

Reconstructing the General Computing Curriculum for Medical Students through Computational Thinking and Artificial Intelligence Literacy

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Abstract – General computing courses in medical universities must respond to artificial intelligence (AI) while preserving the concepts that make data and digital systems understandable. This conceptual study aims to develop a feasible reconstruction framework that integrates computational thinking, AI literacy, medical relevance, and responsible use into an inherited general computing curriculum for medical students. The framework was developed through an interpretive analysis of an anonymised curriculum source base comprising a 171-page legacy lesson plan, ten chapter-based courseware files, and a teaching calendar, together with relevant scholarship on computational thinking, AI literacy, constructive alignment, and medical AI education. The analysis identified four recurrent curriculum tensions: competition between obsolete and contemporary content, uneven medical contextualisation, addition rather than integration of AI, and assessment dominated by recall and software operation. In response, a one-core, four-module, three-level framework is proposed. Its core is responsible computational problem solving in medicine; the four modules are computational thinking, medical data foundations, medical AI applications, and responsible AI and innovation; and learning progresses from recognition to application and design. A recurring seven-step medical problem chain embeds interpretation, verification, and ethical reflection within technical work. A simulated electronic medical record database task further demonstrates how the framework can be implemented with existing laboratory resources and without real patient data. The study therefore provides a coherent and practically implementable design logic for gradual curriculum renewal, while its learning effectiveness remains to be established through future classroom evaluation.

Keywords – Artificial Intelligence Literacy, Computational Thinking, Computing Education, Curriculum Design, Medical Education.

I. INTRODUCTION

Artificial intelligence (AI) is becoming part of the information environment in which medicine is taught, learnt, and practised. Medical imaging, decision support, health-data management, and biomedical research increasingly rely on computational systems used alongside professional judgement [1], [2]. For medical schools, the curriculum question is therefore not simply whether students should be shown a new AI tool. It is what future health professionals need to understand about data, computation, uncertainty, verification, and responsibility so that such tools can be used appropriately.

Recent higher-education literature increasingly frames this need as AI literacy rather than tool fluency. AI literacy combines conceptual understanding, practical use, critical evaluation, creation, and ethical awareness [3]-[5]. Medical education raises the stakes because unsupported inference, data misuse, and misplaced trust can have consequences beyond the classroom. Reviews report growing interest in AI education but also uneven implementation, limited faculty readiness, and insufficient attention to limitations and evaluation [6], [7].

At the same time, many universities already have a general computing course. Such courses contain durable foundations-including information representation, computer systems, databases, networks, security, and

algorithms-but may also retain version-specific software procedures with little current transfer value. Chinese curriculum-reform literature similarly calls for stronger computational thinking, data literacy, AI literacy, and disciplinary integration rather than continued emphasis on software operation alone [8], [9]. Adding new AI content to an inherited syllabus can therefore increase breadth without improving coherence.

This paper addresses a practical design question: how can a legacy general computing course for medical students be reconstructed so that computing foundations, computational thinking, AI literacy, medical relevance, and ethical responsibility reinforce one another? The contribution is conceptual rather than evaluative. It (1) identifies content that should be retained, reduced, or repositioned; (2) proposes a one-core, four-module, three-level curriculum architecture; and (3) illustrates the architecture through a simulated electronic medical record database task that can be implemented with existing laboratory resources.

II. CONCEPTUAL BASIS AND CURRICULUM DIAGNOSIS

A. Computational Thinking and Artificial Intelligence Literacy

Computational thinking provides a bridge between traditional computing foundations and newer AI learning. It focuses attention on decomposition, abstraction, representation, procedural reasoning, automation, and evaluation [10], [11]. In medicine, this does not mean reducing clinical reasoning to algorithms. Rather, students learn to distinguish what can be represented computationally from what still depends on context, human interaction, professional judgement, and accountability. A staged progression is useful because students enter general computing courses with uneven experience; recognition, application, and design provide a practical way to deepen cognitive responsibility without requiring specialist engineering training [12], [13].

AI literacy adds a complementary set of expectations. Medical students do not need to build advanced models from first principles, but they should understand that outputs depend on data and assumptions, that fluent or confident output is not equivalent to verified evidence, and that human responsibility cannot be delegated to an opaque system. The educational emphasis should therefore move from operating tools to asking what a tool can support, what evidence it requires, how its output can be checked, and what decisions remain professional responsibilities [3]-[7].

B. Alignment, Medical Context, and Responsible Use

Constructive alignment requires learning outcomes, activities, and assessment to reinforce one another [14]. Professional contextualisation gives those capabilities a reason to matter. A foundational computing course does not need to become a clinical course; generic topics such as databases, networks, information security, and information retrieval can be reframed through simulated medical-information tasks while preserving the underlying computing concept. Integration should therefore be gradual and purposeful rather than an all-or-nothing replacement of the inherited course [15].

Ethics is treated as a design condition rather than a final lecture. International guidance on AI in health and education emphasises privacy, fairness, safety, transparency, accountability, autonomy, and human oversight [16], [17]. Generative AI adds concerns about hallucination, disclosure of sensitive information, over-reliance, and academic integrity [18], [19]. In classroom tasks, these concerns can become observable habits: use simulated or de-identified data, minimise unnecessary fields, document tool use, verify sources and units, identify uncertainty,

and state what an output cannot justify.

C. Reading the Inherited Curriculum as a Design Problem

The framework was developed against an anonymised medical-university curriculum source base comprising a 171-page legacy lesson plan, ten chapter-based courseware files, and a teaching calendar. The materials were read interpretively rather than coded as a frequency-based dataset. The analysis asked whether each topic had durable conceptual value, whether tasks required decomposition or abstraction, whether medical context was meaningful, whether AI content extended beyond tool familiarity, whether interpretation and verification were required, whether ethical constraints were embedded, and whether assessment produced evidence of the intended capability.

Four tensions were recurrent: temporal layering of obsolete and contemporary content; uneven medical contextualisation; AI added as a later topic rather than built on earlier data and computational ideas; and assessment weighted toward recall and operation. Table 1 converts these tensions into selective reconstruction decisions.

Table 1. Diagnosis of the inherited curriculum and reconstruction responses.

Starting element	Design problem	Reconstruction response
Computer history, hardware, number systems	Durable concepts mixed with high factual density.	Retain representation and systems; link to medical text, images, signals, and devices.
DOS, legacy operating-system procedures	Version-specific operations have low transfer value.	Compress obsolete procedures; emphasise files, permissions, backup, and secure use.
Office applications	Menu-following can remain professionally detached.	Use simulated medical reports, evidence presentations, data cleaning, and visualisation.
Databases, networks, and security	Generic examples hide professional relevance.	Use simulated records, telemedicine, access control, and health-data protection.
AI overview and tool demonstrations	Familiarity can develop without judgement.	Build AI on data and computational ideas; require interpretation, verification, and ethics.
Lecture and operational assessment	Limited evidence of transfer, judgement, or verification.	Use recurring medical problem chains and assess products, checking, explanation, and reflection.

III. CURRICULUM FRAMEWORK FOR RESPONSIBLE COMPUTATIONAL PROBLEM SOLVING

A. Framework Architecture

The proposed framework is organised around one core aim: responsible computational problem solving in medicine. Four mutually reinforcing modules provide curricular content: computational thinking foundations; medical data foundations; medical AI applications; and responsible AI and innovation. Across all four modules, learning progresses from recognition to application and then design. This structure specifies both what students encounter and what deeper engagement should look like.

The framework responds directly to the inherited curriculum. Computational thinking supplies a stable way to reason across changing technologies; medical data foundations make explicit the data structures and quality issues on which AI depends; medical AI applications move beyond tool demonstration toward interpretation and

verification; and responsible AI and innovation embeds privacy, bias, accountability, and human oversight within technical tasks. The architecture is cumulative: data is not a detour before AI, and ethics is not an appendix after it.

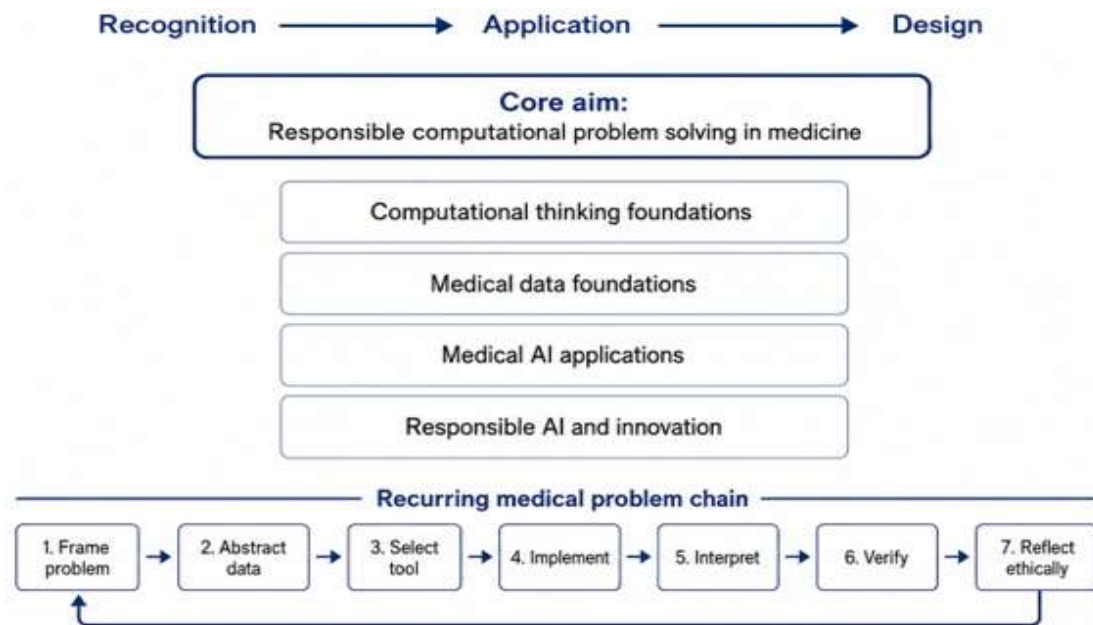


Fig. 1. Integrated curriculum framework for computational thinking and artificial intelligence literacy in medical students' general computing education.

B. Recognition, Application, and Design

Recognition asks students to identify relevant concepts, data types, plausible uses, and risks. Application requires a bounded task with an observable product and a checking process. Design asks students to coordinate concepts, tools, evidence, and constraints into a small workflow or data structure that can be justified. In this context, design does not mean producing a clinical AI system; it means making defensible decisions about how a computational approach should be organised and bounded. Table 2 shows how the progression changes across modules.

Table 2. Progression across the four curriculum modules.

Module	Recognition	Application	Design
Computational thinking	Identify computable elements, representations, and steps.	Decompose a bounded problem and express a workable procedure.	Design and justify a workflow, including what remains outside computation.
Medical data foundations	Recognise data types, quality issues, relationships, and suitable displays.	Clean, organise, query, and visualise simulated medical data.	Design a small data structure or analysis plan with integrity and privacy constraints.
Medical AI applications	Explain basic concepts, inputs, outputs, uncertainty, and limits.	Use an approved tool for a bounded task and independently check the output.	Propose a human-AI workflow with verification and professional boundaries.
Responsible AI and innovation	Identify privacy, bias, hallucination, accountability, and integrity risks.	Apply de-identification, attribution, source checking, and boundary statements.	Design an ethically constrained use scenario with oversight and risk mitigation.

C. The Recurring Medical Problem Chain

A framework becomes educationally meaningful only when it changes what students repeatedly do. The proposed medical problem chain contains seven moves: frame the medical-information problem; abstract relevant data; select a computational representation or tool; implement the task; interpret the output; verify its quality and limits; and reflect ethically. The sequence recurs across technical topics so that students practise a stable reasoning routine even as content changes.

This routine also clarifies responsibility. Teachers define the task boundary, teach the principles needed to work within it, and challenge unsupported conclusions. Students remain responsible for decomposition, representation, tool choice, interpretation, verification, and reflection. AI may provide examples or feedback, but it is treated as supervised support rather than authority. Similar higher-education frameworks have emphasised the value of connecting AI use to human judgement and explicit pedagogical dimensions [20], [21].

IV. ILLUSTRATIVE IMPLEMENTATION: SIMULATED ELECTRONIC MEDICAL RECORD DATABASE

Database teaching is a useful example because it already appears in many foundational computing courses and connects naturally to medical data. The illustrative task uses fictional outpatient records only; it does not involve real patient data, diagnosis, or advanced AI development. Students receive a small simulated dataset and are asked to organise visits and laboratory results so that specified information-management questions can be answered.

Students first identify the information problem before opening software. They decompose the request into data objects, fields, relationships, constraints, and queries. Three tables are used: Patient (patient code, sex, age group), Visit (visit code, patient code, date, department), and LaboratoryResult (result code, visit code, test, value, unit, abnormality flag). Primary and foreign keys establish one-to-many relationships. Students create the tables, set data types and integrity constraints, and import simulated records.

The query sequence moves from retrieval to interpretation. Students construct a date-range query for abnormal results, a summary query by department, and a parameter query returning visits and laboratory results for an entered patient code. They inspect the structured query language view, then verify whether joins introduce duplicates, whether missing values alter results, whether units are consistent, and whether each query answers the question asked. The final boundary statement explains that a database can retrieve and summarise recorded information but cannot determine diagnosis or treatment. A short privacy reflection addresses data minimisation, de-identification, access permissions, and the difference between an abnormality flag and clinical significance. Table 3 presents a compact 90-minute sequence.

Table 3. A 90-minute implementation sequence for the simulated electronic medical record database task.

Phase	Learning Activity	Evidence
Problem framing (10 min)	Define the simulated information-management problem and required questions.	Problem statement and decomposition notes
Data abstraction (15 min)	Identify Patient, Visit, and Laboratory Result entities; define fields, keys, and relationships.	Relationship sketch and field dictionary
Database construction (20 min)	Create tables, data types, keys, integrity constraints, and import simulated records.	Database file and relationship view

Phase	Learning Activity	Evidence
Queries and SQL (25 min)	Create date-range, summary, and parameter queries; inspect SQL.	Three executable queries and SQL statements
Interpretation and verification (10 min)	Check duplicates, missing values, units, joins, and question-result alignment.	Verification checklist and boundary statement
Privacy reflection (10 min)	Discuss data minimisation, de-identification, access, and clinical limits.	Privacy reflection and brief synthesis

V. ASSESSMENT AND IMPLEMENTATION

Assessment should reveal the reasoning that the curriculum claims to value. At the recognition level, evidence can include scenario judgements, concept explanations, error identification, and boundary statements. At the application level, students can submit cleaned datasets, queries, visualisations, documented tool use, and source checks. At the design level, evidence can include a workflow, data model, small project proposal, or responsible-use protocol. Across levels, useful dimensions are foundational understanding, decomposition, data abstraction, tool use, medical interpretation, verification, and ethical responsibility.

Implementation can proceed incrementally in resource-constrained settings. A first stage removes low-transfer procedures and reframes familiar examples. A second stage develops simulated datasets, task sheets, verification checklists, and rubrics. A third stage pilots selected tasks and uses classroom evidence to adjust workload and support. Faculty collaboration need not begin with full co-teaching; early collaboration can focus on case wording, data fields, medical plausibility, and ethical constraints. Institutions should also state which AI tools are permitted, what data may be entered, how AI use should be attributed, and where student responsibility lies [19].

VI. DISCUSSION

The main contribution of the framework is architectural rather than technological. Databases, networks, algorithms, and information security do not lose value when AI enters the curriculum; their relevance becomes clearer because students can see why representation, data quality, access, and verification matter. The reconstruction therefore treats AI as a reason to reorganise the course rather than a reason to discard its foundations. It also operationalises the broader call to embed AI literacy across curricula by connecting literacy to a specific inherited course and to repeated medical-information problems [3], [20].

The framework also clarifies the relationship between computational thinking and AI literacy. Computational thinking supplies a disciplined problem-solving process-decomposition, abstraction, procedural expression, and evaluation-while AI literacy adds the need to interpret probabilistic or generative output, verify claims, and reason about ethical and professional consequences. Professional context changes the constraints under which a computational solution is acceptable: privacy, units, missingness, access, evidential limits, and human oversight become part of technical quality rather than optional context.

The model is intended to transfer as an architecture, not as a fixed syllabus. Different medical programmes may require different examples and technical depth. Its limitations are equally important. The framework has not yet been evaluated through expert review, classroom implementation, student assessment, or longitudinal follow-up, and the source materials come from one institutional course. The next step should therefore be empirical but modest: pilot selected problem-chain tasks, test whether they fit available contact hours, evaluate scoring

consistency, and examine whether explicit verification requirements change how students reason with data and AI [22], [23].

VII. CONCLUSION

General computing education for medical students should not be renewed by simply adding an AI chapter to an already crowded syllabus. This study identified four problems in an inherited curriculum - temporal layering of obsolete and contemporary content, uneven medical contextualisation, weak integration of AI with earlier computing ideas, and assessment focused on recall and operation - and translated them into a coherent reconstruction strategy. The resulting one-core, four-module, three-level framework retains durable computing foundations while organising them around responsible computational problem solving in medicine. Its recurring medical problem chain requires students not only to implement a technical task but also to interpret results, verify quality and limits, and reflect on privacy, ethics, and professional responsibility. The simulated electronic medical record database example shows that these principles can be enacted with familiar teaching resources and simulated data rather than real patient information. For medical universities, the practical implication is that curriculum renewal can begin incrementally by reducing low-transfer procedures, contextualising existing tasks, and aligning assessment with reasoning and verification before expanding advanced AI content. Because the framework is conceptual and based on one institutional source base, it should not yet be interpreted as evidence of improved learning outcomes. Future work should pilot selected tasks and evaluate feasibility, scoring reliability, student learning, and transfer across medical-information contexts.

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Ethics and Data Statement

This conceptual article did not involve human participants, identifiable personal data, or real patient records. The illustrative teaching example is based entirely on simulated data. No empirical data were collected, generated, or analysed.

CONFLICT OF INTEREST

The author declares no conflict of interest.

Declaration of Generative AI And AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, OpenAI ChatGPT (GPT-5.6 Sol, accessed August 2026) was used to assist with manuscript organisation, language revision, sentence-level editing, and formatting. The tool was not used to generate or analyse empirical data. The author reviewed and verified all content and takes full responsibility for the accuracy, integrity, and final scholarly contribution of the manuscript.

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