

INTEGRATING SIMULATION TECHNOLOGIES AND HYBRID ARTIFICIAL INTELLIGENCE IN TEACHING BIOPHYSICS TO MEDICAL STUDENTS

Kozimjonov Nozimjon A'zimjon o'g'li
Andijan State Medical Institute

Abstract

This article proposes an instructional model for integrating simulation technologies and hybrid artificial intelligence (AI) into biophysics teaching for medical students. Hybrid AI is operationally defined as the coordinated use of explicit biophysical rules and computational checks with a neural language component that provides adaptive, source-grounded feedback under teacher supervision. The approach distinguishes scientific simulation from AI-generated explanation: the simulator produces model-based evidence, whereas AI supports interpretation without replacing the student's reasoning. A conceptual instructional-design methodology links learning outcomes, simulation tasks, verification rules, scaffolding, and individual assessment. Six modules are considered: measurement and uncertainty, hemodynamics, membrane transport, bioelectricity, biomedical optics, and ultrasound. The proposed architecture comprises verified content, simulation-based inquiry, symbolic validation, adaptive dialogue, and evidence-based assessment. A 90-minute lesson sequence, a module integration matrix, performance criteria, and implementation safeguards are specified. A hemodynamics example demonstrates how prediction, parameter manipulation, quantitative verification, and critical discussion can be connected within one learning cycle. The central design requirement is that students independently formulate predictions, evaluate numerical evidence, identify model limitations, and defend their conclusions. The contribution is a testable methodological framework rather than an experimentally validated intervention. Its educational value should be investigated through authentic measures of conceptual understanding, quantitative reasoning, delayed retention, and transfer to physical laboratory tasks.

Keywords: Biophysics; simulation-based learning; hybrid artificial intelligence; neuro-symbolic AI; virtual laboratory; medical education; adaptive feedback; formative assessment.

Introduction

Medical biophysics education requires students to connect physical laws with biological processes, measurements, and the operating principles of medical instruments. The instructional challenge is not simply to present an equation but to help learners move between its symbolic form, a dynamic representation, experimental data, and a biological explanation. Simulation technologies offer controllable environments for exploring these relationships, while research on virtual laboratories and guided inquiry provides a basis for combining manipulation with structured reasoning rather than unrestricted exploration [1,2].





A simulation becomes educationally meaningful when students predict an outcome, change a relevant parameter, record observations, and explain discrepancies. For example, a vessel-flow model can support investigation of radius and resistance, while a passive membrane model can connect electrical parameters to a time-dependent response. However, displaying an animation or allowing repeated parameter changes does not itself demonstrate understanding. The proposed approach therefore uses simulations as sources of evidence within a learning task, not as visual substitutes for lectures. TPACK, blended learning, and multimedia learning provide complementary foundations for aligning disciplinary content, instructional activity, and digital representation [3-5].

Hybrid AI introduces a further design possibility. Neuro-symbolic research combines neural learning with explicit knowledge representation and reasoning [6]. In this article, the term refers specifically to a modular educational system in which a neural language component is connected to a biophysical rule base, a numerical checking service, and a record of task-specific learning evidence. The language component interprets questions and formulates explanations, while explicit rules constrain the relationships, units, and assumptions used in feedback. This technical meaning differs from blended learning, which concerns the organization of online and face-to-face teaching. A simulation alone is not AI, and placing an unrestricted chatbot beside a simulation does not establish the proposed integration.

Retrieval-augmented generation provides a way to condition language generation on an external collection of documents [7]. For the present model, that collection would contain teacher-approved explanations, formula definitions, model assumptions, and annotated examples. Retrieved material supports the feedback process but is not treated as a guarantee of correctness. The proposed safeguards require structured computational checks, visible source references, and teacher review of unresolved responses. Feedback should direct attention to the next reasoning step rather than supply a finished answer, consistent with the instructional role of formative feedback [8].

The aim of this article is to develop a practical model for using simulation technologies and hybrid AI in teaching biophysics to medical students. Its objectives are to allocate distinct functions to simulation and AI components, map those functions to six representative modules, specify a repeatable lesson sequence, and define assessment and implementation criteria. The guiding question is how adaptive support can be introduced without weakening scientific validity, learner independence, or the teacher's responsibility for instruction.

MATERIALS AND METHODS

The article adopts a conceptual instructional-design methodology, drawing on guided inquiry, technology-pedagogy-content integration, formative assessment, and teaching as a design process [2,3,8,9]. Literature informs the component principles; the integrated architecture and its classroom procedures are proposed here as a methodological synthesis. This is neither a systematic review nor an empirical intervention study. No participant sample, classroom dataset, trained learner classifier, or experimentally established learning effect is reported.

The design process comprises four stages. First, the teacher specifies a biophysical concept and an observable learning outcome. Second, a learning difficulty is identified, such as confusing proportional relationships, mixing measurement units, or interpreting an idealized model as biological reality. Third, the teacher selects a simulation, its governing assumptions, the applicable verification





rules, and the permitted level of AI support. Fourth, an individual learning product and assessment criteria are defined before the activity begins. Technology is selected only when its function can be connected to this sequence.

The minimum proposed system contains a physics-based simulator, a symbolic knowledge and validation layer, a neural language component, a task-specific learner record, and a teacher interface. The symbolic layer contains equations, variable definitions, admissible parameter ranges, and explicit rules for identifying selected errors. A separate calculation service evaluates numerical relationships. The neural component receives structured results and approved reference passages rather than being asked to invent the physical model. In this modular form, hybridization occurs through the exchange of information between learned language processing and explicit disciplinary reasoning; it does not require training a new neural network.

For each attempt, the system would record the task identifier, model version, submitted prediction, selected parameters with units, computed output, student interpretation, and assistance already provided. Rule checks can identify a missing unit, an invalid parameter, or an answer inconsistent with the specified equation. They cannot establish every aspect of biological plausibility or the quality of a free-text explanation. Ambiguous interpretations therefore require teacher review. Only the information necessary for the learning task should enter the AI context; student names and unrelated personal records are not required.

Table 1. Didactic functions of simulation and hybrid AI components

Component	Instructional function	Required learner action	Evidence of learning
Physics-based simulation	Generate controlled, repeatable model outputs	Predict; vary one factor; record conditions	Parameter record, dataset, and graph
Symbolic rule and calculation layer	Check equations, units, admissible values, and selected error patterns	Inspect a flagged inconsistency and correct it	Revised calculation with an explanation
Neural language component	Formulate targeted questions and explanations from approved sources	Evaluate a hint against the model and evidence	Reasoned acceptance or rejection of feedback
Task-specific learner record	Select a support level from previous responses and checks	Attempt the next task with reduced assistance	Sequence of attempts and independent responses
Learning management and shared workspace	Connect preparation, paired inquiry, and discussion	Submit a prediction and compare evidence with peers	Shared graph plus individual interpretation
Teacher assessment interface	Review unresolved errors and separate assisted from independent work	Defend the final conclusion without generative assistance	Rubric score and individual transfer response



The learner record is deliberately modest. It may indicate, for example, that a student has twice confused radius with diameter or has corrected a unit error after a prompt. Such observations guide the next hint; they do not justify a permanent label of ability. A teacher-authored policy initially offers a conceptual question, then a targeted representation, and finally a worked step when necessary. Subsequent tasks reduce support. This implements task-related differentiation without assuming that unvalidated learning analytics can diagnose a student's general competence [10].

A blended 90-minute session is proposed, with a separate short preparatory activity before class. The classroom sequence allocates 10 minutes to prerequisite retrieval, 10 minutes to an individual prediction, 25 minutes to paired simulation, 15 minutes to AI-supported interpretation and revision, 15 minutes to teacher-led comparison and debriefing, and 15 minutes to an individual transfer task. Generative assistance is withheld during the initial prediction and final assessment. During inquiry, students must submit an attempt before requesting feedback; pairs exchange operator and analyst roles so that manipulation and interpretation are shared.

Six modules retain the disciplinary coverage of measurement, mechanics, transport, electricity, optics, and acoustics. Each combines a short preparatory resource, a controllable investigation, a defined AI support function, and an individual product. Simulation output must be labeled as model-generated. Where measurement noise is introduced, its source and distribution should be stated; random variation must not be presented as authentic clinical data. Table 2 specifies a platform-independent implementation matrix.

Table 2. Integration matrix for simulation and hybrid AI across biophysics modules

Module	Simulation-based investigation	Hybrid AI support and check	Individual learning product
Measurement and uncertainty	Repeat virtual readings while varying noise, resolution, or offset	Separate random spread from systematic offset; check units and significant figures	Measurement table and a justified uncertainty statement
Hemodynamics	Change tube radius, viscosity, length, or pressure difference under stated assumptions	Check the selected flow relation and distinguish radius from diameter	Radius-flow graph with a model-limitation explanation
Membrane transport	Vary concentration difference and permeability in a closed two-compartment model	Check concentration units, flux direction, and conservation under the chosen conditions	Concentration-time interpretation and a causal explanation
Bioelectricity	Change resistance and capacitance in a passive membrane model	Check the time constant and distinguish passive charging from active excitation	Annotated voltage-time graph and an independent prediction
Biomedical optics	Vary concentration and optical path length in a virtual calibration experiment	Check the calibration relationship, units, and whether an estimate is extrapolated	Calibration plot with a calculation and limitation statement
Ultrasound principles	Vary propagation speed, interface depth, and pulse-echo timing	Check time units and the distinction between one-way depth and round-trip travel	Depth calculation with explicit propagation assumptions



RESULTS

The results consist of four design products: a five-layer architecture, the lesson and module integration sequence, an assessment rubric, and implementation requirements. They describe what an intervention should contain and how it could be evaluated; they are not observations of student improvement. The first layer, verified content, contains approved explanations, physical relationships, and model boundaries. The second, simulation-based inquiry, provides controlled manipulation and a record of the resulting evidence. The third, symbolic validation, checks structured responses against the selected model. The fourth, adaptive dialogue, turns relevant evidence and checks into targeted prompts. The fifth, evidence-based assessment, requires independent interpretation and transfer.

The layers form a feedback cycle. A learner's prediction determines which contrast is investigated; the generated data support an explanation; a rule-based check identifies a specific inconsistency; and the language component asks the learner to reconsider the relevant step. A corrected response leads to a related task with less support. The teacher can inspect the original response, verification result, retrieved source, and assistance provided. This makes the instructional pathway reviewable without equating a fluent AI explanation with verified knowledge.

For example, if a student's flow calculation is dimensionally inconsistent, the system should identify the relevant unit conversion before discussing biological implications. Numerical values included in feedback should come from the checking service, not an unconstrained language-model calculation. Generated explanations should cite the approved course passage used. Where the proposed explanation conflicts with the rules or cannot be supported by the available material, it should be withheld in favor of a teacher-authored prompt or instructor review. These safeguards delimit the intended design; their reliability would still require implementation testing.

An illustrative hemodynamics task begins with the Hagen-Poiseuille relationship for steady, fully developed laminar flow of an incompressible Newtonian fluid in a rigid circular tube [12]:

$$Q = \pi \Delta P r^4 / (8 \eta L)$$

Here, Q is volumetric flow rate, ΔP is the pressure difference, r is internal radius, η is dynamic viscosity, and L is tube length. Students first predict how flow changes when radius is reduced by 20% while the other quantities remain constant. Under these assumptions, the new-to-original flow ratio is:

$$Q_2 / Q_1 = (r_2 / r_1)^4 = 0.8^4 = 0.4096$$

Thus, the model predicts 40.96% of the original flow, a decrease of 59.04%. These values are an algebraic illustration, not observed student or patient data. Students generate additional radius-flow pairs, construct a graph, and compare it with their prediction. For a response based on direct proportionality, the first AI prompt asks the learner to identify the power of radius rather than revealing the answer. For a correct number without justification, the prompt asks which variables were held constant. The final individual task requires an explanation of why the ideal tube model is not a complete representation of physiological circulation.

Assessment distinguishes scientific performance from software activity. Table 3 defines six domains, each scored provisionally as 0 for insufficient, 1 for developing, or 2 for competent performance. The resulting 0-12 total is a proposed reporting device, not a validated diagnostic scale. Domain scores and the unassisted transfer response remain more informative than a total alone. The rubric evaluates



the relevance of a student's contributions and verification practices, not the number of clicks, messages, or requested hints.

Table 3. Proposed criteria for simulation-supported and hybrid-AI-supported learning

Domain	Insufficient (0)	Developing (1)	Competent (2)
Scientific accuracy	Uses an incorrect law, variable, or interpretation	Uses the main relationship correctly but omits assumptions	Explains the relationship, units, assumptions, and biological meaning
Quantitative reasoning	Produces inconsistent values or misreads a graph	Produces a usable calculation or graph with prompting	Selects and checks quantitative evidence independently
Simulation inquiry	Changes parameters without a prediction or controlled comparison	Controls a relevant variable with guidance	Predicts, controls the comparison, records evidence, and explains the outcome
Collaborative reasoning	Repeats an assertion without evidence	Responds to peers but only partly revises reasoning	Compares evidence and documents a justified revision
Critical use of AI	Accepts generated feedback without checking it	Checks a source or numerical statement when prompted	Verifies feedback and explains why it is accepted, corrected, or rejected
Reflective transfer	Treats the model as exact reality or cannot explain without AI	Recognizes a limitation with assistance	Independently applies the principle and states relevant limits in a new task

Implementation quality is assessed separately from learning performance. A numerically accurate simulator may still support a poorly designed task, while a coherent lesson can be disrupted by unreliable AI feedback or unequal access. Before classroom use, the teacher should review the model, test representative correct and incorrect answers, rehearse the sequence, and prepare an equivalent non-AI pathway. For stochastic simulations, a recorded seed or a saved dataset enables students and teachers to reproduce the comparison.

Responsible deployment requires transparent data practices and continuing human oversight, in line with UNESCO's human-centered guidance for generative AI in education [11]. Students should know what information is collected, why it is needed, how long it is retained, and which services receive it. Synthetic educational cases are preferable when patient information is unnecessary. The teacher retains final responsibility for assessment, and students must be able to question an automated interpretation without being penalized for challenging the system.





Table 4. Implementation requirements for simulation and hybrid AI in biophysics

Dimension	Required safeguard	Practical evidence
Pedagogical coherence	Link each component to a learning outcome, student action, and assessment	Outcome-task-support matrix and lesson plan
Simulation validity	Review equations, units, assumptions, parameter ranges, and numerical behavior	Expert checklist and reproducible test cases
AI reliability	Use approved sources, structured checks, and an escalation route for uncertainty	Feedback test set, version record, and teacher-review log
Accessibility and continuity	Provide usable interfaces, low-bandwidth materials, and equivalent fallback tasks	Access check, downloadable dataset, and non-AI worksheet
Teacher readiness and assessment	Rehearse prompts, explain the rubric, and preserve independent assessment	Facilitation script and unassisted transfer task
Data responsibility	Minimize records, control access, set retention rules, and disclose AI use	Institutional data-handling procedure and learner information notice

DISCUSSION

The principal contribution is the allocation of distinct epistemic roles to the technologies. The simulation represents a stated physical model, the symbolic layer checks selected relationships, the neural component supports dialogue, and the teacher evaluates meaning and educational appropriateness. This division extends the principle that technology should be integrated through content and pedagogy rather than selected for novelty [3]. It also provides an operational interpretation of hybrid AI: learning-based language processing and explicit reasoning must exchange task-relevant information, not merely appear in the same interface [6].

The proposed mechanism of educational benefit is increased attention to the relationship between prediction, evidence, and explanation. A learner who predicts before seeing an output has a claim to test. A targeted hint can then direct attention to a discrepancy without taking over the task. Guided inquiry and feedback research support these component principles [2,8], but they do not establish the effectiveness of this particular combination. The design therefore treats improved conceptual understanding, more accurate quantitative reasoning, and stronger transfer as hypotheses to be investigated rather than outcomes already achieved.

A further distinction concerns different sources of uncertainty. Measurement uncertainty relates to readings and instrument behavior; model uncertainty concerns idealization and omitted processes; and uncertainty in AI feedback concerns whether the generated explanation is supported and correctly applied. These should not be collapsed into a single confidence score. In the proposed classroom practice, students state which kind of uncertainty affects a conclusion and what evidence could reduce it. This requirement makes critical use of AI part of disciplinary reasoning rather than a separate exercise in software literacy.

Simulation is intended to complement, not eliminate, physical experimentation. Physical and virtual laboratories have different affordances, and their combination should follow the learning objective



[1]. Where equipment is available, a virtual calibration or flow investigation can precede a physical task, followed by comparison of the two sets of observations. Students should explain differences in terms of the modeled and measured conditions. Where equipment is unavailable, prepared measurement data can support interpretation, but analysis of such data should not be claimed to demonstrate hands-on instrument competence.

Adaptive dialogue also introduces a risk of replacing effort with answer consumption. The proposed safeguards are to require an initial attempt, use staged hints, reduce assistance across tasks, and assess transfer without generative support. Collaboration follows the same principle: a shared graph is useful evidence of a group investigation, but it does not establish every participant's understanding. An individual explanation, brief oral defense, or new quantitative problem is needed to determine what each learner can justify. The value of AI support should be judged partly by what the student can subsequently do without it.

The framework has practical limitations. Preparing a reliable rule base, annotated reference collection, and feedback test set requires disciplinary and pedagogical effort. Rules cover only the errors for which they have been designed, while a retrieved passage may be relevant without fully answering a learner's question. Consequently, source-grounded dialogue must remain reviewable, and retrieval should not be equated with scientific validation [7]. Accessibility, teacher preparation, and data governance are equally necessary conditions, rather than secondary additions to a functioning technical system [10,11].

Future empirical evaluation should distinguish the contribution of simulation from the additional contribution of hybrid AI. A feasible design would compare conventional instruction, simulation with teacher-authored guidance, and the same simulation with hybrid AI support. Content, scheduled learning time, and assessment should be comparable, with actual preparation and time on task recorded. The primary outcome could be an independently completed conceptual and quantitative transfer test; secondary outcomes could include delayed retention, graph interpretation, and performance in a physical laboratory. Sample size should be planned from the primary outcome rather than chosen retrospectively. Where classes are allocated as clusters, analysis should account for clustering and baseline performance; non-randomized comparisons require explicit discussion of confounding. Effect estimates with uncertainty, missing data, feedback errors, and implementation fidelity should be reported alongside learner perceptions.

CONCLUSION

Simulation technologies and hybrid AI can be organized within a coherent instructional model for medical biophysics. The proposed framework connects verified content, controlled investigation, symbolic checks, adaptive dialogue, and independent assessment across six modules. Its practical outputs are a 90-minute lesson sequence, a module integration matrix, a six-domain rubric, and implementation requirements addressing scientific validity, accessibility, teacher readiness, and data responsibility.

The defining principle is that computational support should strengthen the student's ability to predict, investigate, calculate, verify, and explain. Simulated evidence must remain distinguishable from real measurements, and generated explanations must remain open to scrutiny. The framework provides a basis for classroom development and transparent evaluation; it does not establish effectiveness in the





absence of authentic learning data. Its success should ultimately be judged by the quality of independent biophysical reasoning and transfer, not by the amount of AI interaction.

REFERENCES

1. De Jong T., Linn M.C., Zacharia Z.C. Physical and virtual laboratories in science and engineering education. *Science*. 2013;340(6130):305-308. doi:10.1126/science.1230579.
2. Lazonder A.W., Harmsen R. Meta-analysis of inquiry-based learning: effects of guidance. *Review of Educational Research*. 2016;86(3):681-718. doi:10.3102/0034654315627366.
3. Mishra P., Koehler M.J. Technological pedagogical content knowledge: a framework for teacher knowledge. *Teachers College Record*. 2006;108(6):1017-1054.
4. Garrison D.R., Kanuka H. Blended learning: uncovering its transformative potential in higher education. *The Internet and Higher Education*. 2004;7(2):95-105. doi:10.1016/j.iheduc.2004.02.001.
5. Mayer R.E. *Multimedia Learning*. 2nd ed. Cambridge: Cambridge University Press; 2009.
6. d'Avila Garcez A., Lamb L.C. Neurosymbolic AI: the 3rd wave. *Artificial Intelligence Review*. 2023;56:12387-12406. doi:10.1007/s10462-023-10448-w.
7. Lewis P., Perez E., Piktus A., Petroni F., Karpukhin V., Goyal N., et al. Retrieval-augmented generation for knowledge-intensive NLP tasks. *Advances in Neural Information Processing Systems*. 2020;33:9459-9474.
8. Hattie J., Timperley H. The power of feedback. *Review of Educational Research*. 2007;77(1):81-112. doi:10.3102/003465430298487.
9. Laurillard D. *Teaching as a Design Science: Building Pedagogical Patterns for Learning and Technology*. New York: Routledge; 2012.
10. Redecker C. *European Framework for the Digital Competence of Educators: DigCompEdu*. Luxembourg: Publications Office of the European Union; 2017. doi:10.2760/159770.
11. Miao F., Holmes W. *Guidance for Generative AI in Education and Research*. Paris: UNESCO; 2023.
12. Urone P.P., Hinrichs R. *College Physics 2e*. Houston, TX: OpenStax; 2022. Section 12.4: Viscosity and Laminar Flow; Poiseuille's Law.

