheme, the research team once worried that adding EBM and AI-related new teaching contents would occupy the learning time of basic ophthalmology knowledge and lead to the decline of students' basic professional level. However, the final test data proved this worry unnecessary. The core reason is that the virtual simulation cases and AI image diagnosis training adopted in the new teaching mode realize repeated consolidated learning of basic knowledge through practical application.

Taking the grading training of diabetic retinopathy fundus images as an example, students need to repeatedly identify image features manually and compare them with AI results. This repeated practical training can strengthen students' ability to identify typical disease characteristics more efficiently than single passive classroom lectures, and realize the organic integration of knowledge learning and practical application [12,13].

4.4. Implications for ophthalmology educators

This research suggests that medical colleges can appropriately promote the integrated teaching of EBM and AI in the undergraduate internship stage of ophthalmology. Although the construction of a complete set of intelligent teaching platforms requires certain human and material resource support, educators can reduce the application threshold by optimizing the scheme according to the actual situation of the college. For institutions with insufficient research and development funds, teachers can use free open-access medical evidence databases (UpToDate, DynaMed) and mature commercial AI diagnostic tools (such as FDA-certified IDx-DR system for diabetic retinopathy screening) to build a simplified version of the integrated teaching mode [14].

In addition to optimizing the teaching platform, teacher ability training is also an indispensable link in the implementation of the new teaching mode. Colleges need to organize special training courses for internship instructors, covering AI basic literacy, EBM latest theoretical knowledge, and virtual case design skills, to help teachers adapt to the innovative teaching mode as soon as possible [15].

4.5. Limitations and future directions

This research still has several objective limitations. First of all, the research samples are all from a single medical institution, and the sample size is small, which limits the popularization and application scope of the research conclusions. Secondly, this research only evaluates the teaching effect within the internship cycle and fails to track the long-term retention effect of students' EBM and AI application abilities after they graduate and engage in clinical work. Thirdly, this research only evaluates students' learning effect from the perspective of education, and does not explore the impact of the new teaching mode on the actual diagnosis and treatment quality of patients. Fourthly, the novelty of the intelligent teaching platform may bring the Hawthorne effect, that is, the improvement of students' performance is partially affected by the new teaching form rather than the teaching content itself.

In view of the above limitations, the research team puts forward the improvement direction for subsequent related research: carry out multi-center joint controlled trials to expand the sample coverage; establish a long-term follow-up mechanism to track the sustainability of students' learning achievements; introduce real desensitized clinical medical data to enrich case resources; add objective evaluation indicators such as OSCE score and patient satisfaction; carry out cost-benefit analysis of the EBM-AI teaching platform to provide data support for large-scale promotion [16–18].

4.6. Practical recommendations

Combined with the platform construction experience and teaching practice effect of this research, the following targeted suggestions are put forward for medical educators who intend to promote EBM-AI integrated teaching reform: First, adopt the progressive promotion strategy, take a single mature AI diagnostic tool for high-incidence ophthalmic diseases as the starting point of teaching reform, and gradually expand the types of tools and teaching cases. Second, compile a simple and operable AI result evaluation checklist for students to help them judge the credibility of AI diagnosis from multiple dimensions. Third, prioritize SCT test instead of traditional multiple-choice questions to evaluate students' clinical reasoning ability under uncertain conditions. Fourth, attach importance to peer mutual assistance learning, encourage students to share platform operation skills and case analysis ideas, and realize complementary advantages among students [19,20].

5. Conclusion

This rigorous randomized controlled trial fully proves that the integrated teaching mode combining evidence-based medicine and artificial intelligence can comprehensively optimize the teaching effect of ophthalmology internship courses. This innovative teaching method can not only help interns systematically master EBM and AI professional knowledge, stimulate their independent learning enthusiasm, but also effectively cultivate high-level clinical decision-making and case analysis ability, without causing a negative impact on students' mastery of basic ophthalmology core knowledge.

EBM provides standardized clinical thinking logic for students to evaluate intelligent tools, while AI technology simplifies the practice process of evidence-based medicine. The complementary and mutually reinforcing relationship between the two makes the integrated teaching mode an important development direction of modern ophthalmology education reform. With the continuous popularization of AI intelligent diagnostic tools in the field of ophthalmology clinics, cultivating interns' ability to use AI technology rationally and evaluate intelligent diagnosis results critically has become an essential part of high-quality ophthalmology talent training.

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Disclosure statement

The authors declare no conflict of interest.

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