



Virtual Care 2.0—a Vision for the Future of Data-Driven Technology-Enabled Healthcare

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Published online: 15 April 2019

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This article is part of the Topical Collection on *State-of-the-Art Informatics*

Keywords Virtual care · Digital health · Artificial intelligence · Clinical decision support · Patient engagement · Population health

Abstract

A busy community cardiologist finished reading eight echocardiograms over lunch and started clinic at 1 pm. As three patients waited, “Jane,” a 45-year-old graphic designer was seen for “skipped heart beat.” She works about 50 h a week, exercises at the local gym, and enjoys eating a healthy diet. About 4 months ago Jane began experiencing her heart “skipping beats.” She initially attributed the symptoms to long hours in the office and caffeine. But, over the holiday, her brother purchased a smart watch and she began digitally recording her cardiac rhythm. About a month ago, the device detected possible atrial fibrillation, so she called and scheduled this visit for a cardiology consultation. Upon that visitation, she and her physician reviewed the device readings. While it appeared to be an irregular rhythm, before either considered a treatment plan, they began to ask questions ranging from the following: “Is this an accurate diagnosis?” “What other data are available to better understand the risk of a cardiac arrhythmia?” “How is this data analyzed so that the best treatment plan can be made?” “And, what type of clinical decision support system is required to ‘virtually’ monitor people like me using digital health devices to improve the efficiency and quality of care delivered in population health?”

Introduction

The widespread gap between the development of new healthcare technologies and the practice of clinical and preventive services argues for a deeper understanding for how effective quality improvement can be designed to meet the needs of patients and healthcare practitioners. With an increasing drive towards the consumerization of healthcare and the rising popularity of new digital health devices the question to what degree might “personalized digital health” be incorporated into larger population surveillance activities becomes increasingly important. Healthcare organizations are seeking to create new strategies by integrating innovations in digital health, precision medicine, and artificial intelligence to improve the quality of care, outcomes, and for cost-effectiveness. They are simultaneously challenged to address key issues such as patient and caregiver experiences, provider satisfaction,

and how new innovations impact clinical workflows. Given the multitude of such requirements, embracing new technologies as a core competency of a modern healthcare organization introduces a number of critical considerations, including the following: (1) what are the organizational factors that guide the development of new digital health clinical programs?; (2) how are new technologies and data analytics integrated to actually improve population health outcomes and the quality of care?; and (3) what type of infrastructure is required to deliver care that is virtual, timely, and effective? (Table 1). Developing systematic approaches for how new data and technology-based innovations are evaluated, integrated and implemented, and to design patient-centric clinical programs will best position our efforts to respond to the aforementioned questions.

Virtual care

Virtual care is broadly defined as the use of health information technology that is exchanged electronically to enhance communication and facilitate a patient’s health. Previously used interchangeably with “telehealth” or “telemedicine” as a means to provide asynchronous or synchronous healthcare visitations over a “virtual” Internet-based program [1], virtual care now encompasses a breadth of rapidly evolving developments including new digital health and smartphone-connected devices, wearable and wireless sensor-based technologies for remote patient monitoring, point-of-care handheld imaging devices [2], and even more recently includes sophisticated artificial intelligence and machine learning approaches to analyze large biomedical datasets in new precision medicine initiatives [3••]. While this pace of development and ongoing technology acceleration is promising in its potential to transform healthcare, it far exceeds the current structure of the healthcare enterprise to adopt such innovations. At the

Table 1. Digital health considerations by domain

Domain	Considerations
Technical	Computation, interoperability, availability
Regulatory	Patient consent, compensation, reimbursement
Risk	Privacy, security, data governance
Clinical	Applicability, reliability, accuracy
Operational	Prioritization, role, workflow, intervention, protocol, efficiency
Patient sociotechnical	Device and application access, health literacy, digital literacy, usability, visuo-spatial capability, cultural and linguistic delivery, data ownership

moment, the lack of generalized adoption is expected since many new innovations have yet to demonstrate value, fit into defined roles and responsibilities, seamlessly integrate into workflows, or have yet to produce outcomes that data-driven and technology-enabled care is safe and cost-effective [4••].

Since healthcare delivery is first and foremost patient-centric, and not primarily technology-focused, we are challenged with how to create models that unify both. Bridging these focal points may be achievable by developing digital population health methods that combine data and new technologies to better inform *person risk*. In contrast to patient risk, person risk (within the context of a population) enables the application of new datasets and technologies to augment our conventional approaches to calculate risk i.e. primary or secondary prevention. By redefining our approach, we can better prioritize how clinicians and the individuals they treat utilize healthcare resources including diagnostic testing and medical therapies. For example, integrating real-time *person-generated* digital data collected from wearable, smartphone-connected devices, or implantable sensor-based technologies with a wide range of health information and data sources can provide a highly granular view of the determinants of health, and specifically a means of characterizing the factors that drive progression from wellness to subclinical disease, and eventually to the onset of symptomatic disease states [4]. Therefore, developing the next phase of Virtual Care—Virtual Care 2.0—on optimally identifying person risk and prioritizing our efforts that merge, analyze, and risk stratify data and technology-derived findings will enable new healthcare programs to continually learn and to enhance our capacity to improve outcomes and the quality of care.

If Virtual Care 2.0 aims to identify and predict changes that are reflective of “real-world” clinical practice, it first requires an understanding of operational factors and for process redesign. Using implementation science principles focused on new technologies, data aggregation, and data analytics to produce clinical decision support systems that are relevant to people, patients, and clinicians, we propose three synergistic priorities described below that are specifically designed to exploit health service delivery with new innovations:

- (1) Aggregate and analyze multidimensional datasets for person risk prediction from electronic health record information, data from social networks, multiomic data from genome sequencing, biomedical imaging, and registries.
- (2) Implement new digital health technologies within the next phase of remote patient monitoring programs to measure physiologic changes, the response to therapies, and to collect patient-reported outcomes in real time.
- (3) Create dynamic clinical decision support tools for patients, providers, and their caregivers that merge person risk with digital health monitoring and to engage care teams to formulate individualized monitoring and treatment strategies.

Multidimensional data

While rich in quantity, currently available health data in medical records are limited in dimensionality and often struggle to accurately reflect the time

dimension across particular datasets. Because patient data is collected during a healthcare encounter, it is potentially biased as it samples individuals during illness, collects changes in medical therapy based on intervals at follow up versus following the course a disease, and computes claims data after accessing healthcare resources. Oversampling such populations skews our approach to risk stratification, leaving unknown the larger composite shaping population health comprised from the those that are healthy or with subclinical disease. A potential approach to overcome such bias is to add dimensions of data (Table 2) that helps to improve our understanding of the mechanisms connecting the macro (symptoms) and micro (physiology) with the biologic in order to elucidate the social determinants, environmental interactions, and person-related factors on health and disease [5]. There are several considerations for how such datasets are applied to advance broader initiatives that improve risk stratification for preventable diseases. These include the following: to better define the problem and process of need, to identify the methods for data collection including structured and unstructured health data, and to develop computational approaches that analyze large aggregated datasets.

It is difficult to know a priori whether larger multidimensional datasets and new analytic methods such as artificial intelligence and machine learning will be sufficient to address issues related to downstream care coordination and how healthcare services are delivered. Therefore, it is important to approach all—data aggregation, analytics, and care integration—simultaneously [6]. Implementing new data streams into clinical settings requires coordinated efforts to first analyze the relationships that define person risk. Initial experiences testing this hypothesis have shown that the convergence of data from laboratory measurements, diagnosis and procedural codes from electronic health records, medication data, and genomic profiles have helped to identify subpopulations of patients with commonly known diseases [7]. Translational informatics approaches such as predictive analytics, deep learning, and topological analysis to multidimensional datasets have identified new phenotypic clusters and distinct subgroups of patients with type 2 diabetes, each characterized by different disease associations: subtype 1 (nephropathy and retinopathy), subtype 2 (malignancy), and subtype 3 (cardiovascular disease and neurologic disease) [8]. Using deep learning and artificial intelligence techniques to analyze high fidelity biomedical imaging datasets, similar heterogeneity has been observed among individuals at risk for heart failure. The analysis of large quantities of digitized echocardiographic data related to myocardial anatomy and function, and incorporation of these findings within electronic health records, has generated important signals that have identified clusters of individuals at risk for heart failure prior to the development of symptoms [9] and those at risk of a hospital readmission [10]. At the population level, BioBanks and Internet-based patient-reported outcome repositories are collecting health data not otherwise available in conventional electronic health records and are approaching the scale of millions of individuals. Prospective collection of multidimensional data merging genetic, phenotypic, magnetic resonance imaging and ultrasonography, environmental, nutrition, and comprehensive family history is on one hand creating a framework for the

Table 2. Examples of multidimensional data sources including digital data

Dimension	Data source example	Sample types of discrete data available
Claims	837 claims file transaction set	Healthcare claim information such as a CPT charge
	Pharmacy	Dispensed Rx name, dosage, quantity
Public registry		
- State	California Integrated Vital Records Data and System	Date of birth, geographic location
	California Cancer Registry	Cancer stage, prevalence, incidence
- National	American College of Cardiology–National Cardiovascular Data Registries (NCDR)	Outcomes after myocardial infarction, heart failure readmission, quality improvement initiatives
	National Inpatient Sample	Inpatient morbidity and mortality, healthcare resource allocation
- Local	County Immunization Registry	Immunization date, outbreaks
Electronic medical record		
- Local	Health system electronic health record (Epic, Cerner, Athena, etc.)	Diagnosis by ICD, medication, laboratory, allergy, procedure, utilization, care team, demographic, social determinants, zip code, family history, imaging, pathology, etc.
- Shared	External electronic health record information (interoperable record exchange)	HL7 file with formatted EHR structured and unstructured data
Public status		
- National	US Census	Age, income, household, demographics, health insurance, disability
- International	Environmental and Pollution using Organization for Economic Co-operation and Development	Air and greenhouse gas emissions
- Regional	Crime in the US 2016	Offenses by state
Research		
- International with national datasets	Participation	Demographics, zip code, disease
	Patient reported outcomes measures (PROMs)	Health gain in hip replacement
Digital health devices		
- Personal	Biosensors and telemetry patches	14–30-day cardiac rhythm
	Implantable sensors	Heart failure home monitoring with wireless pulmonary arterial pressures
	Digital home monitor	Home blood pressure monitoring
	Social media	Data mine social activities

Table 2. (Continued)

Dimension	Data source example	Sample types of discrete data available
Multiomic data		
- Centralized and decentralized	All of US biobank and UK biobank	Lifestyle, biometrics such as height, weight, blood pressure, family history, medical history, stored blood, and urine
- Individual and de-centralized	23andMe gene sequencing	Detection of common gene mutations

determinants of human health and longevity [11] and on the other is generating new insights into the quality of life measures and treatment efficacy among patients with rare diseases [12]. Such examples of multi-dimensional data present opportunities to harness advanced prediction for discovery and to also address the phenotypic heterogeneity between patients and populations as it relates to both health and illness. In this context, emerging data-driven healthcare practices provide a conceptual framework for the creation of “virtual patients” or “digital twins” where individual patterns of disease are paired with digital models that dynamically reflect the status of the disease state [13]. Instead of using average responses to medical therapies within a population, using data to engineer an individual’s molecular and physiologic status over time and the *in silico* representations created from multidimensional datasets may, in a given person, define deviations from the normal before the occurrence of a change in health status and ultimately can create personalized approaches to medical therapies targeted for the same person.

Implement new digital health technologies

High-definition monitoring with digital health devices offers promising methods for disease detection. It is also enabling the discovery of physiologic changes not otherwise captured on routine patient care. An array of new digital health devices are currently available ranging from smartphone-connected ECG and smartphone-ultrasonography, wearable bioshirts for vital sign monitoring, microfluidic technologies for point-of-care laboratory testing, cuffless blood pressure devices, implantable sensors for intracardiac pressure monitoring, and a host of additional devices and “apps” that aggregate health information and collect patient reported outcomes [2]. In general, these may be applied to help with primary, secondary, and tertiary prevention. In contrast to one-off measurements acquired during usual healthcare encounters, profiling individuals using digital approaches with frequent and continuous monitoring of physiologic parameters either through wearable or implantable technologies (or at the intersection of the two) enables us to perform real-time risk stratification and to monitor changes for more precise diagnosis and earlier time to treatment (Fig. 1).

Commonly used digital devices such as fitness monitors created for one purpose—exercise augmentation—are now generating insights into sub-clinical diseases such as screening for sleep disordered breathing through motion tracking during deep sleep [14] and gait and postural changes as markers of motor function in Parkinson’s disease [15]. Deep learning and artificial intelligence networks with multiple layers of neuronal connections presents the type of large-capacity analytics to identify and define signals captured on digital health devices and to correlate such signals to physiologic changes and disease states. Recent analysis of > 90,000 continuous single lead cardiac telemetry recordings from a wearable ECG patch



Fig. 1. Examples of real-world risk stratification using digital health devices. **a** Smartphone and smartwatch ECG monitoring capturing new onset atrial fibrillation in an ambulatory patient. **b** Smartwatch blood pressure monitoring and elevated afternoon blood pressure observed through continuous tracking. **c** Wearable continuous glucose monitoring with capture of severe morning hypoglycemia and the preceding nocturnal decline in glucose concentration. **d** Wireless sensor implanted in the pulmonary artery for ambulatory pulmonary artery pressure monitoring and medication changes (red lines) resulting in reductions in pulmonary arterial pressure that led to improved patient reported outcomes and readmission risk reduction.

reported that a deep neural network for the classification of 12 common cardiac arrhythmias demonstrated an accuracy of greater than 97% when compared to expert cardiologist consensus [16]. Machine learning and feature selection of microvolt and micromillimeter measurements on single lead telemetry captured via a smartphone-connected ECG have been correlated to serum potassium levels, leading to a bloodless method to monitor individuals at risk for hypo- and hyperkalemia [17].

As Virtual Care 2.0 begins to incorporate the developments of digital health technologies which serve as the building blocks for more precise approaches and “electronic phenotyping” to streams of health data, our efforts must be focused on ensuring quality control of such data (normalization and noise reduction), utilize clinical informatics-based approaches for integration into electronic health records (e.g., SMART-on-FHIR and HL7), validate the type of learning methods (supervised and unsupervised), evaluate analytical techniques (e.g., artificial intelligence, machine learning, natural language processing, and cloud computing), and translate standardized algorithmic approaches (eMERGE consortium and the Phenotype KnowledgeBase) to cumulatively quantify risk prediction [4,7]. New methods for integration that leverage the smartphone as an access to cloud-based patient health record with the functionality to access and share electronic health information offer users greater access to their health data and on their mobile devices. Using the same smartphone as the linkage tool to transfer and transmit data from digital health devices provides one potential solution to interoperability challenges and specifically for how digitally captured health data is aggregated and analyzed with data embedded in electronic health records. Initial user experiences have reported easy connectivity between electronic records and smartphones and, as a means to better understand their own health data, facilitate communication with their clinicians and to share information with their network of family and caregivers [18].

Creation of dynamic clinical decision support

The key priorities of clinical decision support (CDS) are to address questions regarding a patient’s care requirements and, in parallel, how clinicians can use health data to deliver care that is efficient and effective. Clinical decision support with automated risk scores calculated from available demographic and clinical data (e.g., coronary artery disease risk calculation, thromboembolism risk prediction in atrial fibrillation, prediction of pulmonary embolism in acute dyspnea), adverse interaction alerts, and guidance on evidence-based care constitutes some of the underlying structures of modern computerized CDS. A strategy to create CDS systems using multidimensional datasets, data from digital health devices, and computational analytics should not mean creating additional tasks for already inundated clinical teams. Rather, there is a need to aggregate data, compute analytics, and prioritize the information that is pushed forward into clinical workflows for clinical consideration. Coordinated workflows that facilitate the identification of eligible individuals within a larger population should match their need with the receipt of services. To individualize CDS to generate more accurate risk prediction requires multifaceted integration that

enables clinicians to identify the right data, to analyze it with the right methods, and to make it accessible to the right person(s) at the right time. While there is a need to develop robust healthcare information technology and CDS resources for data management and predictive modeling, and to accommodate new technologies and data streams with minimal integration barriers, dynamic CDS approaches must be usable in real time across the spectrum of healthcare delivery and interchangeably between inpatient and outpatient settings and during transitions of care [19••].

The application of digital data in virtual care may draw from published work to date in the early detection of septic shock. Our current methods for detection rely on physical examination, invasive hemodynamics, and a multitude of laboratory measurements. The relevant findings captured only after the onset of the shock state, thus leading to low diagnostic accuracy of established risk prediction tools, and are of limited temporal benefit. Several explanations for this limitation range from the type of clinical parameters which establishes the diagnosis, single point-in-time risk calculations in contrast to continuous risk stratification, and limited translation of evidence-based approaches due to the heterogeneity in clinical practice [20]. Sepsis is complex; therefore, new CDS systems require several steps centered on sequential decision-making. First, methods that increase diagnostic accuracy and understanding are needed. As an example, newly developed non-invasive and non-contact sensors record whole-body temperature measurements and thermal images continuously and track physiologic changes both digitally and automatically. Recent validation studies investigating this technology, combined with machine-learning to detect subtle thermal changes for the prediction of shock, have demonstrated high diagnostic accuracy of sepsis in pediatric intensive care units, yielding a diagnosis up to 12-h before hemodynamic derangements identifying the shock-state [21]. Second, CDS requires real-time analytic based on the individual patient context. Initial experiences with reinforcement learning and the creation of “artificial intelligence clinicians” taught from the extraction of large clinical and electronic health record data have demonstrated that artificial intelligence treatment approaches were associated with improved patient outcomes when compared to actual treatment decision by the “human” clinician [22]. While these initial experiences with new data-driven and technology-enabled approaches are promising, to truly develop dynamic CDS systems requires a key third step—incorporate streams of digitized data to produce an output that can be applied into workflows relevant to different clinical scenarios and directly at the patient–clinician interface.

Flexible information retrieval of electronic health records, multidimensional datasets, and digital health device data streams to identify patterns of disease and clinical trajectory requires several overlapping functional criteria: programming with all-purpose interfaces, real-time data processing, and interactive visualizations that translate digitally derived data into clinically useful information. The EHDViz (Electronic Healthcare Data Visualization) toolkit (source code—[ehdviz.dudleylab.org](https://github.com/ehdviz/ehdviz)) is a software framework designed to interactively generate dynamic CDS and information aggregated from open-sourced healthcare data, claims, diagnosis codes, data from electronic health records, and data

from digital health devices [23]. Embedded within are statistical programming, machine learning, and predictive modeling to create sequential CDS dashboards that visualize time series health data captured from digital health and remote monitoring technologies, visual analytics of electronic health record data in clinical settings, and provide risk visualizations to track individual patients and populations simultaneously. This design allows rapid evaluation of various clinical features or predictors for subsequent clinical decisions. It also enables the creation of personalized approaches to monitoring and therapy based on the analysis of real-time data. Through this combination of digitally captured physiologic parameters and the analysis of this data within electronic health information, diseases that are conventionally classified symptomatically or according to common clinical phenotypes can now be

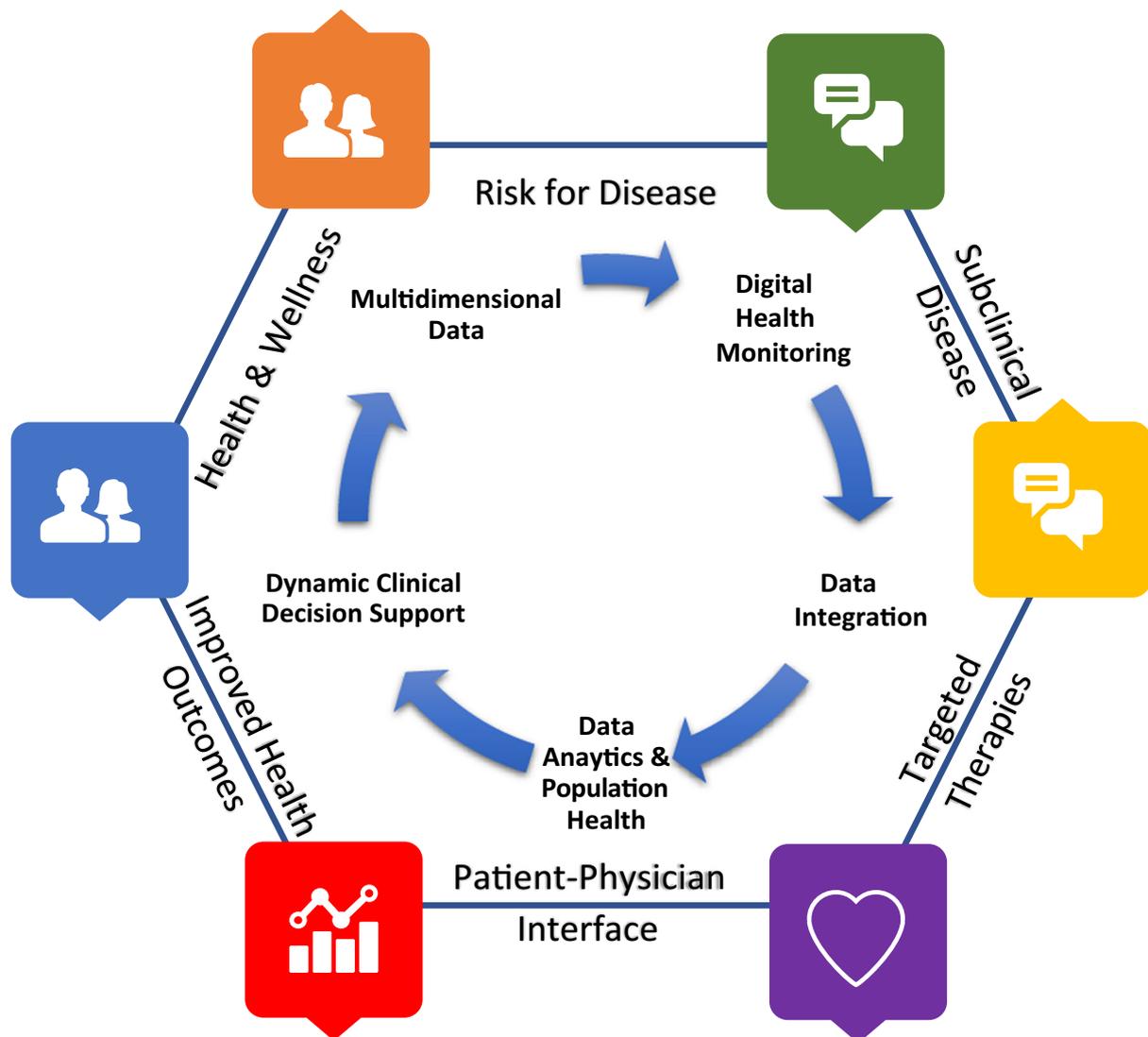


Fig. 2. Virtual Care 2.0. The paradigm and key factors for data-driven technology enabled healthcare.

classified in terms of risk and pathogenicity thereby changing how we approach our workflows to better identify those that will benefit with more efficient process of care.

Virtual Care 2.0

Similar to our clinical scenario outlined at the beginning of this review, for Virtual Care 2.0 to be successful, we must fundamentally change our approach to risk and must move well beyond common representations of patients as two-dimensional vectors, i.e., risk = disease, diagnosis = treatment, treatment = effect, and effect = outcome, when in fact each of these vectors are dynamic and multidirectional (Fig. 2). It is also necessary for us to not just focus on data only for risk prediction but that new data and analytical methods should enable the identification of the social determinants of health, provide screening for social needs, and identify people who will benefit with preventative services such as nutrition, exercise, medication-assisted treatment, and psychological care. While the true breakthrough technology is a rigorous approach to identify people at elevated risk and their response to various medical and non-medical interventions, our efforts to transform the current healthcare delivery system lie with clinical teams that learn optimal care pathways and to predict trajectories through the analysis of multidimensional datasets and data from digital health technologies. In doing so, we will best position the healthcare to improve outcomes for the patients and population that we serve.

Acknowledgements

We thank Alivacor (San Francisco, CA), Dexcom (San Diego, CA), Omron (Osaka, Japan), and Abbott Laboratories (Chicago, IL) developers of the various devices depicted in Fig. 1 as examples of remote patient monitoring technologies in Fig. 1.

Compliance with Ethical Standards

Conflict of Interest

Sanjeev P. Bhavnani is a scientific or medical advisory board member to Analytics 4 Life, Blumio, Misceo Grand Technologies, iVEDIX, and WellSeek and is chair of a data safety monitoring board at Proteus Digital. He serves on the innovation steering committees (nonremunerated) at the American College of Cardiology and at American Society of Echocardiography.

Amy M. Sitapati declares no potential conflicts of interest.

Human and Animal Rights and Informed Consent

This article does not contain any studies with human or animal subjects performed by any of the authors.

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