AI in Education and Education in AI

William Hersh, MD
Professor
Division of Informatics, Clinical Epidemiology, and Translational Data Science
Department of Medicine
School of Medicine
Oregon Health & Science University
Portland, OR, USA
Email: hersh@ohsu.edu
Web: https://billhersh.info/
BlueSky: @billhersh.bsky.social

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AI in Education and Education in AI

William Hersh, MD
Professor
Division of Informatics, Clinical Epidemiology, and Translational Data Science
Oregon Health & Science University
Portland, OR, USA

Outline

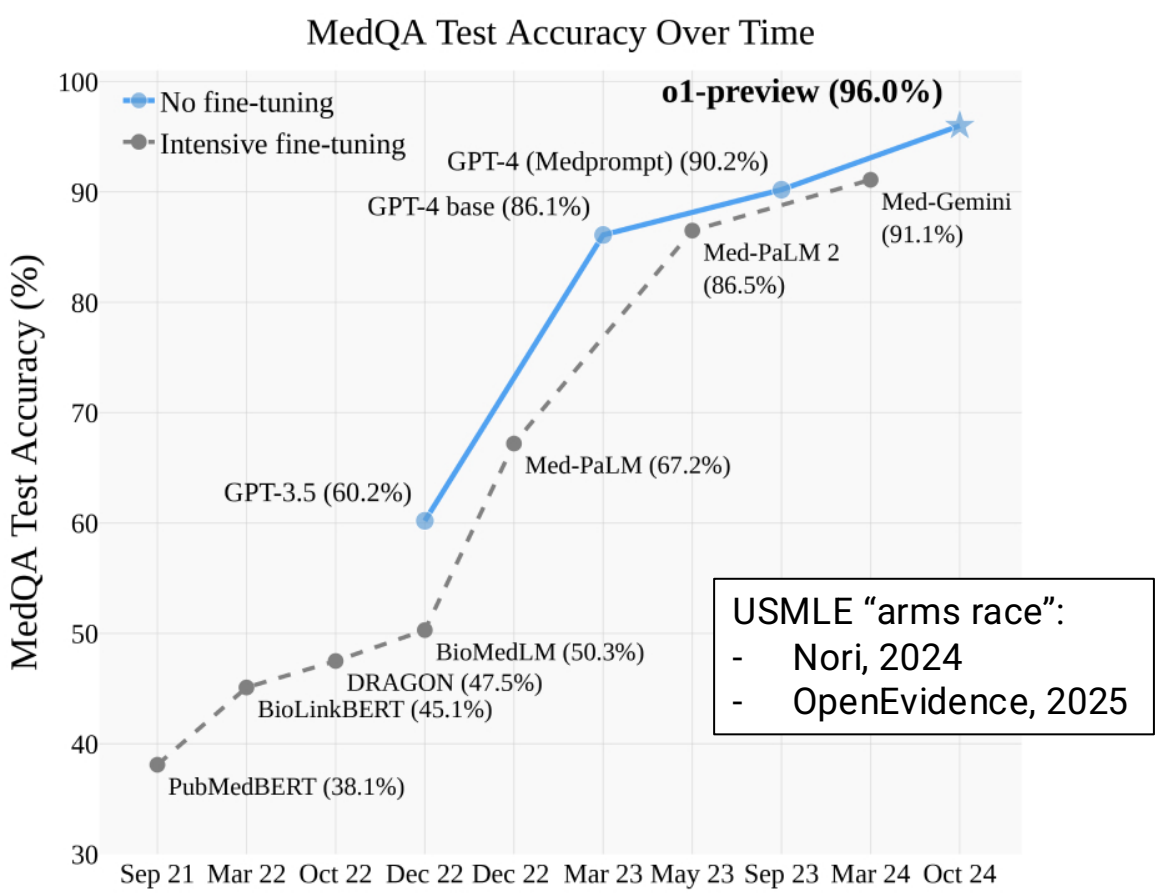
- AI in education
  - Impact of AI in education and its assessments
  - Concerns for AI through the lens of education
- Education in AI
  - Competencies and curricula for diverse learners
  - Developing strategies for optimal use

AI in education (and beyond)

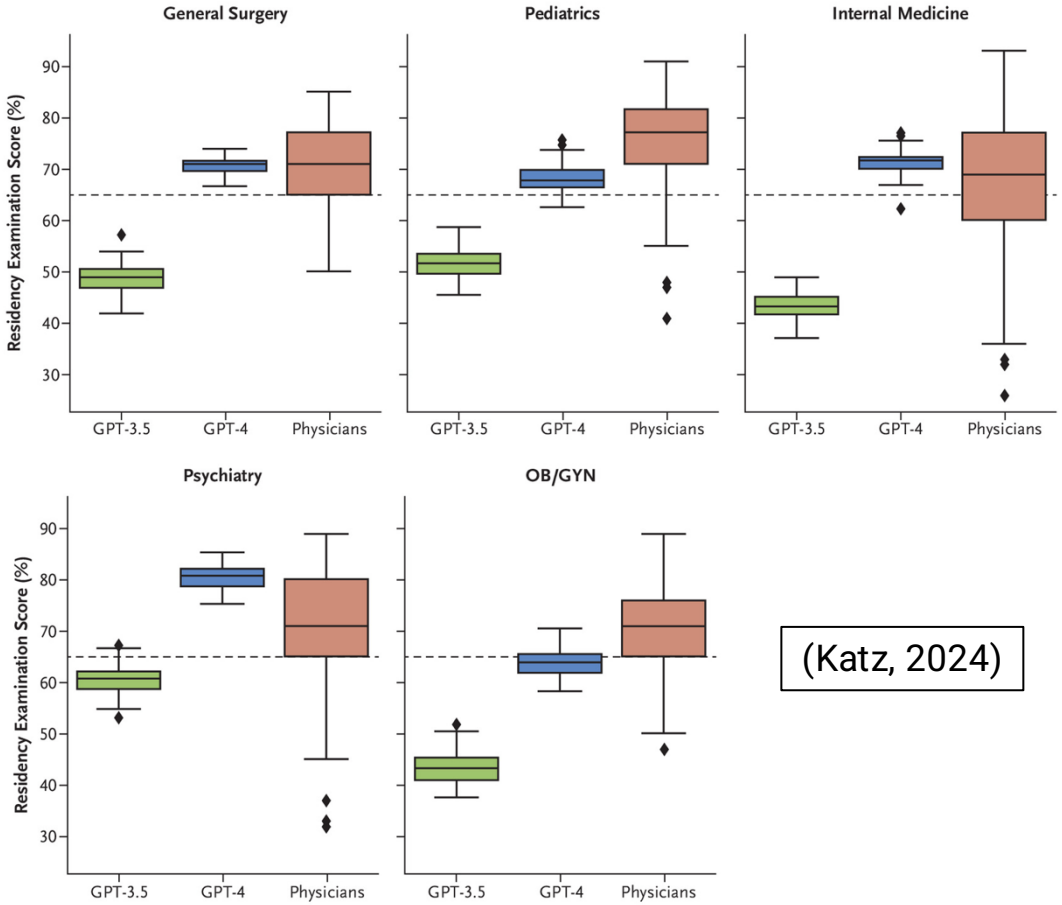
- LLMs perform well in many different types of biomedical education-related tasks and assessments (Hersh, 2025)
  - Medical board exams
  - Graduate school bioscience exams
  - Answering clinical questions
  - Solving clinical cases
  - Conversational diagnostic dialogue
  - Clinical reasoning
  - And more

- LLMs perform well in education in many disciplines beyond biomedicine
  - Passing college entrance and AP exams (Dubey, 2024)
  - Writing computer programs (Poldrack 2024; Denny, 2024; Johnson, 2024)
  - Creating data science pipelines (Cheng, 2024; Hong, 2024)
  - Writing legal briefs (Choi, 2024)
  - Passing undergraduate psychology courses (Scarfe, 2024)
  - Outscoring PhD students on "Google-proof" questions in biology, chemistry, and physics (OpenAI, 2024; Jones, 2024)

Among the many successes of generative AI in medical education



USMLE "arms race":
- Nori, 2024
- OpenEvidence, 2025



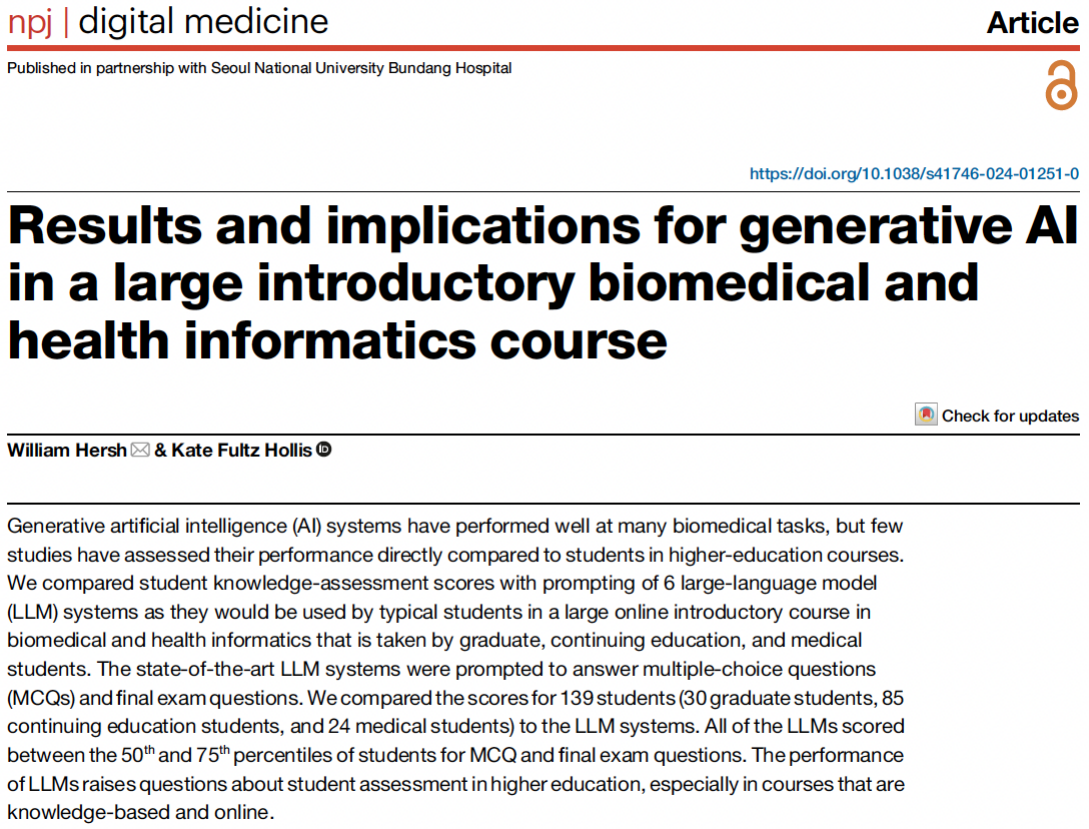
(Katz, 2024)

Results in biomedical education assessments

- Introudctory biomedical informatics (Hersh and Fultz Hollis, 2024)
- Graduate-level biomedical sciences (Stribling, 2024)
- Health informatics programming (Avramovic, 2024)

Goals of study (Hersh and Fultz Hollis, 2024) – working backwards through title

- Large introductory biomedical and health informatics course
  - Same curriculum and (mostly) assessments in courses taught to graduate students, medical students, and continuing education students
- Generative AI
  - Use of large language models (LLMs) in knowledge assessment
- Results and implications
  - How do LLMs fare on student assessments?
  - What does this mean for student assessment in this and other similar courses?



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Article

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Results and implications for generative AI in a large introductory biomedical and health informatics course

William Hersh & Kate Fultz Hollis

Generative artificial intelligence (AI) systems have performed well at many biomedical tasks, but few studies have assessed their performance directly compared to students in higher-education courses. We compared student knowledge-assessment scores with prompting of 6 large-language model (LLM) systems as they would be used by typical students in a large online introductory course in biomedical and health informatics that is taken by graduate, continuing education, and medical students. The state-of-the-art LLM systems were prompted to answer multiple-choice questions (MCQs) and final exam questions. We compared the scores for 139 students (30 graduate students, 85 continuing education students, and 24 medical students) to the LLM systems. All of the LLMs scored between the 50th and 75th percentiles of students for MCQ and final exam questions. The performance of LLMs raises questions about student assessment in higher education, especially in courses that are knowledge-based and online.

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About the course

- Introductory overview of biomedical and health informatics (Hersh, 2007; Hersh, 2022)
  - Taught at OHSU for over three decades (Hersh, 2024)
  - Updated annually
- Taught online using
  - Voice-over-Powerpoint lectures
  - Discussion forums
  - Optional textbook readings
- Assessments include
  - Multiple-choice questions (MCQs) – 10 questions in each of 10 units
  - Final exam – 33 short-answer questions
  - Term paper – not required of medical students, not assessed in this study

Offered in three versions

- BMI 510/610 – graduate-level course required for informatics students and as elective for other (e.g., nursing, public health, basic science) students
  - Completed by 1760 students from 1996-2025
- 10x10 (“ten by ten”) – continuing education course offered in partnership with American Medical Informatics Association (AMIA)
  - Completed by 3449 students from 2005-2025
- MINF 705B/709A – elective course for medical students offered as two-week block or over academic quarter
  - Completed by 188 students from 2020-2025 (starting with pandemic)

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Requirements for different versions

Audience	Unit Assessments – MCQs	Final Exam	Term Paper	Grading
Graduate students	Required	Required	10-15 pages on focused topic	Letter grade
Continuing education students	Required	Optional	2-3 pages application of informatics	Pass-fail
Medical students	Required	Not required	2-3 pages self-reflection on use of informatics	Pass-fail

Course outline – 2023

1. Overview of Field and Problems Motivating It
2. Computing Concepts for Biomedical and Health Informatics
3. Electronic and Personal Health Records (EHR, PHR)
4. Standards and Interoperability
5. Data Science and Artificial Intelligence
6. Advanced Use of the EHR
7. EHR Implementation, Security, and Evaluation
8. Information Retrieval (Search)
9. Research Informatics
10. Other Areas of Informatics

See (Hersh, 2024) for original mid-1990s course outline!

Compared 2023 course student performance with six commercial, readily available LLMs

- LLMs prompted in February-March 2024
  - ChatGPT-4
  - Microsoft CoPilot/Bing – used GPT-4
  - Google Gemini Pro 1.0
  - Claude 3 Opus
  - Mistral-Large
- Prompted in August 2024
  - Meta Llama 3.1 405B – “open-source”

- Prompted via Web interfaces as students would likely do
- Deemed “non-human research” by IRB

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Prompts

- MCQs
  - Each LLM prompted first with, “You are a graduate student taking an introductory course in biomedical and health informatics. Please provide the best answers to the following multiple-choice questions.”
  - Followed by pasting in the MCQs one unit (10 questions) at a time exactly as they appeared in MCQ preview file in LMS
- Final exam
  - Each LLM prompted with, “You are a graduate student taking the final exam in an introductory course in biomedical and health informatics. Answer each of the following questions with a short answer that is one sentence or less.”
  - Followed by pasting in exam, which had 33 questions, separated into 8 sections with a one-sentence heading for each section, exactly as it appeared in LMS exam module

Example questions

Multiple-choice questions

The clinical leader of information systems for a healthcare system is most commonly called?
a. Chief Medical Information Officer
b. Clinical Informatics Subspecialist
c. Chief Information Officer
d. Health Information Manager
e. Nursing Informatician

An image captured from an HD (720p) video having 24-bit color depth takes up how much computer memory?
a. 720 bytes
b. 2.76 kilobytes
c. 2.76 megabytes
d. 22.1 megabytes
e. 2.76 gigabytes
f. 22.1 gigabytes

The most frequent type of error in physician speech recognition data entry comes from?
a. Words erroneously added
b. Words erroneously deleted
c. Words misspelled during editing by clinician
d. Words mispronounced

What would be the best source for drug terminology to use in a SMART on FHIR prescribing app in the United States?
a. CPT-4
b. NANDA-I
c. NDC
d. LOINC
e. RxTerms

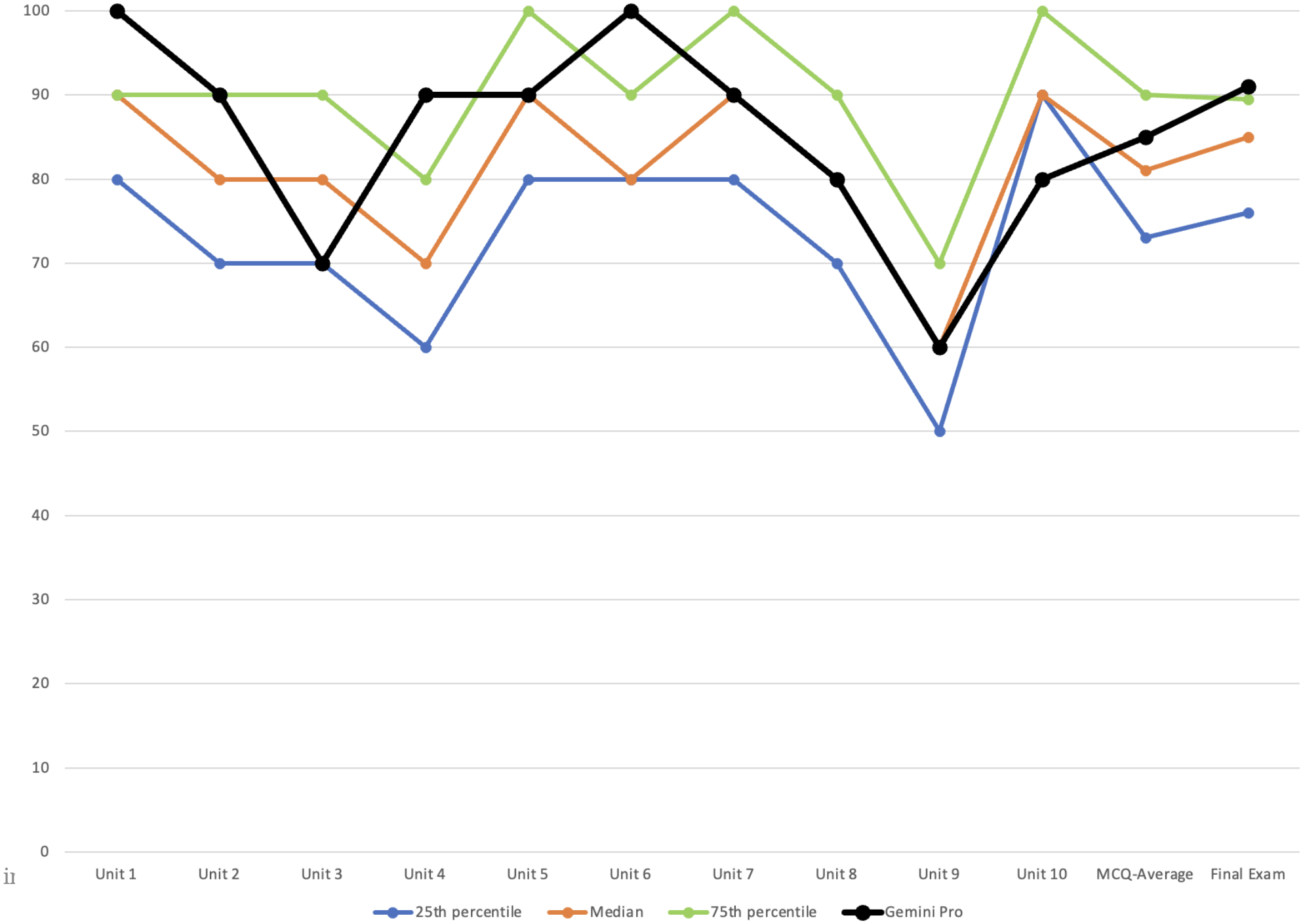
Which of the following is not a defined element of personal health information in the HIPAA Privacy Law?
a. Facial image
b. First and last name
c. Name of hospital where care is obtained
d. Personal email address
e. Twitter handle

Final exam questions

A vendor wants your healthcare system to adopt an app that monitors blood sugar levels in patients with diabetes and recommends tailoring their insulin dose based on those values. What would be the best kind of clinical study to answer the question whether patients who use the app have better health outcomes?

What is the difference between HIPAA and the European General Data Protection Regulation (GDPR) with regards to your personal health information collected by an app on your phone?

Results – overview



Results – detailed

Students/LLMs	MCQ Unit Average	Final Exam	MCQ+Final Combined
Students – 25th percentile	73	76	149
Students – 50th percentile	81	85	166
Students – 75th percentile	90	90	180
ChatGPT Plus	88	76	164
Claude 3 Opus	81	91	172
CoPilot Bing-Precise	88	85	173
Gemini Pro	85	91	176
Llama 3.1 405B	85	88	173
Mistral-Large	83	82	165

Results – clock time (in seconds)

LLM	MCQ Average	Final Exam
ChatGPT Plus	59.2	73
Claude 3 Opus	36.3	49
CoPilot Bing-Precise	21.6	80
Gemini Pro	22.8	25
Llama 3.1 405B	18.8	20
Mistral-Large	15.3	38

- Most time taken due to screen writing, so actual processing even faster

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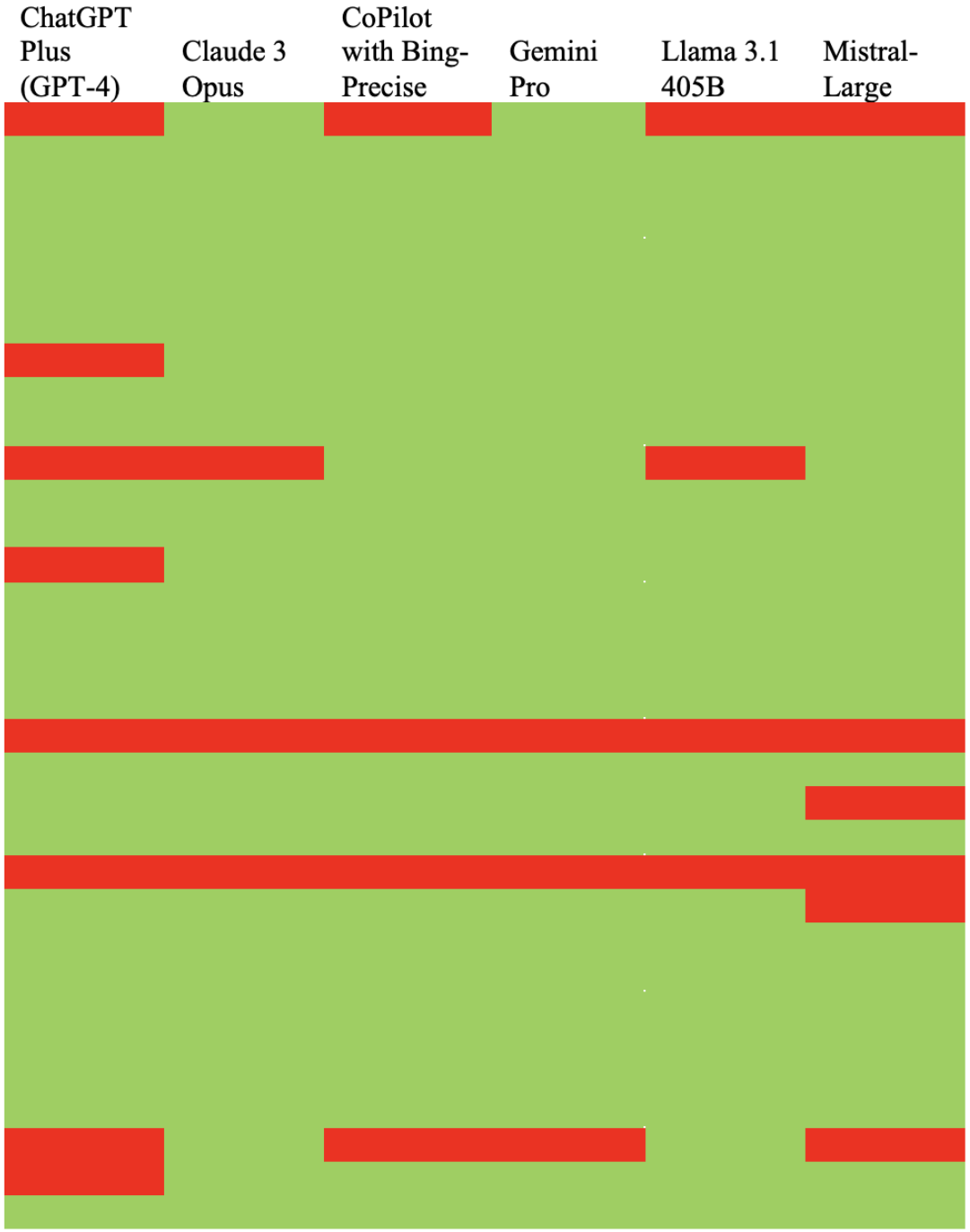
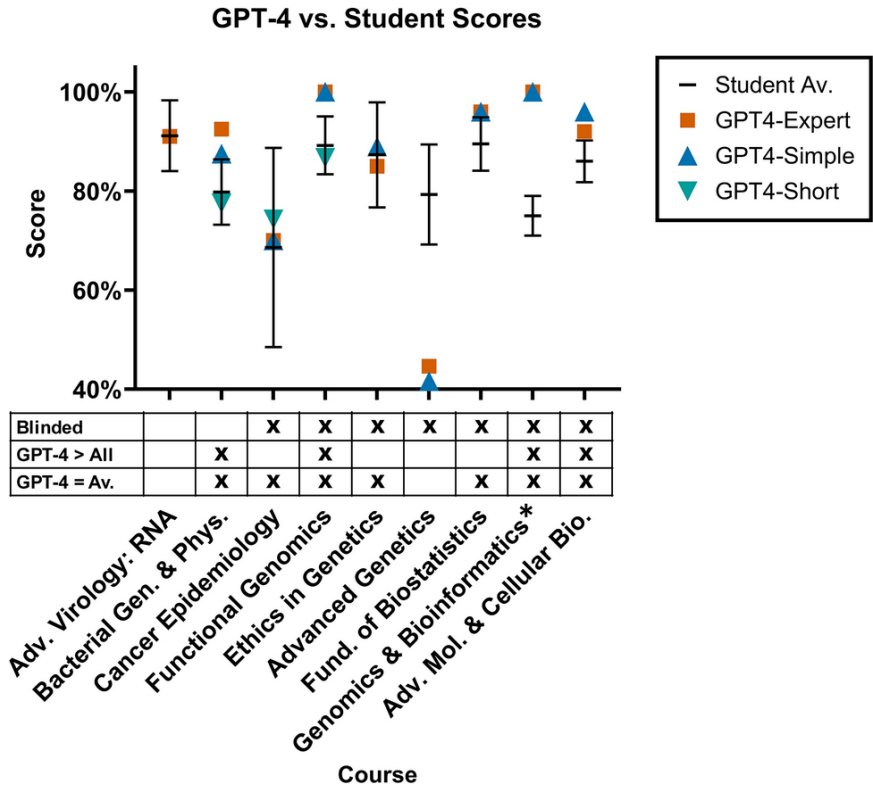
LLMs on final exam questions

Question	Topic
1	Sensitivity
2	Splitting data into training/test
3	Randomized controlled trial
4	PubMed
5	Transfer learning
6	Clinical informatics
7	Microbiome
8	CDS reminder
9	Tethered PHR
10	DICOM
11	Continuity of Care Document
12	FHIR
13	NCPDP SCRIPT or SCRIPT
14	ICD-10-CM
15	LOINC
16	CPT-4
17	MeSH
18	RxNorm or RxTerms
19	Directed or Push HIE
20	Security items that you have
21	GDPR vs. HIPAA
22	HTTPS vs. HTTP
23	Documents retrieved
24	Inverse document frequency
25	Precision
26	Recall
27	Process quality measure
28	Structural quality measure
29	Outcome quality measure
30	Relative risk reduction
31	Number needed to treat
32	PubMed search limits
33	Synchronous telemedicine



Other biomedical courses

- Graduate-level examinations in biomedical sciences (Stribling, 2024)
  - GPT-4 performance on 9 exams
  - Exceeded student average on 7 of 9 exams and all student scores for 4 exams
  - Performed very well on
    - Fill-in-the-blank, short-answer, and essay questions
    - Questions on figures sourced from published manuscripts
  - Performed less well on questions with
    - With figures containing simulated data
    - Requiring hand-drawn answer
  - Some responses included detailed hallucinations
- Use of GitHub CoPilot in health informatics programming course (Avramovic, 2024)
  - Assessed in problems for
    - Database queries with SQL
    - Computational tasks with Python
  - Generated solutions worked well for simple tasks but less well for complex ones
    - Some solutions correct but not most efficient approach



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Other impact of generative AI in education (Hersh, 2025)

- The “homework apocalypse” (Mollick, 2023) and solutions going forward (Mollick, 2024)
- “ChatGPT has transformed the problem of grade inflation from a minor corruption to an enterprise-destroying blight.” (Clune, 2023)
- “I used to teach students. Now I catch ChatGPT cheats.” (Jollimore, 2025)
- “Generative artificial intelligence does not have to undermine education.” (Tan, 2024)
- Concerns of “de-skilling” or even “never-skilling” in medical education (Berzin, 2025)

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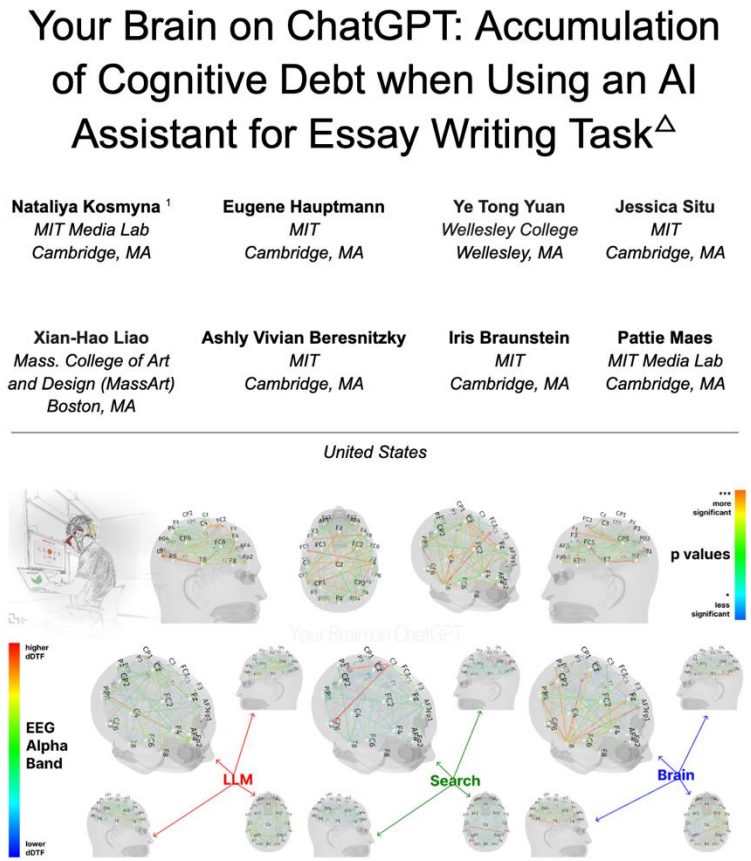
Despite achievements, some concerns through lens of education

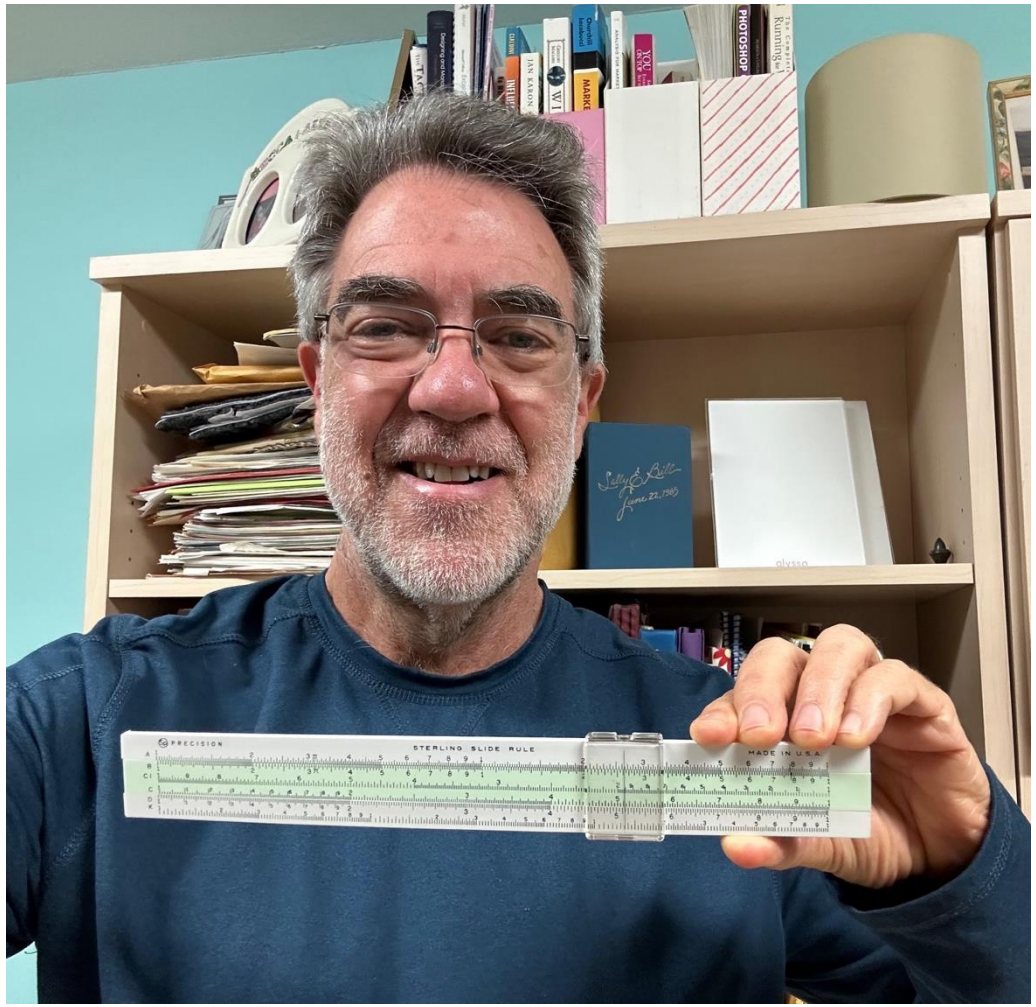
- May inhibit critical engagement with work and lead to long-term overreliance on tool and diminished skill for independent problem-solving (Lee, 2025)
  - When using generative AI, effort invested in critical thinking shifts from
    - Information gathering to information verification
    - Problem-solving to AI response integration
    - Task execution to task stewardship
- Use of LLMs reduced cognitive connections in brain measured by EEG during essay-writing, resulting in (Kosmyna, 2025)
  - More homogeneous output
  - Less ability to recall what was written over time
- Use of LLMs resulted in ”shallower knowledge” than learned via Web search, even when links provided in LLM output (Melumad, 2025)



AI tools work less well in hands of humans

- LLMs in physician diagnostic reasoning (Goh, 2024)
  - 50 physicians randomized to LLM or conventional information resources and assessed with diagnostic performance rubric for 6 diagnostic cases
  - No statistical difference between physicians using LLM (76%) vs. conventional (74%) resources; LLM alone scored better than either (92%)
- LLMs as medical assistants for general public (Bean, 2026)
  - 1298 people assisted on 10 scenarios randomized to LLM or information source of choice
  - Used alone, LLMs completed scenarios accurately, correctly identifying conditions in 94.9% of cases and disposition in 56.3%
  - Participants using same LLMs identified relevant conditions in 34.5% of cases and disposition in 44.2%, similar to control group

Now what? Educational cusps in my lifetime



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First step –

https://billhersh.info/genai-policy

Introduction to Biomedical Informatics & Artificial Intelligence
Course Policy for Use of Generative AI and ChatGPT

This page reflects course policy for my course, *Introduction to Biomedical Informatics & Artificial Intelligence*. There are versions of this course in several programs, including:

- AMIA 10x10 ("ten by ten") course - OHSU-AMIA 10x10 course
- OHSU Biomedical Informatics Graduate program - BMI 510/610 - Introduction to Biomedical & Health Informatics
- OHSU MD curriculum course, MINF 705B/709A

ChatGPT and generative AI systems based on large language models (LLMs) can be a useful tool for learning all kinds of topics, including in biomedical and health informatics. These tools should not, however, be used to substitute one's own knowledge. Students can "converse" with ChatGPT or generative AI systems to get ideas for answers to questions, but the final responses to discussion forums, quiz and test questions, and the term paper, should reflect their own thinking, judgment, and language.

I published a peer-reviewed paper in 2024 showing that ChatGPT and other LLMs can "pass" the knowledge-assessment portions of this course. This policy is based in part on the results of this study.

It is critically important that students not "shortchange" their learning by being overly reliant on generative AI systems. While most scientific fields have long surpassed the amount of knowledge that can be maintained in a human brain, it is important to have a fundamental core of knowledge and understanding in memory to be able to apply critical thinking to problems and analyses. In addition, just as students must attribute use of papers, books, and other sources in their work, they must also attribute use of generative AI when it is used in discussion forums or assignments.

I have adopted the following guidelines for my course activities:

- **Discussion forums** - the purpose of the discussion forums is for students to discuss issues that elaborate on unit course materials. Individual forum postings are not graded, although a component of the course grade is based on participation in the forums, comparable to what used to be participation in live classrooms. While students can "converse" with generative AI to get ideas for responses to forum questions, what is actually posted in the forum by students should represent their own ideas, language, and thought processes.
- **Homework self-assessment** - students can ask generative AI about topics mentioned in the multiple-choice questions but are expected to answer the questions based on their own knowledge of materials covered in the lectures and not use generative AI with the questions themselves until after they have submitted their answers to the questions.
- **Term paper/project** - students can ask generative AI for help in brainstorming about their term paper/project. Generative AI systems do not write long papers, and their output tends to focus on generalities and may be prone to confabulation, especially in generating references. The 10-15 term paper/project should have a focus on a specific topic, and delve into it with coherent discussion and ample references, including recent ones, as outlined in the course syllabus.
- **Final exam** - students must not access generative AI during the final exam, just as they may not consult other humans during the open-book exams that is given.

If you are a student and have a question on whether use of generative AI is appropriate, please reach out directly to me (email is best for initial contact).

As a guiding principle, we expect and require that all work submitted be the student's own, original work. When considering using such a generative AI tool, students should ask themselves: Will the tool's output be something I will be turning in directly? In general, students may use such tools as a source of information, but not to produce output that they intend to turn in or as a replacement for a traditional cited reference.

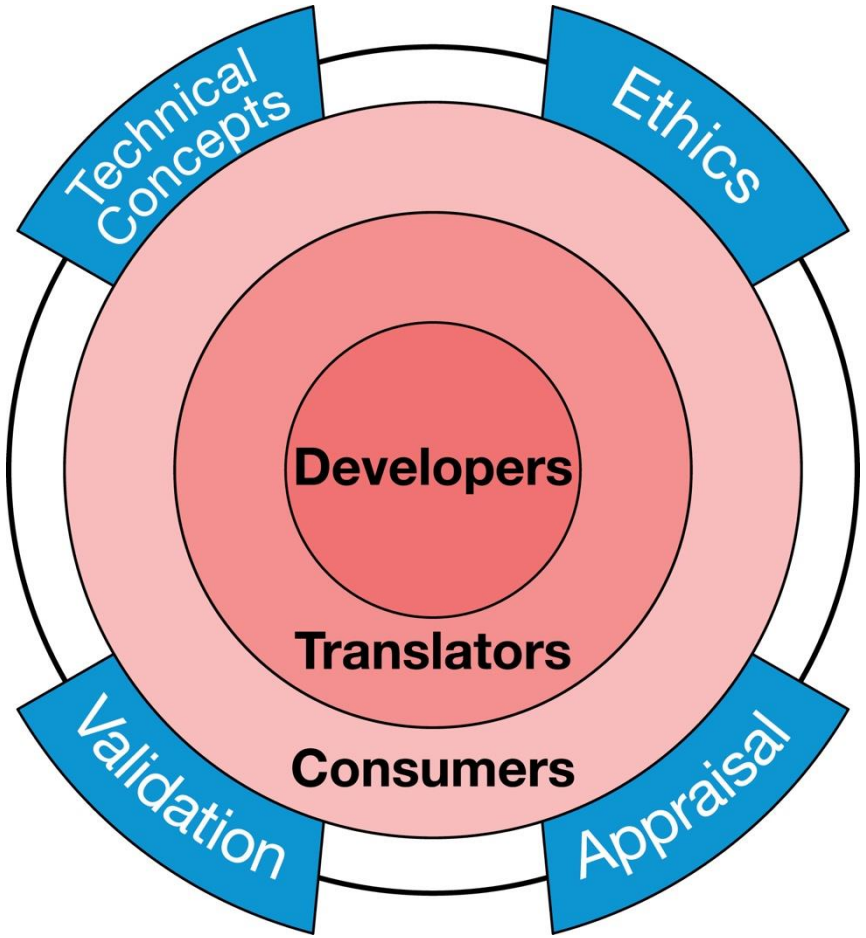
Most ethical and conduct policies in our informatics educational programs, and in the work we subsequently do as professionals, are enforced through an **honor code**. We recognize we cannot police all inappropriate use of AI or other activities. We hope that students will find ways to use LLMs to enhance their learning but not substitute for or become dependent on it.

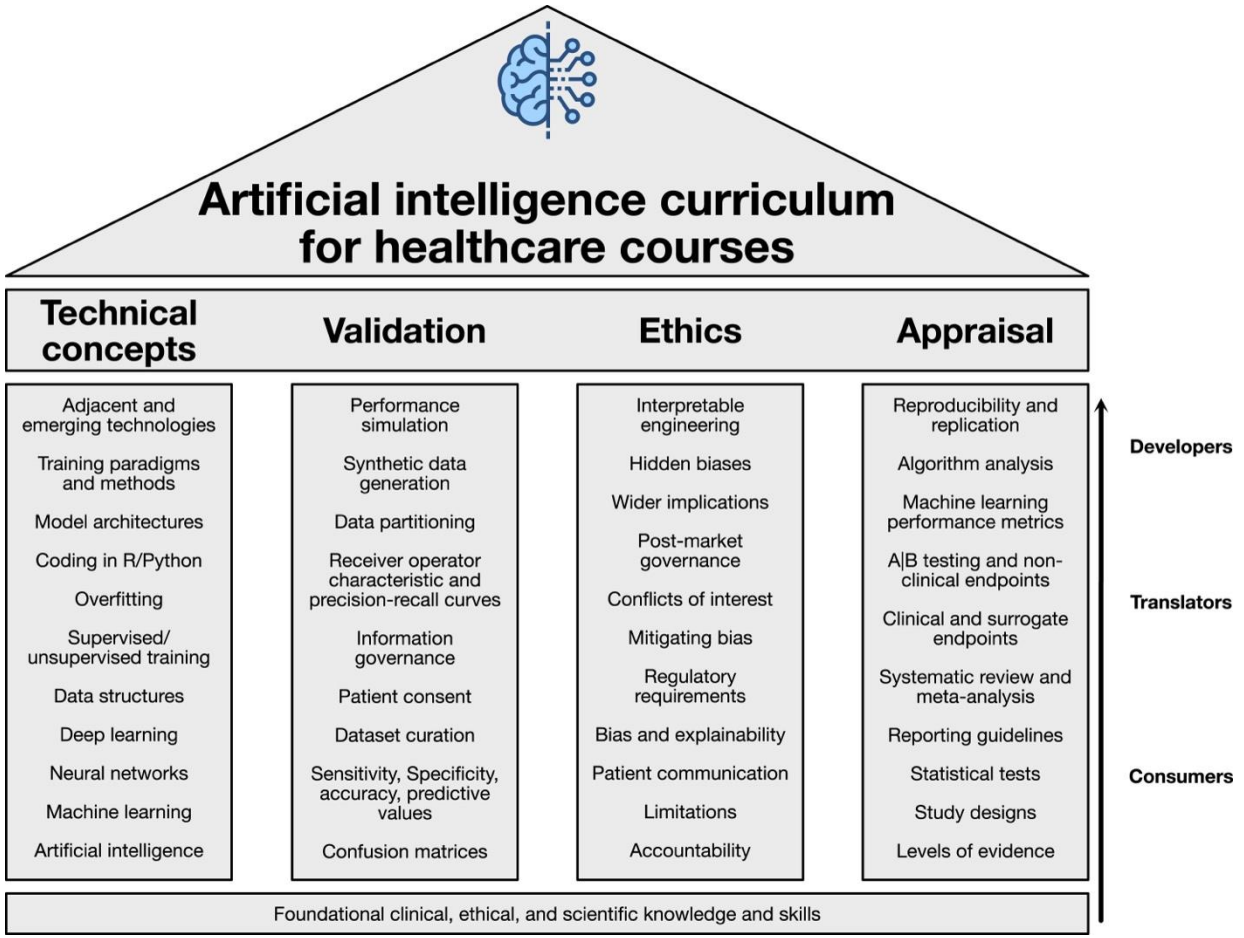
Education and training of clinicians and informaticians

- AI should build on competencies in clinical informatics (Hersh, 2014; Hersh 2020; Hersh, 2023)
- Others note
  - Clinicians must be prepared to practice in a world of AI (James, 2022)
  - Medical schools face dual challenges of needing to teach about AI in practice but also adapt to its use by learners and faculty (Cooper, 2023)
- AI-specific competency frameworks for professionals (Russell, 2023), primary care clinicians (Liaw, 2023) and educators (Pylman, 2025)

1. Find, search, and apply knowledge-based information to patient care and other clinical tasks
2. Effectively read from, and write to, the electronic health record (EHR) for patient care and other clinical activities
3. Use and guide implementation of clinical decision support (CDS)
4. Provide care using population health management approaches
5. Protect patient privacy and security
6. Use information technology to improve patient safety
7. Engage in quality measurement selection and improvement
8. Use health information exchange (HIE) to identify and access patient information across clinical settings
9. Engage patients to improve their health and care delivery though personal health records and patient portals
10. Maintain professionalism in use of information technology tools, including social media
11. Provide clinical care via telemedicine and refer patients as indicated
12. Apply personalized/precision medicine
13. Participate in practice-based clinical and translational research
14. Use and critique artificial intelligence (AI) applications in clinical care

AI education needs different for diverse learners (Ng, 2023)





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Competencies for use of AI-based tools by healthcare professionals (Russell, 2023)

Domains	Details
Basic knowledge of AI	Explain what AI is and describe its healthcare applications
Social and ethical implications of AI	Explain how social, economic, and political systems influence AI-based tools and how these relationships impact justice, equity, and ethics
AI-enhanced clinical encounters	Carry out AI-enhanced clinical encounters that integrate diverse sources of information in creating patient-centered care plans
Evidence-based evaluation of AI-based tools	Evaluate the quality, accuracy, safety, contextual appropriateness, and biases of AI-based tools and their underlying datasets in providing care to patients and populations
Workflow analysis for AI-based tools	Analyze and adapt to changes in teams, roles, responsibilities, and workflows resulting from implementation of AI-based tools
Practice-based learning and improvement regarding AI-based tools	Participate in continuing professional development and practice-based improvement activities related to use of AI tools in healthcare

Educational strategies

- Clinical education (Abdulnour, 2025)
  - Need to be cognizant of de-skilling, never-skilling, and mis-skilling
  - Must be “deft” – discussion, evidence, feedback, teaching
- Need to figure out “opposite of cheating” (Gallant, 2025)
  - Cheating results from students not valuing educational activities and/or being motivated by external needs (e.g., getting into medical school)
  - Students construct, not receive knowledge
  - Students learn from making errors
  - Students must emerge with ethics and integrity in application of knowledge
  - Faculty should apply explicit objectives with meaningful and secure assessments

Final thoughts

- Generative AI has profoundly impacted biomedicine and beyond
- Some unanswered questions
  - What is its optimal role in education?
  - How do we assess students in this era?
  - What is the best way for future clinicians, informaticians, researchers, and others to learn about use of AI?
- Many opportunities for students and faculty to answer these questions!

Questions?

William Hersh, MD, FACP, FACMI, FAMIA, FIAHSI
Professor
Oregon Health & Science University
Portland, OR, USA
Email
hersh@ohsu.edu
Web
https://billhersh.info
Textbook
https://dmice.ohsu.edu/hersh/informaticsbook/