

## Implementing a Specialty-Specific Artificial Intelligence Curriculum for Neurology Residents: A Pilot Educational Initiative

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**Abstract:** **Introduction:** Artificial intelligence (AI) has been increasingly revolutionizing the field of neurology, yet formal training in AI tools, appraisal, and limitations remains limited in residency education. Neurology training should reflect growing advancements in technology, as this gap risks inappropriate reliance or underutilization of AI tools. **Objectives:** To evaluate how a structured, three-session artificial intelligence curriculum for neurology residents improves AI literacy, clinical confidence, and critical appraisal to use AI tools in neurologic practice. **Methods:** We conducted a prospective quality improvement study involving 9 neurology residents at University Health through an AI curriculum consisting of 3 sessions that incorporated case-based learning, ethics discussions, and exposure to real-world AI tools (Appendix A). Using the Kirkpatrick model, we aimed to measure outcomes at 3 levels: reaction, learning, and behavior. To do this, we administered a pre- and post-survey (Appendix B) using 5-point Likert-scale items and open-ended questions. These were analyzed with the Wilcoxon signed-rank test for paired ordinal responses and qualitative analysis. The main themes assessed included confidence and knowledge, adoption and attitude, and risk awareness. Qualitative measures included perceived effectiveness of the lecture series and self-reported, intended behavior change. **Results:** Residents demonstrated improvements in confidence and knowledge, as well as in attitudes and adoption. The highest level of improvement was observed in confidence and knowledge, with a 0.96-point change ( $p$  value = 0.004). In terms of resident attitudes, 89% agreed that the lecture series improved their understanding of AI in neurology, the content was relevant to their practice, and that they are more prepared to engage with AI. Intended adoption and attitudes showed a favorable but non-significant trend, with a 0.17-point improvement ( $p=0.078$ ). Finally, risk awareness had a non-significant, minimal improvement from 0.06 points. **Conclusion/Discussion:** Implementation of a structured, discussion-based AI curriculum significantly improved neurology residents' confidence, knowledge, and skills in AI tools. This project demonstrates that targeted educational interventions can address critical gaps in AI literacy.

**Keywords:** Artificial Intelligence, Graduate Education, Curriculum, Neurology.

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## INTRODUCTION

Novel artificial intelligence (AI) tools are becoming increasingly integrated in neurology, transitioning from theoretical innovation to operational components of medical care. Validated tools are now embedded into diagnostic and therapeutic workflows for a range of neurologic conditions. For example, many acute stroke systems use AI-driven imaging platforms to identify large-vessel occlusions and reduce door-to-intervention time by enabling automated triage and pre-

notification of stroke teams [8-10]. Machine learning-based EEG interpretation systems provide continuous monitoring for early seizure detection in neurocritical patients with epilepsy [1]. Furthermore, deep learning models applied to neuro-ophthalmologic imaging are achieving expert-level precision in differentiating papilledema from nonpapilledema disc abnormalities [9].

Beyond acute care, AI applications in neurology are also expanding into longitudinal disease prognosis. Multimodal inputs, such as speech, gait,

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handwriting, and neuroimaging, improve the early detection of neurodegenerative diseases, improving a patient's quality of life after treatment [18, 19]. These inputs can be acquired from activities of daily living outside of the clinic or voice data from conversation, allowing AI to process consistent biomarkers that show signs of early degeneration.

Despite this rapid integration, neurology education does not include the curriculum required for residents to keep up with the evolving role of AI. While many studies report that neurology attendings and residents generally view AI as a potential assistant, they report minimal formal education in AI concepts, model validation, and clinical limitations [5-12]. During training, exposure to AI tools is generally passive, unstandardized, and incidental, producing physicians who lack confidence in AI tools and demonstrate variable adoption in clinical practice [21]. With the increasing influence of AI on diagnostic prioritization, escalation of care, and allocation of resources, there is an educational gap for future neurologists that risks either over-reliance or dismissal of AI tools. Most medical curricula in the U.S. have yet to develop a dedicated focus on AI systems in clinical care. Current residency programs would benefit from integrating AI-related clinical tools in neurologic board review resources.

Beyond mere unfamiliarity, there are dangers associated with the lack of structured AI literacy. Many AI systems function as opaque “black boxes,” with internal decision-making algorithms that are difficult for end users to understand and interpret in a clinical context [15, 16]. Consequently, neurologists might be unable to recognize significant biases in care allocation due to race, age, gender, or disease prognosis that result from flawed proxy variables and non-representative training data. For example, common health risk algorithms, often deployed in electronic health records, exhibited significant racial bias in qualifying patients to suitable high-risk care management programs despite a comparable disease burden [11]. Without a foundational understanding of how AI systems are developed first-hand, neurologists may be unable to identify resulting skewed outputs or contextualize recommendations in individual patient scenarios. Therefore, AI literacy must extend beyond technical competency to encompass ethical awareness, critical appraisal, and an understanding of the social context of healthcare technology [20].

Recognizing these realities, major regulatory bodies have reframed AI literacy as an inherent professional obligation. The American Medical Association (AMA) House of Delegates adopted policies affirming that physicians must understand how AI tools function, their limitations, and implications for safety in clinical care. These policies emphasize standardized training and physician-led oversight in AI system design [22]. The establishment of the AMA Center for Digital

Health and Innovation further institutionalizes the expectation that clinicians should remain at the center of digital health governance. Additionally, the Accreditation Council for Graduate Medical Education (ACGME) has incorporated digital health competency into the neurology milestones framework, which requires residents to synthesize clinical findings with data from secondary sources, such as AI-generated predictive analysis [23].

While AI can meaningfully and efficiently extract signs of a disease process, it can also easily mask uncertainty by producing results with excessive confidence if neurologists are not skilled in critical appraisal [6-20]. AI literacy, as such, is critical for maintaining clinician accountability, preventing automation bias, and preserving the depth of diagnosis. Furthermore, AI literacy has direct implications in maintaining efficiency and workforce sustainability in neurology. With rising documentation burdens, increasing patient volumes, and persistent workforce shortage, neurologists face burnout with reduced time for meaningful patient interaction [3-17]. Appropriately implemented AI tools have the potential to reduce cognitive load, streamline data interpretation, and improve task delegation across interdisciplinary teams [16-19]. Without adequate training, however, these tools can have the opposite effect of increasing friction, generating alert fatigue, eroding trust within clinicians and staff, and negating potential efficiency gains [5].

As AI adoption in neurology accelerates, the central challenge is no longer the feasibility of technology but human readiness. Collaborating with AI while maintaining ethics requires a structured, application-oriented approach to education. Critical appraisal, workflow integration, and ethical awareness are essential pillars for preparing a resilient, forward-ready neurology workforce. Developing AI literacy as a core competency offers a path toward improved efficiency, enhanced diagnostic precision, and higher-quality neurologic care that ensures AI functions as a collaborative clinical advantage.

## METHODS

To address this gap, we designed a prospective study consisting of an AI curriculum administered along with pre- and post-surveys. The AI curriculum included three 1-hour lectures composed of discussion and case-based content. The lectures covered the following topics: Introduction to AI in Neurology: Ethics and Appraisal, AI in Acute Stroke Workflows and Seizure Detection, and AI Tools in Neurodegenerative Disease Interpretation and Clinical Diagnosis. Lectures were delivered in a hybrid format with presenters being virtual and participants present in-person, watching on a large TV/monitor. This curriculum was developed and instructed by a team of medical students after a thorough literature review of current AI tools in medical practice from peer-reviewed journals. The final presentations and

curriculum were reviewed and edited by the Neurology residency program director.

Pre and post-surveys were distributed to neurology residents at the University of Missouri-Kansas City Medical School (UMKC) to evaluate changes in knowledge, attitude, and perception of AI before and after the 3-lecture series about AI in Neurology. The pre-survey was conducted prior to the start of the first lecture on 2/18/26, with the post-survey completed immediately after the third lecture on 3/4/26. Out of the 12 total Neurology residents, a sample size of 9 residents who were available for the didactic sessions was included in the study. Inclusion criteria for participants included being a neurology resident enrolled in the UMKC Neurology residency program and being present for didactic sessions in which the AI curriculum was taught. Participants volunteered to complete the survey as part of their attendance at the mandatory lectures for their residency curriculum. All participants who completed the pre- and post-surveys attended the same 3 lectures conserving standardization of the content received.

Both the pre- and post-survey questionnaires were administered online through Microsoft Forms and created by the study team. The domains assessed by the pre-survey include background knowledge, training, & perception towards AI, and experience, attitudes, & perspectives on AI. In the post-survey, additional domains of confidence in using AI tools and perceived relevance to clinic practice were assessed. The pre-survey consisted of 14 questions, and the post-survey consisted of 17 questions. Question types in the survey consisted mainly of Likert-scale items on a scale from 0 to 5 (with 0 referring to strongly disagree and 5 referring to strongly agree); in addition to a few multiple-choice questions, along with open-ended short-answer questions. The content of questions was developed based on Kirkpatrick's model for evaluating curriculum effectiveness. Survey questions aimed to analyze the reaction, learning, behavior, and results of the training. Questions assessing reaction included open-ended post-survey specific questions regarding feedback on value and room for improvement on the lecture series.

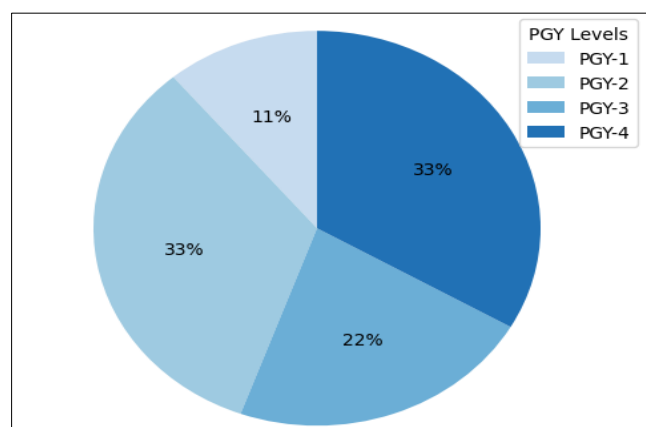
Questions assessing learning included Likert-scale items asking participants to rate their understanding and attitude towards AI in medicine. Questions assessing behavior included Likert-scale questions ranking the likelihood of adopting AI in participants' medical practice and multiple-choice questions about how frequently participants plan to utilize AI in future practice. Finally, results were assessed using the correlation of paired pre- and post-survey responses to assess changes in mean Likert-scale scores.

Post-survey responses were paired with pre-survey responses according to the associated email. No name identification was collected from participants. Completion was monitored by tracking for a post-survey response to match each pre-survey response received. Primary outcomes of the survey were assessed through comparative analysis, the Wilcoxon signed-rank test, for paired ordinal responses, assuming a non-normal sample, and qualitative analysis. Qualitative measures included the effectiveness of the lecture series and changes in behavior. A p-value of less than 0.05 was considered significant.

This study was deemed exempt from IRB. Participant consent was implied via voluntary completion of the survey and individual choice to submit a response. All data was de-identified after it was paired by email address before evaluation of results.

## RESULTS

Our sample size included 9 neurology residents who consistently attended every lecture, 2 of whom were PGY-4, 2 were PGY-3, 3 were PGY-2, and 2 were PGY-1, as seen in Figure 1. Among these, 1 resident reported receiving AI teaching in medicine through extracurriculars and seminars, 2 reported a plan of receiving AI teaching in medicine in the future, 2 reported not receiving AI teaching in medicine, but it had been planned in the past, and 4 reported no plan of having received AI teaching in medicine in the past, as seen in Figure 2.



**Figure 1: Distribution of Education Level**

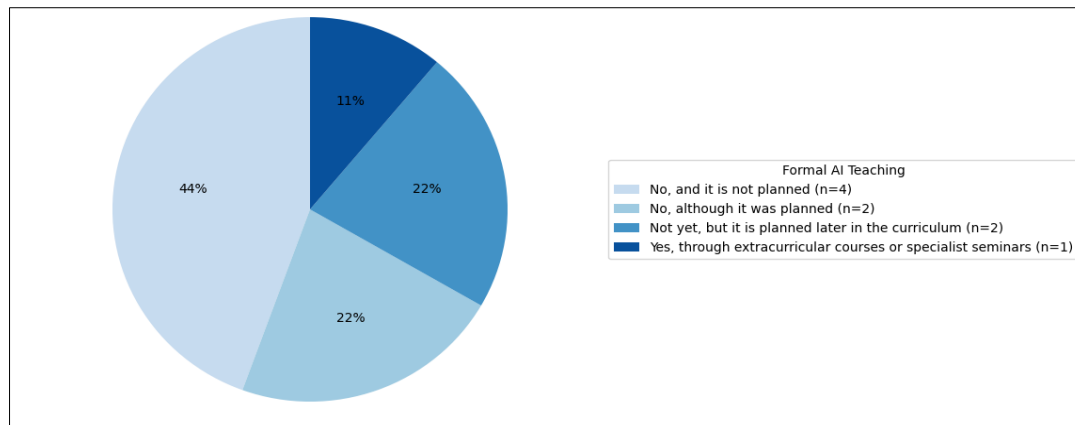


Figure 2: Prior AI Teaching

### Confidence

Residents' confidence in AI tools significantly improved by 0.96 points after the lecture series ( $p=0.023$ ), as seen in Figure 3. This is a critical component of Kirkpatrick Level 2, which suggests that residents have acquired the internal assurance to apply AI tools in the professional environment. Specifically, residents felt confident explaining AI concepts to a colleague ( $p=0.016$ ), discussing AI-related risks with patients ( $p=0.031$ ), and interpreting outputs from AI-based tools ( $p=0.031$ ), as seen in Figure 4. Neurology

residents began with a baseline of shadow learning by using generative AI tools for imaging diagnostics and clinical/therapeutic decision support as they were introduced in the hospital without standardized institutional training. The lecture series effectively provided a structured framework to help bridge the gap between passive tool use and understanding the role of a doctor-in-the-loop who can independently and confidently verify AI alerts. Figure 4 shows a breakdown of point changes per question.

| Category                   | Mean Change | Wilcoxon W | p-value |
|----------------------------|-------------|------------|---------|
| Knowledge & skills         | 0.96        | 0.00       | 0.004   |
| Adoption & perceived value | 0.17        | 4.50       | 0.078   |
| Risk awareness             | 0.06        | 12.00      | 0.844   |

Figure 3: Mean Point Changes in Three Primary Outcome Measures

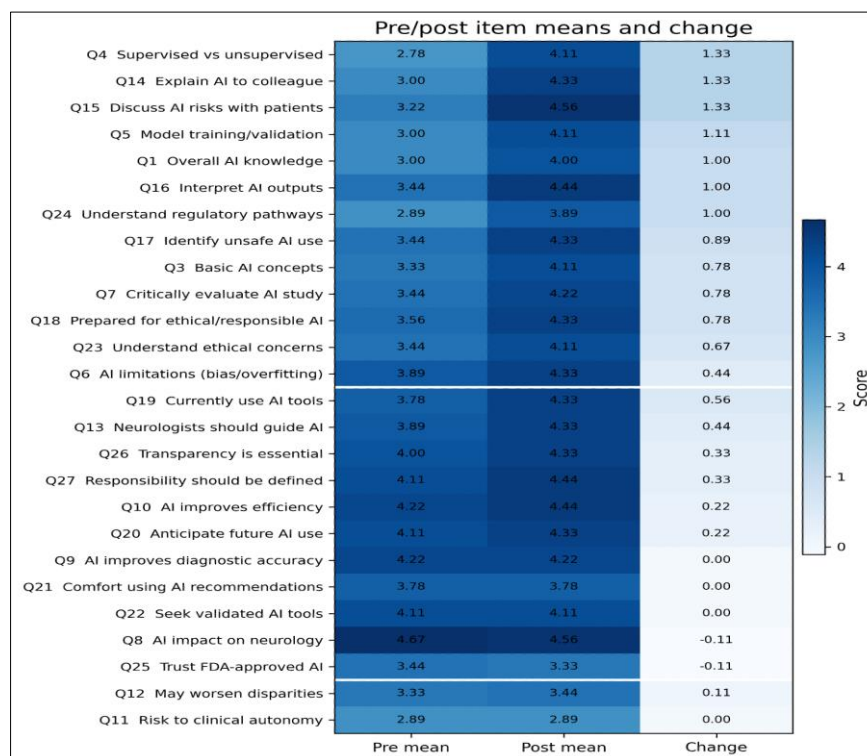


Figure 4: Pre and Post Question Mean Change

### AI Knowledge

While it did not reach the threshold for significance, AI knowledge demonstrated the following lowest p-value, underscoring the common educational challenge of short-term interventions. However, residents did report a significant understanding of regulatory pathways for clinical AI tools following the lectures ( $p=0.031$ ).

### Perceived Knowledge

Perceived knowledge showed no significant improvement, reflecting residents' self-assessment of

their digital literacy. Before the lecture series, 3 residents reported acquiring knowledge through informal channels such as podcasts, articles, and Twitter/X, 2 reported receiving no previous exposure to AI education, and 6 reported acquiring knowledge through clinical usage and/or research involvement, as seen in Figure 5. This demonstrates that while residents may have objectively acquired information regarding statistics and technical implementation, their subjective self-assessments likely lack clinical grounding, which can be enhanced by hands-on skill development.

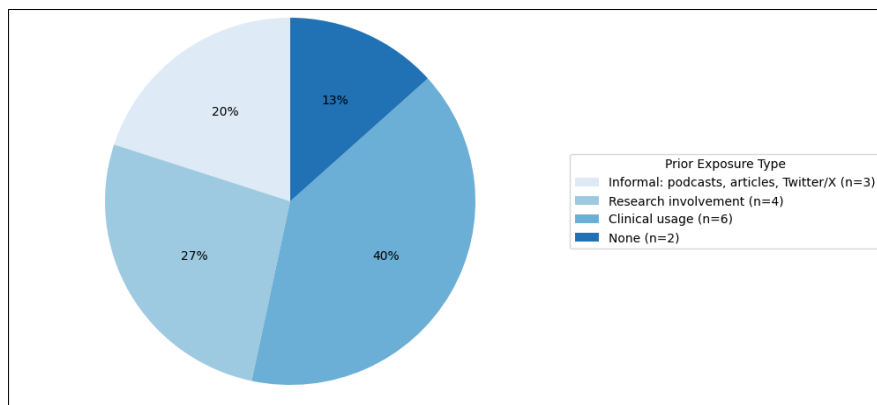


Figure 5: Prior Exposure to AI

### Current and Intended Adoption, Attitudes

Current and intended adoption, followed by attitudes, were factors that showed the least significant improvement after the lecture, as seen in Figure 6. This may be due to the large scope of AI data and development that is currently saturating the medical field, creating a form of information overload that can influence the transition from knowledge to action. While didactic sessions helped address the knowledge gap (Kirkpatrick Level 2), alone, they can fail to achieve a shift in behavior/adoption (Kirkpatrick Level 3) and are better supplemented with a hands-on curriculum that

may reduce concerns about reliability, overreliance, autonomy, and legal liability. The development of hundreds of non-interoperable AI tools competing for attention can keep physicians in a loop of pragmatism without a structured, standardized training program. Furthermore, deeper concerns such as the “black box” issue, racial bias potential, and undefined liability guidelines are significant psychological barriers that require a more thorough, consistent approach to AI education. A cultural institutional shift toward the AI regimen will require a curriculum based on these intentions.

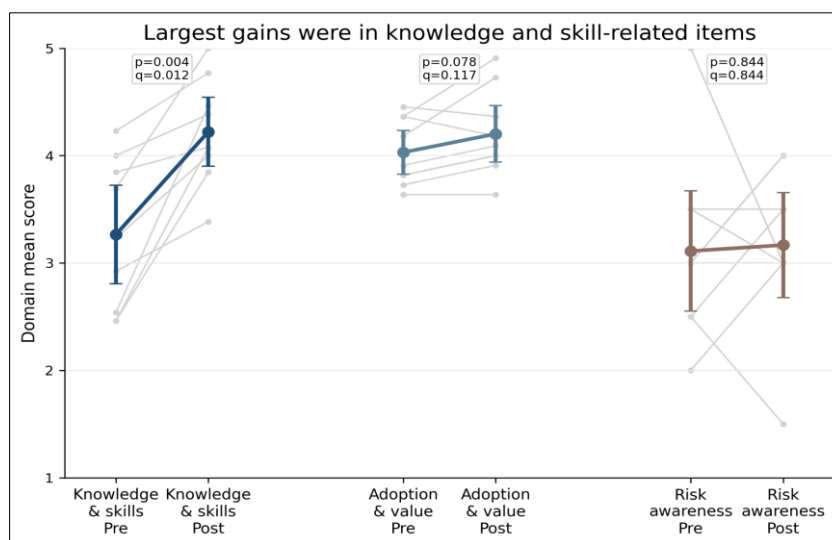


Figure 6: The largest gains were in Knowledge and Skills

## DISCUSSION

Neurology residents were surveyed regarding AI use in daily practice, knowledge regarding AI use in the medical field, and overall confidence in using AI tools. These surveys have been filed in other specialties; thus highlighting the importance and novelty to survey neurology-specific physicians regarding AI use [24]. Interestingly, after the lecture series, the confidence level of residents significantly improved ( $p=0.023$ ), whereas other domains were not statistically significant.

### Limitations

This study faces 3 major limitations: a short time span, a small sample size, and the lack of AI experts in the formation of these lectures. The most notable limitation this study faces is the window of time in which the residents' knowledge was assessed. The post survey was administered immediately after the residents had completed the final lecture, which limits the study's ability to predict the long-term effect of the lecture series on resident confidence, perceived knowledge, AI knowledge, and current and intended adoption.

This limitation is not a unique issue to our study; similar studies have also preferred to test their residents immediately after training rather than after a longer period of time [34]. It is important to understand the immediate effects of the lecture series on resident performance, and examining residents directly following the series is able to provide information on these effects. However, a 6-month or 1-year follow-up survey would characterize the long-term effects of this lecture series and how AI education could be formatted to maximize long-term learning.

Another limitation is the external validity of the study. This study was only performed at one institution with 9 neurology residents varying from post-graduate year (PGY) 1 to 4. The limited size and institutional restrictions of the study decrease its applicability to wider audiences.

Perhaps neurology residents at other institutions have different experience levels and confidence levels with using AI in clinical practice.

While this sample size is smaller than it ideally should be, it is also important to note that it is fairly representative of the UMKC Neurology residency program. The program itself has 12 residents; therefore, the sample size represents a majority of the residents training in this program. Similar to other studies, this small sample size provides a "snapshot" into the effect AI teaching can have within programs [35].

Furthermore, a longitudinal study of AI teaching in this program could also account for the sample size by expanding the time and, therefore, the number of residents who experience this training.

Finally, the curriculum for these lectures was not created by technical experts in AI. It would have been ideal for professionals who are well-versed in the functioning of AI-assisted medical devices to make such a lecture series, as it would provide a deeper perspective on how such technology is best utilized. While the design of this study did not include such experts, it was researched and developed by medical students and approved by leading neurology faculty prior to presentation. The medical educational environment in which these lectures were created led to an emphasis on values relevant to those also in medical training, providing perspectives of similar importance.

### Future Applications

A three-part lecture series may provide an increase in acquiring technical facts, such as specific sensitivity of LVO detection segments, but it is not sufficient enough to create deep objective mastery that overcomes the baseline knowledge which residents have already acquired through incidental exposure. The rapid evolution of these technologies means that even as new knowledge is acquired, the scope of the field expands and leaves residents in a state of perpetual catch-up. To combat this challenge, a potential AI curriculum should go beyond technical teaching of software interfaces, which many tools already share in common, to include tool-agnostic critical appraisal and longitudinal thinking by demonstrating proper AI-usage in case-specific scenarios.

Over 80% of physicians now use AI in their clinical practice and as of 2026, this has doubled since 2023 [25]. One of the only other published studies looking at the incorporation of AI education into the resident curricula is the Data-Augmented, Technology-Assisted Medical Decision Making (DATA-MD) Curriculum, developed at the University of Michigan to teach internal medicine residents the basics of AI/ML. Residents were surveyed on their knowledge after the modules, and it was found that median knowledge scores significantly increased from modules 1 to 3 but not 4. However, residents reported more confidence in evaluating AI and ML literature and using these tools in the future [28]. Thus, the development of curricula to address the changing landscape of AI and medicine is important, as highlighted by DATA-MD and our project. Surveys were the main metric to gauge the change in confidence level of residents before and after the learning modules in DATA-MD and our study.

LLMs have been used to further resident education to generate simulation-based patient cases, mimicking resident interactions with standardized patients. For example, ChatGPT-4 can generate mock patient histories to simulate learning of different disease states without infringing on patient privacy laws [26]. This allows trainees to be exposed to a wider range of scenarios, which may not be frequently encountered during traditional training.

In residency, LLMs have greatly helped residents across all medical specialties in their research pursuits by identifying gaps in current literature and proposing novel research questions. LLMs also enable medical residents to generate comprehensive literature reviews of subjects within minutes or even seconds, allowing for faster data gathering and critical appraisal. Last, LLMs assist in statistical analysis of projects by proposing statistical tests to run for analysis [26].

Medical residents have also benefited from LLMs in managing clinical duties, such as generating discharge summaries, composing entire medical progress or history notes, giving more time for patient care rather than administrative tasks. However, the current systems are not infallible, and with more usage and learning, the error detection capabilities of AI will be augmented [26].

Specific applications of AI in neurology include analysis of imaging to diagnose abnormalities or even early signs of neuropathologies, machine learning models to predict risk of developing neurological diseases based upon genetics and environmental factors, discovering new drug targets via molecular modeling or genetic analyses, and diagnosing diseases and providing individual treatment plans. Examples include the first prognostic device to assess the chances of patients with mild cognitive impairment developing Alzheimer's dementia in 5 years, wearable seizure detection devices, or neural network stroke triage algorithms [27-31].

A common concern is whether AI may negatively impact resident education by reducing opportunities to develop independent clinical reasoning. However, while this concern is valid, rather than avoiding its usage, residency programs can proactively incorporate AI-centered education to ensure that trainees are up to date with both the capabilities of AI and its limitations. The educational curriculum has continuously evolved throughout the years as new advancements in medicine are made, and AI integration represents another step in this progression. While AI can assist in analyzing data and aiding with potential diagnoses, it does not replace the physician's role in making final clinical decisions. AI will have the potential to not only improve clinical efficiency but also allow more time to be dedicated to patient interaction, alongside strengthening the patient-physician.

The unique benefit that AI provides is also, ironically, its unique challenge—the ability to reason through many data points proves it to be an asset, but makes it difficult to pinpoint issues in this reasoning with the current black box problem. It is all the more important now that physicians can critically appraise AI outputs and discern a course of action empowered by AI tools rather than become reliant upon them. The AI revolution in healthcare is not simply a change in the technologies physicians use, but also a change in a

physician's relationship with this technology. Medical education is an important driver in developing a productive relationship between physicians and AI technology today to set up for future progress. Therefore, AI education is an increasingly important part of equipping physicians for medicine's ever-changing landscape.

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