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THEME ARTICLE

Communicating About and With Artificial Intelligence Applications

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Editor's Note

Developments in artificial intelligence (AI) will continue to be of critical importance to medical communicators for the foreseeable future. Accordingly, *AMWA Journal* expects to continue to feature AI-related articles in upcoming issues.

Given how rapidly advancements are occurring in AI as they relate to medical communication, we are striving to be as timely as possible in bringing relevant articles to you. In this spirit, we are supplementing the Summer 2024 *Digital Revolution* theme issue with a timely article titled 'Communicating About and With Artificial Intelligence Applications' by J. Kelly Byram, based on a presentation made by the author at the most recent AMWA Medical Writing & Communication Conference.

This session provided attendees with an overview of the elements of artificial intelligence (AI) that medical communication professionals can use in their decision-making when communicating about and with AI applications. Knowing how to determine if an AI application is reliable and secure guides the professional in their assessment of applications they write about and their choice of applications they use in their practice. In turn, this ability to assess AI applications underpins professionals' abilities to identify and apply best practices for developing and writing about AI. Taken together, this understanding of how AI works, how applications are developed, and how to identify and ethically apply best practices will guide professionals in their communication about and with AI applications.

AI FUNDAMENTALS

The field of AI emerged in the early 1940s, and one touchstone of the field, the Turing test of machine intelligence (designed to determine if a machine can think like a human)[1] dates to 1950. Although initially considered a single field of research, in the intervening decades, researchers have split the study of AI across multiple domains involving myriad disciplines. As a result, AI is defined many ways, but 2 particularly salient definitions are (1) a machine performing a task requiring human intelligence and (2) a machine replicating human intelligence. Both definitions, like the Turing test, evaluate AI in the context of human intelligence (including behavior); however, the AI applications that have been developed thus far lack human traits, such as empathy and creativity, and human reasoning in the frameworks of ethics and complex strategy.

Machine Learning

Machine learning (ML) underpins many of the AI applications that medical communicators will communicate about and with. Patient triage, hospital management, and imaging applications approved by the US Food and Drug Administration use ML. What makes ML applications different from traditional software applications is that most ML does not use explicit or rule-based programming. In explicit programming, a program gives the computer specific commands or lines of code, that is, the function. ML uses statistical and mathematical modeling and incredible volumes of data to learn relationships between variables, that is, it determines the function. The model learns and refines itself as it ingests and processes data. Some common models used in ML include linear regression, logistic regression, Bayesian algorithms, and decision trees.[2]

Deep Learning and Generative Pretrained Transformer Applications

Deep learning (DL), a type of ML that uses an artificial neural network modeled on the human brain and designed to emulate human processing, uses layers of connected nodes that process information and pass the transformed data up to the next layer. It learns from itself and can create new features on its own. It can learn nonlinear, high-dimensional relationships from data that are not just unstructured but multimodal. Throw it all in the mix—imaging, biometrics, audio, visual, and time series data. DL applications include target validation, identification of prognostic biomarkers, analysis of digital pathology CT data, and generative pretrained transformer applications (GPTs).

* This article is based on the presentation Communicating About and With Artificial Intelligence Applications by J. Kelly Byram, MS, MBA, ELS, at AMWA's 2023 Medical Writing & Communication Conference.

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Because DL creates its own algorithms, the models and applications created by DL can lack transparency. This black box effect enhances a distrust of AI in many population segments, and 60% of Americans overall indicated discomfort with the use of AI in their care.[3] It can help to keep this discomfort front of mind when writing for lay audiences.

State of the Science

We typically divide AI into 2 categories: weak and strong (Figure 1). Weak AI is what we have today—systems or machines that have learned how to perform specific tasks in a way similar to how a human would perform the task. Some systems display human intelligence; that is, they have the ability to learn and solve some types of problems, but not all.[4] Although today the mention of AI elicits discussion of GPT applications such as ChatGPT, AI has been a part of the knowledge professional's workflow for so long that it has been taken for granted as the power behind search engines, spam filters, and smart assistants such as Siri and Alexa. Strong AI, or sentience, is the flexible intelligence that can flit from one type of task to another and has advanced reasoning capabilities. HAL from *2001: A Space Odyssey* and Skynet from *Terminator* usually come to mind when discussing this type of AI. Unlike Siri and Alexa, references to HAL and Skynet usually evoke fear and dystopian angst. Depending on one's point of view, strong AI is either an aspirational goal or an existential threat.

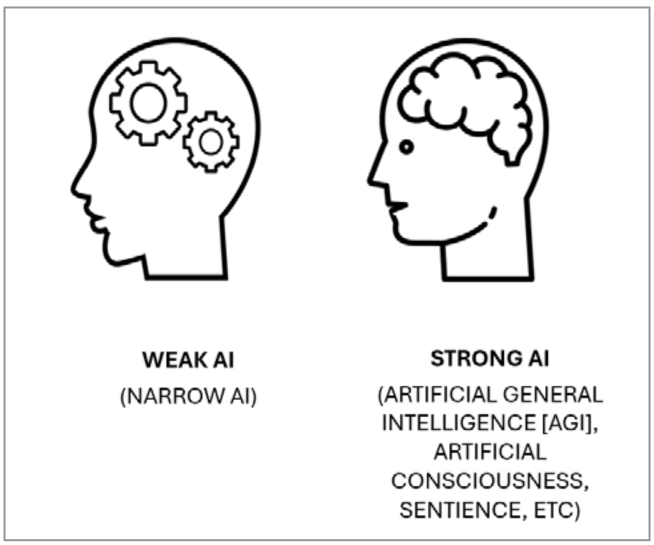

Figure 1. AI is typically divided into 2 categories: weak AI and strong AI. Although strong AI is the goal of the AI field, weak AI represents the current state of the science. AI, artificial intelligence.

AI in Health Care

Three subfields of AI more commonly leveraged in health care research and practice include ML, DL, and large language models (LLMs) as GPT applications. These applications segment images to assist in the identification and segmentation of lesions, identify promising molecules and guide drug development, determine dosage, and assist in genomics and precision medicine, public epidemiology, emergency department triage, and hospital management.[5] Some of these models are standalone software packages, others are slick software-as-a-service applications integrated with electronic health records.

COMMUNICATING ABOUT AND WITH AI APPLICATIONS

Medical writers and editors who work with AI development teams have been writing proposals for AI projects for years. As these projects come to fruition, more communicators will join the effort and find that the complicated and sometimes obscure methods used to develop AI applications can pose a challenge to effective communication about AI. Although many standard research design concerns (eg, hypothesis, sample size, data quality and representativeness, design rigor, multidisciplinary representativeness of the team, generalizability) also apply to AI model development, communicators must also interrogate designs for AI-specific matters (eg, portability of the model, validation and testing plan, human–AI team required for implementation, maintenance plan to address drift). For AI applications being developed for clinical use, the FDA's *Good Machine Learning Practice for Medical Device Development: Guiding Principles* document[6] provides excellent, clear guidance. Many of the points on their list of guiding principles should be considered in the research design development and proposal writing stages, in addition to the funder's explicit requirements.

When writing about AI-based health care apps, the importance of understanding how researchers develop these applications quickly becomes apparent, but, when writing with AI apps, one may ask why any of the technical aspects of AI matter to the end user. Generative AI applications are, after all, a tool—but every good craftsperson knows their tools. Communicators using generative AI in their practice likewise should understand the tools. In the medical writing and editing practices, this largely means understanding GPTs.

GPTs are a type of LLM. LLMs sit at the intersection of DL and natural language processing, an AI domain specific to teaching machines to understand and generate human language. LLMs use DL techniques applied to enormous data sets. Their objective is to understand and generate text based on what they have learned from the data they have ingested. Although their output sounds human, it is the output of a statistical model, like any other GPT. The text is the algorithm's best statistical prediction of what the next word (and then the next and the next) should be. Unlike earlier AI, like predictive text that suggests a word or brief phrase, generative AI takes a holistic approach, creating a more complex model that understands the larger context of sentences and paragraphs and can generate paragraphs of cohesive and coherent human-sounding text. Some medical communication products especially suitable for generative AI production include patient education materials, medical guidelines, package inserts, patient-facing chatbots to answer medical questions, patient discharge instructions, and letters (to insurers, employers, etc),[7] and other plain language materials.

Using Consumer GPTs to Generate Technical Content

Consumer versions of GPTs hit the market big with Dall-E and then ChatGPT in 2022. In the intervening time, the GPT offerings have only multiplied and expanded across tasks, including writing, image generation, programming, and data analysis. Developers train consumer GPTs on the Internet, meaning the GPTs ingest online content, good and bad. Although that is a large amount of data by anyone's standards, a consumer GPT's training is limited to the data to which it had access, including copyrighted material (in violation of copyright laws),[8] but without access to paywalled peer-reviewed content and with training cutoffs that may mean the most recent content is months or years old.† However, high-quality medical communication requires accurate, detailed, and current sources, so the quality of most content generated by consumer GPT applications may not meet those standards, especially for more complicated or technical topics.

The human quality of GPTs' language can cause users to trust the applications' content more than they should. GPTs provide inaccurate and biased information and plagiarize their sources—all issues ethical medical communicators cannot ignore. And, although the human-sounding quality of the content increases the value of GPT-generated content in many contexts, consumer GPTs have a limited ability to generate meaningful technical language.

Using Proprietary or Enterprise Models to Generate Technical Content

To protect intellectual property, including research data and information about a novel technology or design, some companies have implemented proprietary or enterprise purpose-built models, trained on the research corpus specific to their industry and organization. Often these are sparse expert models (<100 billion parameters vs ChatGPT version 3.5's 175 billion parameters), which can be more accurate than larger general models because the data ingested are more specific to the users' needs.

Unlike consumer GPT applications, the models are trained with industry-appropriate information, including paywalled articles, then further trained on the organization's data. Data ingested by private generative models are only available to members of the organization. But, like consumer GPT applications, the tendency of the technology to prevaricate, hallucinate, and plagiarize persists in these models, too.

CONCLUSION

Regardless of the type of AI application being used, whether it is an application for analyzing imaging or one for generating content for a patient education website, current AI applications are imperfect tools for our use. These tools augment human productivity, intelligence, and creativity if used strategically and well, which will result in a shrinking of the workforce.[9] As Erik Brynjolfsson, director of the Stanford Digital Economy Lab, summarized the situation for knowledge workers, "I think if done right, it's not going to be AI replacing lawyers. It's going to be lawyers working with AI replacing lawyers who don't work with AI."[10] Similar to earlier industrial revolutions, the Fourth Industrial Revolution brings technologies that will displace workers who perform work that new technologies can do faster and cheaper. But teams will always have a need for communicators with domain expertise or other exceptional skills who ethically and effectively use these tools in their practice.

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†After this presentation last year, more consumer GPTs have introduced real-time web search functionality. In practical terms, a GPT with real-time search capabilities may have been trained through September 2021, for example, but it can search the internet for information in real time. For many casual users employing a consumer GPT with real-time search functionality, the training date of the GPT has become a distinction without a difference.

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