

# Artificial Intelligence in Teaching Uterine Fibroids to Medical Students.

## Inteligencia artificial en la enseñanza de los miomas uterinos a estudiantes de medicina.

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### Abstract.

Artificial intelligence (AI) is increasingly used in medical education, but task-level guidance on when learners should engage with AI during clinical reasoning remains underdeveloped. This Special Article presents a literature-informed conceptual proposal, not an evaluated educational intervention, using uterine fibroids as an illustrative teaching context. A targeted narrative search of PubMed/MEDLINE and the Spanish Journal of Medical Education website identified literature on AI-supported medical education, clinical reasoning, case-based learning, cognitive load, reflection, assessment, and recent AI-integration frameworks and approaches. We propose a five-step supervised sequence: prepare, reason, interact, verify, and reflect. The conceptual contribution is an AI-specific temporal sequencing principle: learners commit to an independent problem representation before AI exposure; AI is then used as a fallible comparator or feedback source; its claims are checked against an external authoritative source; and discrepancies are closed through reflection. The sequence is designed to address AI-specific risks of answer substitution, uncritical acceptance, and closure without reflection while preserving established case-based and feedback-rich learning. It is intended to be transferable to other specialties when tasks require contextual reasoning, source verification, and professional judgement. The framework has not been implemented or empirically evaluated; its feasibility, acceptability, fidelity, workload implications, and effects on learning, clinical reasoning, and competency development require prospective study.

**Keywords:** artificial intelligence, medical education, medical students, uterine fibroids, clinical reasoning, conceptual framework

### Resumen.

La inteligencia artificial (IA) se utiliza cada vez más en la educación médica, pero todavía existe poca orientación a nivel de tarea sobre cuándo debe interactuar el estudiante con la IA durante el razonamiento clínico. Este Artículo Especial presenta una propuesta conceptual informada por la literatura, no una intervención educativa evaluada, utilizando los miomas uterinos como contexto

docente ilustrativo. Una búsqueda narrativa dirigida en PubMed/MEDLINE y en el sitio web de la Revista Española de Educación Médica identificó literatura sobre educación médica apoyada por IA, razonamiento clínico, aprendizaje basado en casos, carga cognitiva, reflexión, evaluación y marcos y enfoques recientes de integración de IA. Proponemos una secuencia supervisada de cinco pasos: preparar, razonar, interactuar, verificar y reflexionar. La contribución conceptual consiste en un principio de secuenciación temporal específico para la IA: el estudiante se compromete primero con una representación independiente del problema; después utiliza la IA como comparador falible o fuente de retroalimentación; verifica sus afirmaciones frente a una fuente externa autorizada; y cierra las discrepancias mediante la reflexión. La secuencia está diseñada para abordar riesgos específicos de la IA, como la sustitución del razonamiento por una respuesta inmediata, la aceptación acrítica y el cierre sin reflexión, manteniendo al mismo tiempo el aprendizaje basado en casos y la retroalimentación. Se pretende que sea transferible a otras especialidades cuando las tareas exijan razonamiento contextual, verificación de fuentes y juicio profesional. El marco no ha sido implementado ni evaluado empíricamente; su factibilidad, aceptabilidad, fidelidad, carga de trabajo y efectos sobre el aprendizaje, el razonamiento clínico y el desarrollo de competencias requieren estudios prospectivos.

**Palabras clave:** inteligencia artificial, educación médica, estudiantes de medicina, miomas uterinos, razonamiento clínico, marco conceptual

## 1. Introduction

Artificial intelligence (AI), particularly generative AI and large language models, is increasingly visible in medical education. Reviews describe applications in content generation, simulated patient interaction, clinical reasoning, feedback, assessment, and personalised learning, but the evidence remains heterogeneous and educational outcomes vary by task and implementation (1-3). Recent work in this journal likewise shows rapid expansion of AI-related curricula, simulation, faculty development, and institutional guidance, while preserving professional judgement remains a recurrent concern (4).

Recent frameworks and approaches address AI integration at several levels. Some define tiers of AI expertise for clinicians (5), some identify competency domains for curriculum design (6), some propose institution-level implementation pillars linking student literacy, educator capability, and assessment (7), and others redistribute instructional tasks between AI-supported preparation and higher-value human interaction (8). These contributions are important, but they do not answer a narrower task-level question that arises during a single clinical learning activity: when should the learner reason independently, when should AI be introduced, and what should happen after an AI response is received?

Uterine fibroids provide a useful clinical context for examining this question. They are common benign uterine tumours with heterogeneous presentations and management pathways (9,10). Learners must integrate symptoms, imaging findings, reproductive goals, treatment options, and uncertainty rather than rely on a single rule. This makes fibroid teaching suitable for a task-level framework in which AI support is deliberately sequenced around clinical reasoning.

This Special Article therefore presents a literature-informed conceptual proposal rather than an evaluated educational intervention. Its intended contribution is neither a new learning theory nor a claim that five steps are intrinsically superior to established pedagogy. It is a task-level sequencing principle for generative AI: withhold AI until the learner commits to a problem representation; use AI as a fallible comparator rather than an answer authority; require external verification; and close the task through reflection. This temporal orchestration is designed to preserve learner-generated

reasoning while adding safeguards against AI-specific answer substitution and uncritical acceptance. Uterine fibroids are the illustrative context, not the boundary of the framework.

## 2. Literature approach and conceptual basis

### 2.1. Targeted narrative search

For this revision, a targeted narrative search was updated in September 2026 in PubMed/MEDLINE and the Spanish Journal of Medical Education website. The PubMed search combined ("artificial intelligence" OR "generative AI" OR "large language model\*") AND ("medical education" OR "health professions education") AND (framework OR curriculum OR competency OR "clinical reasoning" OR assessment OR feedback). The journal website was additionally searched using the terms "artificial intelligence", "generative AI", and "large language model". A supplementary search combined ("uterine fibroid\*" OR leiomyoma\*) with ("artificial intelligence" OR "machine learning"). Foundational searches used "clinical reasoning" AND "medical education", "case-based learning" AND "health professions education", "cognitive load" AND learning, and reflection AND "health professions education", without a date restriction. AI-specific literature from 2019 to September 2026 in English or Spanish was prioritised. Peer-reviewed reviews, empirical educational studies, conceptual or competency frameworks, and directly relevant guidance were prioritised; sources focused only on technical algorithm performance without an educational component were excluded from the pedagogical synthesis. Reference lists of key reviews and framework papers were also checked for directly relevant sources.

Sources were retained when they directly informed at least one of four pre-specified conceptual domains: (1) learner-generated reasoning before AI exposure; (2) AI as comparison or formative feedback; (3) external source verification, professional judgement, and responsible AI use; or (4) reflection and transferability, or when they provided fibroid-specific clinical context. The synthesis was deductive: retained sources were mapped to these domains and used to justify, delimit, or operationalise the five steps. This was not a systematic review; no formal duplicate screening, quantitative synthesis, or risk-of-bias assessment was undertaken. The purpose of reporting the search and mapping process is to make the conceptual basis more transparent and reproducible while acknowledging that relevant literature may have been missed.

### 2.2. Integrated theoretical logic and conceptual contribution

The five-step sequence integrates established educational functions rather than replacing them. Clinical reasoning requires learners to organise knowledge, construct problem representations, compare alternatives, and revise their thinking as information changes (11). Case-based learning provides contextualised problems in which that reasoning can be made explicit (12). Cognitive-load theory highlights the limited capacity of working memory during complex problem solving and supports deliberate sequencing of instructional support (13). Reflection helps learners connect experience, feedback, uncertainty, and future action across health professions education (14). At the step level, Prepare establishes the learning objective and task boundaries; Reason requires a learner-generated problem representation before exposure to an AI answer; Interact creates a comparison or feedback opportunity only after that commitment; Verify imposes an epistemic check against a source independent of the AI; and Reflect requires the learner to explain discrepancies, uncertainty, and the next action. Faculty supervision, predefined learning outcomes, and task constraints are cross-cutting conditions.

The integrated conceptual logic is organised around three AI-specific failure points that established teaching strategies do not necessarily make explicit. First, immediate AI access can substitute a fluent answer for the learner's own problem representation; the corresponding safeguard is pre-AI learner commitment. Second, AI output can be treated as evidence for itself; the

safeguard is verification against an external authoritative source rather than self-validation by the model. Third, a task can end once an answer appears plausible; the safeguard is reflective closure in which the learner explains discrepancies, remaining uncertainty, and what should change. These are testable hypotheses about mechanism, not demonstrated educational effects.

Accordingly, the proposed advantage is not general superiority over case-based learning, simulation, flipped learning, or other established strategies. The sequence is intended to be layered onto such strategies when generative AI is introduced, making the timing of AI exposure, external verification, and post-AI reflection explicit. Whether these safeguards add measurable educational benefit over well-designed alternatives is a comparative empirical question and is treated as a research priority rather than an assumed outcome.

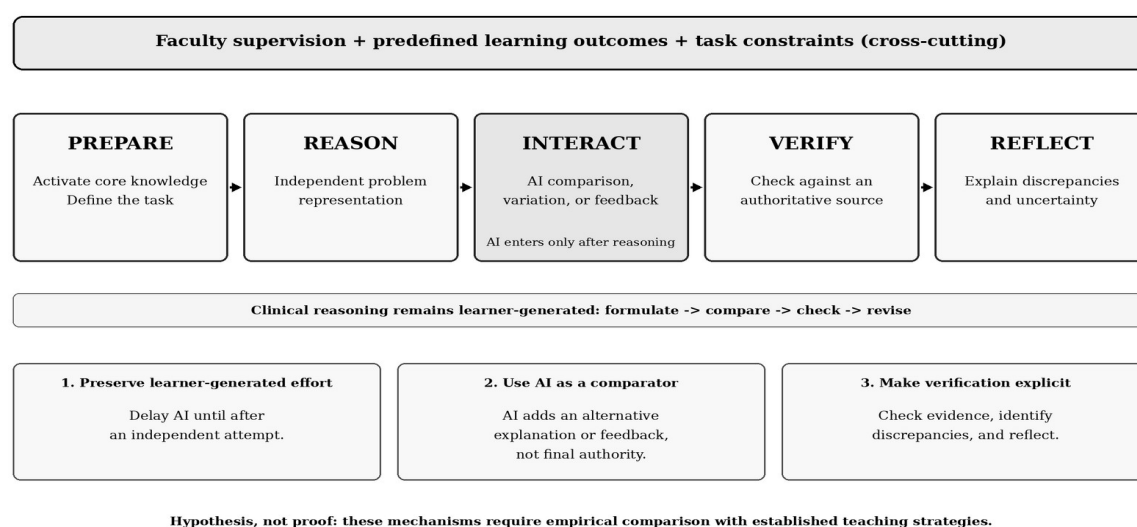


**Figure 1.** Conceptual logic of the proposed five-step supervised AI learning sequence and its hypothesised safeguards. Faculty supervision, predefined learning outcomes, and task constraints span the complete sequence. AI is introduced only after a learner-generated reasoning attempt; its output is treated as a fallible comparator, verification is anchored to an external authoritative source, and reflection closes the discrepancy. The proposed safeguards and mechanisms are hypotheses and have not been empirically validated.

### 2.3. Comparison with recent AI-integration frameworks and approaches

Recent AI-integration frameworks and approaches are complementary because they operate at different educational levels. Table 1 makes the distinction explicit. The present proposal is narrower than competency or institutional frameworks: it focuses on the temporal structure of a single reasoning task and adds three AI-specific safeguards: pre-AI learner commitment, external verification, and reflective closure.

## 3. Why uterine fibroids are a useful teaching context

Uterine fibroids are pedagogically useful because the same pathology can be clinically unimportant in one context and central to bleeding, anaemia, fertility, pregnancy planning, or treatment decisions in another (9,10). Students can therefore be asked to distinguish relevant from irrelevant information, identify missing data, construct a problem representation, and explain why management cannot be determined from a single variable such as fibroid size. The condition is used here as an illustrative context rather than as the theoretical basis of the framework. The transferable unit is the learning task: it should require contextual interpretation, a provisional learner

judgement, and a claim that can be checked against an external standard. Those features occur across many medical specialties and are defined more explicitly in Section 7.

**Table 1.** Comparison of the proposed sequence with recent frameworks and approaches for AI integration in medical or health professions education.

| Framework / approach        | Primary level            | Main emphasis                                                                                                                   | Relation to the present proposal                                                                                                                                                                    |
|-----------------------------|--------------------------|---------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Schubert et al. (5)         | Clinician / curriculum   | Three tiers of medical AI expertise: basic, proficient, and expert.                                                             | Defines depth of AI competence; it does not prescribe the timing of AI within a learning task.                                                                                                      |
| González Soltero et al. (6) | Curriculum / competency  | Critical thinking, interpretation of AI outputs, bias awareness, professional responsibility, and transversal integration.      | Supports verification and professional responsibility; the present model operationalises these within a task sequence.                                                                              |
| Toohey et al. (7)           | Curriculum / institution | Student GenAI literacy, educator capability, and assessment design.                                                             | Provides implementation pillars; the present model addresses the micro-level workflow used during one learning activity.                                                                            |
| García-Estañ (8)            | Course / session         | AI-supported flipped learning: AI can provide explanation, guided practice, and feedback before higher-value human interaction. | Redistributes teaching tasks at the course/session level; the present proposal instead focuses within a clinical reasoning task and withholds AI until after the learner's first reasoning attempt. |
| Present proposal            | Single learning task     | Prepare, reason, interact, verify, reflect.                                                                                     | Adds AI-specific task-level safeguards: pre-AI learner commitment, external verification, and reflective closure. These safeguards are hypothesised and require empirical testing.                  |

#### 4. Educational uses of AI in teaching uterine fibroids

##### 4.1. Knowledge organisation and retrieval practice

At an early stage of learning, AI can help educators draft low-stakes retrieval questions, comparison prompts, or short explanations aligned with predefined objectives. For fibroids, these can address classification, presentation, investigation, reproductive implications, and broad management categories. AI-generated material should be treated as editable teaching material rather than as an authoritative reference; faculty should review accuracy and level before use.

##### 4.2. Case-based reasoning

Once students have sufficient background knowledge, AI can help faculty draft simulated clinical scenarios with controlled variation in age, symptoms, laboratory findings, imaging descriptions, reproductive goals, and treatment preferences. ChatGPT has been used to generate case-based assessment items and clinical vignettes, although human review remains necessary (15,16). A recent scoping review in this journal likewise found growing use of large language models to generate cases in health professions education while emphasising variable quality and the need for evaluation (17).

The educational value lies in the learner task rather than in scenario generation itself. Students should commit to a problem representation and proposed reasoning before seeing AI feedback. The AI response then becomes a comparison object: learners identify what is accurate, omitted, overconfident, or dependent on information not yet available. Deliberate prompting can broaden representation in vignettes, but demographic details still require faculty review to avoid stereotypes (18).

#### 4.3. Image-supported learning

Imaging is central to fibroid evaluation, and AI is increasingly studied for clinical image analysis and decision support in this area (19). In education, however, the objective is not automated diagnosis. Learners should first describe an educator-approved ultrasound or magnetic resonance image themselves. AI may then be used for secondary explanation or question generation, but image interpretations used for teaching should be checked by a qualified educator and linked back to the clinical context.

#### 4.4. Formative assessment and feedback

AI can support formative assessment by generating practice questions, varying task difficulty, or providing a preliminary comparison with a student explanation. This journal has published practical work on AI-assisted generation of case-based multiple-choice questions and script concordance tests (15,20). For fibroids, useful tasks include prioritising information, comparing management principles, explaining the relevance of fertility goals, and identifying why an apparently fluent answer remains incomplete.

**Table 2.** Operationalisation of the five-step supervised AI learning sequence and its educational functions.

| Step     | Educational function and learner task                                                                                            | Appropriate AI role                                               | Educator checkpoint                                                            |
|----------|----------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------|--------------------------------------------------------------------------------|
| Prepare  | Orient the task; review core concepts and learning objectives.                                                                   | Generate low-stakes questions or study prompts.                   | Check accuracy, level, and alignment with the curriculum.                      |
| Reason   | Generate an independent problem representation and record the reasoning before AI exposure.                                      | No AI answer is shown at this stage.                              | Ensure that the task requires explanation and justification, not recall alone. |
| Interact | Contrast the learner's reasoning with an AI-generated alternative explanation, scenario variation, or feedback.                  | Provide comparison, variation, or formative feedback.             | Constrain the prompt and prevent AI from being presented as final authority.   |
| Verify   | Perform an external epistemic check: compare AI claims with an approved source and identify discrepancies or unsupported claims. | Support organisation of comparisons; AI does not validate itself. | Direct students to authoritative clinical references and correct errors.       |
| Reflect  | Integrate feedback: explain what changed, what remains uncertain, and what should be done next.                                  | Generate reflection prompts if useful.                            | Address misconceptions, overconfidence, and inappropriate reliance on AI.      |

## 5. Proposed five-step supervised AI learning sequence

The sequence is intended for tasks in which reasoning and justification matter more than recall alone. Each step has a distinct educational function, and progression is deliberate: AI is not introduced until the learner has made an independent attempt. The sequence can be embedded within an existing seminar, case-based session, simulation, or clinical skills course; it is not proposed as a separate AI curriculum.

## 6. Practical implementation in a medical student teaching session

Implementation should begin with explicit learning outcomes. For example, by the end of a fibroid session students may be expected to recognise major presentations, identify which clinical and imaging information changes the problem representation, explain how reproductive goals influence management reasoning, and distinguish generated information from claims that require verification in clinical guidance.

A session can begin with a short educator-curated preparation activity followed by an individual or small-group reasoning task. Students record their problem representation, information needs, and provisional reasoning before AI is available. AI is then introduced only as a second source of explanation or variation. Students compare the generated output with their own reasoning and with an approved guideline or textbook, record discrepancies, and finish with a short reflection on what changed and why.

### 6.1. Example educator prompt template

You are assisting a medical educator who teaches medical students. Create one simulated clinical learning scenario about uterine fibroids for the learning objective: [INSERT OBJECTIVE]. The scenario should be appropriate for [YEAR/LEVEL] medical students. Include only information needed to make the learner reason about [DIAGNOSIS / INVESTIGATION / MANAGEMENT PRINCIPLE]. Do not reveal the answer in the initial scenario. After the learner submits a response, provide formative feedback that: (1) identifies strengths in the reasoning, (2) identifies missing or incorrectly weighted information, (3) asks one follow-up question, and (4) reminds the learner to verify clinical claims against [INSERT APPROVED GUIDELINE OR TEXTBOOK]. Avoid identifiable patient information and do not invent references.

## 7. Transferability beyond obstetrics and gynecology

Transferability depends on the properties of the learning task rather than on the specialty. The sequence is most plausible when four conditions are met: (1) the task requires contextual interpretation and justification rather than simple recall; (2) the learner can commit to a provisional judgement before AI exposure; (3) an external authoritative reference or faculty standard is available for verification; and (4) AI use can occur within appropriate supervision, privacy, and institutional constraints. In internal medicine, a learner could construct a differential diagnosis for chest pain before asking AI for an alternative explanation and then check recommendations against a guideline. In infectious diseases, the sequence could be used for antimicrobial selection after the learner weighs host factors, microbiology, and stewardship constraints. In radiology or pathology, the learner could first describe an image or specimen, compare the description with AI-supported feedback, and then verify the interpretation with faculty-approved material.

Transferability should not be interpreted as universal suitability. The full sequence is unnecessary for simple factual recall, and it is inappropriate when no independent verification source is available, privacy cannot be protected, or an unsupervised AI output could influence a high-stakes clinical decision. The framework is therefore best understood as a design option for

supervised educational tasks in which reasoning, uncertainty, source checking, and reflection are explicit learning objectives.

## 8. Educator oversight, ethics, and quality assurance

Faculty oversight is a design condition rather than a separate sixth step. Educators define the learning objective, decide whether AI is appropriate for the task, identify the external verification source, and review generated materials when needed. Student perceptions of AI are generally receptive, but curricular recommendations consistently emphasise training in limitations, critical appraisal, and responsible use (21).

Generative models can produce incorrect statements, fabricated references, biased representations, and overconfident explanations. Ethical guidance in health professions education emphasises transparency, accountability, human oversight, privacy, and bias mitigation (22). UNESCO and WHO guidance similarly emphasise human-centred use, safety, accountability, and inclusiveness (23,24). Identifiable patient information should not be entered into public generative-AI systems, and institutions should specify which platforms and data are permitted.

## 9. Limitations and research priorities

The principal limitation is that the proposed sequence has not been implemented or empirically evaluated. There are no data on fidelity of implementation, acceptability, feasibility, learner or faculty workload, knowledge retention, clinical reasoning, confidence calibration, transfer to new problems, or competency development. The proposed mechanisms, safeguards, and transferability are therefore hypotheses rather than demonstrated outcomes. Second, the literature basis is a targeted narrative search rather than a systematic review; no formal duplicate screening, quantitative synthesis, or risk-of-bias assessment was performed, and relevant literature may have been missed. Third, the framework was developed and illustrated using uterine fibroids, so its examples may still privilege reasoning patterns common in obstetrics and gynecology. Fourth, external verification and faculty review may add time and workload, and authoritative sources may themselves differ or change. Finally, generative-AI systems evolve rapidly, so any future evaluation must report the model, version, prompting conditions, permitted sources, and supervision used.

Evaluation should proceed in stages. Initial studies should test feasibility, fidelity, acceptability, and learner/faculty workload. Comparative studies should then test the sequence against well-specified alternatives, such as established case-based learning without AI, unrestricted AI use, or another structured AI-supported approach, rather than against no teaching at all (12, 25). Outcomes should include the quality of the learner's problem representation, source-verification behaviour, detection of AI errors or unsupported claims, confidence calibration, retention, transfer to new problems, and performance in structured clinical assessments. Multispecialty studies are needed to determine whether the same safeguards function similarly across clinical domains and learner levels.

## 10. Conclusions

- This article presents a literature-informed conceptual proposal for sequencing generative AI within a clinical learning task. Its claim is deliberately modest: the five steps are not presented as a new learning theory or as superior to established pedagogy. The proposed contribution is task-level temporal orchestration: learner commitment before AI exposure, use of AI as a fallible comparator, external verification, and reflective closure, so that AI-specific safeguards are explicit within an existing educational strategy.
- Uterine fibroids provide an illustrative context because they require integration of symptoms, imaging, reproductive priorities, and management choices, but the framework

is intended for other specialties when the task meets the transferability conditions described above. Its educational value remains hypothetical and should now be tested for feasibility, fidelity, acceptability, workload, clinical reasoning, and competency-related outcomes.

- Take-home message: when AI is used in a clinical reasoning exercise, require a learner-generated problem representation before AI exposure, verify AI claims against an external authoritative source, and close the task with reflection. This is a testable design proposal, not evidence of educational effectiveness.

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