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Comment Mark Sendak, Freya Gulamali, and Suresh Balu

Introduction

While enthusiasm for the role of artificial intelligence (AI) in healthcare continues to mount, economic analyses demonstrating successful return on investment are scant. In their piece titled "The Potential Impact of Artificial Intelligence on Healthcare Administrative Spending," Sahni and colleagues estimate the total potential savings from AI in healthcare to be $200 billion to $360 billion annually. These estimates will likely spur further investment in the development and adoption of healthcare AI. However, unless stakeholders rapidly align on strategies to overcome barriers and achieve the required activation energy, the potential value of healthcare AI will remain beyond reach.

We represent the Duke Institute for Health Innovation (DIHI) at Duke Health, a multihospital health system with 67,000 inpatient admissions and 4.7 million outpatient visits annually (Duke Health 2023). Similar to Sahni and colleagues, we draw upon a combination of academic and industry experience. We have nearly a decade of experience working on internal innovation projects that design, develop, and integrate novel technologies and care delivery models within Duke Health. Through our work at DIHI, we have developed and implemented over 15 AI solutions internally and have multiple initiatives validating AI solutions in external health systems. We also launched the Health AI Partnership (HAIP) in 2021 to convene stakeholders from health systems across the United States to advance the ethical adoption of AI (Duke Institute for Health Innovation 2021). Through our work at HAIP, we have conducted 85 interviews with clinical, technical, and operational leaders across nearly a dozen health systems in the US to surface and disseminate AI adoption best practices. While we work across care delivery settings and medical conditions, our perspective is primarily grounded in the experience of health systems and physician practices.

In this comment, we present several analyses that complement the work of Sahni and colleagues. First, we describe concrete use cases that reinforce the hospital AI delivery domains and the need to capture both financial and nonfinancial benefits. Second, we present on-the-ground insights that identify gaps in evidence relied upon by Sahni and colleagues. Lastly, we

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identify specific organizational (within-health-system) and seismic (policy-level) interventions that could overcome the activation energy to unlock the value of healthcare AI.

AI Delivery Domains

In this section, we present use cases from DIHI and HAIP that illustrate the AI delivery domains described by Sahni and colleagues. We focus on the six domains related to direct patient care and not related to reimbursement or corporate functions.

The first AI delivery domain is continuity of care, described as "optimizing point-of-service and referrals to improve patient care." Within this domain, our team at DIHI used AI to predict hospital readmissions to optimize postdischarge transfers to skilled nursing facilities (SNFs). Geriatric patients discharged to SNFs are at increased risk of hospital readmission, and AI can prioritize patients for telemedicine support to ensure appropriate postacute care (Krol et al. 2019; Bellantoni et al. 2022). This use of AI can create financial value in value-based care programs by preventing hospital readmissions and nonfinancial value by improving the safety and quality of care provided within SNFs.

Second, network and market insight applications are described as "tracking relationship strength among providers." Within this domain, one of our HAIP sites, Parkland Center for Clinical Innovation, used AI to segment their patient population to design tailored clinical programs for clusters of patients (Tamer et al. 2022). This use of AI creates nonfinancial value by improving patient experience and addressing barriers to access.

Third, clinical operations applications are described as "optimizing clinical workflow and capacity throughout [the] care journey." Within this domain, our team at DIHI used AI to predict admissions to the hospital requiring either intermediate or intensive care unit level care (Fenn et al. 2021). This application of AI can improve patient flow within the emergency department, prompting timely inpatient transfers for patients requiring escalation of care and discharge for patients who can safely return home. This use of AI creates financial value by increasing emergency department throughput and nonfinancial value by improving patient experience.

Fourth, clinical analytics applications are described as "improving patient care journey with data at all points of care delivery." This domain overlaps heavily with clinical operations, especially when optimizations to health system operations align with patient care goals. For example, our team at DIHI used AI to identify patients at high risk of postsurgical complications as well as patients at high risk of inpatient mortality (Corey et al. 2018; Brajer et al. 2020). In both these cases, accurate risk stratification can ensure that invasive surgical and medical interventions align with patient goals of care. These uses of AI create nonfinancial value by improving patient experience, but financial value depends on the reimbursement model. In a fee-for-service model, these uses of AI can have a negative financial impact (i.e., by reducing procedures and treatments), whereas in a value-based care model, these uses of AI can create financial value.

Fifth, quality and safety applications are described as "reducing major adverse events with special attention to patient experience and legal compliance." This domain also overlaps heavily with clinical analytics and clinical operations, and the financial impact depends on reimbursement model. For example, our team at DIHI used AI to identify patients at high risk of sepsis as well as patients at high risk of incident HIV (Bedoya et al. 2020; Burns et al. 2022). In both these cases, infections and their resultant complications can be avoided with timely prevention and treatment. These uses of AI create nonfinancial value by improving patient safety and experience, but like other domains, the financial value depends on the reimbursement model. In a fee-for-service model, these uses of AI can have a negative impact, whereas in a value-based cased model, these uses of AI can create financial value.

The final AI delivery domain is value-based care, described as "improving patient outcomes with value-based care models." This domain resolves much of the tension in the prior domains by asserting the reimbursement model. Within this domain, our team at DIHI used AI to predict progression of chronic kidney disease within an accountable care organization population (Sendak, Balu, and Schulman 2017). Patients at high risk of end stage renal disease can be proactively referred to specialty care to initiate interventions that slow disease progression. These use cases create nonfinancial value by improving patient experience and create financial value by reducing costs associated with advanced chronic disease.

The examples above reveal the complexity of capturing value from AI and the role for total mission value metrics that combine financial and nonfinancial measures. In a fee-for-service reimbursement model, the only domain that consistently generates financial value is clinical operations. In a value-based care reimbursement model, a much broader variety of domains generate financial value. However, the efficient scaling and diffusion of AI in healthcare will ultimately be determined by how much total mission value creates real financial returns. In settings that are unable to fully align incentives across payer, hospital, and physician practice, only a limited scope of AI applications will achieve broad adoption.

On-the-Ground Insights

Three on-the-ground insights derived from our work with DIHI and HAIP reveal gaps in evidence relied upon by Sahni and colleagues. First, the benefits of AI integration presented by Sahni and colleagues are highly optimistic both in terms of timing (immediacy of returns) and magnitude (size of returns). Two quantitative estimates are, first, "In our experience, organizations that deploy AI have twice the five-year revenue compound annual growth rate [CAGR] compared with others that do not"; and second, "Our estimates do not include one-time implementation costs, which in our experience are 1.0 to 1.5 times the annual savings." As described above, most health system and provider practice AI use cases do not generate financial value and would not directly increase CAGR. In a recent McKinsey report, five-year annual CAGR was estimated at 3 percent, down from the prior estimate in July 2022 of 7 percent (Patel and Singhal 2023). All health systems face significant financial pressure in the current environment, due to inflation and high labor costs, which are not entirely addressable with AI. It's unclear how health systems that deploy AI would double their CAGR compared to health systems that don't deploy AI.

Existing evidence also does not support the claim that implementation costs for health AI are 1.0 to 1.5 times annual savings. In fact, health information technology (IT) is notorious for high implementation costs that yield minimal returns. For example, while interoperable health IT was estimated to yield $77.8 billion per year in 2005, despite a $30 billion investment by the US government, the impact of electronic health records (EHRs) on health system finances was minimal (Walker et al. 2005; Beauvais et al. 2021). Many health systems saw financial losses from EHR implementations (Adler-Milstein, Green, and Bates 2013). Without well-documented case studies of AI implementations leading to immediate financial value, it's unclear if health systems and physician practices will achieve the described results.

The second problematic gap in evidence relates to the scalability of current health information technology. The authors claim that "all savings estimates are based on the use of technologies available today and assume that adoption reaches full scale." Unfortunately, the authors do not describe how existing AI solutions can be fully scaled to achieve replicable results across settings. Two factors prevent the efficient scaling of current AI solutions across settings. First, current EHR system implementations are highly customized, and significant effort is required to normalize and harmonize data to conduct analyses across sites. Our team estimated the costs of implementing a single model at a single institution to be nearly $220,000 (Sendak, Balu, and Schulman 2017). Redundant effort to scale that single algorithm across all US hospitals would cost nearly $40 million. More recently, we described the significant effort required for interdisciplinary teams to conduct data quality assurance to develop new algorithms within Duke Health as well as externally validate existing algorithms in external settings (Sendak et al. 2022). Integrating AI systems into legacy IT systems in new settings remains a high-cost endeavor. Without infrastructure that normalizes, harmonizes, and monitors data across EHR systems, there are minimal efficiencies of scale for new settings to adopt AI solutions.

Even if the IT infrastructure were in place to scale an AI solution, organizations must adapt to effectively use and benefit from the technologies.

In 2018, our collaborator Madeleine Elish described Sepsis Watch, an AI-driven sepsis detection system, as *sociotechnical* to emphasize the ways in which the technology and social environment interacted to shape use of the AI system in practice (Elish 2018). Since that time, we regularly engage social scientists in our work to help surface change management opportunities and challenges to ensure successful AI integration (Elish and Watkins 2020; Kellogg, Sendak, and Balu 2022). Unfortunately, our experience building and integrating AI solutions across settings reveals that these technologies are not "turn-key," and significant effort is required from transdisciplinary teams to enable successful organizational adoption.

The final gap relates to organizational characteristics associated with AI software adoption. Sahni and colleagues claim, "Hospitals have piloted AI and are beginning to scale adoption in some domains, with larger hospitals having done more than smaller hospitals." Our own work reveals that health system size is not a factor driving AI adoption. Use of AI is highly concentrated within academic medical centers (AMCs), which only account for 35 percent of hospital admissions in the United States (Burke et al. 2019; Sendak et al. 2020; Price, Sachs, and Eisenberg 2022). Large health systems without internal AI expertise are also more likely to rely on EHR vendors for AI solutions, many of which perform poorly when used in new contexts (Wong et al. 2021). Furthermore, our work with HAIP sites has revealed the importance of centralized AI capabilities and organizational governance structures to ensure safe and effective adoption of AI. This best practice is most mature within AMCs that have significant internal AI development and integration expertise.

Overcoming the Activation Energy

To overcome the challenges listed above, we present multiple potential organizational and policy ("seismic") interventions. First, there are high returns to increasing investment in sociotechnical research of AI integrations in healthcare. There is value at both the policy level (i.e., increases in public sector research funding) and at the organizational level (i.e., sustained investment in social science roles). For example, three systematic reviews of randomized control trials (RCTs) evaluating AI products in healthcare were published between October 2021 and September 2022 (Plana et al. 2022; Lam et al. 2022; Zhou et al. 2021). The reviews included 95 studies across 29 countries. Only 15 AI products were validated in RCTs in the US leveraging broadly available data platforms, including EHR systems and radiology imaging data. Of those AI products, sociotechnical research was conducted for two. A team at PennMedicine conducted several studies examining clinician perspectives of an AI system used to prompt serious illness care conversations for patients with cancer, and multiple sites examined organizational factors related to adoption of an AI system to help triage patients with chest pain in the emergency department (Parikh et al. 2022a, 2022b; Gesell et al. 2018; Bean et al. 2021). Without including sociotechnical research as a standard component of AI development and validation, positive results are unlikely to be replicable in new organizational contexts.

Second, technical and regulatory structures could ensure quality control of AI used by health systems and physician practices. As described above, current EHR systems do not facilitate the efficient diffusion of AI across sites. A market failure currently incentivizes health systems to rely on AI solutions provided by EHR vendors, which often perform poorly (Sendak, Price, and Balu 2022; Wong et al. 2021). Even if a best-in-class solution emerges, integration costs prevent efficient scaling. National infrastructure investment could upgrade the current health IT ecosystem to enable rapid scaling across sites. Similarly, standards and regulation could ensure that AI solutions are validated within health systems and physician practices prior to use. Regulators such as the Office of the National Coordinator could require adoption of this best practice for health IT certification, and third-party accreditation organizations, such as the Joint Commission, can ensure that health systems adopt this best practice as part of organizational governance efforts.

Third, capacity-building programs could upskill the healthcare workforce to effectively use AI. Programs that target individual clinicians, such as our DIHI Clinical Research and Innovation Scholarship, can be scaled across clinical training sites to engage more clinicians in AI product development (Sendak et al. 2021). Similarly, programs that equip organizational leaders, such as HAIP, can equip teams of interdisciplinary professionals to rapidly enhance organizational governance of AI. Funding for this training from the public sector could ensure that the existing digital divide does not widen. Without public sector intervention, AI products will largely remain within the ivory tower of highly resourced AMCs.

Conclusion

In their analysis, Sahni and colleagues estimate the total potential savings from AI in healthcare to be $200 billion to $360 billion annually. While we agree that the opportunity to improve healthcare using AI is enormous, our experiences through DIHI and HAIP reveal a more complex picture. In this comment, we present gaps in evidence that must be addressed to ensure that AI solutions are scalable across sites. We also present policy and organizational interventions that could unlock the value of AI in healthcare. Without coordinated investments in sociotechnical research, technical and regulatory structures, and capacity-building programs, the potential benefits of AI in healthcare will remain out of reach for health systems and physician practices.

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