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SPECIAL ARTICLE

Strategic Considerations for Selecting Artificial Intelligence Solutions for Institutional Integration: A Single-Center Experience

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Abstract

Artificial intelligence (AI) promises to revolutionize health care. Early identification of disease, appropriate test selection, and automation of repetitive tasks are expected to optimize cost-effective care delivery. However, pragmatic selection and integration of AI algorithms to enable this transformation remain challenging. Health care leaders must navigate complex decisions regarding AI deployment, considering factors such as cost of implementation, benefits to patients and providers, and institutional readiness for adoption. A successful strategy needs to align AI adoption with institutional priorities, select appropriate algorithms to be purchased or internally developed, and ensure adequate support and infrastructure. Further, successful deployment requires algorithm validation and workflow integration to ensure efficacy and usability. User-centric design principles and usability testing are critical for AI adoption, ensuring seamless integration into clinical workflows. Once deployed, continuous improvement processes and ongoing algorithm support ensure continuous benefits to the clinical practice. Vigilant planning and execution are necessary to navigate the complexities of AI implementation in the health care environment. By applying the framework outlined in this article, institutions can navigate the ever-evolving and complex environment of AI in health care to maximize the benefits of these innovative technologies.

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The use of artificial intelligence (AI) and related technologies, such as machine learning (ML), natural language processing, and large language models promise to transform the practice of health care.[1] Once implemented, these tools should improve patient quality of life and extend life expectancy through early diagnosis and treatment. These tools can also improve health care provider productivity and maximize time with the patient by minimizing clerical burden, such as time searching for data and test results in the electronic health record (EHR).[2]

As of 2023, the Food and Drug Administration (FDA) has approved over 700 algorithms for use in the United States—with over half of these approvals occurring since 2019.[3] This rapid increase of available AI tools not only provides an opportunity for enhanced health care delivery but also presents challenges. Specifically, health care systems need to prioritize deployment of these innovative technologies while adapting to this dynamic and highly regulated industry.[4]

Several different frameworks have been developed to guide the translation of AI algorithms from the research arena into clinical practice (eg, TRIPOD, DECIDE-AI, CONSORT-AI, and SALIENT).[5-8] These frameworks focus on reporting guidelines for the evaluation of AI algorithms and the application of these guidelines to clinical implementation. Clearly defining the steps involved in developing, testing, and deploying AI into a health care setting lays the foundation for integration of these new technologies.

Health care leaders also need to weigh the expense of creating, integrating, and maintaining AI tools with their quality, safety, and

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efficiency benefits. In many cases, incorporating these algorithms into clinical practice requires purchasing and installing new systems. In most cases, information technology (IT) support and user training is necessary. The associated expense to an institution can be considerable.[9] Unfortunately, with a few notable exceptions, no reimbursement is obtained from the use of these algorithms.[10] Therefore, appropriate selection of validated, clinically vetted AI solutions is crucial to optimize the use of these resources while realizing the promise of these transformative technologies.

This review provides a framework for institutional decision-making regarding translation of AI algorithms to clinical practice (Figure 1). Considerations for selecting AI use cases include determination of institutional readiness, assessment of cost and found benefit of the proposed solution, as well as internal expertise and enthusiasm to ensure user dissemination and early adoption. Although details may differ depending on the specific health care setting, this article describes the overall process at our institution, including real-world examples (Table).

INSTITUTIONAL READINESS

Considering the current enthusiasm for AI in health care, it would be natural to assume that hospitals and medical centers are well prepared to deploy these new technologies. However, even a well-resourced medical practice can benefit from a deliberate approach to AI implementation. In this section, we consider issues related to institutional alignment, engagement, and support—all of which are important to successful deployment of AI.

Alignment to Strategic Priorities

Given the lack of direct reimbursement for most of the available medical AI algorithms, institutional leaders may have to make some tough decisions regarding resource allocation. To support this decision-making process, it can be helpful for hospital leaders to consider their shared values and vision. In some cases, institutional priorities may guide decisions to build or purchase AI tools that advance a particular focus area. Understanding and communicating a shared vision can prevent needless discovery efforts that will not be supported by institutional investment.

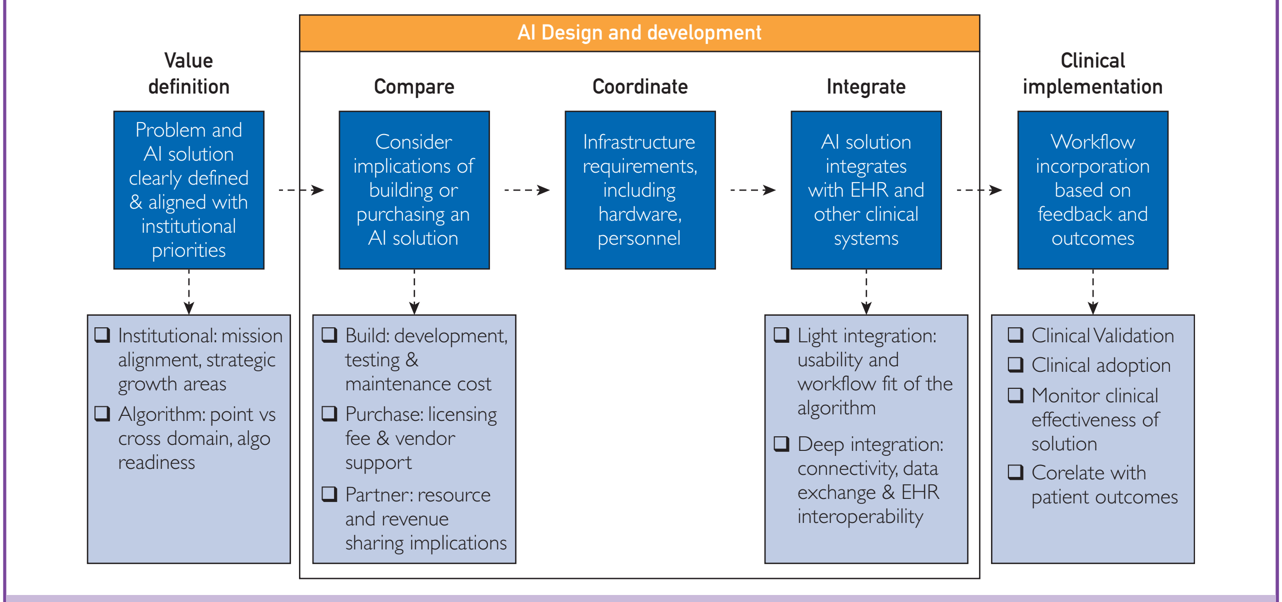

FIGURE 1. Process chart to show artificial intelligence (AI) integration tasks that lead to institutional decisions. The process from left to right shows the major decisions and thinking for institutions to take in their journey of integrating AI into clinical workflow. Not all solutions will spend the same time in each box. EHR, electronic health record.

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TABLE. Summary of a Framework for Strategic Considerations When Selecting AI Solutions for Implementation in a Health Care Setting
Institutional readiness • Alignment to strategic priorities • Staff engagement • Support and infrastructure • Risk mitigation and regulatory considerations
AI algorithm selection • Evaluation of algorithm value • Algorithm cost assessment • Algorithm validation
Ensuring user adoption • User-centric design, user experience, and usability • Contextualization and workflow integration • Continuous improvement and intuitive interfaces
AI, artificial intelligence.

For example, our institution has a stated priority for diagnosis and treatment of patients with "serious and complex" conditions.[11] As a result, we put a high value on AI solutions that focus on these specific types of diseases. One of our earliest AI deployments included an algorithm that analyzed electrocardiogram tracings to determine the likelihood of a patient having cardiac amyloidosis. Although this is a relatively rare diagnosis in the general population, Mayo Clinic is a high-volume referral center for this condition.[12] Having novel methods to predict cardiac amyloidosis risk is a priority for our practice, and implementation of this particular algorithm supports our prioritization of serious and complex care.

Similarly, our institution is devoting considerable efforts toward AI algorithms focused on diagnosis and management of patients with pancreatic cancer. Although the lifetime risk of pancreatic ductal adenocarcinoma is <2%,[13] we have several pancreatic cancer algorithms in various stages of development and deployment. Additionally, we have developed and deployed a specific delivery platform designed to display the results of some of these algorithms to our pancreatic surgeons in an appropriate clinical context. Although these sorts of initiatives are resource intensive, pursuing them is clearly aligned with our explicit institutional strategy.

In contrast, if an institution prioritizes screening of patients for common conditions, initial AI deployments might focus on algorithms that predict cardiovascular mortality risk from chest computed tomography.[14] A busy surgical center might consider an AI algorithm that predicts surgical outcomes based on sarcopenia assessment.[15] A center specializing in orthopedics might favor algorithms that determine fracture risk from hip images or computed tomography scans.[16] Selecting AI use cases based on institutional priorities helps align teams toward a common purpose. This approach also facilitates staff engagement, which is crucial to successful implementation of AI.

Staff Engagement

Staff engagement is a key factor throughout the process of AI implementation. Typically, the end user—or user group—serves as the initial proponent for a particular AI solution. Although some algorithms may be selected by leadership in a top-down fashion, most AI solutions in our practice are proposed and prioritized by clinical proponents working within the practice.

User engagement includes soliciting input and ongoing feedback directly from clinicians, administrators, and other stakeholders. Direct feedback and collaboration should happen while the stakeholder is interacting with the solution and within the clinical workflow. This provides better understanding of user requirements and allows institutions to tailor AI solutions to address specific clinical challenges in alignment with institutional priorities. The collaboration process needs to be stepwise and iterative to efficiently use stakeholder time devoted to solution improvement.

To be successful, institutions must support and encourage clinicians to be engaged and willing to provide responsive feedback. Feedback promotes AI training and validation, as well as workflow improvements. To encourage model training feedback, user interfaces must allow clinicians an iterative and intuitive way to respond.

Support and Infrastructure

Arguably, the most significant and costly institutional consideration is support and infrastructure. Although a full discussion of these infrastructure needs is beyond the scope of this article, there are some basic principles to consider.

Because AI is relatively new in the health care industry, there is little to no standardization among vendors. As a result, many health care institutions are struggling to integrate existing AI platforms into their IT ecosystem, whereas some are attempting to create their own internal platforms. Although most institutions have a robust EHR, not all institutions have a workflow and data infrastructure capable of transmitting the appropriate inputs (typically patient data) into the algorithms. Still, fewer have an environment that can run the algorithms and surface their results on a technology platform that integrates meaningfully with clinical workflows. Some vendors that sell AI algorithms offer a platform to run these algorithms, and in some cases, IT consulting is included to interface with the EHR. Although relatively simple up front, this situation can be difficult to scale and may become a cost barrier to implementation of AI. If an institution wants a vendor-neutral solution, the expense of creating the IT and data infrastructure remains an essential consideration.

Risk Mitigation and Regulatory Considerations

The FDA is rapidly adapting to AI in health care through updating its software as a medical device (SaMD) guidance to incorporate an action plan for AI and ML.[17] This gives guidance to AI developers on standardizing machine learning practices, encouraging transparency of AI to users, and raising awareness of the need to improve robust methods to monitor and address the impact of algorithm bias.

For off-the-shelf AI solutions, the FDA provides an approval process that includes the ability to streamline algorithm updates through a predetermined change plan. If the decision is made to develop AI/ML solutions internally, development teams have access to guidance documents from the FDA's website related to SaMD.[18] The main goal of the SaMD is to develop software that is safe and effective for patient care. Internal development teams should develop SaMD products with the same care and rigor as external vendors.

Health care is a highly regulated industry, and new technologies such as AI are correctly viewed with caution. A full discussion of regulatory issues in AI is beyond the scope of this article. For additional insights, please see the article by Vidal et al[19].

CONSIDERATIONS FOR AI ALGORITHM SELECTION

When selecting individual AI algorithms to deploy, multiple aspects of the solution should be considered, ranging from an estimate of clinical impact to possible regulatory consequences. To prioritize efforts, the problem to be solved should be well defined, and the overall value of each solution to the clinical practice should be assessed. Figure 1 presents a framework to consider these various priorities.

Point Solutions vs Cross-Domain Solutions: Implications for Implementation

Before prioritizing an AI algorithm for implementation, it is helpful to understand the scope of implementation. Currently, most FDA-approved AI algorithms fall into 1 of the following 2 broad categories: point solutions and cross-domain solutions. Algorithms in these 2 categories differ in the intended recipients of the information they produce, which can have implications for the strategies health care institutions use for deployment.

Point solutions are AI algorithms deployed and used within a specific department, division, or work area within an institution. The output of a point solution algorithm is intended to benefit the specific area where it originates, and the information generated by the AI is not directly communicated outside the work unit (Figure 2A, B). Such solutions usually have a lower cost of implementation but may be of more limited clinical benefit.

One example of a point solution is an AI algorithm used by pathologists to differentiate and count cells on a slide. The output of this algorithm is both produced by and used within the pathology department. A similar example would be an AI algorithm deployed in radiology to identify potential abnormalities on a mammogram during image interpretation. The output of this algorithm—AI-generated markers on a computer screen—is produced and used within the radiology department.

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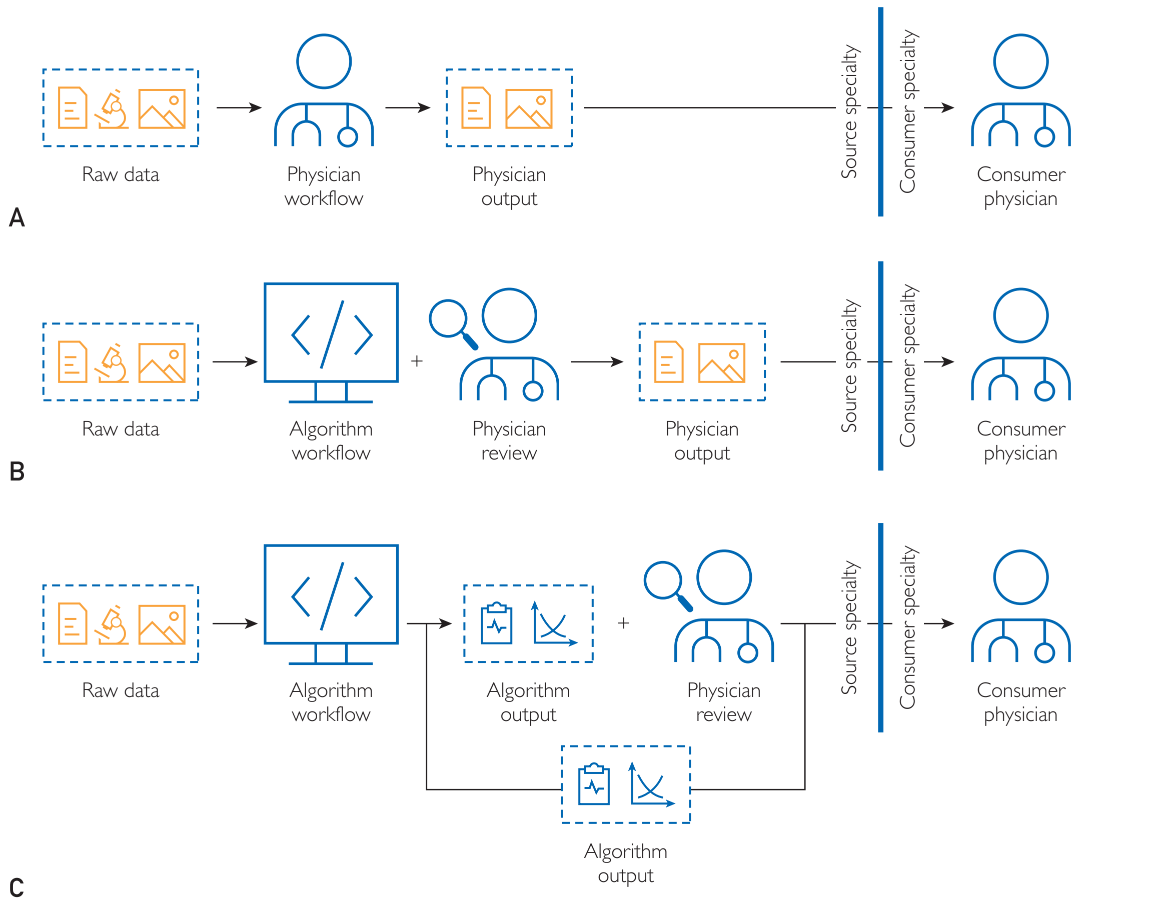

FIGURE 2. Illustrations of various integration patterns of artificial intelligence (AI) algorithms in clinical workflows. (A) Typical clinical consultant workflow without AI. (B) Integration of an AI point solution into a clinical consultant workflow. The information produced by the AI algorithm is incorporated into the consultant workflow, but not directly communicated outside the work unit. (C) Integration of an AI cross-domain solution. The information produced by the AI algorithm is communicated directly to clinical areas beyond the work unit to facilitate medical decision-making. This process can occur with or without a human-in-the-loop validation step.

These types of point solutions can improve accuracy and efficiency for the department where they are deployed and are essentially invisible to the downstream department that receives the result. Once the result is delivered, the ordering provider is more concerned that the result is accurate and timely rather than whether it was compiled using AI. In an ideal world, such solutions streamline time-consuming tasks and allow clinicians to focus on high value work.

Point solutions in health care can also improve the efficiency of nonclinical staff. Examples of such point solutions include using a large language models to generate marketing content, address common human resources questions, or produce a first draft of code for software programmers.[20] As with clinical point solutions, the focus of these algorithms is often to streamline routine tasks. Most of the current FDA-approved AI applications are intended as point solutions, and these are likely to continue to proliferate.

The decision to deploy a point solution can often be made within an individual department or division and institutional strategic planning is typically not required. The cost of implementation is typically straightforward to calculate and the increase in productivity after deployment should be measurable. If the algorithm does not provide sufficient value to justify its ongoing cost, it can be retested and revised or, subsequently, decommissioned.

In contrast to point solutions, cross-domain AI solutions are those in which the output of the algorithm is delivered to a specialty or subspecialty outside the work unit where the algorithm is deployed. In these cases, the information produced by the AI is used by multiple practice areas to facilitate medical decision-making (Figure 2C). Such solutions can have a greater clinical impact than point solutions but, frequently, require larger investment in infrastructure and support. Often, these solutions involve more complex downstream considerations such as delivery notifications, clinical follow-up, and management recommendations.

One example of cross-domain AI is an algorithm which analyzes electrocardiogram tracings to predict the likelihood of left ventricular dysfunction.[21] Although the results of the algorithm may be validated by a local cardiologist, the predictive output of the AI is conveyed to the downstream clinician as data to be incorporated into medical decision-making. This transmission of the AI-generated information outside the originating department is what makes this a cross-domain solution.

In some cases, the output of a cross-domain AI may not be clinically useful to the downstream provider by itself. Information from the patient's medical record may be necessary to provide the appropriate clinical context to interpret whether the AI result warrants clinical management changes and/or surveillance. For instance, an algorithm deployed in a radiology department to measure the volume of the spleen requires additional clinical data to be helpful to an oncologist taking care of the patient. A total spleen volume of 140 cm^2 has different implications in a 40-kg child than it does in an 80-kg adult. Additionally, tracking trends in spleen size over time may be important to assess progression of disease or response to therapy.

In such cases, providing clinical contextualization and workflow integration to realize the benefit of a cross-domain AI requires deeper integration with the EHR. This integration may require creating an infrastructure that captures the AI solution and contextualizes that result with additional patient or cohort information to create specific clinical recommendations (Figure 3). These types of solutions may also combine results from multiple AI algorithms across several different specialties and, ultimately, provide valuable management

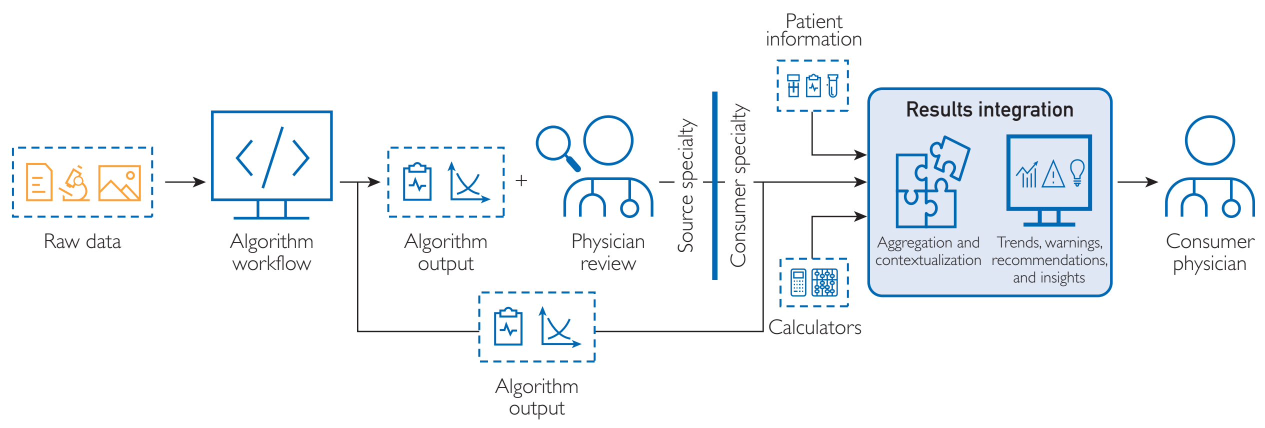

FIGURE 3. Clinical workflow including integration of cross-domain artificial intelligence (AI) algorithm output with information from the patient medical record and embedded calculator functionality. This contextualization of AI results requires deeper integration with clinical systems but can increase the impact of the solution by driving more personalized clinical recommendations. Additionally, aggregation of information from multiple clinical systems in combination with AI outputs can decrease clerical burden of providers and facilitate clinical decision-making.

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guidance at the point of care to busy clinical providers.

Unlike point solutions, the decision to deploy a more deeply integrated, multispecialty AI system usually requires institutional approval. The resources required to develop and implement this type of system, including training, maintenance, and support, are substantial, and the value to the practice of multispecialty AI extends beyond a single clinical department or division. As a result, institutional prioritization and decision-making becomes more complicated.

Assessment of AI Algorithm Value

Determining the value of an AI algorithm involves evaluating the impact on patients, medical staff, and support staff. From a patient care perspective, it is possible to estimate value by considering the number of patients likely to benefit from the AI algorithm. For example, a use case targeting a disease such as autosomal-dominant polycystic disease that affects approximately 500,000 people in the United States[22] has a different potential impact compared with a disease such as coronary heart disease that affected about 12.7 million adults in the United States in 2022.[23]

In addition to the total number of patients affected, it is helpful to understand how an AI solution could create value for these patients. Artificial intelligence algorithms have the potential to provide direct health benefit to patients through early detection, accurate diagnosis, or personalized treatment recommendations. Another possible benefit of AI to patients might be through streamlined care pathways that optimize diagnostic or treatment processes and reduce care variability by eliminating or reducing suboptimal referrals. Additionally, algorithms that identify previously undetected risks to patient health, such as early signs of disease progression or adverse drug reactions, can provide tremendous benefit to patients.

Some algorithms create more indirect patient benefits in terms of cost savings and/or efficiency gains for the health care system. Examples include algorithms that reduce clinical staff time in chart review, decision-making, and documentation. Additional cost savings can be realized through reduced administrative burden and reduced operational expenses by increasing resource utilization. These types of cost savings should be weighed against the additional costs required by support staff and infrastructure.

A crucial caveat to the implementation of point solutions is that benefit in a health care setting can be subjective. Artificial intelligence algorithms that decrease report turnaround time or increase clinical accuracy can often be measured. But, if the algorithm purports to improve quality of the patient or provider experience, it may be more difficult to quantify, particularly given that the impacts may not be realized within a short timeframe.

To ensure a deployed AI tool is useful to the practice, a rigorous postproduction monitoring system is necessary to track algorithm performance. This monitoring system should include user feedback, patient outcomes, and operational efficiency metrics to assess the AI solution's real-world impact. Continuous evaluation and refinement based on feedback and evolving clinical needs are vital for optimizing the tool's effectiveness and relevance over time and maximizing its value in improving patient care and clinical workflows.

Algorithm Cost Assessment

Although improving patient outcomes and reducing administrative burden are excellent goals, the costs and risks of algorithm implementation should also be considered. Cost is a particularly important consideration in health care owing to the previously mentioned lag in reimbursement for AI technologies. The costs described further are not unique as all software installations come with these inherent costs. However, because of the immaturity of AI in the health care industry, IT resources needed to build and maintain these systems may be increased compared with more traditional software solutions.

One important decision to be made when selecting a software solution is whether to purchase an existing product or to develop one using internal resources. Purchasing off-the-shelf AI solutions may involve licensing fees, whereas building a custom solution incurs costs for software development, data integration, and testing. Consideration should also be given to any hardware requirements necessary for deployment. Upgrading existing systems to support a new AI solution can represent a significant expense.

Whether off-the-shelf or custom, one important category of AI algorithm cost is the budget for IT personnel and infrastructure necessary to maintain and support AI solutions, including compensation for data scientists, software engineers, and system administrators responsible for managing and maintaining the AI system. Due to the explosion of AI, data scientists and AI scientists that also have a deep understanding of the health care industry are highly sought after[24] and recruiting for these positions can be a challenge.

To provide a concrete example, a typical department might start with AI scientists and data scientists that are needed to support them. To staff a lean discovery team consisting of 4 experts in AI, an institution would need to allocate salaries and support costs for these individuals. Owing to the current demand for these types of resources, it can be a lengthy process to find the best candidates for the institution's needs. Although there is some variability in salary range,[25] the cost to the institution can be considerable. This AI discovery team would need to show significant progress to justify this degree of expenditure. Institutions may also choose to invest in training of current staff to fill this need or use contracted resources. Regardless of the approach, developing these skills can become a cost consideration for health care institutions delving into AI.

In addition to personnel costs, there are significant expenses related to cloud computing services, storage, and networking. Artificial intelligence algorithms may require more intense processing power than other software solutions and such items are essential for supporting the algorithm workload.[26] Other support expenses for an AI program include software updates, patches, and upgrades to ensure the AI engine remains functional, secure, and compliant with evolving regulatory requirements.[27] Vendors attempt to package these for off-the-shelf products, but our experience is that even with vendor expertise, they must be supplemented with institutional staffing.

Regardless of whether an algorithm is built or purchased, the cost of interfacing between the AI solution and the EHR is essentially unavoidable. Clinicians rely on the EHR, and they tend to resist solutions that exist outside their workflow. These EHR integration costs include expenses for developing and maintaining connectivity solutions, ensuring seamless data exchange, and complying with interoperability standards.[28] Electronic health record vendors are currently adding AI to their platforms, which may relieve some of these costs for health care institutions in the future. Collectively, the infrastructure needs for purchasing or building an AI technology platform may be significant, especially if the institution would like to take advantage of cross-domain AI solutions.

Algorithm Validation

As an AI algorithm matures and becomes clinically ready, it needs to be validated. There are multiple steps in this validation process. We describe 3 crucial validation steps that are necessary to ensure the algorithm's eventual viability in the clinical setting.

First, technical validation confirms the intended functionality of the AI algorithm, ensuring accuracy, reliability, fairness, and robustness across diverse data sets.[29] This initial step is the minimum standard necessary for an algorithm to be considered for use in a health care setting.

Next, the algorithm undergoes clinical validation, which ensures the usefulness of the information provided in clinical decision-making by assessing efficacy and safety through comparison with clinical outcomes. Additionally, during clinical validation, the algorithm is tested on independent datasets and in different settings, providing further evidence of its equitable generalizability and reliability.[30]

Despite an AI algorithm proving highly effective by clearing these first 2 bars, caution is still necessary because of the substantial adoption barrier posed by end users. Even some FDA-approved algorithms have faced difficulties in adoption.[31] Thus, workflow validation is needed to assess the effective integration of the AI tool into the clinical workflow. This step examines whether the tool seamlessly fits into existing workflows, aligns with clinical practices, and provides value to health care providers that will translate into

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improved patient outcomes. Importantly, ensuring human oversight or involvement during the clinical workflow maintains accountability, fosters trust, and safeguards against potential errors or biases introduced by the algorithm.[32] By undergoing these 3 types of validation, AI algorithms demonstrate their technical functionality, clinical utility, and workflow integration capabilities, thereby increasing their viability and use in a patient care setting.

ADOPTION CONSIDERATIONS

Avoiding "Shelfware"

The successful integration of AI tools into EHR and clinical systems requires a holistic approach focused on understanding and meeting user needs, optimizing user experience (UX), usability, and seamless workflow integration. Prioritizing these principles ensures that AI implementation is not only effective but also seamlessly embedded into clinicians' everyday use patterns and mental models, ultimately enhancing patient care delivery. The usability metric for UX lite uses 2 questions to get at the heart of what any user wants: Did this tool meet your requirements? Was this tool easy to use?[33] Using user-centric design and UX best practices in both process and design increases the likelihood of implementation, adoption, and found clinical impact of new tools.

Avoiding shelfware frequently involves an iterative process of design, implementation, and user feedback. One example of this in our practice is our integrated polycystic kidney disease tool, which is used by our nephrology department to monitor patients with polycystic kidney disease and guide appropriate therapy. This tool continues to be improved through iterative user feedback, guided by the usability metric for UX questions.

User-Centric Design

User-centric design principles and processes—with an emphasis on processes—should guide the development of AI interfaces.[34,35] Iterative discovery and design processes, usability testing, and user feedback mechanisms are essential for identifying key user needs, workflow dimensions, and usability issues and refining AI interfaces to match clinicians' mental models effectively. Incorporating clinicians' input throughout the design process ensures that AI tools are intuitive, efficient, and aligned with their specific needs and workflows, ultimately enhancing user acceptance and adoption by solving their real-world problems.

UX and Usability

User experience and usability are fundamental to the successful integration of AI tools.[36] AI interfaces should prioritize simplicity, efficiency, and intuitiveness to facilitate seamless interaction for clinicians.[37,38] Clear navigation, concise feedback, and minimal cognitive load are essential for clinicians to effectively use AI-driven functionalities within their workflow. Incorporating principles of user-centered design ensures that AI tools align with clinicians' needs, preferences, and existing mental models, enhancing overall usability and user satisfaction.

Contextualization

For AI outputs to offer clinical value, it is helpful for the results to be presented at the appropriate timeframe and clinical context and workflow, while displaying appropriate supporting information. For instance, pairing an AI-derived coronary arterial calcification score with a risk calculator such as the Multi-Ethnic Study of Atherosclerosis (MESA) Risk Score and Coronary Age Calculator[39] and/or pooled cohort can help inform clinical action and shared decision-making.

AI results can be viewed through 2 distinct lenses with related contextualization needs as follows:

1. Known conditions or expected results: Clinicians anticipate results for conditions they are familiar with, such as assessing perioperative risk factors in surgical patients or measuring kidney volumes in patients with polycystic kidney disease. Specific, highly tailored information from the medical record can be combined with AI results to streamline clinical decision-making. When done correctly, this contextualization can reduce cognitive burden by surfacing the necessary information within a clinician's workflow, rather than forcing them to search through the EHR.

2. Unknown or unexpected findings: AI algorithms may reveal unexpected insights, such as an elevated risk for pancreatic cancer or undiagnosed atrial fibrillation. When this unexpected information is surfaced appropriately, it can be used as an opportunistic screening test to enable primary prevention. The method of notification, the accompanying information, and any decision support tools can be meaningful in helping a clinician take appropriate action.

In aforementioned both situations, expert clinician review is important to guide decision-making. In our experience, the results of AI algorithms need to be integrated into clinical care pathways in the same way laboratory tests, imaging findings, and genetic test results are today—keeping the patient's clinical context in mind. In the case of AI, the clinician should be able to flag suspicious results and provide feedback. When appropriate, this feedback can be used to improve the algorithm and/or mitigate the risk of drift.

Workflow Integration

Efficient workflow integration is paramount for the seamless adoption of AI tools in clinical settings.[40] AI solutions should be directly integrated into clinicians' daily workflows and seamlessly embedded into their everyday use patterns. This process involves aligning AI-driven functionalities with specific clinical tasks and ensuring interoperability with other health care IT systems. By integrating AI tools directly into clinicians' workflow and matching their mental models, health care organizations can optimize efficiency, reduce cognitive burden, and improve overall workflow performance.

The ultimate usefulness of AI lies in its ability to directly impact patient care or alleviate clinicians' cognitive load by providing added information in actionable ways or streamlining access to relevant data dispersed within the patient record. Understanding clinical workflows, user preferences, and mental models facilitates creating interfaces that prioritize the following:

- Contextual relevance: Presenting AI results alongside contextual data, such as trends or summarizations of patient notes, ensures informed decision-making. Clinicians highly value a "1-stop-shop" approach.
- Human oversight: Integrating mechanisms for clinician oversight, such as reviewing AI-generated draft notes with color-coded markers for quick evaluation, guards against potential biases and fosters clinician engagement.
- Shared decision-making support: Formatting AI results to facilitate shared decision-making processes enhances patient-centered care.

By seamlessly integrating AI into clinical workflows and UXs, health care institutions can harness AI's full potential while ensuring clinicians remain central to decision-making processes and patient care.

Continuous Improvement

Continuous improvement, intuitive user interfaces, and user training are crucial for optimizing UX and usability of AI tools over time.[41] Regular usability assessments, user feedback collection, and iterative design allow for ongoing refinement and enhancement of AI interfaces. Well-designed, intuitive interfaces greatly reduce the need for training for both new users and as an ongoing burden. Intuitive interfaces also make users more likely to use a tool, and it reduces cognitive burden while using it. As needed, comprehensive training and change management programs tailored to clinicians' skill levels and workflow requirements ensure proficient utilization of AI tools and promote user acceptance. By investing in continuous improvement, well-designed interfaces, and training initiatives that match clinicians; mental models and everyday use patterns, health care organizations can maximize the benefits of AI tools, ultimately enhancing patient care delivery and clinician satisfaction.

CONCLUSION

Although AI has the potential to transform health care delivery and improve patient outcomes, its implementation in clinical practice faces multiple challenges. These challenges include the following: (1) selecting appropriate use cases that align with institutional priorities and values; (2) validating AI algorithms for technical functionality, clinical utility, and workflow integration; (3) ensuring user-centric design and usability, and (4) developing a process for the iterative, continuous improvement of all AI tools. To overcome these challenges, health care institutions need to adopt a strategic approach that considers the costs, benefits, risks, and ethical implications of AI solutions.

Health care institutions need to collaborate with AI developers, vendors, regulators, and other stakeholders to ensure interoperability, standardization, and governance of AI systems. By addressing these challenges, health care institutions can harness the full potential of AI while ensuring clinician engagement, patient satisfaction, and quality of care.

Confirmation of institutional readiness, appropriate algorithm selection, and deliberate user engagement are all important considerations when implementing an AI strategy in a health care system. The framework described in this article reflects the approach we have used at our institution to navigate the challenges in our current environment, where standardization is low and risk is high. As AI in the health care industry continues to mature and grow, this seemingly complex environment should become easier for institutional leaders to navigate.

POTENTIAL COMPETING INTERESTS

Dr Blezek reports 25% stock interest in Flow Sigma. Dr Callstrom reports royalty from UpToDate; consulting fees from AstraZeneca, Replimune, Pulse Biosciences, and Varian Medical Systems; reports participation in the advisory board of Boston Scientific; and was the president of the Society of Interventional Oncology. The other authors report no competing interests.

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Abbreviations and Acronyms: **AI,** artificial intelligence; **EHR,** electronic health record; **FDA,** Food and Drug Administration; **IT,** information technology; **ML,** machine learning; **SaMD,** software as a medical device; **UX,** user experience

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