Artificial Intelligence: Implications for Health Professions Education

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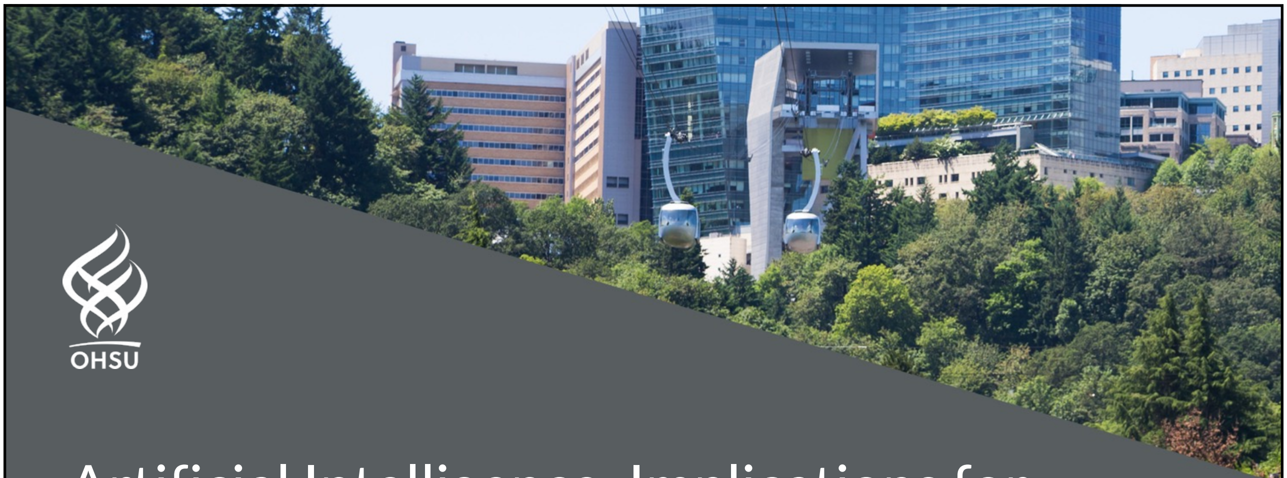

Artificial Intelligence: Implications for Health Professions Education

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Objectives

- After this talk, you will be able to
  - Define major types of AI and their successes and limitations
  - Describe the impact of AI in health professions education
  - Discuss best practices going forward for using AI in health professions education

- Disclosure
  - None

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Artificial intelligence (AI) defined

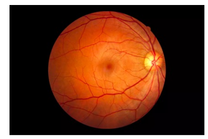
- AI – "information systems and algorithms capable of performing tasks associated with human intelligence" (Rajpurkar, 2022)
- Some classify AI into two broad categories (Khare, 2023)
  - Predictive AI – use of data and algorithms to predict some output (e.g., diagnosis, treatment recommendation, prognosis, etc.)
  - Generative AI – generates new output based on prompts (e.g., text, images, etc.)
- A large part of modern success of AI due to machine learning (ML) – "computer programs that learn without being explicitly programmed" (McCarthy, 1990, attributed to Samuel, 1959; Shah, 2023)
  - Most success with deep learning, based on many-layered neural networks

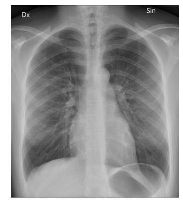
History of AI – first era in mid-20th century

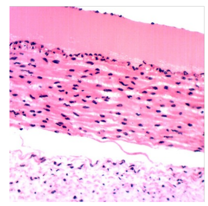
- Earliest paper related to AI and biomedical informatics attributed to Ledley and Lusted (1959, 1960) aiming to model physician reasoning through symbolic logic and probability
- Warner (1961) developed mathematical model for diagnosing congenital heart disease
- In 1960s-1970s, emergence of "expert systems" – computer programs aiming to mimic human expertise (historical overview – Lea, 2023)
  - Rule-based systems – PhD dissertation of Shortliffe (1975) and subsequent work (Clancey, 1984)
  - Disease profiles and scoring algorithms – INTERNIST-1 (Miller, 1982) and DxPlain (Barnett, 1987)
- Limited by approach of manual construction and maintenance of knowledge
  - Not scalable or sustainable
  - Led to "AI winter" between 1990-2010
  - Main remnant is clinical decision support (CDS) for electronic health records (EHRs) that emerged in 1990s for electronic health records (Greenes, 2023)

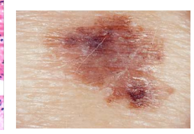
Re-emergence of AI in 21st century

- "Predictive AI" driven by advances in machine learning, increasing availability of data, and more powerful computers and networks (Topol, 2019; Rajpurkar, 2022)
  - Deep learning in imaging breakthroughs by Hinton (2006)
- Most success in image interpretation (Rajpurkar, 2023); examples include
  - Radiology – chest x-rays for diagnosis of pneumonia and tuberculosis
  - Ophthalmology – retinal images for diagnosis of diabetic retinopathy
  - Dermatology – skin lesions for diagnosis of cancer
  - Pathology – breast cancer slides to predict metastasis







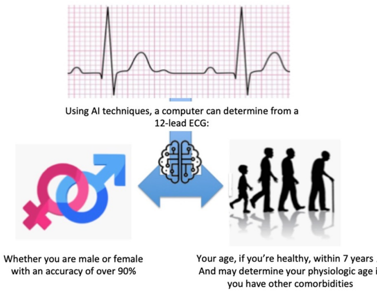


Predictive AI not limited to imaging

- Adverse events in hospitalizations from EHR data (Rajkomar, 2018)
- Generating clinical notes from patient and physician verbal interaction (Rajkomar, 2019)
- Protein folding from amino acid sequences (Jumper, 2021)
- ML model based on past ICD-10 codes and lab results to predict future diagnoses in office visits (Mukherjee, 2023)
- Semantic reconstruction of continuous language from fMRI brain recordings (Tang, 2023)
- Map chemicals to odors perceived by humans (Lee, 2023)

Also success in “seeing” where humans cannot (Topol, 2022)

- Retinal images
  - Age, biological sex, and cardiovascular risk determination from retinal images (Poplin, 2018)
  - Race (Coyner, 2023)
- Electrocardiograms (ECGs)
  - Age and biological sex determination (Attia, 2019)
  - Chronic kidney disease (Holmstrom, 2023)
  - Left ventricular systolic dysfunction from ECG images (Sangha, 2023)
- Chest x-rays
  - Race (Gichoya, 2022)
  - Cardiac function and valvular heart diseases (Ueda, 2023)
  - Diabetes (Pyrros, 2023)
  - Correlation with chronological age in healthy cohorts and, for various chronic diseases, difference between estimated age and chronological age (Mitsuyama, 2023)



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And now, “generative AI”

- Introduction of ChatGPT on November 30, 2022 brought new type of AI into focus: generative AI
- Based on large language models (LLMs) processed by deep neural networks using large amounts of training data and tuned for specific tasks (Omiye, 2024)
  - Trained on massive amounts of text and other content, e.g., large Web crawls, books, Wikipedia, and more for GPT (Roberts, 2022)
  - Use transformer models that predict words in sequence from billions/trillions of words and add measure of importance to “attention” words (Raschka, 2023)
  - Fine-tuned with reinforcement learning from human feedback (RLHF) (Lambert, 2022)
  - Activated by (and importance of) prompting (Liu, 2023; Meskó, 2023)

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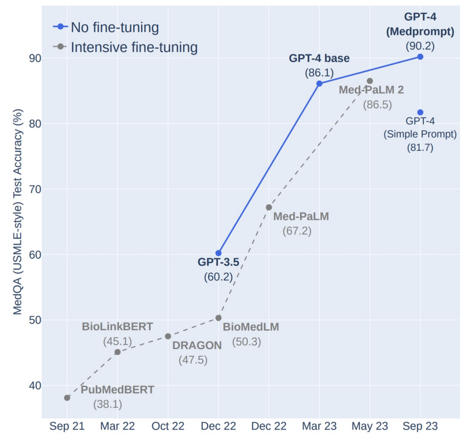
Generative AI is more than ChatGPT

- Adding generative AI to search, including retrieval-augmented generation (RAG) (King, 2023)
  - CoPilot – GPT-4 integrated into Microsoft Bing
  - Google – with Bard and now Gemini
- Plugins enhance functionality
  - BrowserPilot – access live Web sites
  - ScholarAI – search PubMed and other research databases
  - SmartSlides – generate (short) Powerpoint presentations
  - SciSummary – summarize scientific papers
- "Small" language models – Phi-2, Mistral, etc.
  - Clinically-oriented models, e.g., Almanac (Zakka, 2024)

Generative AI at peak of inflated expectations (Meyer, 2023)

Results of ChatGPT and other LLMs

- Medical board exam questions
  - USMLE “arms race,” starting with (Kung, 2023)
    - Now best with GPT-4 and specific types of prompting (Nori, 2023)
    - Even on “soft skills” (e.g., communication skills, ethics, empathy, and professionalism) questions (Brin, 2023)
  - Passing level on most board exam questions (clinical informatics – Kumah-Crystal, 2023; radiology – Bhayana, 2023; neurology – Schubert, 2023) but not others (neonatology – Beam, 2023, used only GPT-3.5)
- Answering questions
  - Vary by subject domain and type, but sometimes wrong and/or incomplete (e.g., Antaki, 2023; Chen, 2023; Goodman, 2023)
- Solving clinical cases
  - Comparable to but not better than expert humans (e.g., Levine, 2023; Kanjee, 2023; Rao, 2023; Benoit, 2023; Levkovich, 2023)



Results of ChatGPT and other LLMs (cont.)

- Communicating with patients
  - Answering questions in public forums (Sarraju, 2023; Ayers, 2023)
  - Writing letters with comparable or better empathy (Ali, 2023, Ayers, 2023)
  - Generating surgical consent forms better than surgeons (Decker, 2023)
  - In simulated (text-based) objective structured clinical exam (OSCE) format, LLM optimized for clinical dialogue achieved better accuracy and communication skills than (with caveats) primary and specialist physicians (Tu, 2024)
- Use of predictive AI (closing the loop with predictive AI)
  - Classifying CXR findings based on previous images and reports (Xu, 2023)
  - Generating CXR reports from new images in ED from prior images and reports (Huang, 2023)
  - Predicting cardiovascular risk comparable to Framingham models (Han, 2023)

But there are some downsides to generative AI

- Dictionary.com 2023 word of year: hallucinate
  – https://content.dictionary.com/word-of-the-year-2023/
- When we search, we may want more than answers, such as references and authority (Hersh, 2024)
  – Fabrication and errors in the bibliographic citations – asked to produce short literature reviews on 42 multidisciplinary topics (Walters, 2023)
    - 55% of GPT-3.5 citations and 18% of GPT-4 citations fabricated
    - 43% of real (non-fabricated) GPT-3.5 citations and 24% of real GPT-4 citations include substantive errors
  – Best LLM with RAG (GPT-4 in CoPilot) achieved about 70% statement-level support and <50% for others (GPT-4, Claude, Mistral, Gemini Pro) (Wu, 2024)
    - Even GPT-4 in CoPilot returned 0 sources 20% of time
    - Most sources from public open sites and not behind firewalls like most journals

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Downsides to generative AI (cont.)

- 8 clinical questions asked of 4 LLMs recapitulated "harmful, race-based medicine" (Omiye, 2023)
- Equally compelling disinformation – humans cannot distinguish between true and false tweets generated by GPT-3 and written by real Twitter users (Spitale, 2023)
- LLMs reflect content (and bias) of text used for training (Schaul, 2023)
- Automated GPT detectors have mixed results (Sadasivan, 2023; Odri, 2023; Desaire, 2023)
  – More likely to classify non-native English writing as AI-generated (Liang, 2023)
  – Humans not able to discern AI writing either (Dell'Acqua, 2023)

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And some downsides to AI in general

- After clinical models deployed, performance may decline due to actual real-world use (Vaid, 2023; Palmer, 2023)
- Inexperienced, moderately experienced, and very experienced radiologists reading mammograms are prone to different types of automation bias when supported by AI-based system (Dratsch, 2023)
- Implementing diabetic retinopathy screening in rural Thailand and India found (Widner, 2023)
  - Challenges related to equipment operation, workflows, and image quality
  - Need for training and attention to human factors
- Concerns about reproducibility (Ball, 2023)
  - Data bias (especially from EHR – Lewis, 2023; Chin, 2023)
  - Data leakage (Kapoor, 2023)
  - Data drift/shift (Finlayson, 2021; Li, 2024)
  - "Literature demonstrates incomplete reporting, absence of external validation, and infrequent clinical implementation" (Heneghan, 2023)

Will AI help or hinder healthcare?

- Real-world use still modest
  - As of Sept 2023, only 21% of medical groups using AI applications in practice (MGMA, 2023)
  - EHR usability, patient communications, and billing outrank AI as top tech priorities among medical groups (MGMA, 2023)
  - AI tools used by only 38% of physicians (AMA, 2023)
- Evidence base still small – systematic reviews of randomized clinical trials (RCTs) of predictive AI systems (Zhou, 2021; Plana, 2022; Han, 2023) show
  - Small numbers of RCTs (dozens) – especially relative to predictive model papers (thousands)
  - Suboptimal methodologies leading to risk of bias
  - Mix of positive/negative results
- "AI won't replace radiologists, but radiologists who use AI will replace radiologists who don't," (Langlotz, 2019)
  - (Plug in your health profession)

AI and health professions education

- Before generative AI there was recognition of need for competencies in clinical informatics for medical education (Hersh, 2014; Hersh 2020; Hersh, 2023)
- Clinicians must be prepared to practice in
  - World of AI (James, 2022)
  - Era of clinical algorithms (Goodman, 2023)

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

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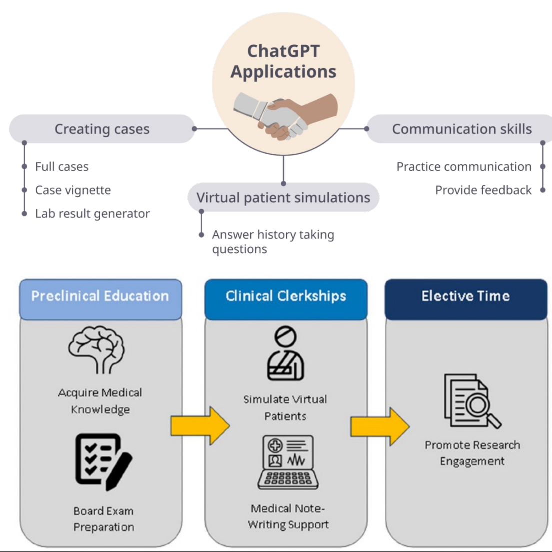
Many opportunities and issues for LLMs in health professions education

- Various applications in medical education (Ratliff, 2023; Benítez, 2024)
- Opportunities, challenges, and directions in medical education (Preiksaitis, 2023) – themes include
  - Test performance and preparation
  - Novel learning strategies
  - Writing and research assistance
  - Academic integrity concerns
  - Accuracy and dependability
  - Potential detriments to learning
- Similar in nursing process and diagnosis (Gosak, 2024)



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Recommendations for medical faculty and institutions (Boscardin, 2023)

Educators

- Increase AI knowledge
- Understand the current landscape of AI use in medical education
- Review strategies for successful AI integration into education
- Become stewards of ethical use of AI

Institutions

- Review and revise school policies (and create new policies as needed) regarding use of generative AI
- Support faculty development about AI and provide resources for teaching
- Offer information-checking tools for originality and plagiarism to faculty

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

Domain	Competency
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

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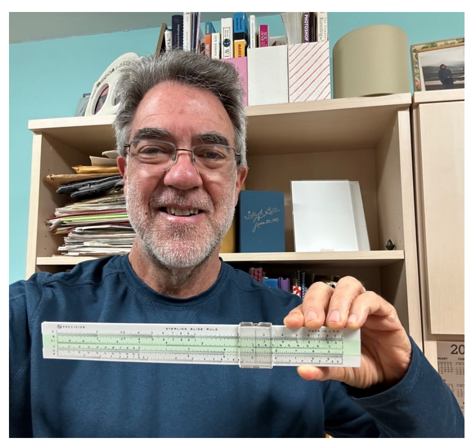
Teaching impact not limited to health professions education

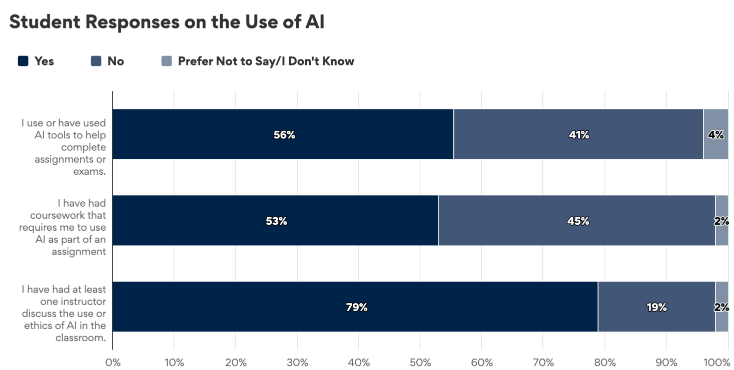
- Computer science
  - LLMs can write code (Poldrack, 2023)
  - Transforming teaching of programming (Denny, 2024; Edwards, 2024)
- Data science
  - Can streamline entire data science pipeline from data cleaning and exploration to mode building and interpretation to presentation of results (Tu, 2024)
- Law
  - For legal brief output, faster task completion and improved quality for lower-skilled students (Choi, 2024)

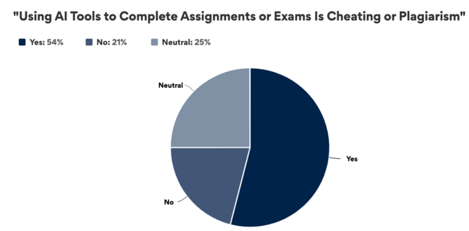
Generative AI and teaching

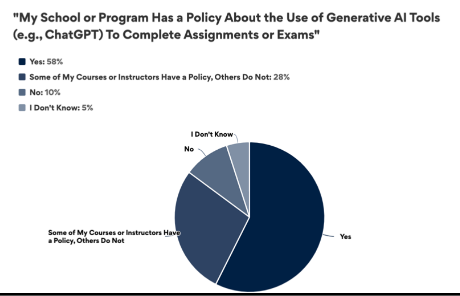
- A transformative cusp?
  - Anyone under 30 know what I am holding?
- Much in our courses can be done by generative AI
- Thought leader in this regard is Ethan Mollick, U of Penn
  - https://www.oneusefulthing.org/
- My approach (so far)
  - Gen AI policy for my courses based on larger policy from OHSU Provost
  - Allow explicit use in certain assignments



Use already widespread – (non-scientific) survey of 1000 college students (Nam, 2023)







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Faculty should be "assigning AI" (Mollick, 2023)

AI USE	ROLE	PEDAGOGICAL BENEFIT	PEDAGOGICAL RISK
MENTOR	Providing feedback	Frequent feedback improves learning outcomes, even if all advice is not taken.	Not critically examining feedback, which may contain errors.
TUTOR	Direct instruction	Personalized direct instruction is very effective.	Uneven knowledge base of AI. Serious confabulation risks.
COACH	Prompt metacognition	Opportunities for reflection and regulation, which improve learning outcomes.	Tone or style of coaching may not match student. Risks of incorrect advice.
TEAMMATE	Increase team performance	Provide alternate viewpoints, help learning teams function better.	Confabulation and errors. "Personality" conflicts with other team members.
STUDENT	Receive explanations	Teaching others is a powerful learning technique.	Confabulation and argumentation may derail the benefits of teaching.
SIMULATOR	Deliberate practice	Practicing and applying knowledge aids transfer.	Inappropriate fidelity.
TOOL	Accomplish tasks	Helps students accomplish more within the same time frame.	Outsourcing thinking, rather than work.

Risks:

- Confabulation
- Bias – from training content
- Privacy – policies not always clear
- Instructional – student over-reliance

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Personal experience so far with generative AI in teaching

- Must address head-on
- Policy
  - Explicit on proper use and when discouraged or prohibited
  - Concerns for when benefits student vs. undermines learning
- Use in an assignment
  - Student term paper can be a conversation with GenAI/LLM about several course topics with dialogue and critique of output

Need policy for generative AI: mine for introductory course
https://dmice.ohsu.edu/hersh/introcourse-generativeAI-policy.html

OHSU *Introduction to Biomedical & Health Informatics* Course Policy for Use of ChatGPT and Generative AI

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This page reflects course policy for the Oregon Health & Science University (OHSU) course that I teach called **Introduction to Biomedical & Health Informatics**. I teach versions of this course in several OHSU programs, including:

- Biomedical Informatics Graduate program - BMI 510/610 - Introduction to Biomedical & Health Informatics
- AMIA 10x10 ("ten by ten") course - OHSU-AMIA 10x10 course
- 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.

This policy is derived from the overall OHSU policy for academic integrity, including the use of AI. The OHSU Biomedical Informatics Graduate Program is developing a general policy for use of generative AI in courses, but in the meantime, I am adopting the following guidelines for 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 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.
- **Term paper/project** - students can ask generative AI for help in brainstorming about their term paper. 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 page term paper 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.

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.

Last update: January 8, 2024

My first foray into generative AI assignments

- Option for short (10x10) and long (BMI 510/610) papers
- For 510: Having a Conversation with GenAI/LLM About Informatics Topics
  - You should choose at least three topics in which you have an interest or questions beyond what is covered in the course
  - You should then use at least two different GenAI/LLM systems (ChatGPT, Perplexity.AI, or those embedded in search engines Google or Bing)
  - Your conversation with the GenAI/LLM systems should involve at least 3 iterations, i.e., initial prompt and follow-up with at least 2 more prompts
  - For each topic, you should follow up with a 1-2 page analysis of the output of the two or more systems, noting the accuracy, completeness, and errors in their analysis.
  - If the systems generate references, you should discuss whether the reference are relevant, whether they actually exist, and if any other sources would be better to cite. You will probably need to do conventional searching to help with this
- For 10x10: one topic, one LLM, three iterations, and analysis

Results

- Uptake in Fall 2023
  - 10x10 – 6/21 students
  - BMI 510 – 3/15 students
- Assessment
  - For the most part, carried out as assigned
  - For 510, most common second LLM was Perplexity.AI
  - Reasonable assessments of output
  - For 510, all had thoughtful analyses
    - One student had copious additional suggested references
    - Another student created a nice table of attributes to evaluate each LLM interaction

Conclusions

- AI will profoundly impact the practice and education of all health professions
- Healthcare professionals must be competent with AI as much as any other tool in their clinical practice
- Educators and students must adapt to generative AI for writing, examination, and other pedagogic tasks
- "Translational AI" is a necessity and opportunity for informatics (Hersh, 2024)

Questions?

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