

Overcoming the Digital Divide in Health Care AI

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Complex, costly new health care technologies have historically tended to be less available to financially, racially, and geographically marginalized groups than to the rest of the population. In the realm of health information technology, this disparity has been labeled the “digital divide.”¹ Available evidence suggests that a further digital divide may develop in the use of artificial intelligence (AI), but we believe that certain policy approaches could help reduce that gap.

The health AI digital divide may take several forms. It may consist of delayed or reduced adoption of AI by health care facilities and professionals that serve marginalized groups. It may also appear in the form of biases within these technologies that adversely affect vulnerable populations. For example, if some groups have historically received fewer services because of access barriers, AI models trained on historical data may recommend that they receive fewer services going forward. The digital divide may also reflect (and reinforce) lower levels of digital health care literacy among people in those groups than in the broader population.

Policy options are available to ameliorate these different types of digital disadvantages. Here, we focus on sources and potential remedies of AI digital divides arising from the delayed or reduced adoption of AI by health care organizations serving marginalized populations. For the most part, these organizations are rural, critical access, and safety-net hospitals and clinics.

Early studies of the adoption of health care AI show that critical access hospitals, rural hospitals, and hospitals serving large numbers of Medicaid patients are less likely than other hospitals to adopt AI.² Lower operating margins, which are prevalent among critical access, rural, and safety-net facilities, are also predictive of reduced rates of hospital AI adoption.²

Pending Medicaid changes will most likely exacerbate the problem by further reducing margins for many of these organizations. Though there is little information on gaps in the use of AI among physicians, their adoption of AI may increasingly reflect patterns in their local hospitals and clinics because increasing numbers of physicians are employed by such organizations.

It could be argued that in the case of dynamic technologies like AI, delayed or reduced adoption will enable safety-net and rural facilities to benefit from the experience of others and perhaps avoid some downsides of early adoption. However, studies have already documented the benefits of at least some AI applications.³ It is ethically problematic to systematically deny marginalized populations access to these potential benefits. Furthermore, less-advantaged facilities should have the opportunity to decide for themselves how to manage AI adoption.

Two factors impede AI adoption by facilities serving marginalized groups. One is lack of financial resources to invest in new technologies generally, including

AI. A second is lack of personnel with the necessary skills to implement AI tools safely and effectively. Proper implementation of health AI requires ongoing testing and validation of AI models to see if they perform well for local patient populations. Personnel with needed skills are often less available to facilities serving marginalized populations, either because skilled workers are locally scarce or because their higher salaries make them unaffordable to financially strapped institutions.

Policymakers have a number of options for remedying these sources of the health AI digital divide. To address financial barriers to AI adoption, federal and state governments can provide dedicated funding for AI implementation. For example, the recently enacted Rural Health Transformation Program (RHTP), which is intended to cushion the impact of Medicaid cuts on rural health care facilities, treats adoption of health information technology, including AI, as an acceptable use of allocated funds.

Though helpful, the RHTP will probably be insufficient to bridge the divide, let alone address the funding shortfall created by the legislation. The law provides \$10 billion per year over 5 years, but estimated cuts to Medicaid in rural areas will total \$137 billion over the same period.⁴ The adoption of AI technologies with uncertain immediate effects on costs and revenues may be a lower priority than projects that will directly or indirectly keep health care organizations' doors open in the short term. And of course,

the RHTP does nothing to help nonrural safety-net institutions.

Other potential financial remedies for the divide include federal or state grants and loans for AI implementation to hospitals that would have qualified for now-suspended disproportionate-share payments. Similar payments could be made to federally qualified health centers and rural health clinics. Congress could also direct the Centers for Medicare and Medicaid Services (CMS) to provide added compensation for Medicare and Medicaid services to rural and safety-net facilities that are implementing health AI. In experiments with new approaches to payment, such as the recently announced ACCESS (Advancing Chronic Care with Effective, Scalable Solutions) model, CMS could also encourage the provision of equitable access to emerging technologies.

The Regional Extension Center (REC) program created by the HITECH (Health Information Technology for Economic and Clinical Health) Act provides one model for addressing the other major barrier to AI adoption in safety-net and rural health care facilities: lack of technical expertise. Focusing on physicians and organizations that provide primary care to marginalized populations, RECs offered free technical assistance with adoption of electronic health records (EHRs) and meeting meaningful-use requirements. RECs are credited with increasing the proportions of participating physicians and hospitals that qualified for CMS meaningful-use payments.⁵ With congressional support, RECs could be revived to assist rural and safety-net facilities with AI implementation. Some RECs might also function as “as-

surance labs” that could assist rural and safety-net facilities with the ongoing validation of AI technologies.

It turns out that many health care facilities are relying on EHRs to offer access to AI applications. Variation in vendors’ incorporation of AI applications is thus becoming a major determinant of health AI adoption and use. The Department of Health and Human Services could expand EHR certification requirements to assure that AI applications included in EHRs in rural and safety-net facilities are designed for ease of implementation.

Thus, tools for overcoming at least one dimension of the health AI digital divide are available to policymakers who wish to employ them. The question is whether officials will choose to do so.

If policymakers believe, as the current administration clearly does, that AI can transform health care delivery for the better, then allowing health facilities serving marginalized populations to lag in AI adoption could compound the many other disadvantages faced by these groups. Furthermore, by empowering safety-net and rural facilities to invest in AI applications that meet their specific needs, efforts to narrow the digital divide could create a market for such applications at a time when the federal administration seems intent on letting market forces dictate how this new technology develops and disseminates.

A policy objective’s importance, however, is no guarantee that federal and state governments will act to achieve it. The current administration evinces little interest in direct governmental involvement in shaping the development

and use of health AI, except to clear the way for the AI industry to flourish. However, the concern about the needs of rural populations that motivated the RHTP may create an opportunity to focus the program more directly on the adoption and use of health AI. In addition, some states may be more amenable to intervening than the federal government. If and when the current political climate changes, the other options available for overcoming the health AI digital divide may prove appealing to future federal policymakers.

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