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Impact of Artificial Intelligence Combined with Task-Driven Learning Methods on Teaching Effectiveness for Medical Interns: A Study in Respiratory Medicine

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Abstract

Objective: This study aimed to evaluate the effectiveness of an artificial intelligence (AI)-enhanced task-driven learning approach in respiratory medicine internship training compared to traditional teaching methods. **Methods:** A retrospective study was conducted involving 53 medical interns, divided into a control group ($n = 27$) receiving conventional teaching and an experimental group ($n = 26$) undergoing AI-enhanced task-driven instruction. The intervention integrated AI tools for clinical simulation with structured task-driven learning activities. Outcomes were assessed through standardized examinations (theoretical knowledge, practical skills, and case analysis) and comprehensive surveys (teaching satisfaction and self-evaluated competency). **Results:** The experimental group demonstrated statistically superior performance across all assessment domains compared to controls. Significantly higher scores were observed in theoretical knowledge (29.58 ± 3.38 vs. 27.11 ± 3.99, $P = 0.02$), practical skills (32.23 ± 3.13 vs. 26.56 ± 2.45, $P < 0.001$), and case analysis (14.85 ± 1.85 vs. 10.96 ± 1.95, $P < 0.001$). Satisfaction surveys revealed significantly more favorable responses from the experimental group ($P < 0.001$), with a higher proportion of "very satisfied" ratings. Self-assessment results indicated markedly improved perceived competency among experimental group participants ($P = 0.02$). **Conclusion:** The integration of AI tools with task-driven learning methodologies significantly enhances respiratory medicine internship training outcomes, improving both objective performance metrics and subjective learning experiences. This innovative approach offers a promising educational model for clinical training, though technical and ethical considerations require continued attention.

Keywords

Artificial Intelligence, Task-Driven Learning, Medical Internship, Respiratory Medicine, Teaching Effectiveness, Educational Innovation

1. Introduction

Respiratory diseases represent a major global cause of mortality and morbidity [1]. The complexity of these conditions is reflected in current epidemiological data: chronic obstructive pulmonary disease (COPD) ranks as the third leading cause of death worldwide [2], with a global prevalence of approximately 10.3% [3]. Asthma affects an estimated 235 - 300 million people globally [4]. Idiopathic pulmonary fibrosis (IPF) shows a global prevalence ranging from 8 to 60 per 100,000 individuals, with higher rates observed in North America and Europe compared to other regions [5]. Furthermore, lung cancer remains the malignancy with the highest global incidence and mortality, posing a serious threat to human health. Given the high incidence of respiratory diseases and their significant impact on public health systems, it is essential to cultivate a well-trained and competent healthcare workforce.

Clinical internship constitutes a crucial phase in undergraduate medical education, designed to develop clinical reasoning and operational skills by bridging textbook knowledge and practical application. Competency-based education helps align national health needs with professional values. Under traditional teaching models, instruction has predominantly relied on lecture-based learning—a teacher-centered approach where instructors deliver predetermined content while interns assume the role of passive listeners, resulting in unidirectional knowledge transfer [6] [7]. This often leads to insufficient student engagement, a lack of clinical reasoning, and weak practical skills. In the 1980s, Prabhu introduced the task-driven learning method, which centers learning around concrete tasks [8]. By setting specific learning objectives, this approach guides students toward autonomous learning and fosters proactivity. It has since been widely adopted across multiple disciplines, improving classroom efficiency, boosting learning motivation, and reducing student distraction. In recent years, task-driven learning has also been explored in medical education. It significantly enhances learning efficiency and comprehensive competency, promoting deeper understanding and knowledge retention [9]. However, its implementation requires students to independently analyze and solve numerous problems, which can be time-consuming and may lead to frustration or discouragement.

Recent advances in artificial intelligence (AI) have introduced new opportunities for reforming medical education. Large language models can serve as virtual teaching assistants, providing students with detailed and relevant information, and potentially enabling interactive simulations [10]. AI-generated virtual cases, developed through deep learning algorithms, can closely mimic clinical characteristics of diseases, allowing students to engage in diagnostic reasoning and treatment planning through interactive practice. Research confirms that such technology significantly improves learning outcomes in simulated clinical environments and accelerates the development of complex case-analysis skills [11]. Building on these advantages, this study integrates task-driven learning methodology with AI tools to explore their application in clinical internship training.

2. Materials and Methods

2.1. Study Participants

A retrospective analysis was conducted on 53 medical interns. Twenty-seven interns (16 males, 11 females; mean age 20.96 ± 0.59 years) allocated to the control group between December 2024 and February 2025 received conventional teaching. In contrast, 26 interns (16 males, 10 females; mean age 21.19 ± 0.75 years) in the experimental group, recruited from March to May 2025, underwent the educational intervention, which combined task-driven methods with AI tools. Instruction was provided by the same teaching team for both cohorts, and the baseline characteristics showed no statistical significance ($P > 0.05$). The research design flowchart is presented in **Figure 1**.

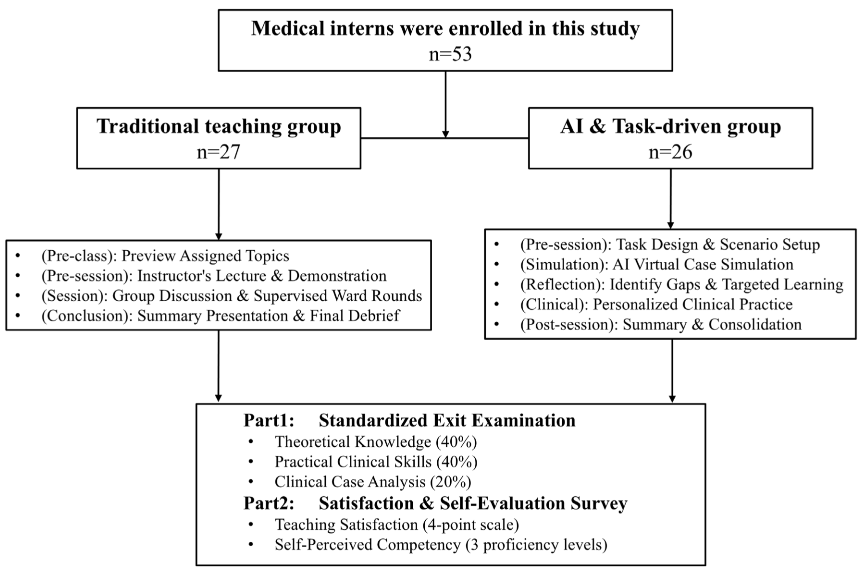

Figure 1. Schematic diagram of the study design.

Interns were divided into a control group receiving traditional teaching methods and an experimental group receiving the AI-enhanced task-driven learning approach. The experimental group engaged with AI tools to simulate patient cases and receive personalized feedback before clinical practice. Outcomes for both groups were assessed through objective examinations and subjective questionnaires.

2.2. Teaching Methods

The control group received conventional teaching following established pedagogical approaches. Instructors developed structured teaching plans based on the standardized syllabus, systematically delivering fundamental theoretical knowledge and demonstrating standardized clinical procedures to ensure students acquired essential competencies. The internship curriculum included: 1) Before class, students were required to preview the textbook materials on common respiratory diseases (such as COPD, tuberculosis, lung cancer, asthma, pneumonia, etc.). 2) Prior to the clinical session, the instructor systematically reviews core theoretical concepts and demonstrates the essential steps of clinical skills in a standardized manner. 3) Case materials are then distributed to prompt small-group discussions. Subsequently, student representatives lead ward rounds, where they practice patient interviewing and physical examination, under the supervision and feedback of the instructor. 4) Each group delivers a summary presentation of their case. The instructor provides comments, answers questions, and guides a final analytical discussion to conclude the ward round.

The experimental group implemented a teaching methodology that integrated AI tools with task-driven instruction. Building upon the conventional teaching framework, specific internship tasks were carefully designed for the students. This involved setting up various disease scenarios, after which interns were required to engage in dialogues with the AI tool. During these interactions, they simulated patient history-taking and physical examination scenarios, independently summarizing the key points. The process primarily included: 1) Instructors or teaching assistants established the disease scenario (e.g., "differential diagnosis of acute dyspnea") and collaboratively defined the learning task framework with the students. 2) The AI tool generated virtual cases based on real patient data, simulating authentic clinical diagnosis and treatment environments. Students simulated the entire process of history collection, physical sign acquisition, interpretation of auxiliary examinations, and differential diagnosis. 3) Students were organized to summarize questions and knowledge gaps identified during the simulation, facilitating targeted learning. 4) Based on the results of the AI-simulated practice, individual learning difficulties and weaknesses were identified for each student, allowing them to proceed to clinical practice with specific questions in mind. 5) Post-internship summary and analysis were conducted.

2.3. Evaluation Metrics

Upon internship completion, both participant groups underwent a standardized comprehensive exit examination utilizing a percentage-based scoring system. The assessment framework included: theoretical knowledge evaluation (40 points), practical clinical skills assessment (40 points), and clinical case analysis competence (20 points), all evaluated according to department-approved standardized scoring rubrics to ensure assessment consistency and validity.

Additionally, comprehensive surveys were administered to evaluate teaching satisfaction and self-perceived competency development. The teaching satisfaction instrument assessed overall perceptions regarding teaching methodology, content relevance, and educational outcomes using a four-point scale (very satisfied, satisfied, fairly satisfied, unsatisfied). The self-evaluation component measured students' perceived mastery of syllabus-defined knowledge and skills categorized into three proficiency levels: well mastered, basically mastered, and not mastered.

2.4. Statistical Methods

Statistical analyses were performed using SPSS version 25.0 (IBM Corporation, Armonk, NY). Continuous variables were presented as mean ± standard deviation (x ± s), with intergroup comparisons conducted using independent samples t-tests. Categorical data were expressed as frequencies and percentages (%), with group differences analyzed using χ^2 tests or Fisher's exact test as appropriate. The threshold for statistical significance was established at $\alpha = 0.05$ (two-tailed).

3. Results

3.1. Intern Exit Exam Scores

The experimental group demonstrated statistically superior performance across all assessment domains compared to the control group (Table 1). Theoretical assessment scores were 29.58 ± 3.38 versus 27.11 ± 3.99 (P = 0.02); practical skills evaluation scores were 32.23 ± 3.13 versus 26.56 ± 2.45 (P < 0.001); clinical case analysis scores were 14.85 ± 1.85 versus 10.96 ± 1.95 (P < 0.001).

These findings indicate that the AI-enhanced task-driven learning approach significantly improved interns' theoretical understanding, practical clinical abilities, and clinical reasoning skills, with particularly notable enhancements in hands-on clinical practice and case-based problem-solving capabilities.

Table 1. Comparison of exit exam scores between the two groups (Points, x ± s).

Group	N	Exit Exam Scores			
		Theoretical	Practical Skills	Case Analysis	Total
Control	27	27.11 ± 3.99	26.56 ± 2.45	10.96 ± 1.95	64.63 ± 5.02
Experimental	26	29.58 ± 3.38	32.23 ± 3.13	14.85 ± 1.85	76.65 ± 5.37
t-value		−2.42	−7.36	−7.43	−8.42
P-value		0.02	<0.001	<0.001	<0.001

3.2. Teaching Satisfaction and Self-Evaluation

The satisfaction assessment revealed significantly more favorable responses from the experimental group compared to controls (P < 0.001). The AI-enhanced task-driven methodology generated substantially higher "very satisfied" responses and reduced "unsatisfied" ratings, indicating strong learner preference for this innovative educational approach (Table 2).

Table 2. Comparison of teaching satisfaction between the two groups (n, %).

Group	Course Satisfaction Evaluation				Total (n)
	Very Satisfied	Satisfied	Fairly Satisfied	Unsatisfied	
Control	3 (11.11%)	7 (25.93%)	13 (48.15%)	4 (14.81%)	27 (100%)
Experimental	12 (46.15%)	10 (38.46%)	3 (11.54%)	1 (3.85%)	26 (100%)
χ^2					13.97
P-value					<0.001

Self-assessment results indicated significantly improved perceived competency among experimental group participants (P = 0.02). The intervention group reported higher "well mastered" and reduced "not mastered" responses, reflecting enhanced self-confidence and knowledge retention attributable to the AI-enhanced learning methodology (Table 3).

Table 3. Comparison of self-evaluation between the two groups (n, %).

Group	Personal Learning Effect Self-Evaluation			Total (n)
	Well Mastered	Basically Mastered	Not Mastered	
Control	3 (11.11%)	17 (62.96%)	7 (25.93%)	27 (100%)
Experimental	10 (38.46%)	15 (57.69%)	1 (3.85%)	26 (100%)
χ^2				8.38
P-value				0.02

The analysis of both teaching satisfaction and self-evaluated learning outcomes revealed statistically significant differences favoring the experimental group. Satisfaction surveys demonstrated a significantly higher proportion of students reporting "very satisfied" and a lower proportion of "unsatisfied" responses in the experimental group compared to the control group. Concurrently, self-assessment results indicated that a markedly higher percentage of students in the experimental group rated their knowledge mastery as "well mastered," whereas the control group had a significantly higher proportion of students reporting "not mastered" (P = 0.02). These consistent findings across both subjective satisfaction and objective self-assessment metrics substantiate that the AI-enhanced, task-driven learning model was not only better received by students but also more effective in fostering a stronger sense of competency and knowledge acquisition.

4. Discussion

Traditional teaching models face limitations such as uneven distribution of educational resources and insufficient personalized guidance, often constrained by varying institutional and regional conditions. As the landscape of medical education continues to evolve, there is a pressing need to identify innovative and effective pedagogical approaches to enhance the competencies of medical students. In the pursuit of more effective teaching strategies, medical education has witnessed the emergence of innovative methods such as problem-based learning (PBL) [12], team-based learning (TBL) [13], and case-based learning (CBL) [14]. While these interactive methodologies have reinvigorated medical education, the search for more scalable and adaptive approaches continues. Task-driven learning has emerged as another significant pedagogical strategy, positioning learning objectives within concrete, clinically relevant tasks to foster greater autonomy and problem-solving capabilities among students. However, its implementation often encounters practical challenges, including significant demands on instructor time and difficulties in providing timely, personalized feedback in resource-constrained environments. These limitations can potentially lead to student frustration and uneven learning experiences. The recent integration of artificial intelligence (AI) into educational frameworks offers a promising pathway to overcome these constraints. By leveraging AI's capabilities in adaptive learning, realistic simulation, and instant feedback, task-driven pedagogy can be enhanced to provide a more scalable, personalized, and effective learning experience [15]. This synergy forms the foundation of our study, which aims to evaluate the impact of combining AI tools with task-driven learning methods in clinical internship training.

Clinical internship teaching represents a crucial component of medical education, serving an indispensable role in developing independent clinical reasoning and standardized procedural skills. Traditional apprenticeship models frequently encounter challenges, including learner anxiety, diminished engagement, and variable motivation levels, often resulting in suboptimal educational outcomes. Consequently, clinical educators must develop structured educational frameworks focusing on core pathological conditions to ensure efficient knowledge acquisition and skill development within constrained rotation periods. Conventional teaching methodologies exhibit significant limitations, predominantly relying on unidirectional knowledge transmission that overlooks the learner's active role in the educational process. This passive learning environment frequently leads to reduced participant engagement and impaired development of critical clinical thinking skills. Our investigation demonstrates that integrating artificial intelligence with task-oriented teaching strategies significantly enhances theoretical knowledge acquisition, practical skill development, and clinical reasoning abilities. Furthermore, the experimental group exhibited superior satisfaction levels and self-perceived competency development, consistent with emerging literature on technology-enhanced medical education [15]. This integrated approach fosters learner autonomy, facilitates clinical reasoning skill development through simulated practice, and promotes integration of theoretical knowledge with clinical application, thereby constructing more robust cognitive frameworks. Clearly defined learning objectives additionally prevent educational aimlessness and enhance learning efficiency. Although this study focuses on comparing AI-enhanced models with traditional teaching, future research should directly contrast them with other pedagogical approaches, such as problem-based learning or case-based learning. Our method shares the student-centered philosophy with these approaches but offers key advantages: AI enables scalable personalized simulation-based instruction and provides instant feedback—features that traditional methods often struggle to achieve.

Recent advancements in artificial intelligence have revolutionized educational methodologies across numerous disciplines. Sophisticated AI platforms, including ChatGPT, Wenxin Yiyan, and Deepseek have demonstrated significant potential in various educational contexts. Leveraging advanced computational capabilities including big data analytics, deep learning algorithms, and natural language processing, AI technologies enable personalized, intelligent educational reforms. Within medical education, AI-enhanced teaching methodologies have shown promising results in enhancing educational quality and efficiency [16]. Our implementation of AI tools for interactive clinical simulations significantly increased student engagement while mitigating traditional clinical learning risks. This integrated approach effectively addresses common challenges in respiratory medicine education including ambiguous learning objectives and insufficient learner motivation, creating immersive clinical scenarios that enhance problem-solving capabilities and overall educational outcomes.

While AI tools can serve as effective aids for students and educators, they cannot replace human intelligence, nor can they fully replicate the complexity and holistic nature of clinical reasoning. For future medical practitioners, instructors should strengthen guidance on the use of AI tools, ensuring that students fully understand the advantages and limitations of related technologies before applying them independently. Moreover, in accordance with national regulations governing generative AI services, students should be guided to comply with laws and administrative statutes, adhere to social morals and ethical principles, and use AI technology in a standardized and responsible manner. Although existing studies have pointed out certain limitations of AI in medical education—such as high dependence on training data, legal and ethical challenges in data usage, and potential underperformance in complex or rare cases due to insufficient data coverage—this study demonstrates through practice that the organic integration of task-driven learning methods with AI tools can achieve significant results in clinical internship training, showing promising application prospects. Integrating artificial intelligence into medical education requires addressing several critical ethical issues. First, patient data used for AI training must undergo proper anonymization and obtain informed consent from students. Second, algorithmic biases within training datasets must be proactively identified and mitigated to ensure a fair and inclusive learning environment. Finally, AI should serve solely as an adjunct to human educators, who remain indispensable in cultivating clinical wisdom and professional values. As an auxiliary means, AI can effectively enhance students' mastery of theoretical knowledge and clinical operational skills, while also improving teaching efficiency and learning satisfaction. One of the limitations of our study was that the sample size was relatively small and derived from a single center, which may limit the generalizability of the findings and affect statistical power. Nevertheless, the positive results observed provide strong preliminary evidence for subsequent research. Another limitation of this study is that both instruction and assessment were confined to the field of respiratory medicine. Therefore, it remains unclear whether the observed skill improvements can effectively transfer to other clinical specialties (such as surgery or pediatrics) or different clinical settings. Validating this transferability is crucial for the widespread adoption of this approach. Looking forward, the deeper integration of AI technology will become an important pathway for promoting the quality of medical education and offering new ideas and directions for the systematic innovation of educational models.

5. Conclusion

This study demonstrates that integrating artificial intelligence with task-driven learning methodologies significantly enhances respiratory medicine internship training outcomes. The AI-enhanced approach improved theoretical knowledge, practical skills, clinical reasoning abilities, and overall educational satisfaction compared to traditional teaching methods. These findings support the continued integration of innovative technologies in medical education while highlighting the importance of addressing technical and ethical considerations. Future research should explore long-term knowledge retention, transfer to clinical practice, and implementation across diverse medical specialties.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Ferkol, T. and Schraufnagel, D. (2014) The Global Burden of Respiratory Disease. *Annals of the American Thoracic Society*, **11**, 404-406. https://doi.org/10.1513/annalsats.201311-405ps

[2] Lozano, R., Naghavi, M., Foreman, K., Lim, S., Shibuya, K., Aboyans, V., *et al.* (2012) Global and Regional Mortality from 235 Causes of Death for 20 Age Groups in 1990 and 2010: A Systematic Analysis for the Global Burden of Disease Study 2010. *The Lancet*, **380**, 2095-2128. https://doi.org/10.1016/s0140-6736(12)61728-0

[3] Naghavi, M., Ong, K.L., Aali, A., Ababneh, H.S., Abate, Y.H., Abbafati, C., *et al.* (2024) Global Burden of 288 Causes of Death and Life Expectancy Decomposition in 204 Countries and Territories and 811 Subnational Locations, 1990-2021: A Systematic Analysis for the Global Burden of Disease Study 2021. *The Lancet*, **403**, 2100-2132. https://doi.org/10.1016/s0140-6736(24)00367-2

[4] Fernandes, L. and Mesquita, A. (2018) Developing Knowledge and Clinical Competency in a Respiratory System-Based Practice of Final-Year Medical Students through a Novel Structured Bedside Teaching Module. *Journal of Education and Health Promotion*, **7**, 82. https://doi.org/10.4103/jehp.jehp_75_16

[5] Wijsenbeek, M. and Cottin, V. (2020) Spectrum of Fibrotic Lung Diseases. *New England Journal of Medicine*, **383**, 958-968. https://doi.org/10.1056/nejmra2005230

[6] Solomon, Y. (2021) Comparison between Problem-Based Learning and Lecture-Based Learning: Effect on Nursing Students' Immediate Knowledge Retention [Response to Letter]. *Advances in Medical Education and Practice*, **12**, 163-164. https://doi.org/10.2147/amep.s305514

[7] Zhang, Q., Tang, X., Zhao, Y. and Wang, Z. (2023) Team-based Learning Vs. Lecture-Based Learning in Nursing: A Systematic Review of Randomized Controlled Trials. *Frontiers in Public Health*, **10**, Article 1044014. https://doi.org/10.3389/fpubh.2022.1044014

[8] Alam, M., Hussain, J., Niazi, D.S. and Mushtaque, M. (2023) Historicity, Significance, and Implication of Adopting Task-Based Learning Framework in the Teaching of English: A Critical Review. *Scholars International Journal of Linguistics and Literature*, **6**, 152-156. https://doi.org/10.36348/sijll.2023.v06i02.009

[9] Liu, Y., Zhang, L., Zhang, J., Sun, X., Wu, L., Liu, G., *et al.* (2025) Enhancing Clinical Problem-Solving Skills in Cardiology Nursing Interns: A Randomized Controlled Study of Case-Based Learning and Task-Driven Learning. *Nurse Education in Practice*, **87**, Article ID: 104449. https://doi.org/10.1016/j.nepr.2025.104449

[10] Lee, H. (2023) The Rise of ChatGPT: Exploring Its Potential in Medical Education. *Anatomical Sciences Education*, **17**, 926-931. https://doi.org/10.1002/ase.2270

[11] Shaw, K., Henning, M.A. and Webster, C.S. (2025) Artificial Intelligence in Medical Education: A Scoping Review of the Evidence for Efficacy and Future Directions. *Medical Science Educator*, **35**, 1803-1816. https://doi.org/10.1007/s40670-025-02373-0

[12] Kilroy, D.A. (2004) Problem Based Learning: Table 1. *Emergency Medicine Journal*, **21**, 411-413. https://doi.org/10.1136/emj.2003.012435

[13] Burgess, A., van Diggele, C., Roberts, C. and Mellis, C. (2020) Team-Based Learning: Design, Facilitation and Participation. *BMC Medical Education*, **20**, Article No. 461. https://doi.org/10.1186/s12909-020-02287-y

[14] Williams, B. (2005) Case Based Learning—A Review of the Literature: Is There Scope for This Educational Paradigm in Prehospital Education? *Emergency Medicine Journal*, **22**, 577-581. https://doi.org/10.1136/emj.2004.022707

[15] Kong, W., Ning, Y., Ma, T., Song, F., Mao, Y., Yang, C., *et al.* (2024) Experience of Undergraduate Nursing Students Participating in Artificial Intelligence + Project Task Driven Learning at Different Stages: A Qualitative Study. *BMC Nursing*, **23**, Article No. 314. https://doi.org/10.1186/s12912-024-01982-1

[16] Kitamura, F.C. (2023) ChatGPT Is Shaping the Future of Medical Writing but Still Requires Human Judgment. *Radiology*, **307**, e230171. https://doi.org/10.1148/radiol.230171