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Chapter 9: Personalizing patient journeys with real-time data streams from wearables and remote health devices

9.1. Introduction

The increase in personal wearable device use enables the continuous measurement of users' health and anthropometric features. Many digitally collected health and behavioral data is already captured. These streams can include physical activity, calorie burn, heart rate, and sleep patterns. Recently, remote health and wellness devices are equipped with options to synchronize the captured data to different real-time aggregation platforms. As of this year, a number of software platforms are available on the market that enable real-time data aggregation of the collected personal wellness and health monitoring devices. All of them provide application programming interfaces (APIs) to manipulate the synchronized data streams. To further foster the aggregation and distillation of personal wellness and health monitoring devices, additional filtering and processing methods are needed to sift through the combined data streams and provide necessary feedback without information overload. Last but not least, these generated systems need to be user friendly with a design that will make the communities adherent and loyal. Anecdotally, this implies that the designed system has taken both inputs and critical insights from the future community of interest to design a system that ultimately benefits those who use it the most. To empirically test that hypothesis, and provide a design pattern of what a successful software ecosystem is for patient engagement, the company's want to understand the community's software usage habits. A few sample questions of interest are assessed and the percentage distribution on each is calculated. Outcomes and aggregate data will be shared with the scientific community within 30 days of receiving the request. It is possible that aggregated data will also be made publicly available and freely shared.The growing use of personal wearable devices has enabled the continuous tracking of users' health and anthropometric data, including metrics such as physical activity, calorie expenditure, heart rate, and sleep patterns. Modern wellness technologies now often support real-time synchronization of this data to various aggregation platforms, with many offering APIs for flexible data manipulation. As of this year, numerous software platforms exist that facilitate this real-time data collection and integration. However, to effectively manage and interpret these extensive data streams, advanced filtering and processing methods are necessary to avoid overwhelming users with excessive information. Crucially, these systems must also be user-friendly and tailored to the needs and behaviors of their intended communities. This means incorporating direct feedback and insights from target users during the design phase to ensure the system fosters long-term engagement and loyalty. To validate these approaches and identify effective design patterns for software ecosystems that support patient engagement, companies are conducting empirical studies on community software usage habits. Sample questions are posed, and the resulting data is analyzed and shared—potentially made publicly available—to benefit the broader scientific and developer communities.

Fig 9.1: Evolution of Wearable Devices with Real-Time Disease Monitoring for Personalized Healthcare

9.2. Background and Literature Review

Analyzing healthcare data streams in real time involves significant opportunities for the assessment of healthcare and biomedical informatics. Translational bioinformatics, which involves genomic and phenomic data analysis and data integration, usually focuses on mined retrospective data from a completed clinical experiment to assess the new health care data's implications. However, the data streams in real-time bioinformatics consist of data that are highly stochastic, non-linear, dynamic and available in real time. Time series modeling of the human physiology data and development of the monitoring software system are well established in critical care. Any essential bioinformatics analysis and modeling require that the data are already well sampled, reliable, secure and some other priors. New opportunities and challenges arise from the real-time and online health care data uncertainty, as the majority of the real-time health care data streams are both low-quality and rather sparse. Standard clinical EMRs have been implemented to store longitudinally collected clinical care information, but the stochastic or wearable data are not stored. Such retrospective datasets are usually semi-normal, as they take the form of normal matrices, where the rows are the time series ids and the columns are the sequential time points. It is essential to examine, model, interpret and use for secondary observations the potential real-time health care data streams that are streaming in whenever the training step is running. Feel free to talk with the patients or patient communities about potential health care data streams with respect to them, but it is highly doubtful they would mention wearables, and even if they do, they may not have a clear idea of how the data are subsequently integrated, analyzed, modeled and interpreted.

9.2.1. Research design

This is a descriptive prospective cohort study using data from the Triage & Acute Care Unit, an ED observation unit at St. Paul's Hospital, Providence Health Care, Vancouver, Canada. Vital sign and ECG waveform data are stored on a high-resolution, time-stamped sensor and transferred in real time to the EDIS. These data are transferred ubiquitously from clinical devices to patient care applications 25 times per second through a telemedicine gateway using the Real Time Health System (RTHS) and custom application program interfaces. The detailed data, with specific time codes, are compiled within an encrypted data file for research use. Waveform data are analyzed by the RTHS for the presence of atrial fibrillation, an irregular, frequently rapid heart rhythm that increases the risk of stroke, as waveform artifacts may affect the accuracy of these calculations. Cardiac arrhythmias such as atrial fibrillation can be detected using a high-resolution, time-synchronized dataset. Wearables and home-use remote health devices increasingly incorporate advanced sensors for generating real-time data streams, creating opportunities to personalize patient journeys. Home-use remote health devices and wearables have been broadly categorized as tracking, diagnostic, and therapeutic.

This evolving technology can record any aspect of an individual's biological state. Remote health devices are used with mobile phones to send recordings and alarms to the managing care provider. A study will quantify the proportion of admitted patients with any clinically-significant arrhythmia detected within 72 h of ED presentation and describe the impact of wave artefact. It offers an extensive methodologic and data management approach that can be employed for the analysis of detailed, time-stamped observation data from ECG monitors in a high-acuity environment. Most studies to date have exclusively used vital sign and demographic admission data, have employed prevalent rather than high-resolution data, and do not focus on the impact of artifact on the interpretation of clinically-useful ECG data.

9.3. The Role of Wearable Technology in Healthcare

In contemporary healthcare, patient observation and subsequent care are primarily confined to clinical settings and often centred around the management of chronic diseases by healthcare professionals (Patel & Shah, 2020; Ghosh & Choudhury, 2021; Patel & Cushing, 2022). Yet, patients spend a small percentage of their time in a hospital or clinic. One implication is that episodes of symptoms or events of interest might not be present during short clinical appointments or exams. Moreover, underlying pathologies are likely to trigger complex reactions and adaptations in body activity before the appearance of easily recognisable signs or symptoms. Wearable technology aims to address these issues by moving beyond the usual hospital setting to continuously record the body signal using non-invasive or minimally invasive devices. The signals, captured via sensors embedded in a wristband, smartwatch, skin patch, or behind the ear, produce time series of physiological and physical quantities such as electrocardiogram (ECG), heart rate, respiratory rate, oxygen saturation, electromyography, physical motion, and skin temperature. Carefully processing these measurements can help in the reconstruction of the physiological processes underlying the data in the most comprehensive way into hyperspectral images.

The shift of wearable devices from gadgets to clinical and therapeutic systems, however, relies on the processing of the huge amount of incoming data. Deep learning algorithms, in particular, have shown impressive generalization capabilities, and enable the learning of increasingly complex hierarchical data representations from labelled data. An efficient implementation of a deep learning pipeline for wearable data is exploiting recent architectures called domain-specific accelerators. In wearable-based healthcare systems, the stream of incoming data is processed by an analog front-end that shapes and digitizes the signal from sensors. The processed data are transferred via Bluetooth or Wi-

Fi to a low power real time processor that must rapidly and efficiently analyze the incoming sensor data to pinpoint the onset of irregularities or detect complex, patient-specific patterns. In a final device, an alert can be subsequently presented to the clinicians, advising therapeutic actions or further in-depth investigation. Some wearable devices can directly perform therapeutic actions themselves.

Wearable devices come in various types and aim to tackle different types of health concerns. A growing type is dedicated to the monitoring of simple daily changes, such as physical activities or sleep. This category includes pedometers, accelerometers, and early-generation sleep trackers. Wearable devices have also graduated to more advanced health sensors. In this category, one can find a variety of bio-sensing devices: electrocardiogram (ECG), electromyogram (EMG), or continuous glucose monitoring devices.

Fig 9.2: Wearable Healthcare Technology

9.3.1. Types of Wearable Devices

Today, individuals increasingly rely on personal health devices providing immediate, real-time data streams. This recent evolution can potentially lead to a proactive patient-doctor interaction. This manuscript introduces an architecture that connects wearables and at-home devices to a framework designed to exploit incoming data in real time.

Devices worn around the wrist are increasingly seen as both trendy and useful. Indeed, most of the smartwatches that include some health functionalities have a particular focus placed on heart rate monitoring. Even with disparate levels of accuracy based on the specific model, the richer amount of data provided by the device has shown to improve aspects such as the real-time detecting of arrhythmia. There are, however, significant differences in design constraints between a wristwatch and other types of wearables. Devices designed for around-the-wrist placement are severely limited in the type of sensors that can be integrated, their size, and their power use. Moreover, the development of health-sensing and diagnosing functionalities is severely constrained by international trade and medical regulations, raising both the monetary costs and time to market.

Portrait penopLAST is a cloud infrastructure dedicated to the transformation of incoming time series data streams into actionable health insights. This framework is designed to support wearables and personal health devices of multiple types such as continuous glucose monitors, chest-worn ECG sensors, thermometer patches, and more. Data is collected in real-time from the patient through these devices, transmitted to an aggregator device (e.g., a smartphone) and from there further forwarded to a cloud infrastructure. The landscape of data collection is formulated by gathering both common features in time series data streams – e.g., the values of each measurement, time of measurement, and the reception of transmitted data – and the discussion of additional expectations specific to the given context. Data and framework design are later described from the device on-body measurement stage to extract data.

9.4. Remote Health Monitoring

Remote health monitoring is currently mostly focused on vital signs, but many other signals can also be monitored (Singh & Gupta, 2020; Wang & Zhang, 2021). These include respiratory sounds, auditory data, gait measurements, activities based on body sensors or ambient sensors, sleep patterns, sweat pH, glucose, alcohol, lactate, activities of daily living, electrodermal activity, electrical conductivity, galvanic skin response, heart rate variability, blood pressure variability, plethysmogram variability, body temperature variability, EEG readings, heart, respiration, and circulation. Consumer devices today already include oximeters, scales, blood analyzers, as well as wristbands measuring heart rate, calories, distances, stairs climbed, stress levels and skin temperature. Pharmaceutical pills can be now used as sensors on skin, with a portable reader providing the readings to mobile devices. Capacitive-touch analyzer measures hydration, fats and proteins in food samples, connected to a smartphone.

Smartphones and wearables are getting better each year in their biomedical measurements but the most important potential for improving the well-being and health of the population lies in passive acquisition of data from the user’s environment and in advanced data analysis. Refocusing the development of devices towards new data that can provide high impact novel information would bring significant improvements to patient care and everyday life. Smartphone apps can now acquire physical activity data of patients. However, the major amount of such data comes from the general population, none of them having consent to be used in clinical practice. Assembly of non-Electronic Health Record data is still an important challenge to take remotely acknowledged and health-relevant decisions. Modern machine learning techniques are optimized for efficient computational processing, at the expense of model intelligibility. Fill the gap between these domains with visual interactive technologies that allow the health expert an interrogative consultation of the hidden knowledge contained in the remote health monitoring datasets.Remote health monitoring has rapidly evolved beyond traditional vital sign tracking to encompass a broad spectrum of physiological and behavioral signals. Modern systems now monitor respiratory sounds, auditory data, gait, sleep patterns, electrodermal activity, and even biochemical markers like sweat pH, glucose, alcohol, and lactate levels. Advanced wearable and ambient sensors can track activities of daily living, heart rate variability, blood pressure variability, plethysmogram signals, and fluctuations in body temperature, EEG, and circulatory patterns. Consumer health tech has expanded to include oximeters, smart scales, blood analyzers, and multifunctional wristbands capable of measuring heart rate, calories burned, steps taken, stress levels, and skin temperature. Innovative pharmaceutical pills embedded with sensors now enable internal monitoring through skin patches and portable readers that sync with smartphones. Even food composition can be analyzed with capacitive-touch sensors that detect hydration, fat, and protein content, illustrating a future where continuous, personalized health insights are seamlessly integrated into everyday life.

9.4.1. Benefits of Remote Monitoring

In recent years, the field of remote health sensors and devices has gained much interest. People have a growing interest in their health status, which has influenced the success of health wearables. The data sources from wearables are very important to support further analysis and early warning of chronic disease diagnosis. Different from data sources based on medical records or presented by patients, real time series data sources from wearables and remote health devices generate real-time data streams. With the boosting of 4G and 5G mobile communication technology, remote patient monitoring services can instantaneously collect remote health devices' data. It is beneficial to analyze these streaming data for timely diagnosis or early warning of chronic disease. There is a depicted effort for this kind of monitoring system where the system can communicate with the health devices and is able to analyze the incoming data online. The volume of data is potentially huge, and efficient algorithms are required for data cleaning and mining. The potential outcomes could provide clinically proven decision support models to diagnose diseases or early warning patients. Model parameters for each patient result in an individualized model, which can provide real-time health risk prediction given the real-time streaming data. Remote monitoring of patient vital signs has shown promise in greatly enhancing quality of life for patients and reducing the overall costs of healthcare. There are expected that low-cost, real-time monitoring systems will be developed that will have a profound and positive impact on the medical industry. With the technological advances in both monitoring hardware and machine-learning methods, personal monitoring systems that can predict various adverse health conditions months or even years in advance become a possibility.

9.4.2. Challenges in Implementation

The digital patient care platform allows population health insights that transform static practices to the holistic personalized care approach for each patient. Digital health platforms collect, standardize, and safely store bio-markers from commercially available wearables and remote health devices in real-time. Priority machine learning algorithms enhance clinical informatics in a secure HIPAA-compliant manner to generate real-time provider notifications without the need to evaluate every individual's data stream. Now, the patient's health record actively updates in real-time, reflecting changes in their health status prior to becoming acute and the standard of care reactions undertaken. There are multiple challenges to realizing this potential. On the technology side, personal patient wearable devices or connected apps often possess unique data formats which must be translated into a uniform structured data in a health record compatible manner. In addition, these technologies require fundamental data analytics to identify clinically meaningful events in biochemistry, physiology, behavior, or mental state, complicating the translation of complex time series data into a simple structured format. Companies producing wearables often restrict access to raw data and do not include medically validated bio-markers available through APIs. The speed at which a broad range of data is created prevents its manual assessment by clinical teams already utilizing a multitude of communication channels with patients including text messages, secure messages, and phone calls. Machine-learning algorithms require sizable amounts of manually annotated data for building robust models. Although real-time biometrics exist for large inpatient devices, efficiency, pricing, and size properties prevent their broad implementation in home monitoring scenarios. Medical overdetection and false alarms might lead to the undermining of patients' confidence in the technology, reducing their long-term impact on patients that would otherwise benefit from early detection.

9.5. Real-Time Data Streams

Big data is more than just big data. Real-time data stream among the top stories in this field. It is only in real time that workflow, patient experience and therapy recommendations may adapt very quickly to the changing monitoring results. This is why the discussions in the context of mobile health often revolve around expectations regarding a patient's possible continuous monitoring.

Fig : Wearable Health Technology for Medical Monitoring and Tracking Devices

Healthcare, however, remains an asynchronous world of diagnoses at the time of a physician's visit. Telemedicine, or virtual care as the doctors put it, covers a web of sensors and apps. Yet, similar to the EMRs from the past, this data post-processes through physicians. This is in contrast to financial services where HFT is growing rapidly. Here, both the systems themselves and the interpretations direct the actions, as practice of algorithmic trading grows. Perhaps, sensitive to these differences, regulators treat real-time healthcare data streams clearly distinct from, let's say, financial growth data.

Plausible or not, the upturn of consumer's protophones and body sensor bands unleashes the real-time biosignals. This is why it is worth allowing for a leap of faith. Google and

Apple do get smarter summarization. Lumify, Blipcare and Scanadu promise real-time aggregation of certain biomarkers. And the Stone seemed to finally resolve the data transfer hassle in the health space. The very same companies are fully capable of aggregating it right in a cloud, likely hosting it anyway. Catalyzed by the always-on lifestyle of Gen Y where email and communication has in a decade evolved from Web 1.0 to the Snapchat, between the Q1 2014 and Q1 2015, there are rapid changes in the would-be big real-time bio streams.

9.5.1. Data Collection Techniques

There are a number of ways to collect real-time bioinformatics and health data streams from wearable devices and remote health monitoring systems. Besides the additional classical mobile and web-based applications used to synchronize wearable devices with cloud storage, many wellness data stream collection systems have been designed and marketed to aggregate patient’s wellness data and store them either locally or on the cloud for real-time Big Data evaluation, analysis and disease risk assessment .

However, while wearables are discrete devices that patients can wear and easily remove or that require frequent battery recharge, most remote health monitoring systems are fixed systems located in the patient's room and may suffer from usability issues. Besides commercial wearable devices and remote health monitoring systems and the companion mobile or web-based applications, regular smartphones and cloud services are used to collect, store and analyze health and real wellness data streams.

Wearable devices, in particular, are an attractive solution to collect health and body-monitoring parameters in an ambulatory and unmet actionables passively state manner. Most contemporary wearables can capture heart rate, sleep, activity, UV exposure, calories etc., but many other critical health and body parameters cannot yet be analyzed by wearable devices, and require chemistry and biology lab tests. However, the information provided by lab tests is not useful in the context of wellness data aggregation from which useful insights can affect preventive medicine.

9.6. Personalization in Healthcare

By wearing a wearable or using a remote health device during the day, a person generates continuous health data streams. What happens if this data is not only collected in real-time, but also analyzed by a health services provider in real-time, and is able to send back recommendations and predictions? How would this affect someone’s health consciousness, and that of his or her significant ones, or a wider public audience? Finally, would someone comply with those recommendations and what would be the implication if it did not? Broadly, these questions correspond to the analysis of a real-time, bi-directional information flow between a patient and a health services provider. Given that over 10s of industries and $100B+ are predicatively considered to be influenced by the continuous health data analysis market in the coming decade, these questions appear to be non-trivial. A conceptual framework of a system prompting these questions, adopting a data driven model for the patient, and evaluating the system performance is demonstrated. Advice on how to move to a healthier zone is also derived: consider the diet as well as the weight, do not rush and stay within limits of increasing the overall activity, including also the circadian behavior in the analysis. Considering patient inputs and patient engagement in the software design, along with the analysis of software usage, is seen as a potential mathematical approach. It spurred the interest of consumers, biomedical industry and public health bodies leading to the emergence of the quantified self-movement and, ultimately, immense wearables and personal health data industry. A prototypical wellness data aggregation system is openly presented along with a standards-compliant interface to such a system. Integration of this system with the existing patient portals, personal health records and health system-wide electronic medical records represents an opportunity to substantially enhance wellness data analysis capacities of the healthcare provider system. Because of this potential market impact, these efforts are considered to align with the definition of translational bioinformatics.

9.6.1. Understanding Patient Needs

Healthcare is a nationally targeted industry due to reform legislation that will be phased in over the coming years, with keen requirements for delivering improved patient outcomes efficiently. The transition presents substantial challenges for healthcare providers, such as the need to tackle efficiency issues while providing exemplary patient-centered care. This article describes personalizing the healthcare of a patient using a real-time wellness data aggregation system that syncs data streams from wearables..

Understanding patient needs is a crucial aspect of successful healthcare delivery. Personalizing healthcare delivery to individual patient’s needs, desires, or objectives, can lead to better patient engagement and ultimately outcomes. However, satisfaction can only be achieved by completely understanding patient requirements, which can be a complex task given the unique needs of every patient. This can be significantly more valuable when providing healthcare delivery to a particular patient. Tailoring the healthcare regimen to the individual patient can substantially drive better results. The pervasive nature of personal data generated via wearables and remote health devices offers an exceptional opportunity to realize this vision for personalized healthcare. Furthermore, upsurge in chronic diseases and aging inhabitants spotlight the necessity for early diagnostics and constant observation, which can be largely backed by leveraging wearables and remote health systems.

9.6.2. Tailoring Treatment Plans

From smart watches, Fitbits and mobile health apps to remote patient monitoring devices, ambulatory ECGs, glucometers, spirometers, and a plethora of "smart" healthcare products, wearables and remote medical technology are swiftly making their way into nursing, clinical medicine, and biomedical research. Patients who have been brushed aside, under-assessed, or those subjected to compliance bias during infrequent office-based measurements can now be comprehensively interrogated with continuous, real-world health monitoring data. The accumulated biological, physiological, bio-behavioral, and lifestyle data from wearables and other remote health monitoring devices powered by patients' smartphones are about to realize the promise of personalized health care. On the cusp of a medical revolution, dormant patient health streams are being tapped into in real-time, offering a holistic and continuous portrait of diseases, wellness, and health trajectories. Meanwhile, there is considerable enthusiasm in using health monitoring data to identify diverse health changes that range from general physical activity levels and sleep patterns to chronic conditions such as heart disease and lifestyle choices like diet and social interactions. Mention of such "continuous, real-world health monitoring" is primarily in reference to the acceleration of wearables and remote health monitoring tech other than the health data stored in databases collected from instruments like labs and imaging. To those ends, physicians as well as a wide array of care providers are poised to receive time-sensitive patient updates in addition to the electronic health records and general records that already inundate provider inboxes. Also in the foreseeable future is the consolidation of multimodal data from perturbed home environments, socioeconomic portfolios, telemedicine chat logs, as well as exposure to toxins and pollutants. All in all, potential time-sensitive adverse health change alerts are myriad. Assuringly, clinicians are well-poised to intervene with a wide array of potential measures; changing doses of medications, implementing lifestyle interventions, and more.

In addition to supporting patient wellness, continuous real-world health monitoring data can be a powerful complement to the electronic health records for informing and facilitating a broad range of clinical decisions. Here are just three examples of how this type of data might be harnessed by care providers. Wearing a wristwatch could provide a trajectory of health at home that could be useful in monitoring wellness as well as quickly diagnosing changes. A clinician prescribing sinusitis medication might tinker with the dosing to improve the recovery experience. A patient population might be prescribed specific medications or interventions that work best with their characteristic physical activity levels.

9.7. Conclusion

Population and Healthcare Inequalities: The increasing burden of NCD (non-communicable diseases) projections requirements induced by an ageing population and declining birth rates are revealed through a greater burden of disease costs. Moreover, income-related inequality in healthcare costs has larger importance than income inequality in other financial measures because of the larger share of healthcare costs in health expenses of low-income individuals. Income can be seen as a direct and indirect indicator of individual living standards. Low-income causes significant care and financial insecurity and these individuals do not have the ability to gain suitable healthcare services. This tends to both financial and utilization inequalities in the healthcare of low-income residents. Finances of low-income individuals are further impacted by poor health. Conversely, high-income individuals can get better health and raise possible services and resources due to having acceptable conditions of living. The measure of income inequality in a population will be taken into account by calculating GINI coefficients. GINI coefficient is the most accepted coefficient and used in such studies. With this in mind, the primary goal is to analyze the relationship between low-income and healthcare costs in Turkey regarding the prediction of an increasing non-communicable diseases-related financial implications in the country.

9.7.1. Future Trends

As the proprietary source of metabolism analysis, continuous glucose monitoring, and sleep diagnosis, mobile phones will become the most irreplaceable streaming and storage platform of physical and mental health data from wearable and remote health devices in clinic and daily life. Also, the compatibility of software and hardware facilities in real-time data streams between wearable and remote medical devices will become the main issue for a future rolling deployment.

It prominently contains the symposium of real-time transfer protocol for a continuous curve of clinical monitoring between wearable and remote medical devices. With the assist of the client in mobile devices of patients and clinicians, the cloud could promptly analyze the streaming of metabolic kinetics and physiology readouts displaying in wearable devices like heart rate monitors, blood oxygen monitors, glucose monitors, brittle monitors, bandwidth monitors, etc. At the same time, the trend curve like pulse, oxygen, and glucose will be automatically recorded in the client interfaces for both doctors and patients. At the beginning, wearable or remote medical devices are indispensable to reach compliance with these APIs. Finally, the demonstration of rolling deployments for the rapid remote monitoring of continuous glucose monitoring from wearable to wearable.

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