Answering

Enhancing provider experience through clinical AI

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The Quadruple Aim, originally conceived as an extension of the well-established Triple Aim, introduces the imperative of improving the experience of healthcare providers alongside the conventional goals of enhancing patient outcomes, reducing costs, and improving population health.[1,2] However, a concern is emerging that in the pursuit of the Quadruple Aim, the scales may be tilting toward improving quality, cost, and patient experience, potentially neglecting the well-being of healthcare providers.[3,4]

Clinical artificial intelligence (AI) can play a pivotal role in rectifying this imbalance. Specifically, AI has the potential to improve efficiency and effectiveness in patient care and population health, leading to a better provider experience through improved satisfaction and reduced burnout.

While using AI may present challenges such as overcoming a learning curve for providers and ensuring equitable model performance, fostering transparency in AI models and aligning them with current clinical judgment are crucial factors for successful adoption. The goal of leveraging AI is to create a positive interactive experience for clinicians, empowering them to make well-informed clinical decisions that elevate their expertise while improving throughput and quality. This, in turn, can significantly enhance the efficiency and effectiveness of patient care and contribute positively to providers' performance under complex value-based care models.

Clinical AI and Provider Experience

Efficiency Gains in Patient Care

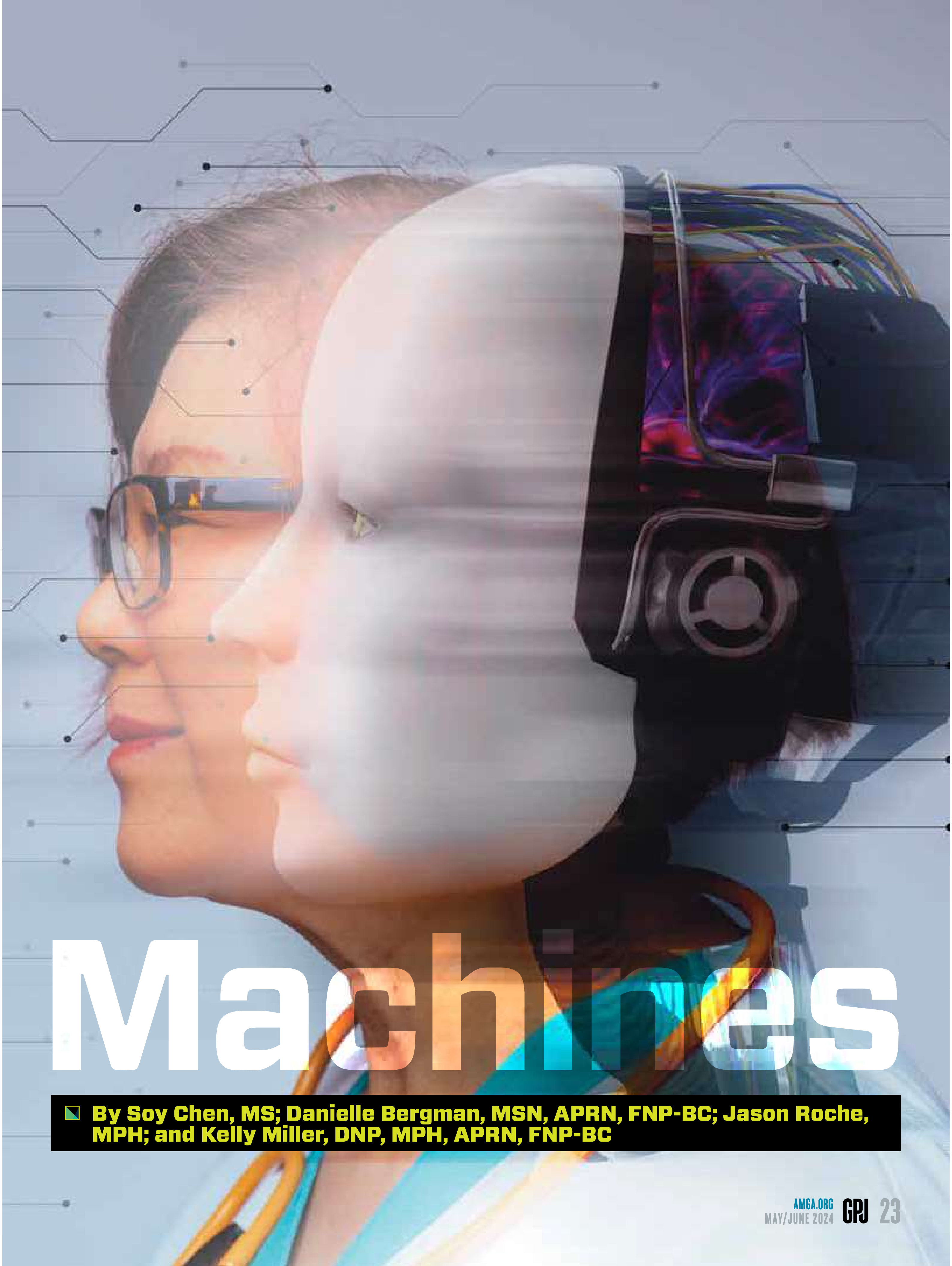
Clinical AI can significantly enhance patient care efficiency by optimizing provider workflows. For instance, AI-driven algorithms can streamline diagnostic processes, automate routine tasks, and facilitate faster decision-making, ultimately reducing the burden on healthcare providers.[5]

In one example, a case study compared care team outreach success rates and found that AI-informed outreach resulted in an 86% connection rate compared to 29% for claims-based outreach.[6] In another example, clinicians saved five minutes per patient alert due to a higher connection rate and more narrowly targeted assessment.[7]

Clinical Patient Care Examples

AI can leverage advanced analytics to analyze large datasets encompassing patient records, diagnostic information, and other relevant sources. By identifying patterns and risk factors, AI can stratify patients into different risk groups, enabling healthcare providers to focus on those at higher risk, even when such risk might not have been immediately apparent (Figure 1).

This targeted approach aligns patient acuity with appropriate care resources and makes proactive, preventative care possible. In addition to identifying increased-risk patients, AI can provide the driving risk factors for individual patients and the recommended interventions to streamline efforts to mitigate patient risk.[8] AI solutions enhance efficiency in patient care by enabling healthcare providers to prioritize and address the needs of patients based on their risk profiles.



Machines

By Soy Chen, MS; Danielle Bergman, MSN, APRN, FNP-BC; Jason Roche, MPH; and Kelly Miller, DNP, MPH, APRN, FNP-BC

Population Health Examples

Beyond individual patient care, efficiency gains extend to population health initiatives. By aggregating and interpreting diverse health data from the community, AI facilitates the identification of trends, risk factors, and potential health disparities. This knowledge empowers healthcare organizations to design and implement targeted interventions, preventive measures, and health promotion campaigns tailored to the community's specific needs.

A 2020 study demonstrated promising results using AI for population health.[9] The area under the curve (AUC) for the primary outcome of inpatient or emergency department (ED) utilization within 90 days was calculated to be 0.84 in the training set and 0.83 in the testing set. These figures indicate a high level of discrimination, suggesting that the machine learning model effectively distinguishes between those patients likely to utilize healthcare services and those who are not. This study highlights the ability to use machine learning to predict healthcare utilization using social determinants of health (SDOH) data alone. This capability underscores the ease with which AI can stratify patients based on risk without direct patient interaction to determine SDOH risk factors while concurrently identifying significant disparities in population health on a larger scale.

Effectiveness/Impact Gains in Patient Care

According to a Microsoft executive, only 3% of healthcare data are currently harnessed, leaving substantial amounts of untapped data that could enhance patient outcomes. The primary obstacle to utilizing a greater portion of the data is the challenge of unraveling and deciphering it.[10] Clinical AI broadens the scope and impact of interventions by giving providers access to a larger set of data elements. AI excels in classifying and predicting, particularly with large datasets and probabilities, contributing to its applicability in healthcare. The utilization of advanced analytics within AI solutions assists clinicians in identifying patterns in clinical and operational data, aiding better decision-making.[11,12]

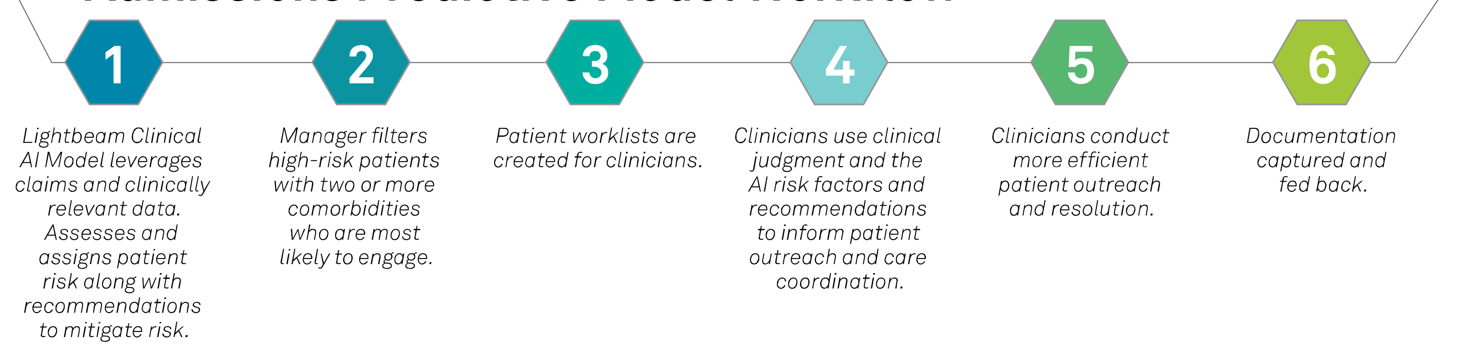
Clinical Patient Care Examples

Clinicians can derive actionable insights for more precise, reliable, and clinically relevant interventions benefiting patients and clinicians.

For instance, AI predictions can help clinicians, such as nurses, anticipate patients likely to experience avoidable inpatient admissions and emergency department (ED) visits. An oncology abstract evidenced these outcomes, demonstrating a 12.3% reduction in unplanned admissions and an estimated cost savings of $212,160 per 100 patients in three months of deployment.[13] Utilizing the same AI solution, another publication cites a 25% relative reduction in readmissions over a six-month period. This reduction is attributed to the strategic targeting of patients at the highest risk for readmission, achieved through the incorporation of AI in clinical decision support.[14]

Figure 1

Reducing Clinician Burden: Lightbeam's Avoidable Admissions Predictive Model Workflow



Population Health Examples

From a population health lens, AI can uncover intricate patterns, correlations, and trends that might be elusive to clinicians and care teams using traditional methods. Through large-scale geographical data, a more granular understanding of the social vulnerabilities and environmental factors enables healthcare professionals to formulate targeted and effective interventions at the block-group level. Focusing on specific barriers to health equity, such as food insecurity and exposure to air pollutants, AI enhances the precision and efficiency of population health initiatives, allowing for proactive and relevant care strategies.[11]

Challenges to Provider Adoption of Clinical AI

While the benefits of clinical AI are promising, healthcare providers face significant challenges in adopting and fully embracing this technology. Realizing the benefits of AI requires overcoming two types of barriers: technology-related and human-related.

Human-related challenges that prevent the widespread adoption of clinical AI stem from barriers in selecting the appropriate use cases, operationalizing them via workflows, and achieving provider trust and buy-in.[15,16] A recent survey conducted among AMGA healthcare executives identified concerns about costs and expertise, and uncertainties about assessing the risk with using AI (see Figure 2).

Trust in the clinical accuracy of AI and integration of AI into clinicians' workflows were also reported as key barriers. The technology barrier is known as the "black box" problem, referring to the lack of transparency in AI systems that creates tension with end-users who question the basis of the output. Human and technology barriers to adoption are wholly intertwined.[17,18]

Transparency of AI Models

Clinical AI, by definition, aims to bolster clinical outcomes. However, clinicians must trust the insights they have been given, and the associated recommendations and data must be meaningful and relevant to effectively inform their work.

Clinician concerns with data can impede trust and understanding in AI, resulting in inefficiencies and missed opportunities.[3,5] Ensuring that healthcare providers have faith in AI-driven decision-making requires transparent models—a non-black-box approach. Incorporating AI within the healthcare domain necessitates considerations of accessibility, transparency, and responsibility, entailing a requisite commitment to garner support from clinicians.[19]

For instance, AI-driven recommendations and data should be tailored to the specific needs of clinicians and integrated into their existing workflows. Instead of presenting a complex algorithmic output, the AI system could provide actionable recommendations based on patient data, such as suggesting individualized outreach approaches or highlighting potential risk drivers. Furthermore, transparency in AI models can be ensured by documenting and explaining the decision-making process. Clinicians should have access to details about how the AI model was trained, the data it utilized, and the rationale behind its recommendations, including the factors driving risk or the "why" behind each recommendation. This transparency is essential for building trust, as it enables clinicians to comprehend and verify the reasoning behind the AI's outputs.[20]

Risk Factors and Drivers

Clinical decision-making relies on evidence-based practice, employing the most reliable available evidence to guide well-informed clinical decisions and provide efficient and effective care.[20] Decision capacity entails comprehending relevant information, recognizing its significance, evaluating potential benefits and contraindications, and deciding on the appropriateness of alternative courses of action.

Recognizing that clinicians heavily depend on evidence for informed decision-making underscores the imperative for supportive data or evidence to drive the application of AI in healthcare. A retrospective case-control study that utilized patient health records from a transition of care management program to assess the efficiency of integrating individual patient insights derived from AI exemplifies this dependence. The program, operationalized by Northwell Health, aimed to identify and mitigate risk factors, such as poor access to care or communication failures, which contributed to readmission events. Patients were categorized based on AI-generated risk assessments, divided into intervention groups receiving AI-generated care risk drivers and recommendations, and a control group not receiving such insights. By incorporating risk drivers and insights into risk predictions, healthcare providers gained an enhanced understanding of the model output. This heightened comprehension facilitated a more effective application of the model's output within clinical practice and led to a statistically significant reduction of 21% in rehospitalization rates compared to the control group.[8]

Verifiable and Research-Validated Interventions

AI models are more readily accepted by clinicians when they align with clinical judgment, offering predictions and interventions validated through research and verifiable data related to identified risk factors. This ensures that AI complements clinical decision-making rather than replacing it, a main necessity highlighted by AMGA clinical executives (Figure 3).

Evidence-based medicine in AI outputs stands as a critical factor in successful integration into clinical workflows, as emphasized by healthcare providers. AI solutions that furnish real-time, evidence-based recommendations to clinicians aid in timely decision-making and personalized treatment planning based on individual characteristics, enhancing targeted clinical decision-making, and efficiently directing scarce care resources to address patients at greatest risk.[21,22]

The emphasis on incorporating evidence-based medicine in AI outputs is critical for overcoming barriers, building trust with the solution, and facilitating successful integration into clinical workflows. Healthcare providers indicate that when AI solutions augment clinical decision-making reliably, there are higher rates of adoption, growing from 85% to 93% in 2022.[26, 27,28]

Addressing Bias

Another substantial challenge in the adoption of clinical AI is the potential for bias in algorithms, which can lead to disparate impacts on diverse patient populations. In the landmark 2019 *Science* article, racial bias carried out by biased algorithms roused the healthcare AI community into an uproar on the topic.[23]

Algorithmic bias is not necessarily exclusive to race. For instance, models addressing sleep quality trained on young participants could lead to bias against elderly patients, or inaccurate cardiovascular models may misdiagnose women due to overrepresentation of males in study focus.[24,25]

Expecting data that feed the building of AI algorithms to be free of bias is unrealistic, as the data merely reflect the systemic inequalities and bias that have long plagued U.S. healthcare. There are no existing industry standards on health equity correction parameters or quantitative metrics for adjusting bias to established measures.

Despite this limitation, AI products should not further reinforce or promote the bias found in observed data. To avoid potentially harmful implications caused by the presence of bias, proper monitoring and assessment of AI algorithms with metrics must be in place at the various stages of the AI product life cycle in order for mitigation and correction to be possible.[26,29] Monitoring processes should have set measured threshold tolerances on established vulnerable groups benchmarked and tracked from AI product design and ingestion to implementation and ongoing production.[30]

Figure 2

AMGA Member Concerns About Costs, Expertise, and Uncertainties Regarding AI Risk Assessment

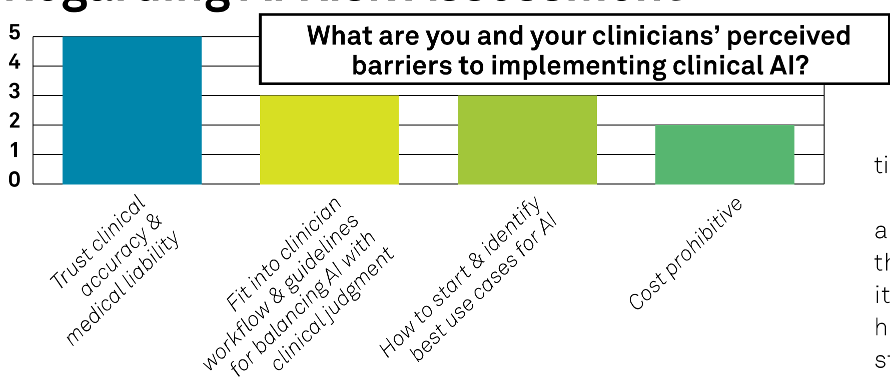
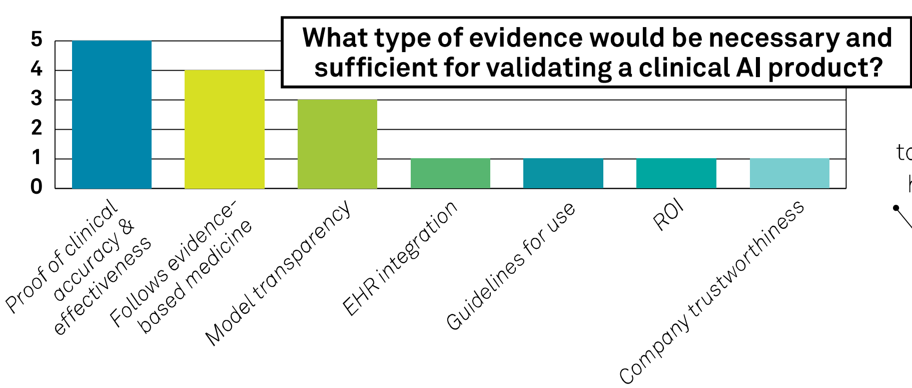


Figure 3

Evidence Necessary for AMGA Members to Use Clinical AI Products



Conclusion

Achieving a balanced Quadruple Aim necessitates prioritizing the enhancement of the provider experience through the thoughtful integration of clinical AI. By realizing efficiency and effectiveness gains in patient care and population health, clinical AI holds the potential to address the risks of lopsided improvements. Healthcare executives are open to embracing clinical AI into workflows. However, transparency in AI models and the proactive mitigation of bias are paramount to ensuring that the adoption of clinical AI aligns with and enhances clinical judgment. The technologists creating AI solutions must be able to provide expertise, build trust within their solution, and craft workflow integration, all while providing robust evidence through case studies and adherence to evidence-based medicine, to facilitate successful integration of vetted AI solutions into clinical practice. Ultimately, AI will play a vital role in a financially sustainable healthcare system that prioritizes whole-person care and leverages proactive, preventative protocols to achieve improved clinical outcomes while elevating healthcare organizations and clinicians alike. GPJ

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