REVIEW ARTICLE

AI IN MEDICINE
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Artificial Intelligence in U.S. Health Care Delivery

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The adoption of artificial intelligence (AI) and its impact on business sectors happen in phases. The use of AI is advanced in many areas, including reinventing how a financial institution provides investment advice and products to its customers, offering "recommendation engines" that suggest the next retail product to buy for a consumer who has just bought one item, and developing driverless cars. In health care delivery, however, AI remains in the early stages.

AI adoption in health care delivery lags behind the use of AI in other business sectors for multiple reasons. Early AI took root in business sectors in which large amounts of structured, quantitative data were available and the computer algorithms, which are the heart of AI, could be trained on discrete outcomes — for example, a customer looked at a product and bought it or did not buy it. Qualitative information, such as clinical notes and patients' reports, are generally harder to interpret, and multifactorial outcomes associated with clinical decision making make algorithm training more difficult. Another challenge is embedding AI output into the already complex clinical workflow. Furthermore, in our experience, the environment in which some health care organizations operate often leads these organizations to focus on near-term financial results at the cost of investment in longer-term, innovative forms of technology such as AI. Health care organizations that prioritize innovation link investment decisions to "total mission value," which includes both financial and nonfinancial factors such as quality improvement, patient safety, patient experience, clinician satisfaction, and increased access to care.

We think that the need for AI to help improve health care delivery should no longer be questioned, for many reasons. Take the case of the exponential increase in the collective body of medical knowledge required to treat a patient. In 1980, this knowledge doubled every 7 years; in 2010, the doubling period was fewer than 75 days.[1] Today, what medical students learn in their first 3 years would be only 6 percent of known medical information at the time of their graduation. Their knowledge could still be relevant but might not always be complete, and some of what they were taught will be outdated. AI has the potential to supplement a clinical team's knowledge in order to ensure that patients everywhere receive the best care possible. Bringing that potential to reality has not been easy, but there are some successes.

There are signs of increased adoption. Economies of expertise — or the development of more robust AI algorithms from more data — have become a key accelerant for a new subindustry, referred to as health care services and technology (e.g., software and platforms, data analytics, and payment services), which has the potential in the next few years to be as large monetarily as the entire payer subindustry is today.[2] The coronavirus disease 2019 (Covid-19) pandemic has also been a catalyst, prompting organizations to accelerate plans to digitalize and deploy AI. At the management and board levels of organizations, the recent public awareness of generative AI has increased conversations regarding AI. In addition, the adoption of AI can have second-order effects, such as alleviating part of the ongoing shortage of physicians and nurses.

In this article, we discuss the emerging use of AI in health care delivery, which is defined as direct and supportive functions related to the provision of health care. By way of full disclosure, we are both employed by a company that provides consulting services for public and private organizations in this area. We also examine the use of AI in the domains of reimbursement, clinical operations, and quality and safety. Finally, we discuss the challenges that health care organizations are facing in deploying AI.

EMERGING HIGH-VALUE USES OF AI

AI is broadly defined as a machine or computing platform that is capable of making intelligent decisions. Two types of AI have generally been pursued in health care delivery: machine learning, which involves computational techniques that learn from examples instead of operating from predefined rules, and natural language processing, which is the ability of a computer to transform human language and unstructured text into machine-readable structured data that reliably reflect the intent of the language.[3,4]

In health care delivery, the role of AI in improving clinical judgment has garnered the most attention, with a particular focus on prognosis, diagnosis, treatment, clinician workflow, and expansion of clinical expertise. Specialties such as radiology, pathology, dermatology, and cardiology are already using AI in the process of image analysis.[1,5-7] In radiologic screening, for example, up to 30% of radiology practices that responded to a survey indicated that they had adopted AI by 2020, and another 20% of radiology practices indicated that they planned to begin using AI in the near future.[8]

The potential of AI, however, extends much further. We have found that uses of AI are emerging in nine domains of health care delivery (Fig. 1). However, most uses of AI in health care delivery have not been subject to randomized, controlled trials. Therefore, the usual level of evidence required for medical decision making may be lacking. We indicate where there is ample evidence and where it is absent. We still aim to provide a perspective based on our conversations with dozens of health care leaders, but we understand that this is not a substitute for a randomized, controlled trial.

Our discussions with U.S. health care leaders suggest that AI adoption in the nine health care domains has been met with varying degrees of success. Newer forms of technology, such as blockchain and generative AI, have not played a major role. Some health care leaders argue that unlocking the potential of AI will require the use of these types of technology, but our experience suggests otherwise. Overall, most organizations are still in the pilot phase of AI adoption and are attempting to validate the benefits. Here, we focus on uses of AI in three domains of health care delivery: reimbursement, clinical operations, and quality and safety.

REIMBURSEMENT

Reimbursement — an area of checks and balances between payers and providers — is key to the financial health of a health care organization. Uses of AI in this domain are both common and among the most advanced uses, with a higher-than-average total mission value (Fig. 1). In what has been termed "the coding wars," AI not only has become an important tool for stakeholders to monitor one another but also has been simplifying and reducing difficulty in the patient's experience with medical payments.

Providers refer to the processing of claims that payers should reimburse (Fig. 2) as revenue-cycle management. This is one of the provider's tasks that is often performed by persons who review a health care professional's billing and provide guidance regarding the completion of the bill in a manner that aligns with the services provided so that the amount actually paid to the organization will be appropriate. With the use of this system, more than 10% of claims are denied or delayed because of eligibility issues and missing data, but up to 85% of those denied claims could have been avoided.[10]

One large health system recognized that AI — specifically predictive analytics — could gen-

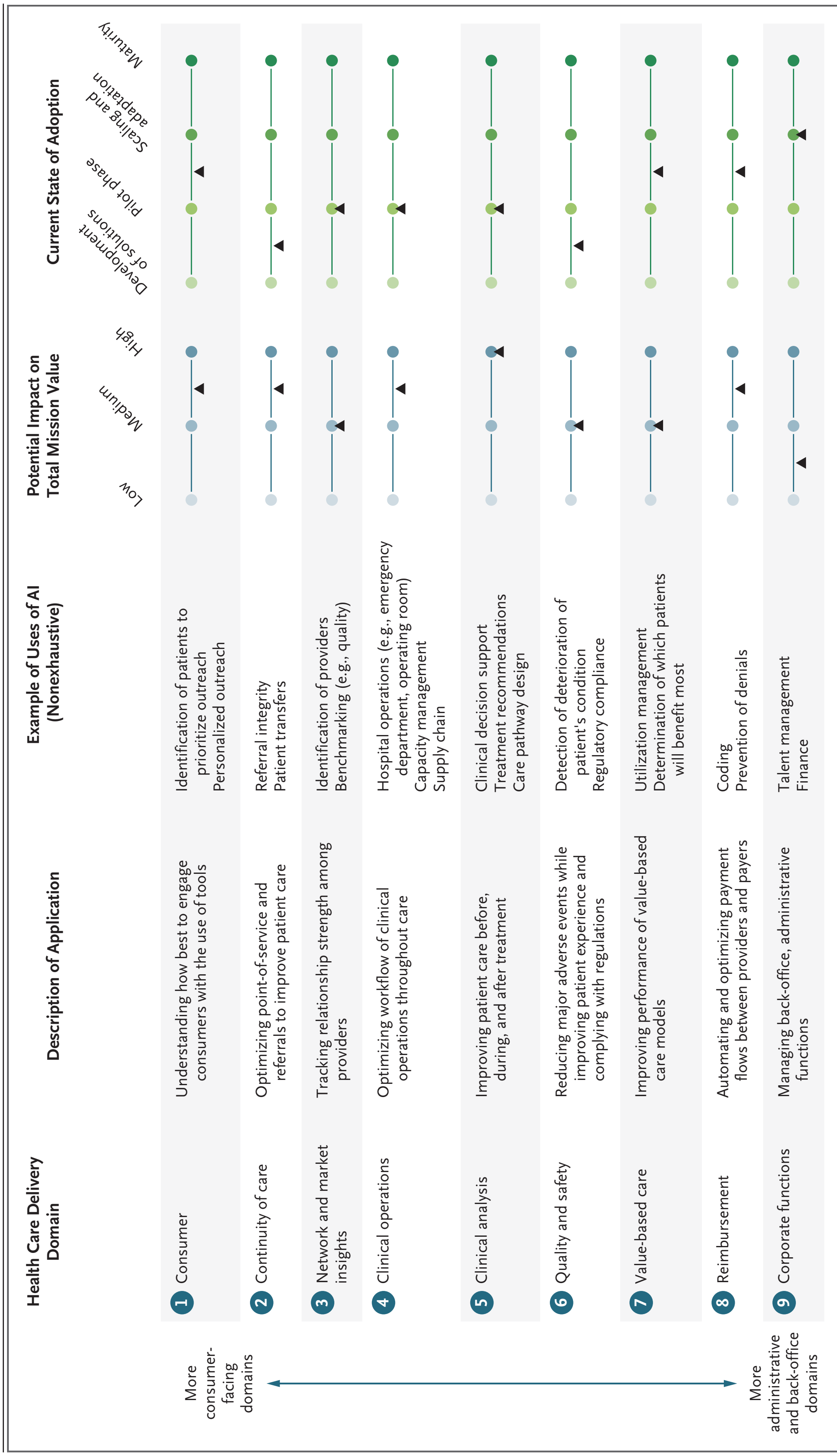

Figure 1. Examples of the Use of Artificial Intelligence (AI) in Health Care Delivery Domains.

Shown is a breakdown of health care delivery domains, with examples of AI use and the current view of its potential effect on total mission value and the state of adoption. Total mission value includes both financial and nonfinancial factors such as quality improvement, patient safety, patient experience, clinician satisfaction, and increased access to care.

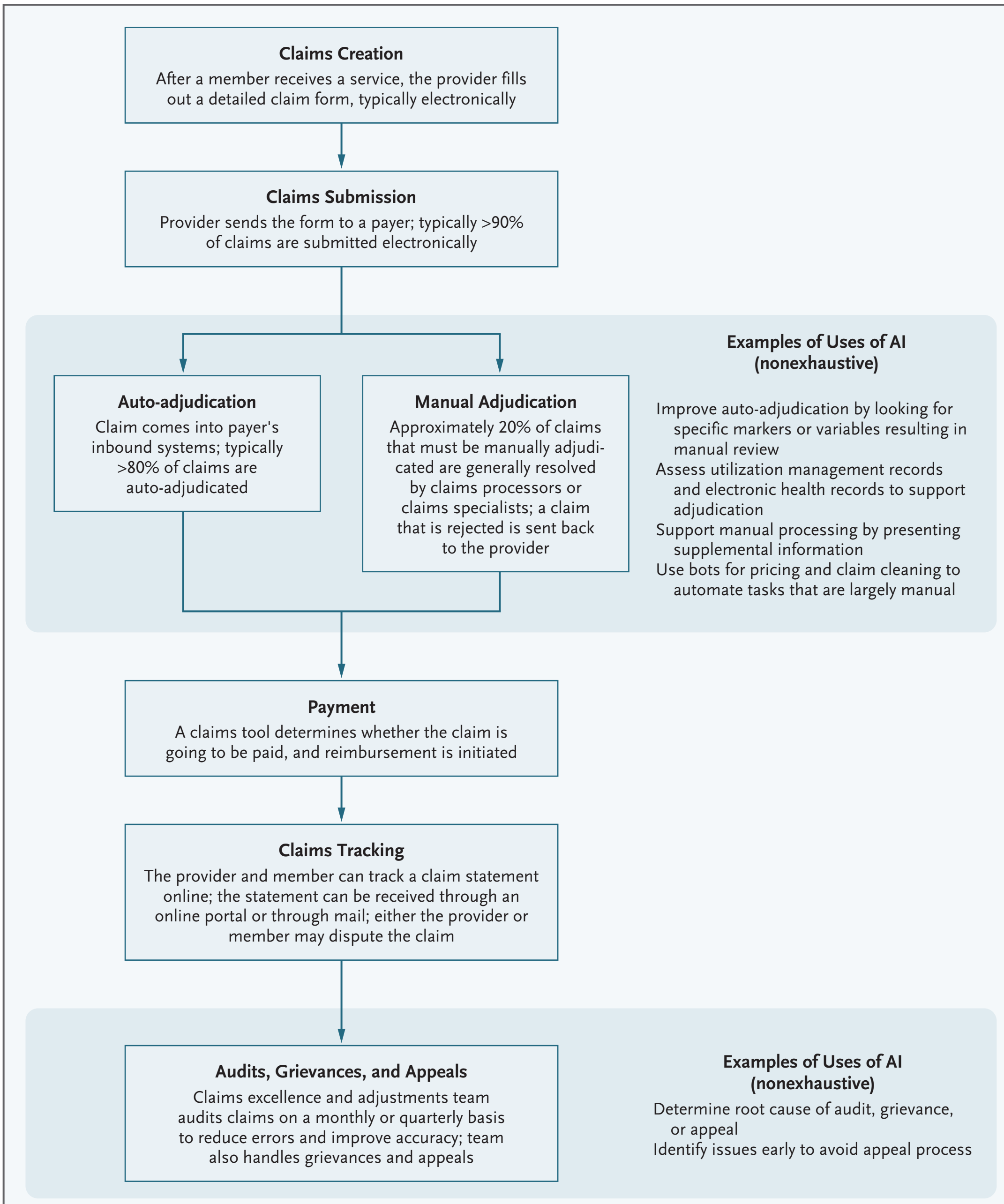

Figure 2. Use of AI in Claims Processing.

In the reimbursement domain, AI can be used at specific points in the processing of a typical claim. The information in this figure is from Sahni et al.[9]

erate cost savings and improve not only cash collection and yield but also the patient's experience. The effort began with a large data set (12 months of claims data representing millions of payer interactions), with a focus on more than 100 claims attributes. The system ran the data through a regression model to find those that correlated most closely with a denied billing claim. With this new predictive model, unsubmitted claims were then prerun, increasing the number of claims identified as likely to be denied by 33%, as compared with a retrospective baseline. In addition, the model identified the most likely root causes of claims denial, such as National Drug Code denial or a specific payer's policy. That health system now has a pilot program that uses the top 10 root causes to flag claims and address them before submission. Over time, the goal is to further develop the model to generate claims-specific root causes of denial and prevent billings from moving forward if they harbor these flaws. This could further improve the denied-claims record of the health system and potentially reduce the administrative spending needed for claims processing and reprocessing, all while improving the patient's experience by reducing the number of frustrating denials.

On the payer side, a large managed-care organization used AI to move from a traditional, labor-intensive model to an AI-based model, with the goal of eliminating upstream errors in a way that could reduce the need for manual claim adjudication. Thus, the organization trained a model that identified and weighted the factors that led to the need for manual intervention, such as specific procedure codes. The model continuously generated output that was based on relative manual effort. With the use of AI by the managed-care organization, the percentage of complex claims that were processed without denial increased from less than 80% to more than 90%. This reduced associated administrative spending by 30% and improved patient experience and clinician satisfaction.

AI is also being used in prior authorization, a process that involves substantial manual labor, with only 21% of prior authorizations automated.[9] The process can be costly because it requires doctors and registered nurses to review requests for authorization. From the payer's perspective, the objective is to ensure that patients are receiving clinically appropriate treatment. Therefore, prior authorization is meant to be a check on what the provider has ordered.

In an attempt to reduce friction in the system, one payer created an integrated, clean database with a sample that included member eligibility and benefits information, historical medical and pharmacy claims, and historical prior authorization requests with clinical decisions, appeals, and outcomes. These data were then fed into a triage engine that categorized requests into four levels of complexity on the basis of such factors as the level of detail shared, the plan member's clinical history, and the knowledge gained from processing similar requests. AI has already begun to reduce the number of steps in the process, as compared with traditional manual workflows, and the majority of low- and medium-complexity prior authorization requests are automatically approved. This has led to reduced turnaround times, more consistent clinical outcomes, and better overall experiences for patients and clinicians. With this foundation in place, the payer's long-term vision is to apply AI to further accelerate decision making.

CLINICAL OPERATIONS

Clinical operations is another health care delivery domain with expanding AI use. Although AI adoption is not as advanced in clinical operations as it is in reimbursement, the total-mission-value potential is similar, and AI has been an area of intense research in clinical operations (Fig. 1). Consider the operating room, one of the most critical assets for clinical care in a health system. The demand for operating rooms is traditionally high, so a missed surgical slot could result in a substantial increase in wait time, not to mention loss of revenue. Scheduling delays owing to surgeries that run longer than anticipated could also have a nonfinancial effect, such as a worse experience for patients and their families as they wait for an operation to end or for a procedure to begin. In health systems in the United States, more effective use of operating-room capacity can increase access to care, which is especially important today because of surgical backlogs and clinician shortages.

In our experience, operating-room optimization can occur in three steps: improving operating-room management, predicting operating-room use, and using operating-room analytics in real time (Fig. 3). Each step has the potential to provide an incremental benefit, but the final two steps are still in development, and their potential benefit is difficult to quantify.

The first step uses descriptive analytics, such as a histogram showing the distribution of operating-room times over the previous 30 days, to identify variations in scheduling. Health systems have used this approach successfully for many years.[11,12] This step has not traditionally involved AI use, nor has it been needed.

In the second step, AI starts to play a central role by predicting operating-room use. Preopera-

	Improving Operating-Room Management	Predicting Operating-Room Use	Using Operating-Room Analytics in Real Time
Level of AI Use	Limited		Predominant
Analytics Approach	Descriptive	Predictive	Prescriptive
Description of Analytics	Analyses of historical operating-room performance to identify and address variation	Predictions regarding preoperative cancellations, in-surgery risk, and postoperative complications	Models that translate predictions into systematic action, including real-time scheduling and reporting
Examples (Nonexhaustive)	Measured key operating-room statistics such as start time, surgical incision time, room turnover time, and patient turnover time (University Hospital, 1994) Measured key operating-room statistics such as start time, turnover, and unavailability (Medical University of South Carolina, 1998)	Predicted operations with high risk of cancellation (West China Hospital, 2018) Predicted risk of death during cardiac surgery (unidentified academic institution, 2020) Predicted duration of elective surgery (Gold Coast Hospital, 2017) Predicted postoperative major complications and death (University of Florida Health, 2019)	Simulated improvement in utilization by 19% and reduction of overtime by 10% (Mayo Clinic, 2015) Simulated reduction in post-anesthesia care unit holds without decreasing operating-room utilization (Lucile Packard Children's Hospital Stanford, 2018)

Figure 3. Use of AI in the Operating Room.
In the clinical operations domain, AI has been adopted for use in the operating room. Sources of information are Mazzei et al.,[11] Overdyk et al.,[12] Luo et al.,[13] Killic et al.,[14] Shahabikargar et al.,[15] Bihorac et al.,[16] Ozen et al.,[17] and Fairley et al.[18]

tive prediction analytics are focused on reducing cancellations and estimating mortality.[13,14] During surgery, predictions generally focus on the duration of the procedure and potential complications while it is being performed.[15,19] Finally, predictions about likely postoperative outcomes aim to identify major complications.[16]

The third step, using operating-room analytics in real time, can turn prediction into action. For example, AI would be used to build prediction of the duration of a procedure into precise scheduling, allow for the coordination of multiple operating rooms being used simultaneously, and integrate predictions such as likely surgery cancellations into operating-room optimization.[20] Organizations such as the Mayo Clinic and Lucile Packard Children's Hospital at Stanford have estimated that utilization would potentially be improved by 15 to 20% if AI were implemented.[17,18] However, this step remains largely in the pilot phase, and whether the improvements will be realized is not known.

Another use of AI in clinical operations is tackling clinician burnout.[21] Physicians now spend more than 50% of their time updating electronic health records (EHRs), and this use of time is a documented contributor to burnout.[22,23] Multiple providers are piloting natural language processing to reduce this burden. If these efforts are successful, natural language processing could turn unstructured data such as clinicians' notes into the structured data needed for the EHR as well as for other uses, such as documenting quality metrics or filling in appropriate Current Procedural Terminology codes. This application of AI would give clinicians more time to spend with patients and on tasks that require human judgment.

QUALITY AND SAFETY

Quality and safety constitute a domain in which a substantial portion of value comes from nonfinancial factors. The current level of adoption of AI in this domain is limited (Fig. 1), as is the evidence on the broad effect of AI on quality and safety, but two uses of AI, focused on patient safety and patient experience, show potential.

In the first use of AI, the objective with regard to patient safety is to reduce major adverse events — specifically, in cases in which current evidence-based methods are less useful in preventing and addressing complications and in which integration of complex, unstructured data with measurable metrics could help in making predictions. Adverse drug events, decompensation, and diagnostic errors have been identified as problems with the greatest potential for improvement with AI.[7] Tackling these problems requires the generation of actionable information. This process uses data from types of sensing technology, including vital-sign monitoring, wearables such as insoles in shoes, pressure sensors, and computer vision, to embed clinical alarms and reports in the workflow.[4]

For example, sepsis has become an area of focus in recent AI efforts, given the high mortality associated with this condition and the importance of early action (Fig. 4). One AI algorithm used EHR data in combination with blood pressure and heart rate measures to predict whether a given patient in the intensive care unit (ICU) might have sepsis.[24] A health system has used AI to monitor data such as vital signs and nursing reports. The AI output then links with clinical workflows to quickly alert hospital staff if a patient could be in trouble and appropriate clinical steps need to be taken to reduce risk. Over a period of 5 years beginning in 2014, this monitoring had reportedly saved approximately 8000 lives across the network of the health system.[25] Another approach used a broader predictive algorithm for clinical deterioration in the ICU; this algorithm reduced mortality in 21 hospitals.[26] In addition, a recent study showed that when a provider confirms an alert, mortality is further reduced.[27]

The second use of AI — to improve patient experience — can involve Consumer Assessment of Healthcare Providers and Systems (CAHPS), a program of the Agency for Healthcare Research and Quality that measures how patients experienced or perceived key aspects of their care, not how satisfied they were with their care. CAHPS scores are also tied to “star ratings” (a five-star scale, with one star representing poor performance and five stars representing excellent performance) for Medicare Advantage plans. One regional payer sought to identify its most dissatisfied members and to understand why they were dissatisfied. The payer used measures traditionally inferred from a variety of encounter, survey, and operational data, as well as assembled member-level data such as claims, enrollment information, call-center contacts, appeals and grievances, monthly member-survey data, and care management data. After identifying proxy variables for dissatisfaction, the payer ran regressions to determine variable significance and relationships.

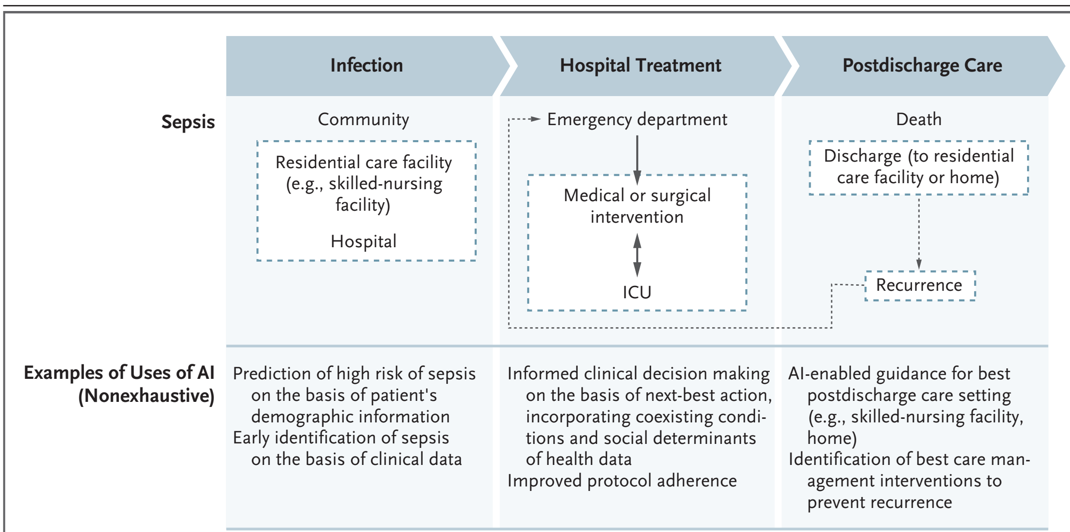

Figure 4. Use of AI to Predict and Manage Sepsis.

In the quality and safety domain, AI has been used in the detection of risk of sepsis and the care of patients with this condition. Boxes indicate areas of greatest potential AI impact. ICU denotes intensive care unit.

AI algorithms were then built to assess the likelihood of disenrollment and the sentiment score for all members. Members were clustered into similar segments and further assessed to understand important dissatisfaction variables in each cluster. This information was then used to prioritize and inform outreach, which improved members' experiences through better identification and resolution of their issues. Overall, the use of AI led to improved allocation of outbound call resources while addressing member challenges. CAHPS scores also improved, contributing to a four-star rating by the Centers for Medicare and Medicaid Services.

SLOW ADOPTION OF AI IN HEALTH CARE DELIVERY

The examples noted above from three domains show that the use of AI in health care delivery is developing and that in some situations, the technology has proved to be effective. Yet health care remains among the business sectors that have been slow to adopt AI.[28] Why is this so?

To answer this question, it is important to understand technology adoption. Generally, it follows an S curve: starting with the development of solutions, then piloting, followed by scaling and adaptation, and finally reaching maturity. In several business sectors, such as banking, AI is already reaching the maturity part of the S curve. In contrast, most of the domains in health care delivery are still developing solutions (quality and safety) or piloting them (clinical operations).

Adoption of AI in health care delivery is lagging behind for several reasons. First, given the many different sources and types of health care data needed, they are known to be more heterogeneous and variable than data in other business sectors (e.g., data to make a movie recommendation in Netflix).[29] This creates challenges in applying AI. Another major reason is the fee-for-service model of payment as compared with a value-based payment model. The latter payment structure would fund measures that improve care or make it safer, which is where the benefit of AI in health care delivery could be of substantial importance. Under a fee-for-service model, these incentives are substantially less prominent or absent altogether. Other documented reasons for the slow adoption of AI in health care delivery are lack of patient confidence, including concerns about privacy and trust in the output; regulatory issues such as Food and Drug Administration approval and reimbursement; methodologic concerns such as validation and communication of the uncertainty of a given AI-based recommendation or decision; and reporting difficulties such as explanations of assumptions and dissemination.[3,6,30-32] These factors will have to be addressed before long-term adoption of AI and full realization of the opportunity that it provides.

Issues within health care organizations may also account for the slow adoption of AI. These challenges must be addressed if AI deployment (a type of digital transformation) is to be successful.[33] We have found that this effort involves six categories encompassing strategic vision, key enabling factors, and implementation, each with specific health care delivery challenges to overcome, as shown in Figure 5.

For example, starting with a strategic vision, one of the greatest challenges is properly defining the costs and benefits of deploying AI. Historically, the decision to invest in AI has been based on financial return. This calculation should be expanded to include nonfinancial factors as well. Otherwise, AI adoption could continue to lag in certain domains in which a large portion of its effect is nonfinancial, such as quality and safety.

Organizations may underestimate the importance of data management, one of the most critical factors enabling successful AI adoption. Data management includes preparing data for use in the information technology system, addressing information gaps, setting up information so that biases are prevented, and ensuring enough availability to achieve scale. Addressing this challenge is not "one and done" but instead requires approaches for continuous testing and validation across multiple providers, geographic locations, and disease use cases.

Finally, implementation is critical for AI adoption within an organization. This category takes the most time and effort, and it is often shortchanged by organizations. One challenge is change management. For example, there may be agreement to move to prescriptive scheduling in the operating room, but the implications of this decision are quite different for a hospital administrator, the chief of surgery, individual surgeons, and the operating-room team. Thus, successful AI adoption is likely to require intentional actions that both help to effect behavioral change and

	Categories of Successful AI Deployment	Goal	Challenges
Strategic Vision	1 Mission-led road map	Ensure a clear view of where the value is going to be and a road map to get there	**Part of the Solution:** Ongoing belief that AI is a "silver bullet" rather than part of a broader solution **Transformative Potential:** Focusing only on the "incremental" opportunity rather than reimagining for the "transformative" potential **Total Mission Value:** Focusing only on financial factors rather than accounting for nonfinancial factors such as quality improvement, patient safety, patient experience, clinician satisfaction, and increased access to care **Focus:** Pursuing many domains rather than 1 or 2 "priority" domains with multiple uses of AI **Timing to Impact:** Misconception that AI is a "quick win" rather than a process that is implemented over multiple years
Key Enabling Factors	2 Talent	Ensure that the correct skills and capabilities are available to execute and innovate	**Skills:** Missing skill sets in workforce to implement and manage AI **Talent Road Map:** Lack of long-term plan for workforce hiring, upskilling, and reskilling as AI use expands **Education**: Underinvestment in making workforce AI-literate
	3 Agile delivery	Increase the speed at which teams are able to deliver work	**Culture:** Negative attitude toward AI or lack of consensus **Funding:** Limited ongoing funding to deploy AI
	4 Technology and tooling	Allow the organization to move quickly, with flexibility and resiliency	**Technology Infrastructure:** Inability to integrate AI into legacy systems, secure AI, or provide necessary computing power **Data Preparation:** Underinvestment in tools to properly prepare data
	5 Data management	Use data intelligence to derive a competitive advantage	**Completeness:** Inability to address data gaps with the use of internal or external sources **Unbiased Data:** Lack of awareness of inherent biases in data, such as data that are limited to one health system site **Availability:** Missing scale in the number of data points to train AI **Data Governance:** Governance to manage data is not formalized
Implementation	6 Change in operating model of the organization	Develop business processes, employee skills, and structures to realize total mission value	**Change Management:** Lack of recognition that translating strategic vision requires different behavior changes for everyone in the workforce, as well as coaching **Workflow Integration:** Failure to integrate AI into clinical workflow to minimize the behavior change needed **Cross-functional Teams:** Not creating fully cross-functional teams, such as clinicians, technologists, and operations professionals **Transparency:** Inability to overcome "black box" nature of AI, such as quantification of assumptions **Interpretable Output:** Not providing easy-to-understand output with relevant information to enhance decision making **Operational Governance:** Not creating a formal governance structure to oversee all aspects of implementation and ongoing management

Figure 5. Examples of Challenges to AI Adoption in Health Care Delivery Organizations.

A breakdown of categories of successful AI deployment and common challenges that organizations experience are shown. Sources of information are Rajkomar et al.,[3] Bates et al.,[6] Shaw et al.,[30] Singh et al.,[31] He et al.,[32] and Carey et al.[33]

address the details holistically, such as creating AI output visualizations that make interpretation easy for clinicians.

Another implementation challenge is workflow integration. The use of AI in clinical operations is more successful when it is treated as a routine part of the clinical workflow.[6,27] In essence, AI output is more effective when viewed as a member of the team rather than as a substitute for clinical judgment.

Although the challenges to successful AI deployment within an organization are real, they can be overcome. Efforts that can help include introducing demonstration projects that test many AI applications focused in a few domains, establishing a balance between building in-house capabilities and partnering with AI technology vendors to access economies of expertise, quantifying the total mission value, and aligning incentives to increase adoption. Investment will be required to achieve these ends. Across business sectors, the higher performers in AI adoption spend 30 to 60% more on AI than the lower performers. In addition, unlike the lower performers, the higher performers expect to continue to increase their AI adoption budgets as implementation takes place.[34]

CONCLUSIONS

AI adoption in health care delivery has lagged behind adoption in other business sectors, but the past few years have shown the potential and promise of AI, which has already begun to shape the operations of payers and providers in some areas. If the promise of AI is realized, the quality of and access to health care delivery will be improved. The promise remains, but realizing it in practice has not been easy.

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REFERENCES

1. Densen P. Challenges and opportunities facing medical education. Trans Am Clin Climatol Assoc 2011;122:48-58.
2. Patel N, Singhal S. What to expect in US healthcare in 2023 and beyond. McKinsey, January 9, 2023 (https://www.mckinsey.com/industries/healthcare/our-insights/what-to-expect-in-us-healthcare-in-2023-and-beyond).
3. Rajkomar A, Dean J, Kohane I. Machine learning in medicine. N Engl J Med 2019;380:1347-58.
4. Choudhury A, Asan O. Role of artificial intelligence in patient safety outcomes: systematic literature review. JMIR Med Inform 2020;8(7):e18599.
5. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med 2019;25:44-56.
6. Bates DW, Auerbach A, Schulam P, Wright A, Saria S. Reporting and implementing interventions involving machine learning and artificial intelligence. Ann Intern Med 2020;172:Suppl:S137-S144.
7. Bates DW, Levine D, Syrowatka A, et al. The potential of artificial intelligence to improve patient safety: a scoping review. NPJ Digit Med 2021;4:54.
8. Allen B, Agarwal S, Coombs L, Wald C, Dreyer K. 2020 ACR data science institute artificial intelligence survey. J Am Coll Radiol 2021;18:1153-9.
9. Sahni NR, Mishra P, Carrus B, Cutler DM. Administrative simplification: how to save a quarter-trillion dollars in US healthcare. McKinsey. October 20, 2021 (https://www.mckinsey.com/industries/healthcare/our-insights/administrative-simplification-how-to-save-a-quarter-trillion-dollars-in-us-healthcare).
10. Change Healthcare. The Change Healthcare 2020 revenue cycle denials index (https://www.ache.org/-/media/ache/about-ache/corporate-partners/the_change_healthcare_2020-revenue_cycle_denials_index.pdf).
11. Mazzei WJ. Operating room start times and turnover times in a university hospital. J Clin Anesth 1994;6:405-8.
12. Overdyk FJ, Harvey SC, Fishman RL, Shippey F. Successful strategies for improving operating room efficiency at academic institutions. Anesth Analg 1998;86:896-906.
13. Luo L, Zhang F, Yao Y, Gong R, Fu M, Xiao J. Machine learning for identification of surgeries with high risks of cancellation. Health Informatics J 2020;26:141-55.
14. Kilic A, Goyal A, Miller JK, et al. Predictive utility of a machine learning algorithm in estimating mortality risk in cardiac surgery. Ann Thorac Surg 2020;109:1811-9.
15. Shahabikargar Z, Khanna S, Sattar A, Lind J. Improved prediction of procedure duration for elective surgery. Stud Health Technol Inform 2017;239:133-8.
16. Bihorac A, Ozrazgat-Baslanti T, Ebadi A, et al. MySurgeryRisk: development and validation of a machine-learning risk algorithm for major complications and death after surgery. Ann Surg 2019;269:652-62.
17. Ozen A, Marmor Y, Rohleder T, Balasubramanian H, Huddleston J, Huddleston P. Optimization and simulation of orthopedic spine surgery cases at Mayo Clinic. Manuf Serv Oper. 2016;18:157-75.
18. Fairley M, Scheinker D, Brandeau ML. Improving the efficiency of the operating room environment with an optimization and machine learning model. Health Care Manag Sci 2019;22:756-67.
19. Devi SP, Rao KS, Sangeetha SS. Prediction of surgery times and scheduling of operation theaters in ophthalmology department. J Med Syst 2012;36:415-30.
20. Bellini V, Guzzon M, Bigliardi B, Mordonini M, Filippelli S, Bignami E. Artificial intelligence: a new tool in operating room management: role of machine learning models in operating room optimization. J Med Syst 2019;44:20.
21. Rotenstein LS, Torre M, Ramos MA, et al. Prevalence of burnout among physicians: a systematic review. JAMA 2018;320:1131-50.
22. Sinsky C, Colligan L, Li L, et al. Allocation of physician time in ambulatory practice: a time and motion study in 4 specialties. Ann Intern Med 2016;165:753-60.
23. Adler-Milstein J, Zhao W, Willard-Grace R, Knox M, Grumbach K. Electronic health records and burnout: time spent on the electronic health record after hours and message volume associated with exhaustion but not with cynicism among primary care clinicians. J Am Med Inform Assoc 2020;27:531-8.
24. Nemati S, Holder A, Razmi F, Stanley MD, Clifford GD, Buchman TG. An interpretable machine learning model for accurate prediction of sepsis in the ICU. Crit Care Med 2018;46:547-53.
25. HCA Healthcare. HCA healthcare using algorithm driven technology to detect sepsis early and help save 8,000 lives. May 16, 2019 (https://investor.hcahealthcare.com/news/news-details/2019/HCA-Healthcare-Using-Algorithm-Driven-Technology-to-Detect-Sepsis-Early-and-Help-Save-8000-Lives/default.aspx).
26. Escobar GJ, Liu VX, Schuler A, Lawson B, Greene JD, Kipnis P. Automated identification of adults at risk for in-hospital clinical deterioration. N Engl J Med 2020;383:1951-60.
27. Adams R, Henry KE, Sridharan A, et al. Prospective, multi-site study of patient outcomes after implementation of the TREWS machine learning-based early warning system for sepsis. Nat Med 2022;28:1455-60.
28. Cam A, Chui M,Hall B. Global AI survey: AI proves its worth, but few scale impact. McKinsey. November 22, 2019

(https://www.mckinsey.com/featured-insights/artificial-intelligence/global-ai-survey-ai-proves-its-worth-but-few-scale-impact).
29. Kruse CS, Goswamy R, Raval Y, Marawi S. Challenges and opportunities of big data in health care: a systematic review. JMIR Med Inform 2016;4(4):e38.
30. Shaw J, Rudzicz F, Jamieson T, Goldfarb A. Artificial intelligence and the implementation challenge. J Med Internet Res 2019;21(7):e13659.
31. Singh RP, Hom GL, Abramoff MD, Campbell JP, Chiang MF. Current challenges and barriers to real-world artificial intelligence adoption for the healthcare system, provider, and the patient. Transl Vis Sci Technol 2020;9:45.
32. He J, Baxter SL, Xu J, Xu J, Zhou X, Zhang K. The practical implementation of artificial intelligence technologies in medicine. Nat Med 2019;25:30-6.
33. Carey D, Charan R, Lamarre E, Smaje K, Zemmel R. The CEO's playbook for a successful digital transformation. Harvard Business Review. December 20, 2021 (https://hbr.org/2021/12/the-ceos-playbook-for-a-successful-digital-transformation).
34. D'Silva V, Lawler B. What makes a company successful at using AI? Harvard Business Review. February 28, 2022 (https://hbr.org/2022/02/what-makes-a-company-successful-at-using-ai).