AI for Operational Efficiency in Virtual Care: An Operations-Focused Framework

Mohammad Delasay[1], Soroush Saghafian[2]

[1]*College of Business, Stony Brook University, Stony Brook, NY*
[2]*Harvard Kennedy School, Harvard University, Cambridge, MA*

Abstract

This chapter examines how Artificial Intelligence (AI) enhances operational efficiency in virtual care, including telehealth, mHealth, remote monitoring, and e-consultations. From an operations management perspective, the chapter analyzes how AI can be employed such that it improves workflow design, capacity utilization, system throughput, and care quality. It reviews current AI applications in virtual care across three functional domains of workflow automation, optimization for risk assessment, and capacity and demand prediction. AI tools currently implemented in these functional domains include AI-driven triage agents, ambient documentation systems, anomaly filtering models, risk stratification algorithms, and no-show prediction algorithms. The chapter also introduces the Operations-Focused AI Adaptation (OFAA) framework, a two-tier model that guides healthcare organizations in evaluating and integrating AI solutions. The first tier assesses the need for an AI solution by evaluating its clinical integrity, operational impact, effect on patient experience, and equity. The second tier provides a four-phase implementation roadmap emphasizing strategic alignment in the care value stream map, workflow and capacity analysis, monitoring and quality control, and continuous governance and improvement. The OFAA framework ensures AI adoption is aligned, measurable, scalable, and sustainable in virtual care systems.

Keywords: AI in healthcare; Virtual care; Telehealth and mhealth; Operational efficiency

1 Introduction

Artificial Intelligence (AI) has improved operational efficiency in various healthcare domains. Our focus in this chapter is on the role of AI in virtual care, including telehealth, mobile health (mHealth) and remote monitoring, and e-consultation applications. We use *virtual care* as a general term to define all clinical interactions and interventions performed virtually. *telehealth* includes both synchronous and asynchronous encounters through digital online platforms, whereas *mHealth* refers to mobile-based tools, such as wearables, smartphone apps, and remote monitoring devices. While both telehealth and mhealth have been widely used to transform healthcare by improving care quality and operational efficiency (see, e.g., Saghafian et al. (2018), Saghafian and Murphy (2021),

and the references therein), the convergence of AI with these virtual care modalities has the potential to create further impact.

AI in healthcare has evolved from simple rule-based diagnostic systems to complicated data-driven models. The rise of smartphones, wearables, and remote monitoring platforms has extended care beyond the traditional clinical encounters and has enabled real-time data collection and personalized interventions (Saghafian and Murphy, 2021). Key milestones, such as AI-assisted image interpretation, predictive analytics for disease risk, and AI-supported virtual consultations, which we explore in this chapter, demonstrate how AI and mobile-enabled care jointly redefine efficiency in virtual care workflows.

In this chapter, we examine the value of AI within virtual care from an operations management (OM) perspective, rather than its clinical diagnostic capabilities. Our focus is on how AI can improve workflows, capacity, and other realted performance measures in virtual care. Section 2 explains the main modalities of virtual care and their operational implications. Section 3 reviews the major AI tools that support the current virtual care applications. Section 4 shows how AI is currently implemented to reduce workflow bottlenecks, automate routine and repetitive tasks, and increase throughput in virtual care settings.

Section 5 includes the main contribution of this chapter: the *Operations-Focused AI Adaptation (OFAA)* framework. OFAA is a two-tier model that could help healthcare organizations evaluate and select among different AI solutions and integrate them into virtual care operations. Tier 1 is a gatekeeper that determines whether an AI solution matches clinical needs, operational workflow, patient experience goals, and equity considerations. Only solutions that pass Tier 1 requirements are considered by Tier 2, which provides a four-phase roadmap for implementation and continuous governance through plan-do-check-action (PDCA) cycles. By combining the justification in Tier 1 and disciplined execution in Tier 2, OFAA provides a useful approach to ensure that AI implementation improves system efficiency, reliability, and scalability.

2 Virtual Care: Modalities, Benefits, and Challenges

Virtual care encompasses a range of clinical interactions that are mediated digitally, including telehealth, mHealth and remote monitoring, and e-consultations. Telehealth refers to delivering health-related services through synchronous and asynchronous communication technologies (Dorsey and Topol, 2016). *Synchronous care* is real-time interactions between patients and providers via video, phone, or secure messaging. *Asynchronous care* relies on technologies to transmit medical data, such as images or test results, for later review by a physician (Agarwal et al., 2025).

mHealth and remote monitoring technologies expand the reach of virtual care by collecting and transmitting medical data from mobile apps, wearables, and other remote monitoring devices (Steinhubl et al., 2015). These capabilities facilitate synchronous and asynchronous data sharing, continuous remote monitoring of patient health conditions, and the possibility of real-time communication with the patient, in need (Marcolino et al., 2018). By enabling frequent self-measurement and early detection of potential medical problems, mHealth tools reduce the need for episodic office visits and allow clinicians to view longitudinal data rather than isolated snapshots (Marcolino et al., 2018; Agnihothri et al., 2020). These platforms support a range of interventions, from reminders and educational messages to direct clinical actions such as medication adjustments. For

patients with mental health issues, for example, using mhealth to personalize self-care strategies (e.g., physical activity, sleep duration, and bedtime consistency) (Lin et al., 2025) and digital phenotyping (Lipschitz et al., 2025) has been shown to offer important advantages.

Virtual care also includes e-consultations, which enable asynchronous communication between primary care physicians and specialists (Vimalananda et al., 2015). These exchanges allow clinicians to share relevant clinical information, such as history, labs, and imaging, for specialist review without requiring a live interaction (Keely et al., 2013). By streamlining triage and reducing unnecessary referrals, e-consultations improve diagnostic accuracy, shorten wait times at the specialist level by reducing the unnecessary referrals, and enables coordination across institutions and specialties.

These modalities have been tested and implemented in several medical practices, including teleradiology (Hanna et al., 2020), teledermatology (Eedy and Wootton, 2001), telepsychiatry (Sharma and Devan, 2023), and teletriage (Saghafian et al., 2018). They offer various advantages, including (Gajarawala and Pelkowski, 2021):

- Expand access to care for geographically isolated or underserved populations.
- Enhance efficiency by reducing travel, wait times, and redundant in-person visits.
- Support continuity of care for chronic conditions through real-time monitoring and adaptive interventions.
- Facilitate collaboration across institutions and specialties.
- Enable proactive care through AI-driven alerts and predictive analytics.

Table 1 summarizes the characteristics of the virtual care modalities discussed above, The adoption of these modalities varies across clinical settings, shaped by technological and operational barriers (some of which are listed in the table) as well as reimbursement policies and regulatory and privacy issues (Scott Kruse et al., 2018; Shachar et al., 2020).

Table 1: Virtual care modalities: features, examples, advantages, and limitations

	Key Features	Examples	Advantages	Limitations
Synchronous	Real-time, two-way interaction	Primary care; behavioral health	Immediate feedback; high rapport	Scheduling and broadband constraints
Asynchronous	Offline communication	Secure messaging; image uploads	Flexible timing; efficient for low-acuity issues	Delayed response; limited for urgent cases
MHealth & Remote monitoring	Data capture via apps, wearables, and connected devices	Glucose monitors; symptom-checker apps; medication reminders	Proactive chronic care; scalable; preventive	Device access; digital divide; data overload; variable app quality
E-consultation	Provider-to-provider asynchronous review	PCP-to-specialist case summaries	Fewer referrals; faster expert input	No direct patient-specialist interaction

The most measurable indicator of the integration of virtual care into formal practice is the utilization of telehealth services. Derived from the CMS *Medicare Telehealth Trends*

Report (Centers for Medicare & Medicaid Services, 2025), Figure 1 illustrates the percentage of Medicare beneficiaries who received at least one telehealth service out of the total eligible population from 2020 through 2024. Figure 1 shows a sudden surge during the initial phase of the COVID-19 pandemic and then a gradual decrease to a stable level of around 15%. While this is lower than the pandemic peak, it is still a substantial increase from the pre-2020 levels.

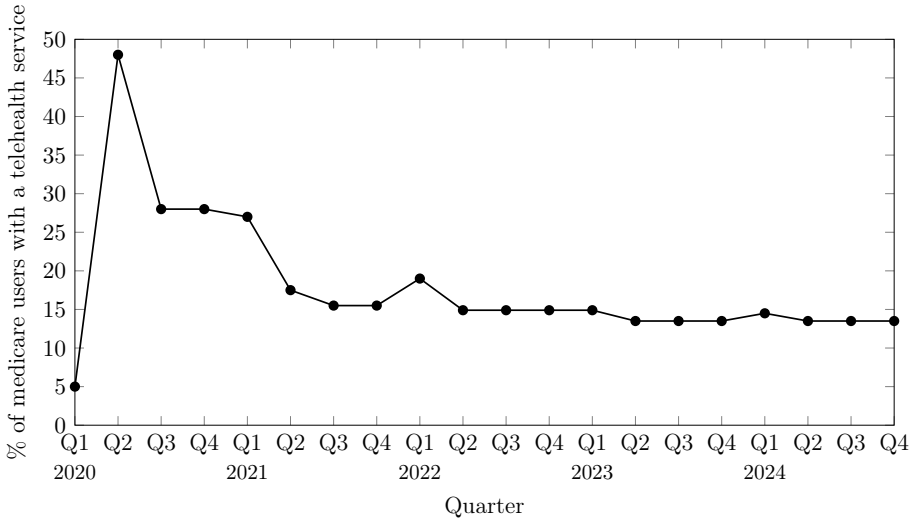

Figure 1: Telehealth adoption in the U.S.

Despite its promise, the full adoption of telehealth and other modalities of virtual care face various barriers (Weinstein et al., 2014). Reimbursement for virtual services is not consistent between payers, which reduces provider incentives to invest in virtual workflows or remote monitoring programs (Shachar et al., 2020; Rajan et al., 2022). Digital literacy gaps, especially among older adults and individuals with limited access to reliable internet, limit equitable participation in virtual care (Arias López et al., 2023). Remote monitoring programs rely on sustained patient engagement (Martin, 2012) and result in significant review burdens on clinicians (Marcolino et al., 2018; Moy et al., 2021). These frictions often prevent the integration of virtual care into some routine practices, contributing to its heterogeneous adoption among different health systems.

Addressing these challenges is essential for equitable access and long-term operational sustainability of virtual care technologies. As the volume of digital health data grow, health systems face more serious operational bottlenecks in triage, monitoring, and follow-up workflows. These challenges highlight the main theme of this chapter: *virtual care cannot scale without tools that improve efficiency, reduce cognitive load, and increase throughput.* The next section introduces the foundations of AI models and describes AI tools useful for the virtual care operational challenges highlighted in this section.

3 AI: Foundations and Healthcare Relevance

AI has been applied in various fields, including computer science, statistics, neuroscience, and control theory. In the medical field, AI helps computer algorithms interpret medical data, recognize patterns, and assist in medical decision-making. Early applications of AI involved symbolic and rule-based expert systems that encoded clinical knowledge into

structured logic for decision support systems. As data availability and computational power increased, AI shifted toward data-driven approaches that learn patterns directly from clinical information. AI now spans multiple related areas (Kaul et al., 2020):

- *Machine Learning (ML)*: Machine Learning is a branch of AI that enables computers to learn algorithms and patterns without the need to be directly programmed (Jordan and Mitchell, 2015). ML includes *supervised learning*, which is often applied in risk prediction in the medical field; *unsupervised learning*, which is utilized for patient categorization and care prioritization; and *reinforcement learning*, which is used to optimize resource allocation and capacity management (Jovel and Greiner, 2021).

- *Natural Language Processing (NLP)*: NLP involves algorithms that enable machines to interpret and generate human language (Hirschberg and Manning, 2015). NLP in healthcare supports automated documentation, clinical coding, summarization, and conversational interfaces used in virtual intake and patient engagement (Kocaballi et al., 2020; Falcetta et al., 2023).

- *Deep Learning (DL) and Computer Vision (CV)*: DL is a subset of ML that uses multilayer neural networks to learn hierarchical representations from large datasets, without humans manually defining the features and patterns (LeCun et al., 2015). In healthcare, DL is particularly strong in image analysis and signal processing by enabling computer vision (CV) models and data integration from multiple sources. These capabilities make DL a core technology behind radiology and anomaly detection in remote monitoring programs, among many other applications (Esteva et al., 2019; Gupta et al., 2021).

AI adoption in healthcare has accelerated significantly in recent years, due to advances in computing power, increased data availability, and growing clinical demand. The COVID-19 pandemic accelerated AI adoption in healthcare, much like its impact on telehealth, bringing tools such as predictive analytics, image interpretation, and virtual triage into mainstream use (Clipper, 2020). The global healthcare AI market grew from \$1.1 billion in 2016 to \$6.7 billion in 2020 and to \$22.4 billion in 2023 (AIPRM, 2024). This reflects a compound annual growth rate (CAGR) of over 45% between 2020 and 2023.

Today's AI tools can analyze large and heterogeneous clinical datasets and signals, including medical images, laboratory results, physiological signals, and longitudinal patient histories, to generate insights ready for decision-making (Topol, 2019). These capabilities are embedded directly into mobile platforms, wearable sensors, and telehealth systems, which enable real-time and personalized recommendations, digital care interventions, and autonomous screening workflows (Bhatt et al., 2022). In clinical practice, AI now supports image interpretation, risk prediction, symptom triage, and continuous remote monitoring. These functions are particularly valuable in virtual care settings where timely decision support and efficient data processing are essential (Andrikopoulou, 2023).

Augmenting the capabilities of AI and ML with the outstanding power of human intuition has even increased the promise of AI-related tools. For example, *centaur* models (Dean et al., 2022; Saghafian and Idan, 2024; Saghafian, 2025) have been shown to outperform some traditional approaches to the development of AI tools, including those used in LLMs. Nonetheless, the surge in AI use in healthcare underscores its growing role

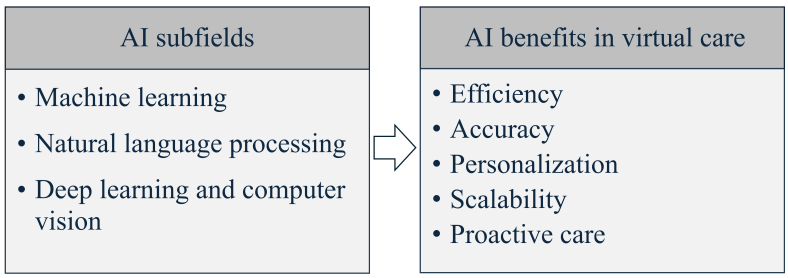

Figure 2: AI subfields and their collective potential benefits in virtual care delivery

in scalable, data-driven care delivery. Rather than being confined to diagnostic tasks, AI now contributes directly to the core operational functions of virtual care. AI's potential spans five operational domains, each addressing a specific constraint and collectively contributing to more efficient and reliable healthcare delivery (Steinhubl et al., 2015; Lin et al., 2019; Topol, 2019; Bohr and Memarzadeh, 2020; Rajpurkar et al., 2022):

- *Efficiency*: AI reduces administrative burden on the clinical team by automating repetitive and time-intensive tasks, including triage, scheduling, intake, and documentation. Such automation increases clinicians' effective service rates and enables the allocation of limited clinical time to more complex cases and direct patient care.

- *Accuracy*: AI can increase diagnostic and operational precision by employing advanced pattern recognition, multimodal data integration, and anomaly detection. These functions decrease variability in decision-making accuracy and facilitate more consistent virtual assessments and interventions.

- *Personalization*: AI can be employed to personalize care recommendations and treatment interventions by using longitudinal data received in real time from wearables, mobile apps, and remote monitoring devices. This capability improves patient engagement and enables care plans specific to individual risk profiles.

- *Scalability*: By increasing the number of patients being treated trough self-screening tools and AI-assisted monitoring systems, AI tools can enable the care team to handle a large number of patients without having to increase their staff proportionally. This is especially important in telemedicine, where the number of patients can easily overwhelm the availability of clinician time.

- *Proactive care*: AI allows for proactive outreach and preventive measures by enabling the early detection of signs of deterioration and the ability to predict future risks. This proactive approach to care is critical in the management of chronic conditions and the prevention of unnecessary escalation in virtual care programs.

These strengths make AI a strategic enabler of modern virtual care, which can improve outcomes, lower operational expenses, and increase accessibility when integrated into telehealth and mHealth solutions. Figure 2 summarizes our discussion of AI subfields and their collective contribution to the operational capabilities discussed above. The next section examines how these capabilities are already being implemented in practice, highlighting examples of AI-driven automation, optimization, and predictive analytics within virtual care.

4 The Current Implementation of AI in Virtual Care

Although the potential of AI has been discussed for decades, its application in virtual care, telehealth, and mHealth has shifted from experimental pilots to essential infrastructure. This transition has been mainly driven by two sources: the explosion of digital data generated by RPM devices and the rapid growth in virtual visit demand (Topol, 2019). As healthcare systems face staff shortages and an increasing number of patients (World Health Organization, 2022), AI has become a practical tool for managing operational capacity (Rajpurkar et al., 2022).

However, we find that the current deployments of AI in digital health include targeted solutions designed to relieve specific operational bottlenecks. These implementations can be clustered into three functional categories of *automation*, *optimization*, and *prediction*. Each functional category addresses a different stage of the virtual care workflow and can be mapped into the operational domains introduced in Section 3. In the following subsections, we discuss each of these categories.

4.1 Automation for Workflow Efficiency

At the front-end of the patient virtual care journey, AI is used to reduce the *friction of entry* (i.e., any technological, administrative, or operational barrier that makes it difficult for patients to initiate, access, or complete virtual care). It is also used to automate high-volume, repetitive tasks that previously consumed a great amount of clinician time (Aggarwal et al., 2020). Examples of AI tools here include AI-driven triage agents, conversational intake systems, and ambient documentation tools. These tools support the operational domains of *efficiency* and *scalability* by increasing the effective *service rate* of clinicians. The following examples illustrate these tools.

AI triage systems. AI triage is the use of automated digital systems that collect patient-reported symptoms or chief complaints, interpret clinical information, and assign an initial urgency level before a clinician becomes involved (Lai et al., 2020). Telemedical triage systems (Saghafian et al., 2018), for example, can benefit substantially from AI-powered tools to expedite triage. Modern AI triage tools operate primarily based on NLP models that are able to conduct adaptive and dialogue-based interviews with patients rather than relying on a set of static questionnaires. The rise of Large Language Models (LLMs) can also significantly enhance the capabilities of these tools.

Examples of AI triage systems include intelligent chatbots, such as Babylon Health and Ada, which use NLP to collect patients' symptoms, their medical history, and other related details, and then route patients to the appropriate level of care (Ćirković, 2020). This ensures that high-acuity cases are escalated to synchronous video visits, while low-risk concerns are managed asynchronously. From an OM perspective, AI triage reduces triage cycle time and the associated waiting times and decreases process variability (Gilbert et al., 2020). In virtual urgent care settings, AI triage agents currently perform the initial screening at various health institutions, including the Cleveland Clinic. Such implementations are reported to achieve diagnostic accuracy rates of around 94% (Dezyit Health Insights, 2024), allowing clinicians to focus on higher-value decision-making tasks.

Automated documentation. Automated documentation refers to AI systems that capture, structure, and summarize clinical conversations without requiring manual note-taking by the clinician (Kocaballi et al., 2020). These tools are also referred to as *AI ambient scribes*. They operate in the background during virtual encounters to generate real-time clinical documentation. For example, AI scribes such as Nuance DAX use DL to transcribe and summarize the interactions between the patient and provider, and automatically populate Electronic Health Record (EHR) fields (Liu et al., 2024). By reducing administrative time, these systems effectively increase system capacity without additional staffing (Tierney et al., 2024). From an OM perspective, automated documentation increases clinicians' effective service rate, reduces process waste and non-value-added time, and enables higher care throughput.

4.2 Optimization through Risk Assessment and Early Detection

AI is also used to optimize care delivery, especially in RPM programs to manage chronic diseases. Optimization in this context refers to AI algorithms that continuously analyze the medical data generated by patients' remote monitoring devices. The goal of such algorithms is to improve decision accuracy, reduce unnecessary workload, and match clinical resources to patient needs more accurately. These tools and algorithms support the domains of *accuracy*, *personalization*, and *proactive care* by converting raw medical data into actionable recommendations.

Anomaly filtering. Traditional RPM programs often generate large volumes of alerts. Many of those alerts are benign changes in patient conditions rather than meaningful health deterioration (Gupta et al., 2021). Modern AI monitoring models establish baselines specific to each patient's medical history and trigger alerts when the wearable and home-monitoring data received for a patient exceed the baselines set for that patient (Shaik et al., 2023). This reduces alert fatigue by lowering false-positive alerts. As a result, clinicians can focus on patients who have the highest risk of deterioration Adebowale (2025). From an OM perspective, anomaly filtering minimizes the workload, stabilizes workflow variability, and increases the effective service rate of monitoring teams.

Risk stratification. Risk stratification AI tools assign dynamic risk scores to patients based on the continuous stream of data received from their monitoring systems. The goal of these models is to provide an estimate of the likelihood of near-term deterioration in a patient's health conditions by integrating physiological signals, symptom reports, and historical trends (Lin et al., 2021; Chen et al., 2023). Such risk scores support escalation decisions to identify when a patient requires clinician outreach, synchronous evaluation, or transition to higher-acuity services (Coffey et al., 2021). Risk stratification helps care teams allocate attention and limited care time more effectively among patients.

Early deterioration detection. Early deterioration detection models identify subtle changes that could signal that a patient is beginning to worsen (Gerry et al., 2020). These AI-based models analyze longitudinal trends, such as rising heart failure risk or deteriorating glucose stability, to identify early signs of worsening conditions before they become acute (Yuan et al., 2025; Ting et al., 2025). Both clinical and remote-monitoring evidence shows that these models can detect deterioration hours or even days before traditional systems (Gallo et al., 2024). This allows care teams to intervene by scheduling

preventive follow-ups rather than reacting only when the patient's health has deteriorated significantly. Operationally, early deterioration models help shift the care workload from unplanned urgent responses to predictable, scheduled interventions. This operational advantage makes the capacity planning process easier and improves overall capacity utilization.

4.3 Prediction for Capacity and Demand Management

AI is also increasingly used to analyze historical and real-time data to predict how patients will interact during their virtual care journey, for example, in response to long appointment wait times. By predicting patients' behavior and enabling demand forecasting, such models can provide estimates of anticipated workload and support the operational domains of *scalability* and *proactive care* by helping healthcare organizations align their resources better with the volume of care that will actually materialize.

No-show prediction. Missed appointments are a source of inefficiency in virtual clinics, which reduces healthcare provider utilization and increases their idle capacity (Adepoju et al., 2022). Even in traditional office-based care, no-show prediction across various areas of care is challenging (Carreras-García et al., 2020), especially when a new treatment technology or care modality is introduced (Saghafian et al., 2023).

In virtual care settings, AI and ML models have been developed that analyze historical patient attendance patterns and their demographic information and social determinants of health to estimate the probability that a patient will miss a scheduled visit (AlMuhaideb et al., 2019; Fan et al., 2021; Dunstan et al., 2023). Even in non-virtual visits, incorporation of no-show probabilities in programs that optimize scheduling and patient prioritization in healthcare practices often yields important benefits Saghafian et al. (2023). In virtual care practices, empirical studies demonstrate that no-show prediction models can improve scheduling efficiency through targeted reminders or selective overbooking strategies (Daggy et al., 2010). Predicted no-shows represent visits that are not likely to materialize. Therefore, these no-show prediction models provide more accurate short-term forecasts of *realized* demand, which allows health organizations to anticipate their actual workload rather than relying only on scheduled appointments. Early evidence suggests measurable improvements from these predictive models in throughput and provider utilization, in telehealth settings (Reategui-Rivera et al., 2025).

Capacity management. AI has also been used for workforce planning and staffing decisions across various healthcare systems, including in virtual care programs (Hazarika, 2020; Saeed et al., 2025). Predictive scheduling algorithms improve staff allocation, reduce burnout, and help organizations anticipate periods of demand surge (Rajkomar et al., 2019; Veernapu, 2023). Beyond scheduling, predictive methods have shown significant improvements in designing optimal patient flow to enhance their care experience (Feizi et al., 2026). ML and AI-enabled workforce planning tools are also used to forecast shortages of specialized clinicians in a geographical region and guide redistribution of health workers across regions (Khan and Sherani, 2025). These applications could be relevant to virtual care, in which system capacity depends on the availability and distribution of clinicians responsible for remote care or monitoring services.

The three categories of AI tools in automation, optimization, and prediction reviewed in this section illustrate how AI is already improving and reconfiguring the virtual care

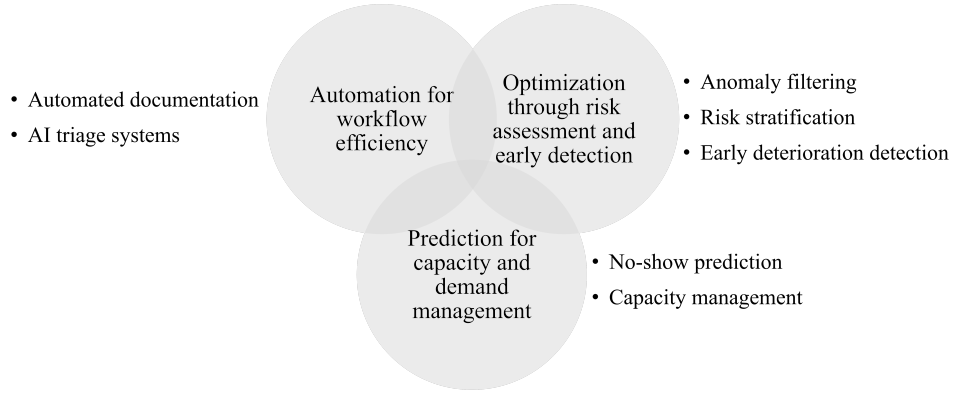

Figure 3: The current AI solutions in virtual Care

operations. These tools, summarized in Figure 3, demonstrate that current AI solutions address process bottlenecks in triage, improve patient monitoring accuracy, and simplify capacity management. The amount of operational efficiency that these tools bring depends on whether their use is aligned with workflow needs and embedded within the day-to-day operations of virtual care delivery. We build on these insights in the next section and introduce a framework that helps organizations evaluate, prioritize, and integrate such tools in a structured way.

5 Operational Framework for AI Adaptation

While the technological capabilities discussed in the previous sections highlight the promise of AI in virtual care, the mere presence of AI does not guarantee operational success. In many health systems, AI implementation fails not due to algorithmic issues, but due to a lack of alignment with existing clinical workflows and a failure to account for human-system interaction (Greenhalgh et al., 2017). In this section, we propose the *Operations-Focused AI Adaptation* (OFAA) framework, which aims to bridge the gap between AI's technical potential and its successful operational execution. This framework is organized into two tiers: Tier 1 serves as the strategic gatekeeper, while Tier 2 provides the execution roadmap. In summary:

- Tier 1 establishes strategic alignment by assessing clinical and operational values that AI can bring to to virtual care process. The goal is to ensure that the organization pursues only those AI solutions that address documented clinical needs and solve major operational bottlenecks without creating new bottlenecks and inefficiencies in other parts of the process.

- Tier 2 is a four-phase execution plan that guides the integration of the selected AI solution from Tier 1 into the clinical workflow and maintains a continuous governance loop through PDCA cycles.

The OFAA framework shares aspects of some other new technology implementation ideas in healthcare and synthesizes them with concepts from OM to introduce an operational perspective for AI integration in virtual care. In particular, OFAA shares concepts from the NASSS (Non-adoption, Abandonment, Scale-up, Spread, and Sustainability) framework (Greenhalgh et al., 2019) by recognizing that technology adoption in healthcare depends on alignment across clinical workflows, organizational context, and patient

engagement. OFAA operationalizes this alignment through a structured filtering process (Tier 1), which evaluates the necessity of an AI solution and its operational impact measured through various performance indicators. Similarly, the DECIDE-AI framework (Vasey et al., 2022) emphasizes staged clinical evaluation and real-world testing of AI solution before implementation, and the TEHAI (Translational Evaluation of Healthcare AI) framework (Reddy et al., 2021) assesses capability, utility, and adoption components of AI adoption in healthcare with attention to ethical and translational dimensions. However, OFAA extends beyond just validation and assessment by incorporating workflow analysis, capacity modeling, and continuous governance and quality monitoring mechanisms to ensure that AI functions as a sustainable capacity multiplier within virtual care systems.

Finally, earlier technology implementation frameworks in healthcare, such as the Integrated Technology Implementation Model (ITIM) (Schoville and Titler, 2015), emphasize aligning new technologies with clinical workflows, organizational readiness, and stakeholder engagement. However, these models do not explicitly address AI-enabled workflow transformation or the measurable ways AI solutions can increase capacity in virtual care environments. OFAA integrates insights from implementation science, AI tools assessment, and quality management areas, while uniquely embedding them within an operations management architecture that links strategic justification to measurable system-level performance measures. The two tiers of OFAA ensure that AI evolves from a standalone tool into a sustainable, high-performance collaborator for care delivery. The following subsections examine each tier in detail, beginning with the Tier 1 assessment dimensions.

5.1 Tier 1: The Four Assessment Dimensions

The integration of AI into virtual care is often driven by *technological push*, which refers to implementing a solution simply because it is innovative or trending. However, in a high-stakes clinical environment, technology must be pulled and be a direct response to a specific operational or clinical need. Tier 1 of the OFAA framework serves as this strategic filter. Before any technical development or procurement begins, a proposed AI solution must be rigorously justified against four assessment dimensions:

1. *Dimension 1–Clinical Workflow and Decision Integrity*: Evaluates whether the AI provides meaningful clinical advantage or it results in unnecessary informational and cognitive load.

2. *Dimension 2–Operational Efficiency and System Throughput*: Determines if the AI reduces operational bottlenecks, such as wait times or backlogs, without creating new operational delays or inefficiencies.

3. *Dimension 3–Patient Experience and Engagement Continuity*: Assesses the AI's ability to support patients through their virtual care experience. The goal is to ensure the tool strengthens the patient–provider relationship rather than introducing confusion, distance, or unnecessary complexity.

4. *Dimension 4–Equity, Access, and the Digital Divide*: Assesses accessibility across all patient demographics and technological literacy levels. It ensures the solution does not exacerbate existing disparities in healthcare access. Similarly, assessing

whether the AI is trained sufficiently on a diverse set of patient demographics and across different communities is essential in various applications.

Figure 4 provides a visual summary of the Tier 1 assessment process. It shows how an identified operational or clinical need initiates the evaluation process and how the proposed AI solution must move through the four assessment dimensions: clinical integrity, operational efficiency, patient experience, and equity and access. Each dimension functions as a gate that must be satisfied before the proposal for an AI solution can advance to the technical development or procurement phase.

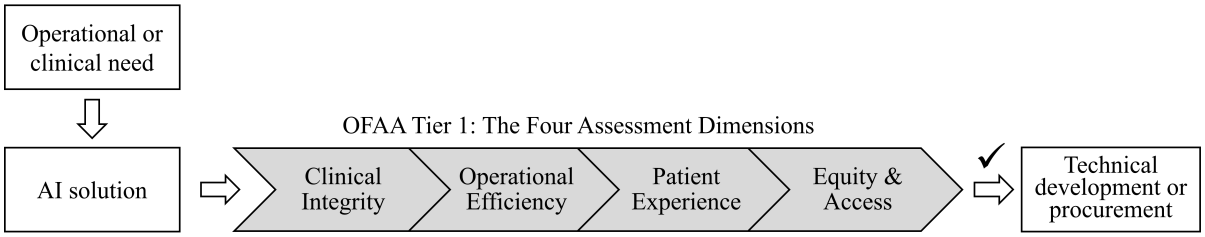

Figure 4: OFAA Tier 1: The four assessment dimensions

The next subsections explain each of these four Tier 1 assessment dimensions in greater detail.

5.1.1 Dimension 1: Clinical Workflow and Decision Integrity

The first dimension evaluates whether the AI will be a meaningful contributor to the clinical process or it will merely add to the existing *digital clutter*. In telehealth, this clutter often arises from a broader *data deluge*, where the unmanageable volume and velocity of continuous remote-sensor streams obscure clinically meaningful signals and exceed human processing capacity (Bawa et al., 2025). RPM and wearable sensors generate a continuous stream of data that clinician can realistically monitor in real-time. Consequently, the clinical assessment of AI must focus on its ability to precisely filter data, suppressing unnecessary signals while ensuring that every clinically important event is accurately prioritized for immediate review.

Decision-makers must analyze whether the AI moves beyond simple reporting to provide insights that enable decision making. For example, a heart-rate monitoring AI that flags every minor tachycardia event is operationally destructive because it induces alert fatigue and wastes clinical time. Conversely, an AI tool that analyzes trends across multiple variables (combining heart rate, activity levels, and sleep data) to predict a potential cardiac event before it occurs can create substantial clinical value (Mullankandy and Patil, 2025).

The evaluation in this dimension should focus not only on whether the AI provides the correct diagnosis but also on its ability to reduce *clinical decision latency*: *Does this AI solution reduces the time between a patient's physiological change and a clinician's life-saving intervention?*. In a virtual care setting, an accurate alert is only valuable if it reaches the provider fast enough and clearly enough to allow for a timely decision. If the AI requires more time to manage and validate than the manual process it replaces, it fails this dimension and should not proceed to implementation.

5.1.2 Dimension 2: Operational Efficiency and System Throughput

The second dimension focuses on the entire healthcare system. In this dimension, AI's potential is evaluated on whether it can act as a multiplier of provider's existing capacity, rather than just replacing medical staff, by automating time-consuming non-clinical tasks. By handling routine data collection and low-acuity patient inquiries, the AI allows the existing clinical workforce to manage a much larger population of patients effectively. This shift is essential in virtual care, where the goal is to increase the total volume of patients served (i.e., *system throughput*) while maintaining a fixed staffing level and without sacrificing care quality.

In many telehealth systems, the primary bottleneck is the intake and triage process (Napi et al., 2019). If an AI-powered chatbot can autonomously handle 40% of routine inquiries (such as medication refills or post-operative wound checks) asynchronously, it basically unlocks 40% more capacity for the physician to perform synchronous virtual visits for complex cases. Integration is operationally justified only when it demonstrates a measurable potential to reduce the *cost per encounter* and a significant increase in the proportion of *provider utilization* dedicated to high-value clinical interaction without contributing to staff burnout.

A clear illustration of this capacity challenge appears in specialty referrals. In many cases, primary care physicians possess most of the clinical information needed to manage a condition, but are delayed by the small portion of the case that requires specialist confirmation. In traditional workflows, this gap triggers a full in-person referral, generating additional documentation, scheduling delays, and administrative burden (Pearl and Wayling, 2022). AI-supported e-consultation platforms could help alleviate this bottleneck by automating the surrounding workflow, such as summarizing clinical notes, routing cases to the appropriate specialty, and ensuring that key diagnostic information is included before review. Although the clinical judgment remains with the specialist, these AI-augmented workflows enable specialists to resolve a substantial share of cases asynchronously. Health systems using e-consult models report that a significant proportion of specialty-related questions can be addressed electronically without a formal visit (Osman et al., 2019). Operationally, this reduces unnecessary referrals, shortens time for clinical decisions, and preserves synchronous specialist capacity for the most complex cases.

5.1.3 Dimension 3: Patient Experience and Engagement Continuity

The third dimension recognizes that a virtual care system is only as effective as the patient's willingness to engage with it (Srinivasan et al., 2020). Many such initiatives fail not because the technology is flawed, but because the digital friction is too high. Digital friction examples could include the technical obstacles to access the digital applications, confusing interfaces, or extensive data-entry requirements that discourage patient participation. This dimension assesses the AI's ability to mitigate these challenges by acting as an intelligent interface that guides the patient through the care journey, simplifies complex instructions, and ensures a seamless transition between virtual and in-person touchpoints.

The assessment in this dimension must determine if the AI strengthens the patient-provider bond or replaces it with an impersonal experience. For instance, Generative AI can be used to translate complex, jargon-heavy clinical notes from a video visit into a personalized plan sent directly to the patient's mobile device. If the AI makes the

patient feel understood, as reflected in higher *app retention rates* and stronger *care plan adherence*, it passes this check. However, if its interactions feel unreal, it drives up the *interaction abandonment rate*, and the system begins to hinder care delivery instead of supporting it. In mHealth applications, for example, *user habituation* is often discussed as a major barrier for delivering effective interventions (Nahum-Shani et al., 2016; Saghafian and Murphy, 2021).

5.1.4 Dimension 4: Equity, Access, and the Digital Divide

The final dimension ensures that the system works reliably for all users, not only those with ideal technology. In virtual care, equity is not just an ethical concern but a practical requirement. The AI must handle a wide range of inputs, including lower-quality connections or older devices. A virtual care system is fundamentally flawed if its AI tools function well only with high-speed broadband or the latest hardware. This dimension, therefore, examines whether the technology performs consistently across users with strong digital access and those with limited connectivity or outdated equipments.

Operational excellence requires that the AI tool work well across different levels of connectivity and device quality. For example, an mHealth diagnostic tool must be validated to perform with the same accuracy on low-resolution images from older smartphones as it does on high-definition files. Failure to do so introduces clinical risk and system-wide *quality defects* (i.e, errors or inconsistencies that arise because the technology is not robust) when serving rural or low-income populations. More broadly, operational excellence of mhealth tools is largely tied to the scientific and regulatory challenges faced in the mHealth ecosystem (Saghafian and Murphy, 2021).

In some applications, decision-makers must also conduct *algorithmic bias audits* (Obermeyer et al., 2021) to ensure the AI's predictive logic remains demographically robust, maintaining high performance across different skin tones, languages, and cultural contexts. Integration is only justified when the AI demonstrates that its operational benefits, such as faster triage or remote monitoring, are accessible to the entire patient population, regardless of their digital infrastructure.

Tier 1 summary. The four assessment dimensions of Tier 1 of the OFAA framework ensure that any proposed AI tool is grounded in clinical value, operational logic, patient-centered design, and equitable access before an organization commits resources to development or procurement. Table 2 provides a concise overview of these dimensions and the core questions they are designed to address. Tier 1, therefore, determines whether an idea is worth pursuing at all. Once an AI solution has met these requirements, the focus shifts from justification to execution.

The next section introduces Tier 2 of the OFAA framework, which outlines the four-phase implementation pathway that guides the integration, testing, refinement, and governance of a validated AI concept within the telehealth or mHealth workflow.

5.2 Tier 2: The Four Execution Phases

While Tier 1 provides the guiding principle for the adoption of an AI solution by defining success factors and readiness, Tier 2 provides a structured roadmap to operationalize AI. In this framework, Tier 1 acts as the diagnostic input; the specific performance gaps and organizational constraints identified during the assessment phase dictate exactly where

Table 2: Tier 1 assessment dimensions and their core evaluative questions

Dimension	Core Assessment Question
Clinical Workflow and Decision Integrity	Does the AI meaningfully support clinical reasoning by reducing noise and highlighting information that requires timely action?
Operational Efficiency and System Throughput	Does the AI relieve identifiable bottlenecks and expand the system's ability to serve more patients with the same staffing level?
Patient Experience and Engagement Continuity	Does the AI reduce digital friction and strengthen the patient's willingness to stay engaged throughout the care journey?
Equity, Access, and the Digital Divide	Does the AI perform reliably across varied devices, connectivity levels, and demographic groups, ensuring that no population is disadvantaged by its use?

and how the following roadmap is applied. For transition from assessment to action, the execution roadmap follows a four-phase cycle:

1. *Phase 1–Strategic Alignment and Value Mapping*: Using Lean methods to identify sources of waste and define the operational pull that justifies an AI intervention.

2. *Phase 2–Solution Design and Capacity Modeling*: Applying process flow modeling tools, for example, queuing models and simulation, to confirm that the proposed AI solution functions as a true capacity multiplier before deployment.

3. *Phase 3–Deployment, Monitoring, and Refinement*: Implementing the AI–human interface and using quality control charts to monitor process outcomes under real-world variability.

4. *Phase 4–Governance and Continuous Improvement*: Establishing safeguards against algorithmic drift and embedding a continuous improvement loop into routine operations.

Figure 5 illustrates the Tier 2 execution cycle. Unlike the sequential steps of Tier 1, this figure emphasizes the iterative and circular nature of AI integration. The process begins with identifying systemic waste in Phase 1, moves to quantifying the AI's expected impact on throughput and resource capacity in Phase 2, and continues through deployment, performance monitoring, and system calibration in Phase 3. Phase 4 introduces governance and continuous improvement mechanisms that feed directly back into the start of the cycle. This visual structure reinforces the principle that AI implementation and integration is a dynamic process that demands ongoing optimization and oversight to remain effective. The following sections explain these four phases.

5.2.1 Phase 1: Strategic Alignment and Value Mapping

Execution begins by identifying the clinical bottleneck where human intervention is currently the limiting factor. This is achieved through *value stream mapping* (VSM), a Lean

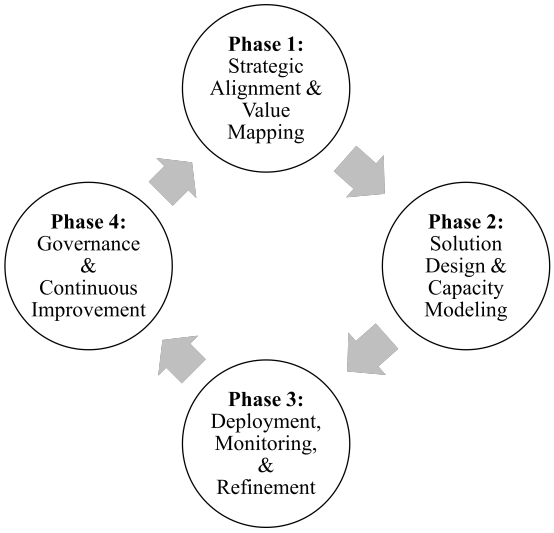

Figure 5: OFAA Tier 2: The four execution phases

diagnostic tool used to visualize the entire flow of information and care from the patient's initial symptom to final resolution (Marin-Garcia et al., 2021). VSM allows managers to differentiate between *value-added time*—activities that directly contribute to diagnosis and treatment—and *non-value-added time*, such as troubleshooting video links or completing redundant digital forms. By quantifying these delays, organizations can identify the specific operational pull for AI, ensuring technology is integrated to eliminate waste rather than simply automating existing inefficiencies.

The visual flow in Figure 6 provides an illustrative example of the contrast between active clinical care and structural waiting. While the specific durations are conceptual, they highlight an operational reality: the *value-added ratio* (i.e., value-added time/total flow time) in traditional telehealth is often suppressed by administrative and clerical burdens and process delays. Based on this illustrative model, totaling the segments reveals a *total flow time* of approximately 5 days, 1 hour, and 37 minutes, contrasted against a value-added time of only 20 minutes. This results in an efficiency ratio of approximately 0.27%, indicating a large amount of non-value-added time that can be targeted for improvement.

To address these inefficiencies, the VSM uses *Kaizen Bursts* (Pyzdek, 2021)—jagged symbols that mark points in the workflow where targeted improvements are needed. A Kaizen Burst is a short, team-based effort aimed at quickly improving a specific part of the process within the broader philosophy of continuous improvement. In this framework, each burst identifies where AI could meaningfully reduce waste or relieve a bottleneck. For example, an ambient AI scribe burst is placed over the documentation step to remove clerical delay, while an AI e-consultation burst is placed over the specialty-gap triangle to shorten the multi-day wait for expert input (Pearl and Wayling, 2022). These bursts show that AI is being introduced not for its own sake but as a direct response to a clearly mapped inefficiency.

These Kaizen Bursts represent potential AI interventions, each offering a different level of impact, and part of the purpose of the VSM is to surface these opportunities so their value can be assessed more rigorously. The list below illustrates the types of improvements identified in the VSM of Figure 6:

- *AI chatbot*: Captures comprehensive patient data through an interactive dialogue,

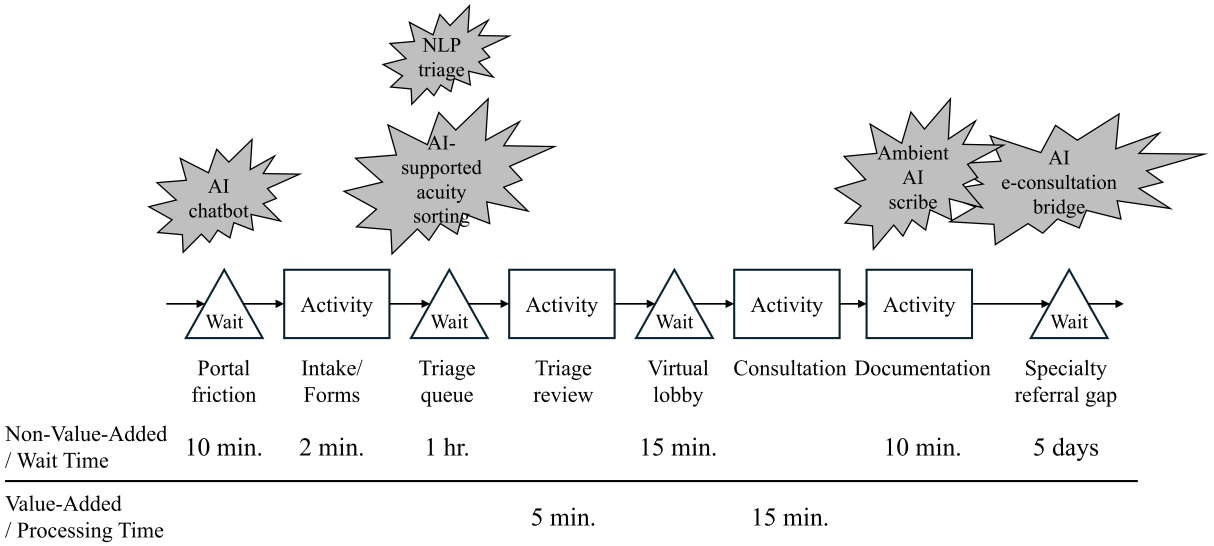

Figure 6: Illustrative VSM of a telehealth journey

reducing manual intake and clerical lag.

- *NLP triage*: Reviews patient text to flag clinical concerns and supply the information needed for automated routing.
- *AI-supported acuity sorting*: Utilizes machine learning models to reorder the patient queue in real time based on clinical urgency to remove the manual triage bottleneck by ensuring high-risk patients are prioritized through predictive scoring.
- *Ambient AI scribe*: Generates clinical documentation during the visit, eliminating after-visit clerical tasks.
- *AI e-consultation bridge*: Provides rapid specialist input to primary care, avoiding multi-day referral delays.

To measure the success of these AI interventions, *baseline KPIs* (*key performance indicators*) must be established that focus on how efficiently the process flows (Chuo et al., 2020). Examples include:

- *Clinical decision latency:* Time from patient data upload to clinician action.
- *Documentation-to-care ratio:* Minutes spent on manual data entry relative to minutes spent in direct patient care.
- *Interaction abandonment rate:* Percentage of patients who drop out of the virtual journey due to digital friction.
- *Specialty resolution rate:* Percentage of specialty inquiries resolved through AI-supported e-consultations without requiring an in-person referral.

By quantifying these baseline metrics, the effect of each AI Kaizen Burst can be compared with how the process performs today. This creates the evidence needed to move into Phase 2, where these measured time savings are translated into concrete design choices. In Phase 2, each potential AI tool is tested in a modeled version of the care system

to see whether it truly removes a bottleneck, how it changes the flow of patients, and how much additional care capacity it could create if implemented. In other words, the baseline KPIs from Phase 1 become the inputs for the simulations, flow analyses, and queueing models that determine which AI solutions are worth pursuing and how they would reshape the system.

5.2.2 Phase 2: Solution Design and Capacity Modeling

The primary goal of Phase 2 is to move from the diagnostic findings of the VSM to a simulated future state of the virtual care system. Before any AI technology is deployed, the proposed solution is tested to ensure it meaningfully changes how the system operates rather than simply speeding up an inefficient process. This phase involves selecting specific AI tools (such as NLP for triage or generative AI for documentation) and modeling how each one would affect the overall flow of care. By viewing the telehealth and mHealth journey as an interconnected system, it becomes possible to determine whether an AI tool truly removes a bottleneck or merely shifts the delay to another point in the patient pathway.

To do this, several analytical modeling methods can be used (Laguna and Marklund, 2025):

- *Process flow analysis*: A detailed review of the care journey that identifies how AI-supported steps interact with manual tasks. This helps ensure the process remains *balanced*—that increases in speed at one stage (e.g., automated intake) do not overwhelm later stages (e.g., specialist scheduling). Modeling these dependencies shows whether a proposed AI tool creates smooth flow or simply produces a new bottleneck downstream.

- *Discrete event simulation (DES)*: A method that models the telehealth journey as a sequence of time-based clinical events. DES captures the *variable* nature of healthcare, where patient arrival rates and activity service times are treated as random variables rather than fixed values. The goal is to observe how the AI–human workflow performs under peak demand and high variability, ensuring the system can absorb real-world fluctuations without queues growing uncontrollably.

- *Sensitivity analysis*: A structured *what-if* approach used to test how changes in AI performance affect the system. For example, if an AI scribe's accuracy falls from 95% to 70%, sensitivity analysis quantifies how much manual correction time is added back into the clinician's workload. This helps identify performance thresholds and informs the safeguards needed to keep the system stable.

Complementing these tools, *queueing theory* provides a mathematical framework for understanding how the system performs under different levels of demand. Queuing theory studies waiting lines and is used to estimate wait times, queue lengths, and the likelihood that the system becomes overloaded (Shortle et al., 2018). In a healthcare system, the clinician functions as a *finite resource* whose capacity is governed by stochastic system-wide variables. Classical queueing models allow the team to test whether an AI tool truly increases effective capacity before it is deployed. A central concept in this analysis is the *utilization rate* (ρ), defined as the ratio of the patient arrival rate (λ) to the clinician's service rate (μ): $\rho = \lambda/\mu$.

In a traditional human-only workflow, the service rate μ is constrained by the expected service time $E[S]$ (i.e., the average time required for an encounter), which includes both value-added clinical care and the non-value-added clerical labor and procedural documentation identified in Phase 1. AI interventions increase μ by compressing the non-value-added components of $E[S]$. For example, if an ambient AI scribe eliminates 10 minutes of documentation from a 30-minute encounter:

- Pre-AI: $E[S] = 30$ min $\implies \mu = 2$ patients/hour.
- Post-AI: $E[S] = 20$ min $\implies \mu = 3$ patients/hour.

This 50% increase in μ prevents the system from reaching a state of instability. As utilization (ρ) approaches 1, the *expected wait time in queue* increases exponentially; by widening the margin between arrival and service rates, AI provides a protective buffer of residual capacity. This capacity cushion enables the system to absorb stochastic fluctuations and demand surges without the persistent backlogs that typically lead to provider burnout.

The final output of this phase is a validated future-state model. By simulating the Kaizen Bursts identified in Phase 1, such as an AI e-consultation bridge that streamlines data synthesis and referral triage to close the *specialty gap* (the delay between primary referral and specialist review), the model shows how a five-day wait can be reduced to a matter of hours. This validation confirms that the proposed AI solution is appropriately matched to real demand. It also prevents a *bottleneck shift*, where faster AI-supported intake or triage would otherwise overwhelm downstream clinicians. In doing so, the model ensures that improvements at one stage do not destabilize another, keeping the entire virtual care system in balance.

5.2.3 Phase 3: Deployment, Monitoring and Refinement

Phase 3 focuses on the operational stability of the AI-human interface. The input for this phase consists of the AI tools that were identified as opportunities in Phase 1 and then confirmed as promising through the modeling work in Phase 2. This transition ensures that only interventions with a mathematically proven impact on capacity are moved into the clinical environment. Deployment follows a controlled, phased rollout to ensure that the AI integration does not introduce unpredictable systemic errors.

The primary monitoring tool in this phase is *statistical process control* (SPC), which utilizes mathematical boundaries—specifically *lower and upper control limits* (LCL and UCL)—to monitor the live performance of the AI-enhanced workflow (Benneyan et al., 2003). By plotting metrics like clinical decision latency or documentation time on a *control chart*, managers can differentiate between *common cause variation* (inherent, expected daily fluctuations) and *special cause variation* (systemic failures or performance drifts).

This real-time monitoring prevents catastrophic system failure by identifying issues early. For example, if a control chart shows a sudden spike in the *interaction abandonment rate*, it signals a special cause variation (Figure 7). This indicates a specific event, such as a software update that increased digital friction, rather than a random fluctuation. This allows managers to pivot immediately, adjusting the AI parameters or the required human review steps before the bottleneck destabilizes the virtual care's throughput.

As the AI handles increasing volumes of non-value-added tasks, the data collected is used to recalibrate the VSM from Phase 1 and the capacity analysis models from Phase 2.

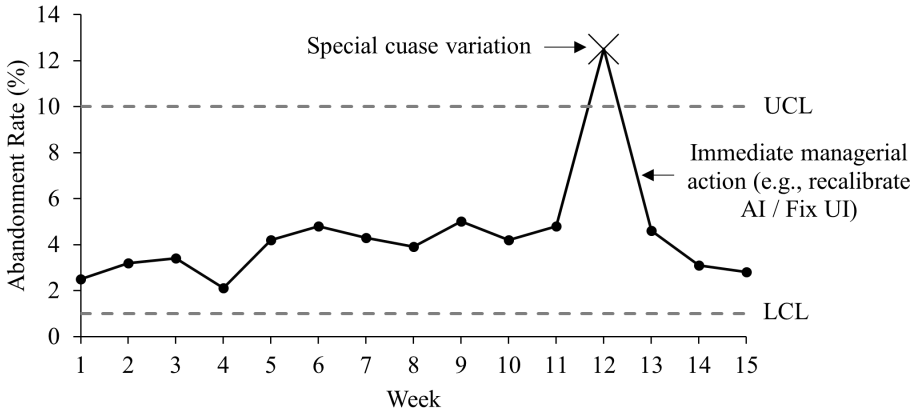

Figure 7: Illustrative control chart for interaction abandonment rate

This iterative approach ensures that the OFAA framework is not a one-time intervention but a permanent management system that enables the virtual care system to scale in proportion to evolving patient demand.

5.2.4 Phase 4: Governance and Continuous Improvement

The final phase addresses the inherent *entropy* of AI. Unlike traditional static software, AI models are subject to *data drift* and *concept drift* (Patchipala, 2023). *Data drift* occurs when the statistical properties of the input data change, such as shifts in patient demographics or referral patterns. *Concept drift* refers to the degradation of predictive accuracy as clinical protocols or medical standards evolve. Left unmanaged, these shifts result in a failure where the system remains operational but provides increasingly inaccurate clinical insights.

Operational governance in this phase moves beyond simple uptime monitoring to include *equity audits* and *model recalibration* (Saleiro et al., 2018). Leadership employs the PDCA cycle (Taylor et al., 2014) as a permanent governance loop, ensuring the AI is treated as a dynamic clinical collaborator rather than a static implementation. These audits are essential to detect quality defects by analyzing the *residual error*, which represents the mathematical difference between the AI's predicted output and the actual observed outcome. When SPC from Phase 3 or audits detect significant error spikes, *model recalibration* is initiated to retrain the algorithm's parameters using the most recent data.

Ultimately, Phase 4 serves as the operational stabilizer of the framework. By institutionalizing this loop, the organization protects the system against clinical inertia and ensures that clinical safety and ethical integrity are maintained despite the evolution of the underlying data. These insights feed back into the Phase 1 VSM, allowing managers to re-identify waste in the virtual care system. This continuous optimization ensures the AI remains a high-performance, equitable, and sustainable component of the care delivery model.

Tier 2 summary. Tier 2 translates the strategic intent established in Tier 1 into a disciplined execution cycle that ensures AI tools are integrated safely, efficiently, and sustainably. Across its four phases, Tier 2 moves from diagnosing system constraints, to modeling future-state performance, to designing workflow integration, and finally to

establishing continuous operational governance. This sequence verifies that each AI solution is technically feasible, operationally balanced, and resilient under real-world demand. By the end of Tier 2, the organization has not only validated the AI's impact on capacity and flow but also built the monitoring and recalibration mechanisms needed to maintain long-term system stability.

6 Conclusion and Future Work

This chapter examined how AI can strengthen the operational foundations of virtual care, which includes telehealth visits, asynchronous communication, and mHealth-supported remote monitoring and intervention. We began by outlining the main virtual care modalities and the practical challenges they create, such as uneven patient engagement, high alert volumes in remote monitoring, delays in triage, and staffing constraints that limit how many patients a system can reliably serve.

To show how AI can help address these issues, the chapter reviewed the core methods behind today's AI tools, including systems that interpret language, analyze images, and learn patterns from data. These methods now appear inside many digital health tools, from symptom checkers and chatbots to automated documentation systems and monitoring algorithms.

Building on this foundation, the chapter described how AI is currently used in virtual care through three main types of tools. Automation tools—such as AI-driven triage agents, conversational intake systems, and ambient documentation—reduce the time clinicians spend on routine tasks and make it easier for patients to enter the system. Optimization tools, including anomaly filtering models, risk scoring systems, and early-deterioration detectors, help teams focus on the patients who need attention most and reduce unnecessary alert review. Prediction tools, such as no-show models and AI-supported workforce planning, help organizations anticipate demand and adjust staffing or scheduling before problems arise. Across these examples, a consistent theme emerged: AI adds value when it is used to solve specific operational problems rather than applied broadly without a clear purpose.

Finally, the chapter discussed the OFAA framework, which brings these lessons together into a practical approach for adopting AI in virtual care. Tier 1 helps organizations decide whether an AI tool is worth pursuing by examining its alignment with clinical needs, workflow logic, patient experience goals, and equity considerations. This tier acts as a strategic filter, ensuring that only well-justified ideas move forward. Tier 2 then provides a step-by-step process for putting the selected tool into practice, including planning, piloting, evaluating, and refining the system through continuous improvement cycles. Together, these tiers offer a clear path for turning AI from a promising idea into a reliable part of everyday virtual care operations, helping organizations adopt technology in a way that is thoughtful, efficient, and sustainable.

In closing this chapter, we note that the future developments in virtual care may depend on several factors. These include advances in both AI and the hardware required to collect higher-quality patient data and to enhance the underlying computations. While health systems are moving toward integrated virtual care platforms that integrate scheduling, billing, and EHR conductivities, further advancements in AI (e.g., via causal reinforcement learning) are required to provide fully dynamic and adaptive treatment regimes (Chakraborty and Moodie, 2013; Saghafian, 2024) that can yield meaningful

improvements in patient outcomes. The next generation of smartphones, sensors, and wearables can also significantly contribute to how future healthcare systems benefit from and integrate virtual care models.

References

Adebowale, J. (2025). Real-time vital sign monitoring and AI-based alerts.

Adepoju, O. E., Chae, M., Liaw, W., Angelocci, T., Millard, P., and Matuk-Villazon, O. (2022). Transition to telemedicine and its impact on missed appointments in community-based clinics. *Annals of Medicine*, 54(1):98–107.

Agarwal, P., Fletcher, G. G., Ramamoorthi, K., Yao, X., and Bhattacharyya, O. (2025). Uses of virtual care in primary care: Scoping review. *Journal of Medical Internet Research*, 27:e55007.

Aggarwal, N., Ahmed, M., Basu, S., Curtin, J. J., Evans, B. J., Matheny, M. E., Nundy, S., Sendak, M. P., Shachar, C., Shah, R. U., et al. (2020). Advancing artificial intelligence in health settings outside the hospital and clinic. *NAM Perspectives*, 2020:10–31478.

Agnihothri, S., Cui, L., Delasay, M., and Rajan, B. (2020). The value of mhealth for managing chronic conditions. *Health Care Management Science*, 23(2):185–202.

AIPRM (2024). AI in healthcare statistics: 100+ facts and trends. Accessed October 2025.

AlMuhaideb, S., Alswailem, O., Alsubaie, N., Ferwana, I., and Alnajem, A. (2019). Prediction of hospital no-show appointments through artificial intelligence algorithms. *Annals of Saudi medicine*, 39(6):373–381.

Andrikopoulou, E. (2023). The rise of AI in telehealth. In *Emerging Practices in Telehealth*, pages 183–207. Elsevier.

Arias López, M. d. P., Ong, B. A., Borrat Frigola, X., Fernández, A. L., Hicklent, R. S., Obeles, A. J., Rocimo, A. M., and Celi, L. A. (2023). Digital literacy as a new determinant of health: a scoping review. *PLOS Digital Health*, 2(10):e0000279.

Bawa, D., Ghazal, R., Kabra, R., Pham, N., Ahmed, A., Katapadi, A., Bansal, S., Colombowala, I., Darden, D., Pothineni, N. V. K., et al. (2025). Role of artificial intelligence in reducing data deluge from cardiac implantable electronic devices. *JACC: Advances*, 4(10_Part_2):102057.

Benneyan, J., Lloyd, R., and Plsek, P. (2003). Statistical process control as a tool for research and healthcare improvement. *BMJ Quality & Safety*, 12(6):458–464.

Bhatt, P., Liu, J., Gong, Y., Wang, J., and Guo, Y. (2022). Emerging artificial intelligence–empowered mhealth: scoping review. *JMIR mHealth and uHealth*, 10(6):e35053.

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

Carreras-García, D., Delgado-Gómez, D., Llorente-Fernández, F., and Arribas-Gil, A. (2020). Patient no-show prediction: a systematic literature review. *Entropy*, 22(6):675.

Centers for Medicare & Medicaid Services (2025). Medicare telehealth trends report. Accessed October 2025.

Chakraborty, B. and Moodie, E. E. (2013). *Statistical methods for dynamic treatment regimes*, volume 2. Springer.

Chen, Y.-H. J., Lin, C.-S., Lin, C., Tsai, D.-J., Fang, W.-H., Lee, C.-C., Wang, C.-H., and Chen, S.-J. (2023). An AI-enabled dynamic risk stratification for emergency department patients with ECG and CXR integration. *Journal of Medical Systems*, 47(1):81.

Chuo, J., Macy, M. L., and Lorch, S. A. (2020). Strategies for evaluating telehealth. *Pediatrics*, 146(5):e20201781.

Ćirković, A. (2020). Evaluation of four artificial intelligence–assisted self-diagnosis apps on three diagnoses: two-year follow-up study. *Journal of Medical Internet Research*, 22(12):e18097.

Clipper, B. (2020). The influence of the COVID-19 pandemic on technology: adoption in health care. *Nurse leader*, 18(5):500–503.

Coffey, J. D., Christopherson, L. A., Glasgow, A. E., Pearson, K. K., Brown, J. K., Gathje, S. R., Sangaralingham, L. R., Carmona Porquera, E. M., Virk, A., Orenstein, R., et al. (2021). Implementation of a multisite, interdisciplinary remote patient monitoring program for ambulatory management of patients with COVID-19. *NPJ Digital Medicine*, 4(1):123.

Daggy, J., Lawley, M., Willis, D., Thayer, D., Suelzer, C., DeLaurentis, P.-C., Turkcan, A., Chakraborty, S., and Sands, L. (2010). Using no-show modeling to improve clinic performance. *Health informatics journal*, 16(4):246–259.

Dean, A., Orfanoudaki, A., Saghafian, S., Song, K., Chakkera, H. A., and Cook, C. B. (2022). Algorithm, human, or the centaur: How to enhance clinical care? Technical report, HKS Working Paper RWP22-027, Harvard Kennedy School, available at SSRN ....

Dezyit Health Insights (2024). Cleveland clinic achieves 94% accuracy in virtual triage. `https://www.dezyit.com/post/cleveland-clinic-achieves-94-accuracy-in-virtual-triage`. Accessed January 2026.

Dorsey, E. R. and Topol, E. J. (2016). State of telehealth. *New England Journal of Medicine*, 375(2):154–161.

Dunstan, J., Villena, F., Hoyos, J., Riquelme, V., Royer, M., Ramírez, H., and Peypouquet, J. (2023). Predicting no-show appointments in a pediatric hospital in chile using machine learning. *Health Care Management Science*, 26(2):313–329.

Eedy, D. and Wootton, R. (2001). Teledermatology: a review. *British Journal of Dermatology*, 144(4):696–707.

Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G., Thrun, S., and Dean, J. (2019). A guide to deep learning in healthcare. *Nature medicine*, 25(1):24–29.

Falcetta, F. S., De Almeida, F. K., Lemos, J. C. S., Goldim, J. R., and Da Costa, C. A. (2023). Automatic documentation of professional health interactions: A systematic review. *Artificial Intelligence in Medicine*, 137:102487.

Fan, G., Deng, Z., Ye, Q., and Wang, B. (2021). Machine learning-based prediction models for patients no-show in online outpatient appointments. *Data Science and Management*, 2:45–52.

Feizi, A., Orfanoudaki, A., Saghafian, S., and Hodgson, N. (2026). Vertical patient streaming in emergency departments. *Management Science (forthcoming)*.

Gajarawala, S. N. and Pelkowski, J. N. (2021). Telehealth benefits and barriers. *The Journal for Nurse Practitioners*, 17(2):218–221.

Gallo, R. J., Shieh, L., Smith, M., Marafino, B. J., Geldsetzer, P., Asch, S. M., Shum, K., Lin, S., Westphal, J., Hong, G., et al. (2024). Effectiveness of an artificial intelligence–enabled intervention for detecting clinical deterioration. *JAMA internal medicine*, 184(5):557–562.

Gerry, S., Bonnici, T., Birks, J., Kirtley, S., Virdee, P. S., Watkinson, P. J., and Collins, G. S. (2020). Early warning scores for detecting deterioration in adult hospital patients: systematic review and critical appraisal of methodology. *BMJ*, 369.

Gilbert, S., Mehl, A., Baluch, A., Cawley, C., Challiner, J., Fraser, H., Millen, E., Montazeri, M., Multmeier, J., Pick, F., et al. (2020). How accurate are digital symptom assessment apps for suggesting conditions and urgency advice? A clinical vignettes comparison to GPs. *BMJ open*, 10(12):e040269.

Greenhalgh, T., Abimbola, S., et al. (2019). The NASSS framework-a synthesis of multiple theories of technology implementation. *Stud Health Technol Inform*, 263(263):193–204.

Greenhalgh, T., Wherton, J., Papoutsi, C., Lynch, J., Hughes, G., Hinder, S., Fahy, N., Procter, R., Shaw, S., et al. (2017). Beyond adoption: a new framework for theorizing and evaluating nonadoption, abandonment, and challenges to the scale-up, spread, and sustainability of health and care technologies. *Journal of Medical Internet Research*, 19(11):e8775.

Gupta, D., Gupta, M., Bhatt, S., and Tosun, A. S. (2021). Detecting anomalous user behavior in remote patient monitoring. In *2021 IEEE 22nd International Conference on Information Reuse and Integration for Data Science (IRI)*, pages 33–40.

Hanna, T. N., Steenburg, S. D., Rosenkrantz, A. B., Pyatt Jr, R. S., Duszak Jr, R., and Friedberg, E. B. (2020). Emerging challenges and opportunities in the evolution of teleradiology. *American Journal of Roentgenology*, 215(6):1411–1416.

Hazarika, I. (2020). Artificial intelligence: opportunities and implications for the health workforce. *International Health*, 12(4):241–245.

Hirschberg, J. and Manning, C. D. (2015). Advances in natural language processing. *Science*, 349(6245):261–266.

Jordan, M. I. and Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245):255–260.

Jovel, J. and Greiner, R. (2021). An introduction to machine learning approaches for biomedical research. *Frontiers in Medicine*, 8:771607.

Kaul, V., Enslin, S., and Gross, S. A. (2020). History of artificial intelligence in medicine. *Gastrointestinal Endoscopy*, 92(4):807–812.

Keely, E., Liddy, C., and Afkham, A. (2013). Utilization, benefits, and impact of an e-consultation service across diverse specialties and primary care providers. *Telemedicine and e-Health*, 19(10):733–738.

Khan, M. and Sherani, A. M. K. (2025). Leveraging AI for efficient healthcare workforce management: Addressing staffing shortages and reducing burnout. *Global Journal of Computer Sciences and Artificial Intelligence*, 1(1):43–54.

Kocaballi, A. B., Ijaz, K., Laranjo, L., Quiroz, J. C., Rezazadegan, D., Tong, H. L., Willcock, S., Berkovsky, S., and Coiera, E. (2020). Envisioning an artificial intelligence documentation assistant for future primary care consultations: a co-design study with general practitioners. *Journal of the American Medical Informatics Association*, 27(11):1695–1704.

Laguna, M. and Marklund, J. (2025). *Business Process Analytics: Modeling, Simulation and Design*. Chapman and Hall/CRC.

Lai, L., Wittbold, K. A., Dadabhoy, F. Z., Sato, R., Landman, A. B., Schwamm, L. H., He, S., Patel, R., Wei, N., Zuccotti, G., et al. (2020). Digital triage: novel strategies for population health management in response to the COVID-19 pandemic. In *Healthcare*, volume 8, page 100493. Elsevier.

LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *nature*, 521(7553):436–444.

Lin, A., Kolossváry, M., Motwani, M., Išgum, I., Maurovich-Horvat, P., Slomka, P. J., and Dey, D. (2021). Artificial intelligence in cardiovascular imaging for risk stratification in coronary artery disease. *Radiology: Cardiothoracic Imaging*, 3(1):e200512.

Lin, S., Saghafian, S., Lipschitz, J. M., and Burdick, K. E. (2025). A multiagent reinforcement learning algorithm for personalized recommendations in bipolar disorder. *Proceedings of the National Academy of Sciences Nexus*, 4(8):pgaf246.

Lin, S. Y., Mahoney, M. R., and Sinsky, C. A. (2019). The promise of artificial intelligence in process improvement. *Nature Medicine*, 25(12):1802–1808.

Lipschitz, J. M., Lin, S., Saghafian, S., Pike, C. K., and Burdick, K. E. (2025). Digital phenotyping in bipolar disorder: Using longitudinal fitbit data and personalized machine learning to predict mood symptomatology. *Acta Psychiatrica Scandinavica*, 151(3):434–447.

Liu, T.-L., Hetherington, T. C., Dharod, A., Carroll, T., Bundy, R., Nguyen, H., Bundy, H. E., Isreal, M., McWilliams, A., and Cleveland, J. A. (2024). Does AI-powered clinical documentation enhance clinician efficiency? A longitudinal study. *NEJM AI*, 1(12):AIoa2400659.

Marcolino, M. S., Oliveira, J. A. Q., D'Agostino, M., Ribeiro, A. L., Alkmim, M. B. M., and Novillo-Ortiz, D. (2018). The impact of mhealth interventions: systematic review of systematic reviews. *JMIR mHealth and uHealth*, 6(1):e8873.

Marin-Garcia, J. A., Vidal-Carreras, P. I., and Garcia-Sabater, J. J. (2021). The role of value stream mapping in healthcare services: A scoping review. *International journal of environmental research and public health*, 18(3):951.

Martin, T. (2012). Assessing mhealth: opportunities and barriers to patient engagement. *Journal of Health Care for the Poor and Underserved*, 23(3):935–941.

Moy, A. J., Schwartz, J. M., Chen, R., Sadri, S., Lucas, E., Cato, K. D., and Rossetti, S. C. (2021). Measurement of clinical documentation burden among physicians and nurses using electronic health records: a scoping review. *Journal of the American Medical Informatics Association*, 28(5):998–1008.

Mullankandy, S. and Patil, S. C. (2025). Machine learning solution for healthcare efficiency for ai-based ecg alert system to address alert fatigue. In *2025 3rd International Conference on Business Analytics for Technology and Security (ICBATS)*, pages 01–13. IEEE.

Nahum-Shani, I., Smith, S. N., Spring, B. J., Collins, L. M., Witkiewitz, K., Tewari, A., and Murphy, S. A. (2016). Just-in-time adaptive interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support. *Annals of behavioral medicine*, pages 1–17.

Napi, N., Zaidan, A., Zaidan, B., Albahri, O., Alsalem, M., and Albahri, A. (2019). Medical emergency triage and patient prioritisation in a telemedicine environment: a systematic review. *Health and Technology*, 9(5):679–700.

Obermeyer, Z., Nissan, R., Stern, M., Eaneff, S., Bembeneck, E. J., and Mullainathan, S. (2021). Algorithmic bias playbook. *Center for Applied AI at Chicago Booth*, 7(8).

Osman, M. A., Schick-Makaroff, K., Thompson, S., Bialy, L., Featherstone, R., Kurzawa, J., Zaidi, D., Okpechi, I., Habib, S., Shojai, S., et al. (2019). Barriers and facilitators for implementation of electronic consultations (econsult) to enhance access to specialist care: a scoping review. *BMJ Global Health*, 4(5).

Patchipala, S. (2023). Tackling data and model drift in AI: Strategies for maintaining accuracy during ML model inference. *International Journal of Science and Research Archive*, 10(2):1198–1209.

Pearl, R. and Wayling, B. (2022). The telehealth era is just beginning. *Harvard Business Review*, 1.

Pyzdek, T. (2021). *The Lean Healthcare Handbook: A Complete Guide to Creating Healthcare Workplaces*. Springer International Publishing, 2nd edition.

Rajan, B., Sainathan, A., Agnihothri, S., and Cui, L. (2022). The promise of mhealth for chronic disease management under different payment systems. *Manufacturing & Service Operations Management*, 24(6):3158–3176.

Rajkomar, A., Dean, J., and Kohane, I. (2019). Machine learning in medicine. *New England Journal of Medicine*, 380(14):1347–1358.

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

Reategui-Rivera, C. M., Cui, W., Escobar-Agreda, S., Rojas-Mezarina, L., and Finkelstein, J. (2025). Machine learning-based prediction of no-show telemedicine encounters. *Telemedicine Reports*, 6(1):109–119.

Reddy, S., Rogers, W., Makinen, V.-P., Coiera, E., Brown, P., Wenzel, M., Weicken, E., Ansari, S., Mathur, P., Casey, A., et al. (2021). Evaluation framework to guide implementation of AI systems into healthcare settings. *BMJ health & care informatics*, 28(1):e100444.

Saeed, M., Jalil, M. S., Dahwal, F. M., Mehedy, M. T. J., Snigdha, E. Z., et al. (2025). The impact of AI on healthcare workforce management: Business strategies for talent optimization and IT integration. *The American Journal of Medical Sciences and Pharmaceutical Research*, 7(03):136–156.

Saghafian, S. (2024). Ambiguous dynamic treatment regimes: A reinforcement learning approach. *Management Science*, 70(9):5667–5690.

Saghafian, S. (2025). *Insight-Driven Problem Solving: Analytics Science to Improve the World*. Cambridge University Press.

Saghafian, S., Hopp, W. J., Iravani, S. M., Cheng, Y., and Diermeier, D. (2018). Workload management in telemedical physician triage and other knowledge-based service systems. *Management Science*, 64(11):5180–5197.

Saghafian, S. and Idan, L. (2024). Effective generative AI: The human-algorithm centaur. *Harvard Data Science Review*, (Special Issue 5).

Saghafian, S. and Murphy, S. A. (2021). Innovative health care delivery: The scientific and regulatory challenges in designing mhealth interventions. *National Academy of Medicine (NAM) perspectives*, 2021:10–31478.

Saghafian, S., Trichakis, N., Zhu, R., and Shih, H. A. (2023). Joint patient selection and scheduling under no-shows: Theory and application in proton therapy. *Production and Operations Management*, 32(2):547–563.

Saleiro, P., Kuester, B., Hinkson, L., London, J., Stevens, A., Anisfeld, A., Rodolfa, K. T., and Ghani, R. (2018). Aequitas: A bias and fairness audit toolkit. *arXiv preprint arXiv:1811.05577*.

Schoville, R. R. and Titler, M. G. (2015). Guiding healthcare technology implementation: a new integrated technology implementation model. *CIN: Computers, Informatics, Nursing*, 33(3):99–107.

Scott Kruse, C., Karem, P., Shifflett, K., Vegi, L., Ravi, K., and Brooks, M. (2018). Evaluating barriers to adopting telemedicine worldwide: a systematic review. *Journal of Telemedicine and Telecare*, 24(1):4–12.

Shachar, C., Engel, J., and Elwyn, G. (2020). Implications for telehealth in a postpandemic future: regulatory and privacy issues. *JAMA*, 323(23):2375–2376.

Shaik, T., Tao, X., Higgins, N., Li, L., Gururajan, R., Zhou, X., and Acharya, U. R. (2023). Remote patient monitoring using artificial intelligence: Current state, applications, and challenges. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 13(2):e1485.

Sharma, G. and Devan, K. (2023). The effectiveness of telepsychiatry: thematic review. *BJPsych Bulletin*, 47(2):82–89.

Shortle, J. F., Thompson, J. M., Gross, D., and Harris, C. M. (2018). *Fundamentals of Queueing Theory*. John Wiley & Sons.

Srinivasan, M., Phadke, A. J., Zulman, D., Israni, S. T., Madill, E. S., Savage, T. R., Downing, N. L., Nelligan, I., Artandi, M., and Sharp, C. (2020). Enhancing patient engagement during virtual care: a conceptual model and rapid implementation at an academic medical center. *NEJM Catalyst Innovations in Care Delivery*, 1(4).

Steinhubl, S. R., Muse, E. D., and Topol, E. J. (2015). The emerging field of mobile health. *Science Translational Medicine*, 7(283: 283rv3).

Taylor, M. J., McNicholas, C., Nicolay, C., Darzi, A., Bell, D., and Reed, J. E. (2014). Systematic review of the application of the plan–do–study–act method to improve quality in healthcare. *BMJ quality & safety*, 23(4):290–298.

Tierney, A. A., Gayre, G., Hoberman, B., Mattern, B., Ballesca, M., Kipnis, P., Liu, V., and Lee, K. (2024). Ambient artificial intelligence scribes to alleviate the burden of clinical documentation. *NEJM Catalyst Innovations in Care Delivery*, 5(3):CAT–23.

Ting, L. P.-Y., Chen, H.-P., Liu, A.-S., Yeh, C.-Y., Chen, P.-L., and Chuang, K.-T. (2025). Early detection of patient deterioration from real-time wearable monitoring system. *arXiv preprint arXiv:2505.01305*.

Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine*, 25(1):44–56.

Vasey, B., Nagendran, M., Campbell, B., Clifton, D. A., Collins, G. S., Denaxas, S., Denniston, A. K., Faes, L., Geerts, B., Ibrahim, M., et al. (2022). Reporting guideline for the early stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI. *bmj*, 377.

Veernapu, K. (2023). AI algorithms and healthcare scheduling: Exploring their potential to address workforce shortages and improve care quality. *Progress in Medical Sciences*, 7(3):PMS–E170.

Vimalananda, V. G., Gupte, G., Seraj, S. M., Orlander, J., Berlowitz, D., Fincke, B. G., and Simon, S. R. (2015). Electronic consultations (e-consults) to improve access to specialty care: a systematic review and narrative synthesis. *Journal of Telemedicine and Telecare*, 21(6):323–330.

Weinstein, R. S., Lopez, A. M., Joseph, B. A., Erps, K. A., Holcomb, M., Barker, G. P., and Krupinski, E. A. (2014). Telemedicine, telehealth, and mobile health applications that work: opportunities and barriers. *The American Journal of Medicine*, 127(3):183–187.

World Health Organization (2022). Global strategy on human resources for health: workforce 2030: reporting at seventy-fifth world health assembly. Technical report, World Health Organization. Document A75/15.

Yuan, S., Yang, Z., Li, J., Wu, C., and Liu, S. (2025). AI-powered early warning systems for clinical deterioration significantly improve patient outcomes: a meta-analysis. *BMC Medical Informatics and Decision Making*, 25(1):203.