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Application and Governance of Generative Artificial Intelligence in Clinical Teaching

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Abstract: The iterative development of generative artificial intelligence (GenAI) and large language models has enabled them to support multiple aspects of clinical teaching at a functional level, including language support, virtual consultations, clinical reasoning and feedback support, skills simulation training, and writing and research assistance. This paper reviews the current status and evidence limitations of these typical application scenarios and proposes a GenAI governance model suitable for clinical teaching scenarios, considering the high-stakes nature of clinical teaching. Focusing on issues such as "hallucination" outputs and factual deviations, over-reliance, academic integrity, privacy, and data security, this paper proposes governance recommendations centered on clarifying responsibility boundaries and retaining key evidence. It advocates for the establishment of verifiable and correctable processes and regulatory mechanisms through collaboration between teaching institutions and development platforms, providing a reference for the standardized evaluation and reliable application of GenAI in clinical teaching.

Keywords: Generative artificial intelligence; Clinical teaching; Large language models; Medical education; Medical education governance

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1. Introduction

With the rapid development of generative artificial intelligence (GenAI), medical education is undergoing profound structural changes. Tools based on large language models (LLMs), such as ChatGPT and GPT-4/5, leverage their capabilities in language understanding, knowledge generation, multimodal processing, and interactive feedback [1], enabling GenAI to rapidly expand its role in clinical teaching from knowledge retrieval to various levels, including virtual consultations, diagnostic reasoning training, and language expression assistance [2]. This provides medical education with more flexible and scalable technical support.

In the practice of medical education in China, clinical teaching often seeks to balance limited teaching resources with growing training demands [3]. The scarcity and non-replicability of real clinical scenarios [4], the compression of teaching time by clinical work [5], and the significant differences among learners pose challenges to personalized guidance and immediate feedback in case analysis, communication training, operational skills, and research writing. How to improve training efficiency and feedback density while ensuring teaching quality remains a key focus for ongoing optimization in clinical teaching.

Thanks to model iteration and improved computing power, GenAI enables these scarce scenarios to be transformed into scalable teaching support: enhancing the repeatability of consultation and communication training through contextualized dialogue [6]; strengthening clinical thinking training through prompt-based reasoning and collaborating with simulation platforms such as VR to enable repeatable simulation practice and feedback for low-frequency, high-risk operations [7]. However, clinical teaching directly relates to clinical decision-making and patient safety, with high-stakes tasks throughout the entire process of learning, training, and assessment. GenAI still poses non-negligible risks in terms of content reliability, learning dependency, academic integrity, and data security [8]. Once erroneous information or misleading reasoning enters the learning chain, its impact may accumulate along the teaching path and transfer to real clinical scenarios. Therefore, it is essential to clarify usage boundaries based on the risk level of clinical teaching tasks and establish effective governance mechanisms. Based on this, this paper systematically reviews the typical application scenarios of GenAI in clinical teaching and their evidence-based foundations and proposes actionable recommendations at the course and institutional levels regarding safety boundaries and governance priorities, providing a reference for the standardized and sustainable implementation of GenAI in clinical teaching.

2. Main applications and limitations of GenAI in clinical teaching

To systematically present the main application methods of GenAI in clinical teaching, this paper categorizes them into five core scenarios (**Table 1**) according to the clinical teaching chain and typical tasks. Each subsection outlines the key functions, existing evidence, and main limitations, providing a basis for subsequent risk analysis and governance strategies.

Table 1. Overview of the five core dimensions and key characteristics of GenAI clinical teaching applications

Application dimension	Typical functions	Main teaching value	Evidence and limitations
Language support and terminology learning	Term explanation; register conversion; expression standardization	Improves understanding and expression standardization	Can assist in medical text understanding and professional expression [9], but high-risk information still carries risks of mistranslation [10]
Virtual consultation	Dynamic virtual patients; structured questioning; immediate feedback	Enhances reasoning training and practice density	Can improve consultation and communication training effectiveness, but simulation of non-verbal cues remains insufficient [11–14]
Clinical reasoning and personalized feedback	Learning behavior data analysis; personalized tutoring	Improves learning specificity and engagement	Can identify knowledge gaps and support feedback [15], but the reasoning process is opaque [16], and can easily lead to misleading conclusions [17]
Multimodal integration; skill simulation training	Interpreting complex knowledge; real-world scenario simulation training	Improves understanding efficiency; repeated training and outcome evaluation for high-risk procedures	Can improve understanding and training efficiency [7,18–20], but may increase cognitive load [15,21,22], and simulation realism remains limited
Medical writing and research training	Language polishing; structural optimization; logic prompts	Improves writing efficiency and standardization	Can lower the barrier to writing, but vigilance is needed against fabricated references [23,24]

Note: This table summarizes the main enabling directions of GenAI in clinical teaching based on a literature review, covering typical functions, teaching contributions, and risk type indications. For the boundary of graded scenarios and minimum safeguard settings for different tasks, see **Table 2**.

2.1. Language support and terminology learning

Medical terminology is highly specialized and context-dependent, with clinical texts often containing abbreviations, synonymous substitutions, and variations in expression across different scenarios. GenAI can aid students in understanding professional terminology and enhance the standardization and accuracy of their expression in medical record reading, ward round reporting, and doctor-patient communication through terminology explanation, context judgment, and stylistic adjustment [9,25]. Research indicates that LLMs demonstrate high precision in expressing most medical terms [26], but they are still prone to mistranslations for high-risk information points (such as adverse event terminology, drug names, dates/times) [10].

2.2. Virtual consultation

Training GenAI-based virtual patient systems can dynamically simulate disease progression, supporting training in consultation, communication skills, and decision-making thinking [11]. A controlled study showed that students trained in GenAI consultations significantly improved their communication scores in the Objective Structured Clinical Examination (OSCE) by 0.48 standard deviations compared to the control group [27]. However, current virtual consultations fall short in simulating non-verbal cues such as tone, facial expressions, and gestures, as well as complex scenarios like conflict communication, limiting their substitutability for real clinical interactions [14].

2.3. Clinical reasoning and personalized feedback

LLMs extend clinical reasoning training from one-time classroom discussions to a continuous process of repeatable practice, question closely, and immediate feedback [28]. By analyzing learning behavior data, they identify knowledge weaknesses and deliver targeted exercises and feedback [15], enabling sustained personalized learning support in environments with limited teaching resources. However, the convenience of immediate feedback may induce learners' reliance on model conclusions, weakening their active thinking abilities [29]. Additionally, evidence suggests that GenAI may fabricate information when generating initial differential diagnoses and treatment plans [17], leading to potentially misleading conclusions.

2.4. Multimodal integration and skills simulation

Training multimodal large language models (MLLMs) can transform abstract concepts into chart interpretations, process illustrations, animated explanations, or contextualized case studies, reducing the cognitive load of single-text learning and improving comprehension efficiency [15]. However, if learners lack information discrimination abilities, excessive materials may increase cognitive burden and induce dependence.

At the skills simulation level, the integration of GenAI with virtual reality (VR) breaks through the temporal and spatial limitations of traditional operational teaching, enabling repeated practice of low-frequency, high-risk operations in a safe environment with immediate scoring and feedback [7,18]. Research shows that a VR training system combining GenAI with haptic feedback reduced clinical operation errors by 45%, saved 38% in training time, and significantly improved trainee confidence [30]. However, existing systems still face issues such as task simplification, insufficient coverage of non-technical skills, unrealistic simulation of haptic and physiological responses, and bulky equipment [31].

2.5. Academic writing and research training assistance

GenAI can lower the writing threshold and enhance expression standardization through functions such as grammar correction, paragraph logic optimization, abstract generation, and writing template demonstration [29]. A survey from West China Medical School revealed that 100% of participants used ChatGPT for English polishing of academic papers, and 92% used it for real-time translation and grammar correction [32], reflecting its high demand and utilization at the language level. However, GenAI-generated text may still produce unsourceable factual generation and fictional literature [24]. When it comes to interpreting research results, forming core arguments, and citing references, reliance on original literature and author judgment remains essential.

3. Risks and dilemmas of GenAI intervention in teaching

GenAI holds application potential in medical education but still faces limitations in content reliability, learning behavior, ethical norms, and platform accessibility. Given the high-stakes nature of clinical teaching, related risks need to be managed through graded approaches based on task types (see **Table 2**).

Table 2. Schematic diagram of five-dimensional applications and three-level risk matrix

Application dimension	Low risk, directly usable	Medium risk, use with constraints	High risk, prohibited or mandatory review
Language support & terminology learning	Concept explanation, style conversion, study note organization	Case presentation, communication scripts, terminology optimization	Drug names, dosages, adverse events, and other safety-critical information
Virtual consultation	Standardized history-taking training, consultation process rehearsal	Differential diagnosis training, complex communication scenario simulation	Diagnostic/treatment decisions and prescription-level advice
Clinical reasoning & personalized feedback	Reasoning framework guidance, knowledge point visualization	Personalized learning path recommendation, feedback prompts	Substituting GenAI recommendations for course objectives and evaluations
Multimodal integration & skill simulation training	Basic action decomposition practice, low-risk process familiarization	Complex situation response rehearsal, simulation debriefing	Directly using simulation results for practice authorization
Medical writing & research training	Grammar correction, paragraph structure optimization, abstract rewriting	Research proposal conceptualization, discussion framework suggestions	Generating conclusive arguments, generating or citing unverified references

Note: The basis for risk classification is the potential impact of output errors on patient safety and teaching quality, as well as the difficulty in detecting and correcting these errors.

3.1. Content accuracy and "black box" output risk

GenAI can provide relatively fluent explanations for common questions, but it is prone to generating content that "appears reasonable but is factually incorrect" when dealing with complex conditions, rare diseases, or ambiguous questions, known as "hallucination output" [16]. Meanwhile, generative models typically operate with a "black box" structure, where their internal decision-making logic is opaque and the output lacks interpretable justification (**Figure 1**). If students directly accept such outputs, it may weaken their training in diagnostic reasoning and evidence chain inference, and hinder the transfer of model-generated content to real-world clinical scenarios. Therefore, content reliability and interpretability should serve as important criteria for risk classification and management in high-stakes teaching tasks.

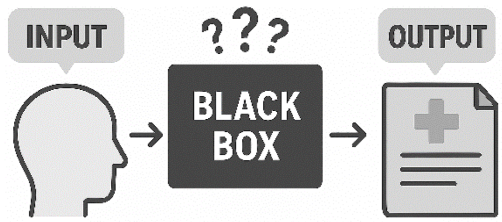

Figure 1. Schematic diagram of the "black box" structure of generative artificial intelligence

3.2. Over-reliance and deterioration of learning ability

The application of GenAI can significantly enhance learning efficiency, but frequent use for writing, translation, and question-answering tasks may weaken students' abilities in literature search, logical reasoning, and critical thinking [29]. In clinical teaching scenarios, if students view GenAI as an "answer system" rather than a "cognitive scaffold," their independent reasoning abilities may not be adequately trained. The combination of high-frequency use and instant feedback may even lead to long-term skill degradation due to reliance on model conclusions, affecting the transfer to real-world clinical scenarios.

3.3. Academic ethics and data security risks

In writing training and assignment evaluation, GenAI can blur the lines between "assistance" and "ghostwriting," leading to issues such as unclear contribution attribution, compromised originality, and unverifiable citations [33]. In scenarios such as case discussions and preparation of teaching materials, improper handling of real data may also trigger privacy breaches and data security risks [34]. These issues are particularly sensitive in medical education, where the lack of institutionalized rules and audit mechanisms can quickly accumulate individual violations into compliance risks at the teaching system level.

3.4. Platform accessibility and usage gap

The usability of GenAI is constrained by factors such as platform, computational power, digital literacy, or regional policies, leading to imbalances in accessibility and resource acquisition among different learners [35], which may accumulate into significant gaps over the long term [36]. If courses and assessments lack unified, clear rules for tool use, learning outcomes may be driven by "tool differences" rather than "ability differences," undermining the reliability and validity of evaluations.

4. Governance and implementation pathways for GenAI in clinical teaching

The application of GenAI in clinical teaching is still in a rapid iteration phase, with its capabilities and reliability fluctuating significantly with changes in models, data, and usage scenarios. Relevant evaluation evidence and practical experience still need to be continuously accumulated [37]. Therefore, the governance goal should not aim for zero risk in the short term but rather focus on bringing risks within a controllable range and supporting continuous improvement in teaching quality through traceable, verifiable, and correctable mechanisms. Based on this, the governance framework should revolve around two main themes: “clarifying responsibility boundaries” and “ensuring traceability of evidence,” which should be translated into actionable tasks for teaching units and software development platforms, with traceability information converted into quality evaluation indicators to support continuous improvement.

For teaching units, the key is to incorporate GenAI use into a procedural and institutionalized management system. To control implementation costs and maintain cross-course generality, the following four steps can be followed. First, clarify the responsibility boundaries of various levels, including institutions, course teams, clinical instructors, and students, in terms of rule-making, operational supervision, application vetting, deviation correction feedback, and submission of verifiable outputs. Second, identify major risk points based on task nature (**Table 2**) and define the usage boundaries and applicability of GenAI. Then, plan corresponding review nodes and intervention methods in the teaching process. Finally, ensure evidence traceability at key stages and establish a standardized, verifiable, and accountable mechanism through sampling inspections, sign-offs, or reviews.

For software development platforms, the focus should be on providing actionable technical support for the aforementioned governance logic, making evidence retention a default configuration of medical GenAI systems rather than an additional burden. Platforms can offer structured traceability and auditable record functions across different application dimensions. For example, supporting security-critical information verification and uncertainty prompt recording, traceability of reasoning processes, danger item omission prompts in virtual consultations, preservation of simulation training process data and debriefing records, and traceability of GenAI use disclosure and fact-checking in writing and research. **Table 3** provides specific summaries of key traceability evidence that should be retained for each dimension, serving as a reference for aligning platform functionality design with teaching governance requirements, thereby enhancing the operability and generality of governance measures without significantly increasing the burden on frontline teaching.

Table 3. Practical recommendations for risk points and key traceability evidence in GenAI clinical teaching applications

Application dimension	Key risk points	Evidence to retain for GenAI involvement
Language support & terminology learning	Misleading safety-critical content	1. Safety point verification record (annotated: confirmed / pending confirmation / uncertain); 2. Source of reference (specific source/location of textbook/guideline/standard);
Virtual consultation	Omission of dangerous items	1. Key information record (symptoms, signs, etc. that should have been asked / were asked / were missed); 2. Chain of evidence-based reasoning (list evidence → direction → differential sequence); 3. Explanation of uncertainties (contextual boundaries, known conditions, degree of evidence matching);
Clinical reasoning & personalized feedback	Misleading conclusions; missing reasoning process	1. Reasoning process (evidence → hypothesis → differential ranking); 2. List of uncertainties and followup questions; 3. Feedback principles, instructor review, and intervention records;
Multimodal integration & skills simulation training	Neglect of nontechnical skills; overinterpretation of simulation scores	1. Process data summary (mastery of key knowledge, completion rate of critical steps, error types, and frequency); 2. Debriefing record (existing problems → causes → corrective strategies → targeted training plan); 3. Statement on assessment nature (formative assessment results are not equivalent to clinical competence);

Application dimension	Key risk points	Evidence to retain for GenAI involvement
Medical writing & research training	Fictitious citations and ghostwriting	1. GenAI use disclosure (which part and to what extent it was used); 2. Factchecking record (verification of data, literature sources); 3. Sourceconclusion alignment (each core conclusion corresponds to a verifiable source);

Note: Traceability evidence refers to the verification materials that must be retained when GenAI is involved in teaching and training, used for teachers or supervisors to review, sample, and audit retrospectively.

5. Future development directions

Future efforts should shift from pursuing functional usability to verifying teaching effectiveness and establish an outcome evaluation system covering knowledge and skill performance, reasoning logic quality, uncertainty management ability, and long-term retention rates [27]. Meanwhile, standardization of process evidence in teaching should be promoted, making fact-checking, reasoning chains, uncertainty prompts, and debriefing reports collectible and analyzable teaching outputs. Standardized evidence chains can support teaching quality monitoring and facilitate the integration of GenAI tools with course platforms, case libraries, and simulation systems, gradually transforming GenAI from an auxiliary tool into an assessable and governable teaching infrastructure.

6. Conclusion

GenAI has formed a series of practical applications in multiple aspects of clinical teaching, but its reliability and risk boundaries still fluctuate with changes in models and scenarios. Therefore, the joint efforts of teaching units and development platforms are still required. Based on the classification of task risk levels, both parties should incorporate key evidence traceability into a traceable, verifiable, and correctable teaching process by clarifying the division of responsibilities in development, supervision, and use, thereby establishing a unified GenAI application evaluation system. As models and usage boundaries continue to be calibrated in practice, governance strategies are iteratively updated, and more solid empirical evidence is gradually accumulated, GenAI is expected to be more stably integrated into routine clinical teaching.

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The authors declare no conflict of interest.

References

[1] Huang R, 2024, Integration of Large AI Models into Education: Conceptual Transformation, Form Reshaping, and Key Measures. People's Tribune·Academic Frontier, (14): 23–30.

[2] Cheng S, Cong L, Hu W, et al., 2024, Current Status and Reform Trends of Medical Practice Course Teaching Models in the Era of "AI+Education." Medical Innovations, 34(08): 950–956.

[3] Jiang Q X, Horta H, Yuen M, 2022, International Medical Students' Perspectives on Factors Affecting Their Academic Success in China: A Qualitative Study. BMC Med Educ, 22(1).

[4] Zeng JH, Liang S, Zhang XT, et al., 2022, Assessment of Clinical Competency among TCM Medical Students Using Standardized Patients of Traditional Chinese Medicine: A 5-Year Prospective Randomized Study. Integr Med Res, 11(2).

[5] Huang JM, Huang CX, Mo ZW, et al., 2024, Current Situation and Influencing Factors of High-Level Role Conflict among Clinical Teachers: A Cross-Sectional Study. Medicine, 103(25).

[6] Topaz M, Peltonen LM, Michalowski M, et al., 2024, The ChatGPT Effect: Nursing Education and Generative Artificial Intelligence. J Nurs Educ, 2024: 1–4.

[7] Dunlop K, Dillon G, McEvoy A, et al., 2024, The Virtual Reality Classroom: A Randomized Control Trial of Medical Student Knowledge of Postpartum Hemorrhage Emergency Management. Front Med, 11.

[8] Chen X, Deng R, Wu C, 2024, Exploration of Generative Artificial Intelligence Large Language Models in Medical Education Practice. Journal of Clinical Emergency, 25(6): 310–314.

[9] Valencia OAG, Thongprayoon C, Jadlowiec CC, et al., 2025, Advancing Health Equity: Evaluating AI Translations of Kidney Donor Information for Spanish Speakers. Front Public Health, 13.

[10] Hakim JB, Painter JL, Ramcharran D, et al., 2025, The Need for Guardrails with Large Language Models in Pharmacovigilance and Other Medical Safety Critical Settings. Sci Rep, 15(1).

[11] Peralta Ramirez AA, Trujillo Lopez S, Navarro Armendariz GA, et al., 2025, Clinical Simulation with ChatGPT: A Revolution in Medical Education? J CME, 14(1): 2525615.

[12] Moser M, Posel N, Ganescu O, et al., 2025, Twelve Tips: Using Generative AI to Create and Optimize Content for Virtual Patient Simulations. Med Teach, 47(11): 1745–1751.

[13] Aster A, Ragaller SV, Raupach T, et al., 2025, ChatGPT as a Virtual Patient: Written Empathic Expressions During Medical History Taking. Med Sci Educ, 35(3): 1513–1522.

[14] Cross J, Kayalackakom T, Robinson RE, et al., 2025, Assessing ChatGPT's Capability as a New Age Standardized Patient: Qualitative Study. JMIR Med Educ, 11.

[15] Bewersdorff A, Hartmann C, Hornberger M, et al., 2025, Taking the Next Step with Generative Artificial Intelligence: The Transformative Role of Multimodal Large Language Models in Science Education. Learn Individ Differ, 118.

[16] Holderried F, Stegemann-Philipps C, Herrmann-Werner A, et al., 2024, A Language Model-Powered Simulated Patient with Automated Feedback for History Taking: Prospective Study. JMIR Med Educ, 10: e59213.

[17] Shoja MM, Van de Ridder JMM, Rajput V, 2023, The Emerging Role of Generative Artificial Intelligence in Medical Education, Research, and Practice. Cureus, 15(6).

[18] Li Y, Liu G, Wang X, et al., 2020, Application of a VR Interactive Technology-Based Automatic Evaluation System for Thoracentesis in Teaching. Chongqing Medicine, 49(21): 3676–3678.

[19] Kobayashi M, Katayama M, Hayashi T, et al., 2023, Effect of Multimodal Comprehensive Communication Skills Training with Video Analysis by Artificial Intelligence for Physicians on Acute Geriatric Care: A Mixed-Methods

Study. BMJ Open, 13(3).

[20] Lu MY, Chen BW, Williamson DFK, et al., 2024, A Multimodal Generative AI Copilot for Human Pathology. Nature, 634(8033).

[21] Lin CJ, Wang WS, Lee HY, et al., 2025, Advancing Self-Directed Learning in STEM Education: Integrating GPT-Based Learning aid with Multimodal Learning Analytics. J Res Technol Educ.

[22] Janumpally R, Nanua S, Ngo A, et al., 2024, Generative Artificial Intelligence in Graduate Medical Education. Front Med (Lausanne), 11: 1525604.

[23] Yoo JH, 2025, Defining the Boundaries of AI Use in Scientific Writing: A Comparative Review of Editorial Policies. J Korean Med Sci, 40(23).

[24] Manley K, Salingaros S, Fuchsman AC, et al., 2025, Using ChatGPT to Write a Literature Review on Autologous Fat Grafting. J Plast Reconstr Aesthet Surg, 105: 292–304.

[25] Lyu Q, Tan J, Zapadka ME, et al., 2023, Translating Radiology Reports into Plain Language Using ChatGPT and GPT-4 with Prompt Learning: Results, Limitations, and Potential. Vis Comput Ind Biomed Art, 6(1): 9.

[26] Yi Y, Kim KJ, 2025, The Feasibility of Using Generative Artificial Intelligence for History Taking in Virtual Patients. BMC Res Notes, 18(1).

[27] Yamamoto A, Koda M, Ogawa H, et al., 2024, Enhancing Medical Interview Skills Through AI-Simulated Patient Interactions: Nonrandomized Controlled Trial. JMIR Med Educ, 10.

[28] Savage T, Nayak A, Gallo R, et al., 2024, Diagnostic Reasoning Prompts Reveal the Potential for Large Language Model Interpretability in Medicine. NPJ Digit Med, 7(1): 20.

[29] Qadhi S, Alduais A, Chaaban Y, et al., 2024, Generative AI, Research Ethics, and Higher Education Research: Insights from a Scientometric Analysis. Information, 15(6): 22.

[30] Kumar A, Saudagar AKJ, Kumar A, et al., 2025, Innovating Medical Education using a Cost Effective and Scalable VR Platform with AI-Driven Haptics. Sci Rep, 15(1).

[31] Popov V, Mateju N, Jeske C, et al., 2024, Metaverse-Based Simulation: A Scoping Review of Charting Medical Education Over the Last Two Decades in the Lens of the Marvelous Medical Education Machine. Ann Med, 56(1).

[32] Li JK, Zong H, Wu EM, et al., 2024, Exploring the Potential of Artificial Intelligence to Enhance the Writing of English Academic Papers by Non-Native English-Speaking Medical Students - The Educational Application of ChatGPT. BMC Med Educ, 24(1).

[33] Karabacak M, Ozkara BB, Margetis K, et al., 2023, The Advent of Generative Language Models in Medical Education. JMIR Med Educ, 9: e48163.

[34] Parente DJ, 2024, Generative Artificial Intelligence and Large Language Models in Primary Care Medical Education. Fam Med, 56(9): 534–540.

[35] Malesevic A, Kolesárová M, Cartolovni A, 2024, Encompassing Trust in Medical AI from the Perspective of Medical Students: A Quantitative Comparative Study. BMC Med Ethics, 25(1): 11.

[36] Xu T, Weng H, Liu F, et al., 2024, Current Status of ChatGPT Use in Medical Education: Potentials, Challenges, and Strategies. J Med Internet Res, 26: e57896.

[37] Wang Y, Wang X, Liu C, 2024, Research on the Ethical Risk Management Framework for the Application of Generative Artificial Intelligence in the Field of Education. E-Education Research, 45(10): 28–34 + 42.