Received: 1 February 2022 | Accepted: 1 March 2022

DOI: 10.1111/poms.13850

POMS

SPECIAL ISSUE ARTICLE

Designing AI-augmented healthcare delivery systems for physician buy-in and patient acceptance

Tinglong Dai[1,2] | **Sridhar Tayur**[3]

[1]Carey Business School, Johns Hopkins University, 100 International Drive, Baltimore, Maryland 21202, USA

[2]Hopkins Business of Health Initiative, Johns Hopkins University, 100 International Drive, Baltimore, Maryland 21202, USA

[3]Tepper School of Business, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, Pennsylvania 15213, USA

Correspondence
Sridhar Tayur, Tepper School of Business, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, Pennsylvania 15213, USA.
Email: stayur@cmu.edu

Handling Editor: Subodha Kumar and Christopher S. Tang

Abstract

The role of artificial intelligence (AI) in augmenting healthcare is expected to grow substantially in future decades. Current research in medical AI focuses on developing, validating, and implementing point-level AI applications in an ad hoc manner. To harness the full power of AI to improve the patient experience and outcomes at a societal scale, however, requires a gestalt shift—with a systematic understanding of AI in the context of healthcare—and so results in its widespread adoption. This translates to four pillars of incorporating AI into healthcare workflow, including physician buy-in, patient acceptance, provider investment, and payer support (the "4Ps"). To achieve these 4Ps, it is imperative to design AI-augmented healthcare delivery systems in view of (1) how physicians integrate AI into their clinical practice and (2) how patients perceive the role of AI in healthcare delivery. This will in turn boost provider investment and payer support. In this paper, we draw from the literature to discuss a series of research questions, including barriers to physician buy-in and patient acceptance, transparency and disclosure, service design, and strategies for increasing AI uptake. We shed light on the principles of purposeful design for AI-augmented healthcare delivery systems and propose a research agenda for operations management scholars to consider as they continue to strengthen their engagement with both healthcare professionals and AI developers.

KEYWORDS

artificial intelligence (AI), service design, human–AI interaction, economics of AI, healthcare operations management

1 | INTRODUCTION

Contrary to popular belief, artificial intelligence (AI) is not the future of healthcare. It is already a *reality* in medicine, and its importance in improving healthcare delivery is expected to grow substantially in future decades (Rajpurkar et al., 2022). As evidence of medical AI being already here, the US Food and Drug Administration (FDA) had authorized over 300 AI-based medical devices as of June 2021 (FDA, 2021). Equally significantly, AI has been applied in various types of patient–physician encounters and has demonstrated satisfactory clinical outcomes in randomized controlled trials (Rajpurkar et al., 2022).[1]

For example, IDx-DR, an autonomous AI system based on a convolutional neural network algorithm, was approved by the FDA for clinical use in 2018 (Wolf et al., 2020). The purpose of IDx-DR is to automatically detect diabetic retinopathy (DR), a sight-threatening complication of diabetes that can result in vision loss and blindness. To be diagnosed as having DR, a patient would normally need to be referred by an endocrinologist or primary care physician (PCP) to an eye care professional (ECP) for a dilated diabetic eye exam, which may take up to 2 h. Using the autonomous AI system, by comparison, patients can be evaluated at a primary care facility with minimally trained human operators assisting in the capture of retinal pictures while AI provides rapid screening results in a matter of minutes. The AI system has been demonstrated to be able to achieve high accuracy, with an 87% sensitivity and 91% specificity in detecting DR, compared to a 35% sensitivity and a 95% specificity for clinical experts (Abràmoff et al., 2018; Wolf et al., 2020). More importantly, using AI for DR screening can significantly

Accepted by Subodha Kumar and Christopher S. Tang, after one revision.

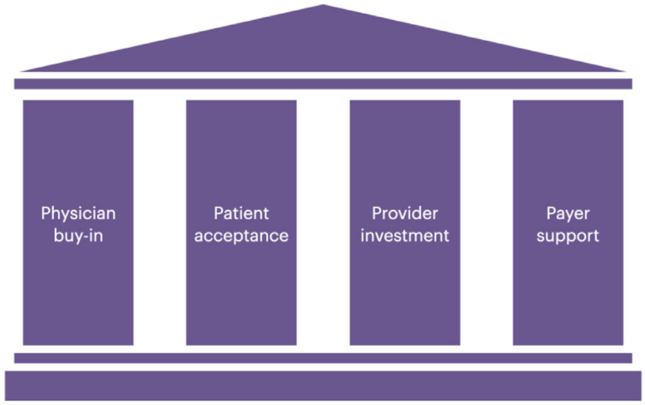

FIGURE 1 Four pillars of incorporating artificial intelligence into healthcare workflow [Color figure can be viewed at wileyonlinelibrary.com]

increase *patient adherence* to referrals (i.e., the percentage of patients with a positive screening result who will see an ECP) as evidenced by a recent study by Wolf et al. (2021) that shows 95% of patients receiving positive AI screening results chose to schedule visits with specialists for further diagnosis, compared to an adherence rate of 49% when they were only referred by PCPs and did not receive AI screening results.

Despite significant investments and efforts to develop AI applications such as IDx-DR and validate their clinical efficacy, their uptake in clinical practice remains low (Rajpurkar et al., 2022). To accelerate AI adoption and improve the patient experience and outcome, four pillars are required, which we refer to as the "4Ps" in this paper (see Figure 1): (1) physician buy-in, (2) patient acceptance, (3) provider investment, and (4) payer support. The last two elements are relatively well-understood as reflected in substantial investments made by major healthcare providers (especially academic medical centers) and insurance firms (Bohr & Memarzadeh, 2020). However, we have yet to achieve a good understanding of what motivates physicians' and patients' acceptance of AI systems, which is crucial for two reasons.

First, as Russell and Norvig argue in their classic textbook *Artificial Intelligence: A Modern Approach*, it is *physicians, not patients*, who ultimately decide whether and how to use AI in clinical practice (Russell & Norvig, 2015, p. 1051):

> In designing medical expert systems … the actions should be thought of not as directly affecting the patient but as influencing the physician's behavior. If expert systems become reliably more accurate than human diagnosticians, doctors might become legally liable if they don't use the recommendation of an expert system.

Second, the ultimate goal of AI-augmented healthcare is to improve patient outcomes and experiences. Patients are not passive recipients of medical attention (Andritsos & Tang, 2018). Rather, they observe, infer, and experience each care episode, and their trust in physicians and the healthcare delivery system as a whole has a significant impact on the quality of care. Thus, physicians and healthcare leaders need to design AI-augmented systems with patient experience in mind (Agarwal et al., 2022; Dai et al., 2021).

To attain these 4Ps requires a systematic perspective on how AI impacts a patient's experience through each episode of care. For example, if a physician decides to use an AI tool to diagnose a patient's condition, the patient may draw from that decision to form an opinion about the physician's skill level or, in certain situations, about the amount of effort the physician puts into the diagnostic process (Adida & Dai, 2022; Dai & Singh, 2020). In anticipation of the patient's perception, the physician may opt to use (or not use) AI in ways that are not necessarily in the patient's best interests. Another example is the argument that as AI gets more precise, physicians should be held accountable for patient harm if they make suggestions that deviate from what the AI proposes (Price et al., 2019; Russell & Norvig, 2015). However, the implication of such a proposition is that physicians may intentionally avoid using AI—even when AI can help mitigate uncertainty by providing a second opinion—because doing so increases their liability when adverse patient outcomes occur (Dai & Singh, 2021).

Without understanding and purposefully incorporating these considerations, we may end up with healthcare delivery systems in which AI is underused, overused, or misused (Fihn et al., 2019), jeopardizing the prospect that collaborative human and machine intelligence can help mitigate uncertainty, which is a key feature underlying many healthcare problems (Arrow, 1963). For instance, in anticipation of potential liability associated with the use of AI, physicians may limit their use of AI to low-uncertainty cases where AI tends to confirm, rather than contradict, physicians' diagnoses (Price et al., 2019).

Our paper echoes the operations management community's growing recognition of the critical role of behavioral, incentive, and policy considerations in healthcare operations (Dai & Tayur, 2018). The 4Ps framework echoes the perspective of the healthcare ecosystem, according to which AI is part of the "circle of innovation," which can only have a positive impact on healthcare delivery when it is integrated into the financing structure, policy environment, and delivery models (Dai & Tayur, 2020). Recognizing how AI is used in practice has ramifications beyond service design, as it informs health policy, physician compensation schemes, and healthcare financing.

The remainder of the paper begins in Section 2 with a discussion of several considerations that may constitute barriers to physician buy-in and patient acceptance of medical AI. Section 3 examines service sequencing, drawing from the service operations literature and recent advancements in medical AI. In Section 4, we discuss whether patients should be informed about the use of AI. Section 5 examines the role of financial incentives in motivating physicians to use AI appropriately to improve healthcare delivery. We conclude in Section 6.

2 | BARRIERS TO PHYSICIAN BUY-IN AND PATIENT ACCEPTANCE

In this section, we discuss three key barriers to physician buy-in and patient acceptance of medical AI, including legal liability, reputation concerns, and uniqueness bias. Although our discussion does not address all of the reasons preventing the wider use of medical AI, it builds on prior research and has implications for the operations management topics discussed in the remainder of the paper. For each of these barriers, we spotlight research opportunities for operations management scholars.

We begin by considering a medical diagnosis problem in which a patient seeks medical advice from a physician to determine whether he or she has a medical condition. The physician has access to AI but may or may not use it in the diagnostic process. Suppose the patient's prior probability of having the medical condition is p, which is a value between 0 and 1. If p is close to 0 or 1, diagnosing the patient is associated with little uncertainty. When p is intermediate (i.e., close to 0.5), the patient is in a state of high uncertainty. While one might expect the physician to use AI primarily for patients with intermediate p, there are at least three reasons why the physician might not do so.

2.1 | Legal liability

One reason that physicians might avoid using AI in high-uncertainty cases (corresponding to patients with intermediate p) is that as Price et al. (2019) point out in a seminal *JAMA* article, doing so may expose physicians to liability that they would not otherwise face. Traditionally, adhering to the standard of care shields the physician from liability even when adverse patient outcomes occur. When the physician uses AI, the situation changes. In the past few years, both AI and medical practitioners (e.g., Russell & Norvig, 2015; Sullivan & Schweikart, 2019) have argued that as AI becomes more precise, physicians may face legal consequences if they deviate from AI's advice. For example, if AI suggests a treatment plan that differs from the standard of care, the physician may be held liable for potential harm if he or she continues to use the standard treatment plan despite AI advice. Because of such legal implications, the physician may avoid using AI in the first place, especially in cases of high uncertainty in which the physician is most likely to disagree with AI advice. Ironically, such high-uncertainty cases are also the ones for which AI can potentially help patients the most.

Inspired by Price et al. (2019), a recent stream of literature (Pezzo et al., 2022; Price et al. 2021; Tobia et al. 2021) uses scenario experiments to test potential jurors' perceptions of physician liability when using AI in medical decisions. These studies back up some of the key points made by Price et al. (2019), such as the physician's ability to avoid legal liability by agreeing to AI advice. However, these studies are not in full agreement with Price et al. (2019) regarding whether legal concerns will deter physicians from using AI.

Theoretical and empirical studies about the legal implications of using AI in medical practice are scant. Using a decision-theoretical framework, Dai and Singh (2021) analyze a physician's decision with regard to whether to use AI under various emerging liability schemes. Their findings support the concern that physicians may avoid using AI for high-uncertainty cases that would benefit the most from it due to legal liability concerns. They also show that, rather counterintuitively, as AI improves in precision, physicians may have a *stronger* incentive to avoid using AI in their medical practice.

We are only now beginning to grasp the legal ramifications of physicians' using AI in screening, diagnostic, and treatment decisions. It is worth noting that all of the current experimental studies have focused on determining liability after a physician has used AI. Future experimental and empirical studies can investigate how physicians consider such factors when deciding whether or not to use AI. To the extent that AI can help improve outcomes, future research may uncover a policy solution to encourage AI adoption, namely, designing a liability regime that induces physicians to use AI in a way that reduces clinical uncertainty rather than confirming their own intuition.

2.2 | Reputation concerns

Physicians value their reputation among peers and patients not only for the boost to their self-esteem but also for the increased income, career prospects, and speaking and consulting opportunities that come with having a strong professional reputation (Navathe & David, 2009). Conceivably, physicians may have an incentive to choose their practice styles to manage others' perceptions of their skills and, as a result, their professional reputation.

While it is unknown how using AI affects a physician's reputation, previous research alludes to the prospect that if a physician uses AI extensively, he or she may be deemed to have low (or redundant) skills. In the context of computer-assisted diagnosis, a body of literature (e.g., Arkes et al., 2007) indicates that physicians who use computer-based diagnostic aids are frequently regarded as inferior diagnosticians by their peers and patients, whereas physicians who diagnose without using these digital tools are regarded as highly skilled diagnosticians. Interestingly, this reputational effect persists even among patients who work in information technology (J. R. Wolf, 2014).

Aligned with the above experimental findings, Dai and Singh (2020) show in a theoretical investigation that physicians' decisions to use (or not use) AI give them opportunities to influence peer perceptions of their diagnostic abilities. To that end, the desire to appear highly skillful can lead physicians to underuse AI for high-uncertainty cases (i.e., those with intermediate p). This underutilization of AI is not solely motivated by physicians' self-interest: Physicians who are more altruistic may be more likely to forego AI even when it is beneficial to patients. Nor is it about financial incentives: Attempts to incentivize the use of AI may unintentionally exacerbate such avoidance behavior.

In the context of medical AI, various research opportunities exist to better understand how the use of AI affects an observer's perception of a physician's skill level as well as how such perceptions influence the physician's decision to use AI. While behavioral experiments are a natural starting point, more systematic data collection efforts can result in large datasets that can be used to conduct rigorous empirical research. In addition to behavioral and empirical research, operations management scholars can continue to develop theoretical models that inform optimal design principles while taking into account reputational concerns associated with the use of medical AI in healthcare delivery.

2.3 | Uniqueness bias

Despite the promise of more personalized and precise healthcare (Ayvaci et al., 2018; Hopp et al., 2018), there is a common perception that AI is inferior to human physicians because it provides less customized medical advice relevant to the individual patient and is simply a statistical result based on the relevant population (Yokoi et al., 2021). Additionally, a recent experimental study by Longoni et al. (2019) reveals that patients who perceive themselves to be more unique than others tend to avoid medical AI in favor of the human touch provided by physicians.

Valuing uniqueness poses a significant challenge for neoclassical economics, as it requires modeling consumers' multidimensional, incommensurable, and frequently subjective preferences for products and services such as movies, books, homes, legal advice, and physician services (Karpik, 2010). Currently, no rigorous economic models exist for predicting unique individual expectations for healthcare services in the presence of AI.

This gap in the literature creates numerous research opportunities that can help address the following questions: What factors influence individuals' perceptions of their own uniqueness when it comes to healthcare? Can the uniqueness bias be mitigated through the use of another AI tool? Is the uniqueness bias applicable to all types of services or only to a subset of them? How can healthcare providers develop an AI strategy while taking into account the preferences of various types of consumers for AI versus human doctors (or, in certain cases, AI-assisted humans vs. human-assisted AI)? To tackle these questions, it is likely that a combination of theoretical, empirical, and experimental approaches will be required.

Before concluding this section, we summarize key research questions related to each of the three potential barriers to AI adoption in Table 1.

TABLE 1 Research questions related to barriers to artificial intelligence (AI) adoption

Barrier to AI adoption	Research questions
Legal liability	1. How physicians consider liability concerns when deciding whether to use AI 2. How to design a liability regime that induces physicians to use AI in the most beneficial way possible?
Reputation concerns	1. How the use of AI affects an observer's perception of a physician's skill level as well as how such perceptions influence the physician's decision to use AI 2. How to design AI-augmented healthcare by considering reputational concerns associated with the use of AI?
Uniqueness bias	1. What factors influence individuals' perceptions of their own uniqueness when it comes to healthcare? 2. Is the uniqueness bias applicable to all types of services or only to a subset of them? 3. How can healthcare providers develop an AI strategy while considering the preferences of various types of consumers for AI versus human doctors?

3 | TRANSPARENCY AND DISCLOSURE

Before delving into design principles for AI-augmented care, we briefly discuss the issue of AI-use transparency. It is often unclear in clinical practice whether the physician has used AI during a care episode. Whereas the issue of AI-use transparency, or lack thereof, is not unique to the healthcare industry, it has received less attention than in other consumer-oriented service industries.

In the literature on non-medical AI, discussions of the lack of transparency usually revolve around the use of chatbots. With today's AI technologies, it is still possible to distinguish between a chatbot and a human agent. Yet, "the problem that we face is not that AI is so convincing that a committed person cannot identify it as synthetic. Instead, the problem is that the time required to do so is prohibitive" (Engler, 2020). In some instances, customers are unaware that they have been interacting with chatbots for an extended period of time. Unidentified chatbots can be as effective as salespeople, but their effectiveness drops by nearly 80% once their identity is revealed, according to a recent study (Luo et al., 2019). Given the low variable cost of deploying AI in customer service scenarios, businesses clearly have an incentive to use chatbots without disclosing their existence, even if it means violating consumers' right to know (Engler, 2020).

Healthcare presents a unique set of challenges and concerns. One cannot rule out the possibility that unethical healthcare providers will use AI to manipulate patients' perceptions of the necessity of costly but unnecessary medical procedures.[2] When such manipulative behavior occurs, it may result in unnecessary care or adverse patient outcomes. As AI becomes more easily integrated into healthcare via telemedicine, which has gained a vast increase in utilization since the onset of the Coronvavirus Disease 2019 (COVID-19) pandemic (Friedman et al., 2022), we believe that disclosing the use of AI is critical, particularly if AI is shown to increase the occurrence of such manipulative behavior. Future research may shed light on the dangers of unethical providers manipulating AI-powered systems in a variety of patient care contexts.

In addition, using AI in healthcare without disclosing its existence may raise concerns about privacy, data collection and transfer, and patients' right to know. Related to these concerns is the critical issue of patient trust. If a patient is uncertain about the use of AI in healthcare delivery, how does this affect the patient's perception of care quality? How does the disclosure of AI use affect patients' trust in the physician and healthcare delivery system? Answering these questions necessitates a policy analysis of the benefits and drawbacks of requiring physicians to disclose their use of AI in clinical practice. Research in this area will contribute to the operational transparency literature (e.g., Bray, 2020; Buell et al., 2017), which has established the benefits of operational transparency in various service operations settings without taking into account how the presence of AI systems affects the overall service experience.

On a more fundamental level, even though trust is a well-studied subject, the majority of the trust literature in operations management focuses on the context of buyer–seller transactions in non-healthcare supply chains (Brinkhoff et al., 2015; Ebrahim-Khanjari et al., 2012; Özer & Zheng, 2018). Notwithstanding the importance of patient–physician trust in the era of AI (Armstrong, 2018), both the definition and measurement of trust in clinical encounters remain ambiguous (Hall et al., 2001). The examination of whether to disclose the use of AI will provide a promising basis for developing a better understanding of key determinants of trust in the context of healthcare delivery.

4 | SERVICE DESIGN FOR AI-AUGMENTED CARE

AI-augmented healthcare is essentially a service process consisting of multiple activities that lead up to a diagnosis, treatment, or advice. These activities, taken together, can be viewed as a *service package* (Goldstein et al., 2002), which can be defined as a series of service activities organized in a specific sequence to provide a service experience to customers. Thus, how to sequence such activities is a research question that requires careful examination of various behavioral, incentive, and operational considerations.

The service operations literature has studied the problem of service sequencing (e.g., Das Gupta et al., 2016; Li et al., 2021) in the absence of the AI context. The behavioral effects of memory decay (i.e., the remembered utility of an activity declines with the passage of time) and acclimation (i.e., given the same average utility, customers prefer positively changing utilities to a constant utility) are the primary considerations in this literature.[3] The broadly defined operations management community has only recently started examining service sequencing in the context of AI-augmented healthcare (Singh & Dai, 2022).

Consider a scenario in which a patient is evaluated by both an AI system and a physician to determine whether the patient has a specific medical condition. The AI system is more sensitive than a physician, but it is also slightly less specific (R. M. Wolf et al., 2020). As a result, the patient may benefit from being diagnosed by both AI and the physician. Prior studies have examined the scenario of using autonomous AI to screen patients prior to referring them to specialists (R. M. Wolf et al., 2020; Xie et al., 2020). However, specialists increasingly turn to AI before making final diagnostic decisions, creating a "physician-in-the-loop" situation. When a patient is seen by both a physician and AI, how *sequencing* impacts demand for AI-assisted care, patient perception of service quality, and patient outcomes in a system has yet to be studied. We organize our discussions of service sequencing according to whether the patient interacts with the physician first or with AI first.

4.1 | When the patient sees the physician first

We consider the case in which the patient sees the physician first. In this case, the physician must make several decisions, including, for example, whether to conduct a detailed or brief consultation. A thorough consultation allows the doctor to better understand the patient's risk level, but it may require the physician to "perform an extensive clinical record review, listen comprehensively and gather history from patients and families, engage in collaborative consultations with all relevant specialists, generate multispecialty team discussions, use diagnostic decision support and other online knowledge resources, and explore the published literature in depth," which may not be observable or reimbursable (Berenson & Singh, 2018, p. 1830). In other words, the physician faces the decision of how much effort to expend in diagnosing a patient. The presence of the AI option suggests that the physician may lean on AI and reduce the diagnostic effort for at least some patients. While the problem of endogenous diagnostic effort has been studied in the healthcare operations management literature (Adida & Dai, 2022), the literature has yet to examine the physician's diagnostic effort decision in light of the possibility of using AI.

An AI-augmented physician's diagnostic effort is far from the only decision he or she must make. For example, the physician must determine which patients should be seen by AI. As mentioned in Section 2, the decision to use AI or not use AI can be influenced by a variety of non-clinical factors such as reputational concerns, legal liability, and patients' uniqueness bias. As a result of these factors, the physician may avoid using AI, even if it provides value in high-uncertainty cases.

If the physician uses AI, how the physician applies his or her own judgment as well as the AI's output will have a significant impact on the accuracy of the diagnosis. Conceivably, the physician's pre-AI judgment may have an anchoring effect on how the physician interprets the AI output and may, in some cases, lead to the dismissal of AI signals that could have led to a more accurate diagnosis (Singh & Dai, 2022).

4.2 | When the patient sees AI first

If the system requires the patient to interact with AI first, the AI avoidance issue (see Section 2) is no longer relevant. However, how the physician uses the AI output affects whether patients trust the diagnostic outcomes and follow the physician's medical advice.

First, it is unclear whether the physician should have access to the AI output. Having access to the AI output, intuitively, can aid the physician in streamlining the diagnostic process. However, significant anchoring effects have been reported in the literature (Gaube et al., 2021; Jussupow et al., 2021)—when AI provides an incorrect diagnosis, the physician is more likely to misdiagnose as well. Furthermore, with a negative AI diagnosis, the physician is more likely to examine a case perfunctorily, if not skip it entirely. In this case, AI may end up becoming a gatekeeper rather than an assistant as it is sometimes designed to be.

Second, *how* the physician utilizes the AI output warrants further investigation. In a case study about incorporating AI into radiologists' clinical workflow, Jones (2021) documents a situation in which AI detected signs of pulmonary embolism (PE) that radiologists missed. However, radiologists frequently have to exert some effort to confirm a missed PE diagnosis. When the requirement for confirmatory effort is combined with the fact that AI frequently reports false-positive findings, radiologists may choose to disregard AI's findings, a phenomenon similar to the phenomenon of alarm fatigue that is frequently documented in various healthcare contexts (Laker et al., 2018; Mitka, 2013).

Finally, in a resource-constrained setting, particularly in many poorer countries with a scarcity of specialists, allowing patients to consult AI first may help expand access to healthcare while allowing specialists to focus on high-uncertainty cases. Simultaneously, this may increase the likelihood that patients who visit specialists will receive a false positive diagnosis, given that they previously received positive screening results. This may also raise concerns about fairness, as many patients may receive false-negative results as a result of AI alone, without the opportunity to consult specialists to confirm the results.

As summarized in Table 2, healthcare providers should weigh the benefits and drawbacks of the "physician-first" (see Section 3.1) and "AI-first" (see Section 3.2) approaches before deciding on the optimal service sequence. It is worth noting that the optimal sequence is not necessarily a one-size-fits-all strategy. Singh and Dai (2022) demonstrate how the optimal service sequence of an AI-augmented diagnosis system can vary according to the degree of ambiguity in each case as well as the cost of visits. In addition to theoretical analysis, healthcare providers may wish to conduct scenario experiments and empirical analyses of available patient experience data to determine the effect of service sequencing on patient satisfaction.

TABLE 2 Research agenda related to service sequencing

Service sequencing	Research agenda
When the patient sees the physician first	1. Understanding the physician's decision regarding the diagnostic effort before deciding whether to use AI 2. Understanding the physician's decision regarding whether to use AI, which may be influenced by both clinical and non-clinical factors 3. Understanding how the physician interprets the AI output, which may be anchored by the physician's clinical judgment formed prior to using AI
When the patient sees AI first	1. Analyzing whether the physician should have access to the AI output before seeing the patient 2. Understanding how the physician utilizes the AI output, especially when AI frequently reports false-positive findings 3. Investigating the possibility of using AI as a gatekeeper to expand access to healthcare

5 | INCENTIVES AND NUDGE TO BOOST PATIENT ACCEPTANCE

Despite their demonstrable benefits, adoption of AI systems such as IDx-DR remains limited, particularly in resource-constrained settings in the United States and around the world that could benefit from such systems to increase patient access (to disease screening) and adherence (Rajpurkar et al., 2022). The gap emphasizes the importance of designing AI-augmented systems with the goal of overcoming barriers to AI adoption. Existing research indicates that the potential financial burden on patients may act as a barrier to the widespread use of AI in patient care (Richardson et al., 2021), even when adopting AI may lower the overall cost of patient care. However, little research has been conducted on how to design related interventions that will help overcome these barriers to AI uptake.

The impact of financial incentives in influencing individual decisions has been studied in a variety of health contexts (Liao & Chen, 2021). For example, researchers discovered through a survey that legalizing payments for kidney donations elicits polarized responses but may result in a significant increase in donation rates (Elías et al., 2019). In the case of blood donation, there is conflicting evidence and opinion about whether financial incentives increase or decrease people's willingness to donate (Lacetera & Macis, 2010). Several recent studies show that statewide lottery programs helped increase COVID-19 vaccination rates (Barber & West, 2022), while others found little or no effect (Dave et al., 2021).

Currently, patients can sometimes be responsible for an out-of-pocket cost to be seen by AI. This serves as a baseline for analyzing two types of incentives: (1) eliminating out-of-pocket expenses, allowing patients to interact with AI for free; and (2) patients receiving a cash reward (or a discount on out-of-pocket expenses) for agreeing to interact with AI. While the second option may appear to be able to increase patient participation, it is unclear whether it increases a patient's likelihood of adhering to medical advice. Comparing these incentive schemes may help us understand the conditions under which health maintenance organizations should provide financial incentives to their members to use AI for screening (e.g., pay them to download an AI app and use it for screening at home), as this can lead to earlier detection of health issues and lower overall healthcare costs.

Another potential approach to boosting patients' acceptance of AI systems is to employ the nudge technique, which has been well established in the behavioral economics literature (Thaler & Sunstein, 2008) and has found widespread application in a variety of manufacturing and service—including healthcare—settings (Dhanorkar & Siemsen, 2021; Jung et al., 2021; Kush & Tayur. 2022; Tong et al., 2018). The effectiveness of nudge techniques in influencing patients' acceptance of AI systems has yet to be determined, but preliminary findings are promising: For example, Robertson et al. (2021) show that a nudge from a PCP toward AI, as well as assurance that the AI clinic would listen to the patient's unique perspectives, increased patients' acceptance of AI-augmented diagnosis.

Notably, whether to use a nudge system is frequently determined by ethical considerations as well as demonstrable benefits, particularly in a healthcare context (Cohen, 2013). As a result, future research should look into the ethics as well as the efficacy of using nudge techniques to improve patient acceptance of AI systems. Such ethical implications may impose operational constraints on the design of AI-augmented healthcare systems in some cases, but they may also inspire creative operational solutions in other cases.

6 | CONCLUDING REMARKS

Despite tremendous investment and effort in creating and certifying medical AI applications, their uptake in clinical practice remains modest. In this paper, we propose that to embed AI into healthcare workflow and harness its power to enhance patient experience and outcomes, four important components are necessary (the "4Ps"): (1) physician buy-in, (2) patient acceptance, (3) provider investment, and (4) payer support. Because the roles of the latter two Ps (provider investment and payer support) are more easily recognizable, we focus on discussing service design considerations to enhance the first two Ps, that is, physician buy-in and patient acceptance.

We envision a future in which physicians routinely use AI to supplement their decision-making; we do not believe that physicians will be completely replaced by AI. In this regard, AI plays a role similar to how microscopes, magnetic resonance imaging, computed tomography, and X-rays aid in the pathophysiological understanding of a patient's medical conditions (Mendel, 2013). Put differently, AI should improve the capabilities of the healthcare profession. However, efforts to increase AI adoption face unique challenges not encountered with other technologies, including several issues outlined in our paper. Thus, it is critical to gain a better understanding of barriers to physician buy-in and patient acceptance and to incorporate them into the design of AI-augmented healthcare delivery systems. Our discussions have implications for other technology-mediated healthcare scenarios such as telehealth (Crodina et al., 2022).

We have outlined a number of research questions regarding the barriers to physician buy-in and patient acceptance of AI, the transparency of AI use, service design, and incentive and nudge strategies to increase AI use. Taken together, we believe that the operations management community has an opportunity to provide a valuable system-level perspective by incorporating incentives (financial and non-financial) and behavioral insights when dealing with humans (patients) at their most vulnerable in what has been viewed as an often impenetrable system. While we focus on issues confronting hospitals, particularly large academic medical centers, some of the issues discussed may be relevant to other types of healthcare providers as well.

Our paper leaves out several important developments in the field of AI and health. First, much of AI is based on computation, both in pattern recognition and in the identification of pattern mutations using noisy data. Improvements in computational devices and techniques, including quantum computing and unconventional computing inspired by physics, will enable even more powerful medical AI applications. Second, as we move toward a post-racial future in medicine (Newkirk, 2016), one free of racial discrimination and prejudice, medical AI becomes more fine-grained and personalized in terms of characterizing individual conditions. For instance, warfarin dosage can now be personalized based on individual genomes rather than race (Ng et al., 2008). Third, unlike many non-AI systems, routine user sharing of big data is critical to improving the accuracy of medical AI and ensuring that it is current and representative of clinical reality. Sharing data, on the other hand, frequently exposes health systems to the risk of identity theft and unauthorized data access. This presents an intriguing opportunity for operations management researchers to investigate the value of data sharing, which will advance the literature on the value of information sharing (Gavirneni et al., 1999; Lee et al., 2000), and develop innovative business models to operationalize big data sharing on a regular basis, resulting in continuous

AI algorithm improvement that further enhances physician buy-in and patient acceptance.

ACKNOWLEDGMENTS

The authors would like to express their gratitude to Professors Christopher S. Tang and Subodha Kumar for inviting them to write this paper. Discussions with Nathan Congdon, Michael Ellenbogen, Qihong Liu, Shubhranshu Singh, Simrita Singh, Risa Wolf, and Haiyang Yang inspired some of the paper's core ideas. In addition, they thank Ramayya Krishnan and Alan Scheller-Wolf for their comments on earlier versions of the manuscript. Tinglong Dai gratefully acknowledges the financial support provided by a 2021 Hopkins Business of Health Initiative (HBHI) seed grant and the Johns Hopkins Discovery Award (2021-2022).

ORCID

Tinglong Dai https://orcid.org/0000-0001-9248-5153
Sridhar Tayur https://orcid.org/0000-0002-8008-400X

ENDNOTES

[1] In this paper, we focus on a subset of medical AI, which assists physicians in making medical decisions (e.g., screening, diagnostic, and treatment), while noting that other types of AI applications in healthcare setting, such as error detection and correction, process improvement, and automatic transcription (Haque et al., 2020), are beyond the scope of our discussion. By focusing on medical decision-making, we can examine instances in which AI may threaten physicians' authority (Starr, 2017) and thus face scrutiny and resistance.

[2] An unethical healthcare provider can manipulate patients with or without AI, but using AI may lower the variable cost of such manipulative actions.

[3] For example, in the case of a concert, the organizers focus on maximizing the audience's remembered utility at the end of the concert by sequencing activities (e.g., songs, interactive performances, and games). Because of the memory decay effect, it may not be best to schedule the most engaging activity at the start of the concert because the audience may have forgotten about it by the end of the concert. Furthermore, to manage the audience's expectations during the concert, organizers need to create some ups and downs to reflect the acclimation effect, which states that the audience has a higher expectation for later activities as they enjoy earlier ones. (Li et al., 2021).

REFERENCES

Abràmoff, M. D., Lavin, P. T., Birch, M., Shah, N., & Folk, J. C. (2018). Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices. *npj Digital Medicine*, *1*(1), 1–8.

Adida, E., & Dai, T. (2022). *Incentive design for diagnostic effort and testing*. Johns Hopkins University.

Agarwal, R., Dugas, M., & Gao, G. G. (2022). Augmenting doctors with AI: Addressing grand challenges and transforming healthcare. Johns Hopkins University Working Paper.

Andritsos, D. A., & Tang, C. S. (2018). Incentive programs for reducing readmissions when patient care is co-produced. *Production and Operations Management*, *27*(6), 999–1020.

Arkes, H. R., Shaffer, V. A., & Medow, M. A. (2007). Patients derogate physicians who use a computer-assisted diagnostic aid. *Medical Decision Making*, *27*(2), 189–202.

Armstrong, K. (2018). If you can't beat it, join It: Uncertainty and trust in medicine. *Annals of Internal Medicine*, *168*(11), 818–819.

Arrow, K. J. (1963). Uncertainty and the welfare economics of medical care. *The American Economic Review*, *53*(5), 941–973.

Ayvaci, M. U. S., Alagoz, O., Ahsen, M. E., & Burnside, E. S. (2018). Preference-sensitive management of post-mammography decisions in breast cancer diagnosis. *Production and Operations Management*, *27*(12), 2313–2338.

Barber, A., & West, J. (2022). Conditional cash lotteries increase COVID-19 vaccination rates. *Journal of Health Economics*, *81*, 102578.

Berenson, R., & Singh, H. (2018). Payment innovations to improve diagnostic accuracy and reduce diagnostic error. *Health Affairs*, *37*(11), 1828–1835.

Bohr, A., & Memarzadeh, K. (2020). The rise of artificial intelligence in healthcare applications. *Artificial Intelligence in Healthcare*, *2020*, 25–60.

Bray, R. L. (2020). Operational transparency: Showing when work gets done. *M&SOM*. Advance online publication. https://doi.org/10.1287/msom.2020.0899

Brinkhoff, A., Özer, Ö., & Sargut, G. (2015). All you need is trust? An examination of inter-organizational supply chain projects. *Production and Operations Management*, *24*(2), 181–200.

Buell, R. W., Kim, T., & Tsay, C. J. (2017). Creating reciprocal value through operational transparency. *Management Science*, *63*(6), 1673–1695.

Cohen, S. (2013). Nudging and informed consent. *The American Journal of Bioethics*, *13*(6), 3–11.

Crodina, J., Fowkes, J., Malani, R., & Medford-Davis, L. (2022). *Patients love telehealth–physicians are not so sure*. McKinsey & Company.

Dai, T., Gleason, K., Hwang, C. W., & Davidson, P. (2021). Heart analytics: Analytical modeling of cardiovascular care. *Naval Research Logistics (NRL)*, *68*(1), 30–43.

Dai, T., & Singh, S. (2020). Conspicuous by its absence: Diagnostic expert testing under uncertainty. *Marketing Science*, *39*(3), 540–563.

Dai, T., & Singh, S. (2021). *Artificial intelligence on call: The physician's decision of whether to use AI in clinical practice*. (Working Paper), Johns Hopkins University.

Dai, T., & Tayur, S. (2018). *Handbook of healthcare analytics: Theoretical minimum for conducting 21st century research on healthcare operations.* John Wiley & Sons.

Dai, T., & Tayur, S. (2020). OM forum—Healthcare operations management: A snapshot of emerging research. *M&SOM*, *22*(5), 869–887.

Das Gupta, A., Karmarkar, U. S., & Roels, G. (2016). The design of experiential services with acclimation and memory decay: Optimal sequence and duration. *Management Science*, *62*(5), 1278–1296.

Dave, D., Friedson, A. I., Hansen, B., & Sabia, J. J. (2021). Association between statewide COVID-19 lottery announcements and vaccinations. *JAMA Health Forum*, *2*(10), e213117.

Dhanorkar, S., & Siemsen, E. (2021). How nudges lead to improved energy efficiency in manufacturing: Evidence from archival data and a field study. *Production and Operations Management*, *30*(10), 3735–3757.

Ebrahim-Khanjari, N., Hopp, W., & Iravani, S. M. R. (2012). Trust and information sharing in supply chains. *Production and Operations Management*, *21*(3), 444–464.

Elías, J. J., Lacetera, N., & Macis, M. (2019). Paying for kidneys? A randomized survey and choice experiment. *American Economic Review*, *109*(8), 2855–2888.

Engler, A. (2020). *The case for AI transparency requirements*. *The Brookings Institution*.

FDA. (2021). *Artificial intelligence and machine learning (AI/ML)-enabled medical devices*. Food and Drug Administration. https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-aiml-enabled-medical-devices

Fihn, S., Saria, S., Mendonça, E., Hain, E., Matheny, M., Shah, N., Liu, H., & Auerbach, A. (2019). Deploying AI in clinical settings. *Artificial intelligence in health care: The hope, the hype, the promise, the peril* (pp. 145–179). National Academy of Medicine.

Friedman, A. B., Gervasi, S., Song, H., Bond, A. M., Chen, A. T., Bergman, A., David, G., Bailey, J. M., Brooks, R., & Smith-McLallen, A. (2022). Telemedicine catches on: Changes in the utilization of telemedicine services during the COVID-19 pandemic. *American Journal of Managed Care*, *28*(1), e1–e6.

Gaube, S., Suresh, H., Raue, M., Merritt, A., Berkowitz, S. J., Lermer, E., Coughlin, J. F., Guttag, J. V., Colak, E., & Ghassemi, M. (2021). Do as AI say: Susceptibility in deployment of clinical decision-aids. *npj Digital Medicine*, *4*(1), 1–8.

Gavirneni, S., Kapuscinski, R., & Tayur, S. (1999). Value of information in capacitated supply chains. *Management Science*, *45*(1), 16–24.

Goldstein, S. M., Johnston, R., Duffy, J., & Rao, J. (2002). The service concept: the missing link in service design research? *Journal of Operations Management*, *20*(2), 121–134.

Hall, M. A., Dugan, E., Zheng, B., & Mishra, A. K. (2001). Trust in physicians and medical institutions: What is it, can it be measured, and does it matter? *The Milbank Quarterly*, *79*(4), 613–639.

Haque, A., Milstein, A., & Fei-Fei, L. (2020). Illuminating the dark spaces of healthcare with ambient intelligence. *Nature*, *585*(7824), 193–202.

Hopp, W. J., Li, J., & Wang, G. (2018). Big data and the precision medicine revolution. *Production and Operations Management*, *27*(9), 1647–1664.

Jones, J. (2021). *Integrating AI into the clinical workflow*. American College of Radiology. https://www.acr.org/Practice-Management-Quality-Informatics/Imaging-3/Case-Studies/Information-Technology/Integrating-AI-into-the-Clinical-Workflow

Jung, M., Cho, D., & Shin, E. (2021). Repairing a cracked mirror: The heterogeneous effect of personalized digital nudges driven by misperception. *Production and Operations Management*, *30*(8), 2586–2607.

Jussupow, E., Spohrer, K., Heinzl, A., & Gawlitza, J. (2021). Augmenting medical diagnosis decisions? An investigation into physicians' decision-making process with artificial intelligence. *Information Systems Research*, *32*(3), 713–735.

Karpik, L. (2010). *Valuing the unique: The economics of singularities.* Princeton University Press.

Kush, J., & Tayur, S. (2022). Video intervention to increase decedent tissue donation by next-of-kin. *Production and Operations Management*, 31(5), 2256–2267.

Lacetera, N., & Macis, M. (2010). Do all material incentives for pro-social activities backfire? The response to cash and non-cash incentives for blood donations. *Journal of Economic Psychology*, *31*(4), 738–748.

Laker, L. F., Froehle, C. M., Windeler, J. B., & Lindsell, C. J. (2018). Quality and efficiency of the clinical decision-making process: Information overload and emphasis framing. *Production and Operations Management*, *27*(12), 2213–2225.

Lee, H. L., So, K. C., & Tang, C. S. (2000). The value of information sharing in a two-level supply chain. *Management Science*, *46*(5), 626–643.

Li, Y., Dai, T., & Qi, X. (2021). A theory of interior peaks: Activity sequencing and selection for service design. *M&SOM*, *24*(2), 993.

Liao, C. N., & Chen, Y. J. (2021). Design of long-term conditional cash transfer program to encourage healthy habits. *Production and Operations Management*, *30*(11), 3987–4003.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research*, *46*(4), 629–650.

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science*, *38*(6), 937–947.

Mendel, D. (2013). *Proper doctoring: A book for patients and their doctors*. New York Review of Books.

Mitka, M. (2013). Joint commission warns of alarm fatigue: Multitude of alarms from monitoring devices problematic. *Jama*, *309*(22), 2315–2316.

Navathe, A., & David, G. (2009). The formation of peer reputation among physicians and its effect on technology adoption. *Journal of Human Capital*, *3*(4), 289–322.

Newkirk, V. R. (2016, June 8). How precision medicine could move health care beyond race. *The Atlantic*. https://www.theatlantic.com/politics/archive/2016/06/precision-medicine-race-future/486143/

Ng, P., Zhao, Q., Levy, S., Strausberg, R., & Venter, J. (2008). Individual genomes instead of race for personalized medicine. *Clinical Pharmacology & Therapeutics*, *84*(3), 306–309.

Özer, Ö., & Zheng, Y. (2018). Trust and Trustworthiness. In Donohue, K., Katok, E., & Leider, S. (Eds.), *The handbook of behavioral operations* (pp. 489–523). John Wiley & Sons, Ltd.

Pezzo, M. V., Nash, B. E. D., Vieux, P., & Foster-Grammer, H. W. (2022). Effect of having, but not consulting, a computerized diagnostic aid. *Medical Decision Making*, *42*(1), 94–104.

Price, W. N., Gerke, S., & Cohen, I. G. (2019). Potential liability for physicians using artificial intelligence. *Jama*, *322*(18), 1765–1766.

Price, W. N., Gerke, S., & Cohen, I. G. (2021). How much can potential jurors tell us about liability for medical artificial intelligence? *Journal of Nuclear Medicine*, *62*(1), 15–16.

Rajpurkar, P., Chen, E., Banerjee, O., & Topol, E. J. (2022). AI in health and medicine. *Nature Medicine*, *28*(1), 31–38.

Richardson, J. P., Smith, C., Curtis, S., Watson, S., Zhu, X., Barry, B., & Sharp, R. R. (2021). Patient apprehensions about the use of artificial intelligence in healthcare. *npj Digital Medicine*, *4*(1), 1–6.

Robertson, C. T., Woods, A. K., Bergstrand, K., Findley, J., Balser, C., & Slepian, M. J. (2021). *Diverse patients' attitudes towards artificial intelligence (AI) in diagnosis*. Social Science Research Network.

Russell, S. J., & Norvig, P. (2015). *Artificial intelligence: A modern approach* (3rd ed.). Prentice Hall.

Singh, S., & Dai, T. (2022). *Optimal patient pathway design for AI-augmented healthcare*. (Working Paper), Johns Hopkins University.

Starr, P. (2017). *The social transformation of American medicine: The rise of a sovereign profession and the making of a vast industry* (Updated ed.). Basic Books.

Sullivan, H. R., & Schweikart, S. J. (2019). are current tort liability doctrines adequate for addressing injury caused by AI? *AMA Journal of Ethics*, *21*(2), 160–166.

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness.* Yale University Press.

Tobia, K., Nielsen, A., & Stremitzer, A. (2021). When does physician use of AI increase liability? *Journal of Nuclear Medicine*, *62*(1), 17–21.

Tong, J., Feiler, D., & Larrick, R. (2018). A behavioral remedy for the censorship bias. *Production and Operations Management*, *27*(4), 624–643.

Wolf, J. R. (2014). Do IT students prefer doctors who use IT? *Computers in Human Behavior*, *35*, 287–294.

Wolf, R. M., Channa, R., Abramoff, M. D., & Lehmann, H. P. (2020). Cost-effectiveness of autonomous point-of-care diabetic retinopathy screening for pediatric patients with diabetes. *JAMA Ophthalmology*, *138*(10), 1063–1069.

Wolf, R. M., Liu, T. Y. A., Thomas, C., Prichett, L., Zimmer-Galler, I., Smith, K., Abramoff, M. D., & Channa, R. (2021). The SEE study: Safety, efficacy, and equity of implementing autonomous artificial intelligence for diagnosing diabetic retinopathy in youth. *Diabetes Care*, *44*(3), 781–787.

Xie, Y., Nguyen, Q. D., Hamzah, H., Lim, G., Bellemo, V., Gunasekeran, D. V., & Yip, M. Y. T., Lee, X. Q., Hsu, W., Lee, M. L., Tan, C. S., Wong, H. T., Lamoureux, E. L., Tan, G. S. W., Wong, T. Y., Finkelstein, E. A., & Ting, D. S. W. (2020). Artificial intelligence for teleophthalmology-based diabetic retinopathy screening in a national programme: An economic analysis modelling study. *The Lancet Digital Health*, *2*(5), e240–e249.

Yokoi, R., Eguchi, Y., Fujita, T., & Nakayachi, K. (2021). artificial intelligence is trusted less than a doctor in medical treatment decisions: Influence of perceived care and value similarity. *International Journal of Human–Computer Interaction*, *37*(10), 981–990.

How to cite this article: Dai, T., & Tayur, S. (2022). Designing AI-augmented healthcare delivery systems for physician buy-in and patient acceptance. *Production and Operations Management*, *31*, 4443–4451. https://doi.org/10.1111/poms.13850