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Short Paper

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Abstract

Remote patient monitoring (RPM) refers to clinicians' capabilities for maintaining and adjusting their patients' plan of care by utilizing remotely gathered data such as vital signs to proactively make medical decisions that improve health outcomes and well-being. The focus of this healthcare capability has grown during the COVID-19 pandemic as it allows for patients to remain at home and thwart the spread of the highly contagious coronavirus and payee policies were quickly changed to adapt to the novel situation. We synthesize the literature and present a four-component digital infrastructure framework to think through the design and implementation of remote patient monitoring projects. We identify research questions that emerge from our description of each component. We believe this framework will be useful to research studying remote patient monitoring as it provides a holistic viewpoint of the technologies involved and how those core elements may interact.

Keywords: Remote Patient Monitoring, Digital Infrastructure, Clinical Care Pathways

Introduction

Remote patient monitoring (RPM) refers to clinicians' capabilities for maintaining and adjusting their patients' plan of care by utilizing remotely-gathered data such as vital signs to proactively make medical decisions that improve health outcomes and well-being (Vegesna et al. 2017). However, we have a limited understanding of how to best develop and deploy RPM solutions to save lives, manage safety risks, and promote public health (Mueller et al. 2020). Leveraging RPM to enhance clinicians' decision-making, while also minimizing the risks to patients and providers, involves carefully coordinating people, processes, and systems within the defined clinical care pathways that establish standards, allocate resources, sequence activities, and evaluate outcomes for patient care. As such, an appreciation of the complete infrastructure of RPM solutions is necessary to inform practice on how best to provide these important technologies. Considering the digital infrastructure leveraged in these solutions allows us to recognize previous IS lessons (Øvrelid and Kempton 2019; Swanson 2021), and the importance of clinicians (Aakhus et al. 2018) and patients (Anderson and Agarwal 2011) in the design and use of the systems.

While RPMs had been gaining momentum for the last decade, the onset of the COVID-19 pandemic created an environment that necessitated an acceleration in remote patient care solutions (Birkmeyer et al. 2020). Surges in vulnerable off-site patient populations coupled with severe on-site shortages of personnel, equipment, and capacity in hospitals and emergency departments drove the U.S. federal government and private payers to revise regulations and reimbursement rules and allow greater use of new and existing technologies to care for remote patients (Mann et al. 2020). This policy shift to digital health during an unfolding crisis enabled key health systems decision-makers – clinicians, technologists, and hospital leaders – to consider broadly implementing a variety of hardware devices and software tools to remotely collect, transmit, store, analyze, and summarize patient data (Coffey et al. 2021). Fueled by the demands placed on healthcare systems by the pandemic and coupled with these major policy shifts impacting reimbursement rules, technologies that could be used to provide remote patient care were suddenly in focus.

In this short paper we synthesize the literature to develop a RPM infrastructure framework (see Figure 1). We describe each in detail and highlight the existing knowledge gaps and challenges associated with each component in order to set a research agenda for future work. We believe the introduced framework will be helpful to scholars studying this important phenomenon.

Defining Remote Patient Monitoring

> *"Digital health represents new technology-driven and data-driven approaches to monitoring and improving patient and population health. Digital health transforms how medicine is delivered and managed: instead of relying on the acute, episodic collection of health information at doctor visits, digital health technologies offer a more comprehensive portrait of an individual patient's health by offering new access to care and greatly enhanced monitoring outside the clinic visit. When these data are aggregated, analyzed, and interpreted, digital health can lead to health strategies that can be applied to entire populations. … to reduce inefficiencies, improve access, reduce costs, increase quality, and further personalize medicine."* (Lowery 2020, p. 215)

As described above, *digital health* is an emerging inter-disciplinary field at the intersection of the medical informatics, public health, and business domains. Digital health encompasses an array of convergent information and communication technology (ICT) platforms including: telemedicine, electronic health records, wearable devices, mobile computing, software applications, machine learning, and artificial intelligence (Shaheen 2021). Private and public sector responses to the outbreak of COVID-19 have catalyzed new research and development (R&D) efforts and policy reforms in pursuit of digital health as an integral part of the vision for the future of U.S. healthcare systems (Peek et al. 2020).

Within the aforementioned set of ICT platforms within digital health, our focal infrastructure is specifically the *remote patient monitoring* (RPM) component. As stated earlier, RPM is the capability for clinicians to maintain and alter patient medical care plans by considering data gathered about the patient remotely (Vegesna et al. 2017). By synthesizing the literature, we understand RPM to involve four core elements as depicted in Figure 1: **(1) collection**; **(2) transmission and storage**; **(3) algorithmic analysis**; and **(4) presentation** of remote patient data. We define these core elements and outline the key technologies and enablers as well as the key people and processes for each in our proposed RPM infrastructure framework. By exploring the literature across components, we surface key research questions important to each element, which is summarized in a proposed research agenda (Table 1).

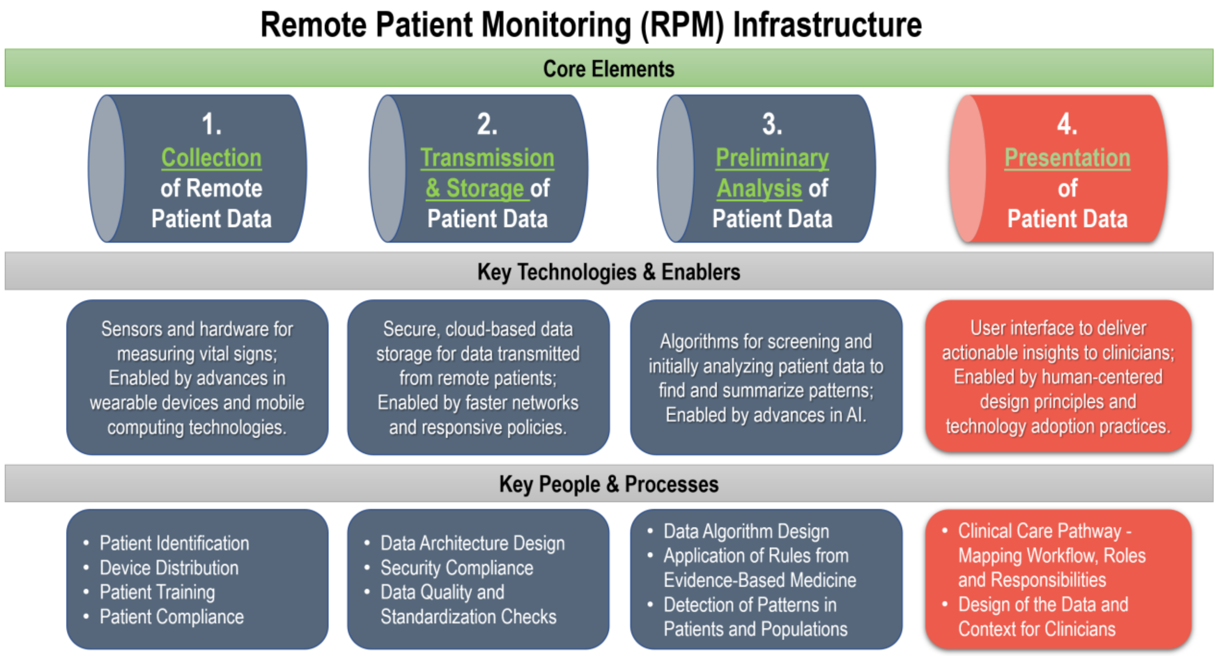

Figure 1. The Four Components of Remote Patient Monitoring Infrastructure

Collection of Remote Patient Data

A defining aspect of RPM is that data is captured outside of a typical clinical setting. Therefore, patient data must be gathered remotely by utilizing sensors and hardware such as wearable devices, mobile phones, and/or portable equipment installed in a patient's home or workplace (Baig et al. 2017). One approach is to rely on data collected from general-purpose smart health consumer electronics devices purchased off-the-shelf by the patient, while an alternative is to rely on data from specialized devices prescribed or ordered for the patient by the provider. Enabled by ongoing technological advances, all of the following are examples of relevant data collected via devices operating within RPM infrastructure: electrocardiogram (ECG), electroencephalogram (EEG), heart beats and respiration rate, oxygen volume in blood or pulse oximetry, signals from the nervous system, blood pressure, body/skin temperature, blood glucose level, patient weight, and sleep patterns (Jagadeeswari et al. 2018). One important consideration is what combination of metrics should be collected for a patient? Growing evidence suggests that RPM initiatives will be more successful if multiple metrics are considered in combination. For example, simultaneously compiling indicators from multiple physiological sensors for measuring heart rate, blood oxygen saturation, and blood glucose levels can provide a more complete picture of a patient's health, which is especially important for patients with co-morbidities and complicating factors. According to the CDC, 51.8% of US adults have at least one chronic condition, and 27.2% have multiple chronic conditions such as obesity, diabetes, and cardiovascular disease (Nguyen et al. 2021). This implies that the diagnostic value of data collected from individual sensors can be made even more useful when viewed holistically with concurrent data from multiple sensors.

Another key issue to collection involves patient compliance in order to generate usable data. Beyond the general demographic characteristics of age, gender, race and ethnicity, which are all known to be associated with variations in the level of adherence with RPM protocols, another important predictor of patient compliance is their individual level of health knowledge (Vandenberk et al. 2019). To address this issue, clinicians providing patients with training and access to their personal data from RPM may be a possible solution, although not without pitfalls. Like other healthcare studies, willingness to disclose personal health information is rooted in emotion and trust in provider (Anderson and Agarwal 2011). When bundled with appropriate training for interpreting the results, giving patients secure access to their own readings may help empower patients to take action in improving their health. However, as a recent study cautions, "when patients combine devices that are not intended for use with other devices, or when patients use any unauthorized devices, new risks are introduced" (Dimentstein et al. 2022). These risks cannot be ignored by patients or clinicians and the collection of patient data must account for this unintended consequence of wider RPM use.

Transmission and Storage of Patient Data

After the remote patient data is collected by sensors and devices, it is then transmitted via communications networks and stored in cloud-based systems. In this element of RPM infrastructure, technical advancements and responsive policies are key enablers. For network connectivity, remote devices operated at the patient's location require a reliable broadband wired link or high-speed wireless link. This fundamental requirement underscores the importance of increased investment in "digital inclusiveness" and "connecting the unconnected" to overcome growing inequalities in Internet access that exacerbate existing disparities in healthcare access (Saeed et al. 2020, p. 1). Sustained investments in upgrading networks are needed to fully realize the potential of RPM as an essential component of national infrastructure, not only for combating the COVID-19 pandemic, but also for expanding individual treatment options and improving public health outcomes for chronic diseases. The inequities of limited internet access have been documented (Hsieh et al. 2008; Leidig and Teeuw 2015), but more research is needed to develop solutions to serve these populations successfully with RPM solutions.

Another key issue for the transmission and storage of RPM data involves solutions for optimal security. As part of the transmission process, to interoperate and exchange patient data with cloud-based web services such as third-party storage systems, RPM infrastructure typically incorporates a standardized application programming interface or API (Braunstein 2018). For example, the Representational State Transfer (REST) API is a widely adopted software architecture built upon open standards for efficient, scalable, simple, uniform, modifiable and reliable interactions between clients and servers with a clear separation between user interfaces and data storage systems. In terms of federal privacy regulations, under the U.S. Health Insurance Portability and Accountability Act (HIPAA), data (such as the number of steps and heart rate) generated by wireless devices directly purchased by a consumer and not prescribed by a physician are not classified as personal health information (Muzny et al. 2020). However, as soon as this data is transferred into an electronic health record (EHR), it is automatically subject to HIPAA regulations as part of the patient record. While the transmission and storage of remote patient data in cloud-based solution has some notable advantages in terms of efficiency and economies of scale, there are also potential disadvantages in terms of susceptibility to cybersecurity attacks and intrusion attempts. So-called "medjacking" or the hacking of medical devices is a growing concern (Adashi and Thomasian 2020, p. 1), prompting the U.S. Food and Drug Administration (FDA) to issue formal guidance regarding countermeasures for mitigating the risks of evolving cybersecurity threats (Kramer and Fu 2017). Like so many broader security concerns in information systems, RPM solutions would benefit from new ideas that secure patient data without limiting access.

In addition to security measures to keep patient data from being accessed by unauthorized users, other concerns related to patient privacy should be considered. If audio or video streams are being captured, patients may expose unintended private recordings to their healthcare team (Kara 2001). Further, vital signs being collected constantly gives access to daily patterns and intimate life details, not routinely shared during occasional patient visits. For example, basic activity tracker devices for personal use have been used to determine potential sexual activity (Landsverk 2019), and health insurance companies have seen the benefits of collecting patient data via wearables to potentially change coverage rates (Olson 2014). Frequently research in this RPM studies unintended access as privacy breaches, without considering if patients intended to share, or understood the implication of sharing, their patient monitor data with healthcare workers.

Algorithmic Analysis of Patient Data

After the remote patient data is transmitted and stored, it is automatically screened and initially analyzed to find and summarize patterns and trends in individual patients and patient populations (Lowery 2020).

Algorithms may use static rule logic (e.g., draw attention to results over a certain threshold), or leverage machine learning techniques that dynamically adapt and learn from large sets of patient data (e.g., dynamically adjust the threshold rule based on similar patients with similar conditions recorded in the data) (El-Rashidy et al. 2021). Yet this distinction (static vs. dynamic rules) is important and has implications that should be explored. Applying static rules derived from evidence-based medicine is familiar to healthcare (e.g., vital sign thresh holds), but there are potential upsides to machine learning to help identify concerning medical situations with more fluidity to take in a wider set of predictor data (Pianykh et al. 2020). In RPM patient data will likely be collected more frequently, so machine-learning algorithms will have access more data (which, in turn, can make the results more accurate and robust). Yet, an unbalanced dataset containing a significant under- or over-representation of a specific group of patients may limit the diagnostic value or skew the predicted outcomes for members of the group and the overall patient population (Gianfrancesco et al. 2018). A series of benchmarking and validation studies documents numerous examples of inadvertent bias occurring within many different clinical care pathways when training datasets are insufficiently diverse across the age, gender, race, ethnicity, and socioeconomic status of patient populations (Cahan et al. 2019; Kaushal et al. 2020). Further, patterns can be found within patient data and across patient data. Yet more research is needed to know which approach is optimal and under what conditions.

Presentation of the Patient Data to Clinicians

The results of the preliminary analysis must be presented to clinicians in a way that enables the remotely gathered data from their patients to be meaningfully integrated into the decision-making process for the relevant clinical care pathway (Gold et al. 2018). We contend that the presentation layer of the RPM infrastructure is perhaps the most important, but least understood aspect to fully realizing the benefits of RPM to treat patients. Previous work has focused on the sensor technology deployed to patients, including the challenges of device cost, patient discomfort, and accuracy of the readings (e.g., (Abdolkhani et al. 2019; Patel et al. 2012)), security issues of data storage (e.g., (Mainanwal et al. 2015; Ondiege et al. 2017), and the algorithms used to analyze the data (e.g., (Iranpak et al. 2021). In fact, in a comprehensive review, previous studies were organized around these three components: sensor technology, database technology, algorithm techniques (Malasinghe et al. 2019). Despite the promise of RPM, a study evaluating the clinical outcomes of some RPM programs found no statistical significance between patient groups being remotely monitored (Noah et al. 2018). We believe this is due to a failure to consider the clinician decision-making process within the RPM infrastructure design. A recent study notes that after notification of elevated blood pressure measurements from patients in a RPM program, most physicians left the plan of care unchanged, suggesting the need for more refined alerts (Lee et al. 2022).

We believe that applying and expanding upon the lessons involved in digital nudge work may hold the key to improving the integration of RPM data into clinical care pathways by enhancing our understanding of presentation layer design needs. Digital nudging describes “the use of user interface design elements to guide people’s behavior in digital choice environments” (Schneider et al. 2018). Digital nudging frames choices, spotlights contextual cues, or filters information to subtly and constructively direct or redirect clinicians’ attention at the point of care (Shah and Adusumalli 2020). There are typologies that articulate the various instances of nudges to drive human behavior – from offering incentives, to soliciting precommitment, to selecting a default setting, to leveraging social influence signals in the message (Bammert et al. 2020; Nwafor et al. 2021) – which highlight the value of embracing a human-centered design approach to tackling these problems. However, these studies usually focus on non-experts, or people making decisions outside of their individual areas of expertise, such as nudging consumers towards healthier food choices or nudging patients to consider self-care (e.g., Jesse and Jannach 2021; Möllenkamp et al. 2019). The context of RPM enables researchers to explore digital nudges along a new dimension; the use of digital nudges to facilitate experts making decisions

Finally, it is important to acknowledge the potential of data formatted to augment decision making to be over relied upon by human decision makers (Gianfrancesco et al. 2018; Veale et al. 2018). If this happens algorithmic biases or malfunctions may not be detected by humans. This potential dark side of enhanced data presentation should be considered and measured for any RPM solutions.

Collection	Transmission & Storage	Algorithmic Analysis	Presentation
What breadth of data should be collected to enable patient treatment?	How can populations with limited internet access participate in and benefit from RPM?	What are the inherent differences and implications of using static rules vs. machine-learning techniques of algorithmic analysis?	How should digital nudges be designed to inform *expert* decision making?
What patient training initiatives and data transparency may make RPM more successful?	How can data architecture balance security and accessibility of patient data?	How is evidence-based medicine best incorporated into algorithm design?	How can presentation designs augment decisions without causing over-reliance?

Table 1. Component-Specific RPM Infrastructure Research Questions

Cross-Component Discussion & Future Directions

We offer the Remote Patient Monitoring infrastructure framework organized across four core components (see Figure 1) as a summary of the current body of knowledge of the technologies involved to generate RPM capabilities. During our description, we identified some of the existing knowledge gaps and offer guiding research questions for future work (see Table 1). We hope the introduced framework will be helpful to scholars studying this important phenomenon as a foundation to understand the systems landscape relevant and adjacent to their research interests.

Additionally, we see an important call for work that takes into consideration the potential tensions across multiple components of the RPM infrastructure. For example, the ideal data presentation to clinicians may require a reassessment of the data collection frequency or processes. Security and access may be at odds when designing systems for patients to utilize. Data collection processes may skew data sets and create imbalances that machine learning algorithms do not take into consideration. Therefore, in addition to addressing singular components of this infrastructure, we hope this framework provides a way to think through how a recommended change or design of one system may have additional consequences across the framework.

Finally, we have focused on the core technologies that must work in tandem to provide RPM solutions to healthcare. Involved in each key process is a set of stakeholders. Future work should consider the infrastructure needs and design from these stakeholder vantage points. Their unique needs, concerns, and potential benefits from the capability should be studied and addressed in order to improve adherence and avoid resistance.

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