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Analysis of the Application Effect of an AI-Powered Personalized Adaptive Learning Model in Standardized Residency Training for Tumor Metastasis

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Abstract: *Objective:* To explore the application effect of an AI-powered personalized adaptive learning model in the standardized residency training (SRT) teaching of tumor metastasis. *Methods:* A total of 62 SRT trainees rotating through the Department of Medical Oncology in the hospital from December 2024 to December 2025 were selected and divided into a control group and an observation group using a random number table method, with 31 trainees in each group. The control group received traditional SRT teaching, while the observation group was provided with an AI-powered personalized adaptive learning platform in addition to traditional teaching. The platform automatically pushed stratified resources based on trainees' learning profiles, conducted simulated case training, and dynamically adjusted learning paths. After the 4-week training, the two groups' Objective Structured Clinical Examination (OSCE) scores, delayed test scores in the 4th week post-training, knowledge retention rates, and self-directed learning behavior indicators were compared. *Results:* The observation group's scores in each OSCE station and total score, delayed test scores, knowledge retention rate, weekly average self-directed learning duration, learning task completion rate, and error correction rate were all significantly higher than those of the control group (all $P < 0.05$). *Conclusion:* The AI-powered personalized adaptive learning model helps bridge the individual differences among SRT trainees in the specialized study of tumor metastasis, enhances comprehensive clinical capabilities, delays knowledge forgetting, and improves self-directed learning behaviors. It can serve as a feasible path for the digital teaching reform of oncology specialized residency training.

Keywords: Artificial intelligence; Adaptive learning; Standardized residency training; Tumor metastasis

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1. Introduction

Tumor metastasis is the core link in the deterioration of prognosis for patients with malignant tumors, and it

is also a key and difficult point in oncology specialized SRT teaching [1]. The learning content of this topic spans multiple levels, including molecular mechanisms, imaging interpretation, pathological differentiation, and comprehensive treatment decision-making. The knowledge points are interconnected, and clinical scenarios are highly variable. Taking bone metastasis as an example, trainees must not only understand its occurrence mechanism and predilection sites but also formulate individualized treatment plans based on imaging signs, pathological results, and performance status scores. Any shortcomings in any of these links may affect the final diagnosis and treatment decisions. SRT trainees have significant differences in their knowledge structure, rotation experience, and self-learning ability acquired during their undergraduate studies. How to enable trainees with different foundations to receive adequate training in such high-density topics is a practical issue faced by clinical teaching. Traditional SRT teaching usually organizes instruction according to a unified curriculum and courseware, with content and progress designed for the "average level" of all trainees. Classroom feedback is delayed, making it difficult for teachers to accurately grasp the weak points of each trainee. Those with a weak foundation cannot keep up with the pace, while those with a solid foundation need to repeatedly study content they have already mastered, resulting in inefficient allocation of teaching resources. There is a clear contradiction between this homogenized arrangement and the individualized learning needs of the tumor metastasis knowledge system. Advances in artificial intelligence (AI) technology have provided the possibility to resolve the aforementioned contradiction. Adaptive learning systems continuously collect answering and learning behavior data to establish personal learning profiles and dynamically match learning content of appropriate difficulty, making "one person, one path" personalized teaching a reality [2]. In the field of medical education, AI has been applied in multiple areas such as clinical thinking training, exam question generation and intelligent scoring, and personalized assessment feedback, and its exploration in residency training is also increasing year by year [3]. Compared with traditional teaching, adaptive learning places greater emphasis on data-driven learning decisions. Teachers can dynamically adjust teaching focuses based on platform feedback, which theoretically makes it more suitable for specialized topic teaching with high knowledge density and large variations in trainee foundations. However, there are still few reports systematically evaluating the overall teaching effect of the adaptive learning model using a randomized controlled design, specifically focusing on the topic of tumor metastasis. This study took 62 oncology SRT trainees as the research subjects to compare the implementation effects of the AI-powered personalized adaptive learning model and the traditional teaching model in the teaching of tumor metastasis, aiming to provide a reference for the digital teaching reform of oncology specialized residency training.

2. Materials and methods

2.1. General information

A total of 62 residents undergoing standardized residency training who rotated through the Department of Medical Oncology at our hospital from December 2024 to December 2025 were selected and randomly divided into a control group (n=31) and an observation group (n=31) using a random number table method.

Inclusion criteria: Full-time master's degree residents undergoing standardized residency training entering the medical oncology rotation; having completed basic oncology theory courses but not yet systematically studied the topic of tumor metastasis; able to proficiently use computers and mobile learning software, voluntarily participating in the study and signing informed consent forms; completing the training

in its entirety, with absence time not exceeding one-fifth of the total class hours. Exclusion criteria: Those participating in other teaching reform projects during the same period; those with previous clinical work experience in the oncology department; those unable to complete online learning tasks.

2.2. Teaching methods

Both groups underwent a 4-week, 40-hour special training on tumor metastasis, with identical teaching content covering mechanisms of tumor metastasis, metastatic pathways and common sites, imaging and pathological interpretation of metastatic lesions, comprehensive treatment of advanced metastatic tumors, and management of metastatic emergencies. The offline teaching faculty, classroom lectures, and bedside teaching arrangements for both groups were the same to minimize the interference of individual teacher differences on teaching evaluations.

The control group adopted conventional residency training teaching: centralized theoretical lectures weekly, delivered by senior physicians from the Department of Medical Oncology on basic theories and guidelines of tumor metastasis; case discussions held weekly, focusing on reporting, Q&A, and commentary around typical metastatic cases; explanation of key points for physical examination and management of metastatic lesions combined with hospitalized patients during ward rounds; exercises assigned after class for independent review by residents, and unified assessment after training.

The observation group retained all offline teaching supplemented by an AI adaptive learning platform, divided into four components. First, establishing learning profiles: before training, residents completed baseline assessments; the system identified knowledge gaps and tagged weak modules such as brain metastasis emergencies and bone metastasis imaging differentiation. Second, tiered delivery of learning resources: matching learning materials based on profiles, pushing micro-lessons and basic cases to those with weak foundations; pushing difficult cases, cutting-edge literature, and simulated MDT diagnosis and treatment to those with stronger foundations; immediate grading upon completion of exercises, pushing explanations for incorrect answers, and dynamically adjusting difficulty. Third, simulated case training: residents completed history taking, differential diagnosis, metastasis risk assessment, and treatment plan formulation on the platform, with the system commenting on diagnostic and therapeutic approaches and pointing out logical flaws. Fourth, dynamic supervision: the platform automatically recorded learning data and set learning reminders; teaching faculty reviewed backend data, provided individual tutoring to residents lagging in progress, and integrated common difficulties into offline classes.

2.3. Observation indicators

Unified assessment and evaluation were organized after training. OSCE assessment scores were independently scored by two associate chief physicians from the Department of Medical Oncology who did not participate in teaching, using a unified scoring rubric, with the average score taken; theoretical tests and delayed tests used the same question bank for test composition, with personnel composing and grading tests blinded to resident grouping.

(1) Baseline data: Statistics on gender, age, educational composition, and pre-rotation baseline assessment scores of residents in both groups.

(2) Clinical competency assessment: A multi-station OSCE was adopted, with 4 stations including history taking and physical examination, auxiliary examination interpretation, treatment plan formulation, and

doctor-patient communication and humanistic care; each station was scored 100 points for a total of 400 points, assessing residents' comprehensive management capabilities for tumor metastasis cases.

(3) Knowledge retention: A theoretical test was conducted at the end of training, with a maximum score of 100 points; an unannounced delayed test was conducted in the 4th week after training, with a maximum score of 100 points, with questions from the same source as the theoretical test, adjusting question and option order; knowledge retention rate = delayed test score/theoretical test score at end of training × 100%.

(4) Self-directed learning behaviors: The teaching management system uniformly recorded the average weekly extracurricular self-study duration, post-class learning task completion rate, and incorrect answer correction rate of residents in both groups during training. The control group's incorrect answer correction was tallied using paper error logs, while the observation group's was automatically tallied by the platform's error module, with incorrect answer correction rate = number of incorrect answers correctly answered after correction/total number of incorrect answers × 100%.

2.4. Statistical methods

SPSS 26.0 software was used for data analysis. Measurement data were expressed as (), with *t*-tests used for inter-group comparisons; count data were expressed as cases (%), with χ^2 tests used for inter-group comparisons. $P < 0.05$ was considered statistically significant.

3. Results

3.1. Comparison of baseline data between the two groups

Comparisons of gender, age, educational composition, and pre-rotation baseline assessment scores between residents in both groups showed no statistically significant differences (P > 0.05), indicating balanced and comparable baseline data between the two groups. See **Table 1**.

Table 1. Comparison of baseline data of residents undergoing standardized residency training between the two groups

Item	Control group (*n*=31)	Observation group (*n*=31)	t/χ^2	*P*
Gender (male/female, cases)	15/16	14/17	*0.065*	*0.799*
Age (years)	25.94±1.85	26.13±2.02	*0.416*	*0.679*
Education (bachelor/master and above, cases)	23/8	21/10	*0.313*	*0.576*
Pre-rotation baseline assessment score (points)	72.58±4.63	73.06±4.41	*0.427*	*0.671*

3.2. Comparison of OSCE assessment scores between the two groups

The observation group had higher scores than the control group in all four stations and in the total score (all $P < 0.001$), as shown in **Table 2**.

Table 2. Comparison of OSCE assessment scores between the two groups

Group	Medical history taking and physical examination	Ancillary test interpretation	Treatment plan development	Doctor-patient communication and humanistic care	Total score
Control Group (*n*=31)	76.42±5.87	73.89±6.24	72.14±6.58	78.36±5.41	300.81±20.19
Observation Group (*n*=31)	83.15±5.16	81.67±5.53	80.93±5.87	84.72±4.86	330.47±18.36
t	*4.801*	*5.191*	*5.548*	*4.874*	*6.049*
P	*<0.001*	*<0.001*	*<0.001*	<0.001	<0.001

3.3. Comparison of knowledge retention between the two groups

At the end of the training, the theoretical test scores of the observation group were higher than those of the control group; the delayed test scores and knowledge retention rate at the 4th week after the training were also higher than those of the control group (both $P < 0.001$), as shown in **Table 3**.

Table 3. Comparison of theoretical test scores, delayed test scores, and knowledge retention rate between the two groups

Group	Theoretical test score (points)	Delayed test score (points)	Knowledge retention rate (%)
Control group (*n*=31)	78.52±5.93	68.43±6.72	87.15±4.38
Observation group (*n*=31)	85.14±4.87	79.28±5.46	93.12±3.26
t	*4.799*	*6.978*	*6.077*
P	<0.001	<0.001	<0.001

3.4. Comparison of self-directed learning behavior indicators between the two groups

The weekly average extracurricular self-directed learning duration, learning task completion rate, and error correction rate in the observation group were all higher than those in the control group (all $P < 0.001$), as shown in **Table 4**.

Table 4. Comparison of self-directed learning behavior indicators between the two groups

Group	Weekly average autonomous learning duration (h)	Task completion rate (%)	Error correction rate (%)
Control group (*n*=31)	3.42±0.86	82.64±8.37	68.53±10.24
Observation group (*n*=31)	5.17±1.02	94.18±5.62	86.71±8.49
t	7.296	6.377	7.605
P	<0.001	<0.001	<0.001

4. Discussion

This study applied an AI-powered personalized adaptive learning scheme to the standardized residency training in the field of tumor metastasis. The results showed that the observation group outperformed the control group in OSCE scores, delayed test performance, knowledge retention levels, and self-directed learning indicators. This model effectively enhances trainees' comprehensive clinical abilities, consolidates learning outcomes, and stimulates self-directed learning awareness, which aligns with the findings of existing

studies on AI-assisted medical education [4].

The core advantage of adaptive learning lies in refining the alignment of teaching resources and learning pace from the entire class level to the individual learner. Relying on baseline tests and learning process data, the platform dynamically updates trainee profiles to enable tiered delivery of learning materials: trainees with weaker foundations prioritize mechanism animations and classic cases, while those with stronger foundations can directly engage in discussions on difficult cases and simulated MDT (Multidisciplinary Team) deductions. This reduces repetitive learning and improves learning efficiency per unit time, echoing existing research perspectives that personalized teaching alleviates teacher pressure and optimizes learning efficacy.

During their rotations, resident physicians rarely have the opportunity to comprehensively encounter various tumor metastasis cases. Metastatic cases often rely on multidisciplinary collaborative diagnosis and treatment, leaving trainees with limited opportunities to make independent clinical decisions. The built-in simulated cases on the platform deconstruct history taking, differential diagnosis, risk stratification, and treatment plan formulation into repeatedly practicable modules. It provides instant feedback on cognitive loopholes after answering, constructing a low-risk, high-frequency training scenario for clinical reasoning. By completing multiple simulated exercises before encountering real patients, trainees show reduced hesitation in decision-making when facing metastatic cases. The OSCE multi-station assessment evaluates clinical competence comprehensively across dimensions such as inquiry, imaging and pathology interpretation, clinical decision-making, and doctor-patient communication [5]. The mutual reinforcement between online simulation training and offline assessments drives the improvement of comprehensive abilities in the observation group. Existing literature has confirmed that clinical reasoning training based on a simulated case database can facilitate the cultivation of professional competency in resident physicians.

Knowledge retention rate measures the durability of learning outcomes. The observation group performed better in delayed tests and knowledge retention, indicating that personalized review planning and targeted push of incorrect questions are beneficial for consolidating long-term memory. Incorrect question training is not limited to repetitive answering; the platform provides complementary knowledge point explanations and generates variant exercises to help trainees distinguish between conceptual confusion and memory lapses. The completion status of learning tasks and data on incorrect questions are fully traceable, allowing instructors to intervene with trainees who are falling behind and guide them to actively address their shortcomings. The observation group showed higher weekly average study hours and incorrect question correction rates, reflecting improved self-directed learning habits. This is consistent with the conclusion that AI-based intelligent scoring and individualized feedback assist resident physicians in targeted learning [6].

The implementation effectiveness of this teaching model is constrained by the quality and continuous updating capability of the platform's teaching resources. The diagnosis and treatment concepts in the field of tumor metastasis evolve rapidly; if simulated cases and question banks fail to keep pace with the latest clinical guidelines, the timeliness of teaching content will decline [7–8]. Furthermore, AI platforms cannot replace real bedside physical examinations, doctor-patient communication, and clinical skills training. Excessive online learning can also increase screen fatigue among some trainees. The application of AI in medical education still faces issues regarding data reliability, algorithmic transparency, and teaching ethics, which necessitates the establishment of a comprehensive teaching management system [9–10].

This study is a single-center exploration with a limited sample size and a short follow-up period; it did not track the impact of this model on trainees' graduation examinations and long-term clinical work.

Although the OSCE adopted a method of averaging scores from two examiners, the scoring results may still be influenced by subjective factors. The study did not conduct subgroup analyses based on trainees' initial baseline levels, so the differences in benefits among trainees with varying foundations remain unclear. Subsequent multi-center, long-term follow-up studies can be conducted to explore the optimal integration scheme of AI adaptive learning and bedside teaching, as well as differentiated teaching strategies for trainees with different baselines. During the promotion phase, consideration can be given to incorporating adaptive learning into the residency training management system, defining the ratio of online learning to offline practice hours, and concurrently conducting digital capacity training for instructors.

In summary, the AI-powered personalized adaptive learning model can provide tiered learning paths tailored to the individual differences of residency trainees, strengthen the theoretical reserves and comprehensive clinical abilities regarding tumor metastasis, mitigate knowledge forgetting, and improve self-directed learning status. It can serve as a feasible scheme for teaching reform in oncology residency training.

Disclosure statement

The authors declare no conflict of interest.

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