Modeling Daily Behavior and Routines from Smartphone
and Wearable Devices

Another Perspective on Remote Patient Monitoring

A Thesis Prospectus Submitted to the

Faculty of the School of Engineering and Applied Science
University of Virginia • Charlottesville, Virginia

In Partial Fulfillment of the Requirements of the Degree
Bachelor of Science, School of Engineering

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Technical Project Team Members

On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Introduction

With the current rise of remote patient monitoring and telemedicine in the medical industry, the doctor-patient relationship is changing, but perhaps for the worse due to the loss of interaction and quality of care. Previous studies have evaluated the benefits and consequences of this change in the industry for the patients, but such has not been done for those within the medical industry itself. As a result, the doctor-patient relationship will be further analyzed from the doctor's perspective and through a technical project involving the ability to model daily behavior and routines from smart devices, the practicality of remote patient monitoring can be better understood.

Technical Topic

In order to predict and model the daily behavior of students for mental health outcomes such as stress and depression, the technical project involves three main components: the collection of data from wearable devices, visualization of such data, and analysis through machine learning models.

Data will be collected using passive and automatic sensing data from smartphones, smartwatches, and other wearable devices. Devices such as the Apple Watch allow users to export or privately share their health data using APIs such as Apple HealthKit. As a result, user health data can be automatically collected and directly processed through a machine learning model for training or prediction purposes. To best model the routines of students, the number of steps, heart rate, movement, and calorie intake of users may be utilized in addition to other relevant behavior data. However, as the data cannot directly reflect the mental health of the users, surveys, questionnaires, or interviews will provide a means to generate a mental health score, necessary for predictions. Lastly, in order to increase the size of the dataset, various public databases will be searched for similar health and behavior datasets.

After the analysis of the data through graphical models and correlation methods, several machine learning models will be constructed, trained, and tested to predict the previously mentioned, mental health score. This score will most likely consist of categories such as unhealthy and healthy. Thus, classification models such as Support Vector Machines or Random Forest Classifiers will be utilized. An ensemble learning approach, in which multiple models are combined, may also be completed to increase the prediction accuracy. However, if mental health scores cannot be found within the dataset, clustering methods may be utilized instead. For example, K-Means Clustering can determine similarities present within the data and group the data accordingly. With the resulting groups or clusters, the mental health of each group can be inferred based on previous studies while the characteristics of the group can serve as the key factors necessary to predict mental health outcomes.

However, due to time and resource constraints, the sample size of the data may be limited, resulting in bias. Most data will be collected from UVA students which is not representative of the general student population. As a result, behaviors among students may be similar, but this can be mitigated through the use of large public datasets, if present. Inaccuracies can also be found in the interviews of the testing subjects due to the sensitivity of such mental health data, resulting in subjects hiding the true status of their mental health.

In order to perform this project, data collection will be first completed through previously mentioned online sources, surveys, and the creation of software in which subject health data can be automatically gathered. Throughout this process, the data and findings will be documented and can be expected to be complete after two months. Once collected, the data will be analyzed and based on whether it is labeled, the data will be utilized on a machine learning model to determine trends or the specific factors related to stress and depression among students. This will be completed in a group of three to seven students. A report will then be written, detailing the findings of the machine learning model and can be expected to be complete within the remaining two months of the semester.

STS Prospectus

Introduction

Raised in a family of doctors, I am passionate about the medical field but in my pursuit of computer science, I have become fascinated by the future and potential role of medical technologies. Rapidly growing is the use of wearables and remote patient monitoring (RPM) to continuously track patient health through data. Currently, RPM is being experimented with using Fitbits and other wearable devices, but such is expected to grow and could become an industry standard due to its potential for lower costs and higher efficiency in the medical field. As a result, RPM as well as telemedicine, the use of online platforms to conduct appointments, could expand rapidly in the next few years and throughout the world. Traditionally, doctors have become accustomed to developing face-to-face and personal relationships with their patients whom they see when needed or periodically for check-ups. However, the rise of RPM threatens this paradigm and could create not only technical, but social and ethical challenges as well.

Research Question

I would like to study the advantages and disadvantages of RPM and its implications on the medical industry. For doctors, RPM can improve their ability to provide effective care and to more patients, increasing their revenue streams. Similarly, patients can be more aware of their health and have doctors alerted in case of emergencies. As of now, wearable technologies such as the Apple Watch and Oura smart ring can track blood pressure, blood oxygen, respiratory rate, heart rate, sleep, and more. Thus, such technologies can be extremely useful for preventive care, but is dependent upon the accuracy of the data and the ability for doctors to utilize the data, presenting potential technical challenges. According to the University of Cambridge, RPM can also lead to "reductionism" in that doctors may not be able to determine the context of the data and understand the mental health of the patient, resulting in a lack of trust of the devices. The over-reliance of data may induce a false sense of complacency by both doctors and patients who look solely to the data for diagnoses resulting in misdiagnoses and overdiagnoses, increasing patient anxiety. As a result, RPM faces both optimism and skepticism from doctors and patients, creating a wicked problem with the involvement of multiple stakeholders such as the medical industry, patients, and wearable technology companies. Thus, the role of RPM in the future of the medical industry could benefit from an STS investigation. Understanding the benefits and especially, the limitations of RPM will also allow technology companies and relevant social groups to determine where innovations and improvements need to be made.

Literature Review:

Telemedicine, or telehealth, in comparison to in-person appointments, has shown to be as effective, but with reduced costs. According to a study describing the differences between an in-person and tele-geriatric consultation, evidence suggests that observation through videoconferencing provides equal benefits to an in-person meeting (Betkus et al., 2020). At the same time, costs decreased by over $15,000 for 62 consultations due to travel savings and a decrease in consultation prices because of the ability for doctors to treat more patients (Betkus et al., 2020). As a result, (Clark et al., 2020) argues that telemedicine allows patients in various locations to receive the quantity and quality of care deserved. The reduced healthcare costs, faster treatment, and reduced travel improve patient satisfaction. Patients can also take a more active role in their health with the security of their doctors, decreasing their anxiety (Clark et al., 2020). Such is the case for telemedicine, but the benefits of RPM with the use of wearables highly depends on the data accessible and its accuracy. (Silvera-Tawil et al., 2020) highlights the various forms of wearables such as watches, smartphones, and garments required to measure blood pressure, blood glucose, blood oxygen, heart rate, respiration, brain activity, motion, and acceleration. Although much of the use of wearables is conducted in research environments rather than commercial, accuracy of the wearables is comparable to currently utilized medical devices. Mainstream devices are able to reliably measure heart rate, steps, and sleep with a slight edge to smartphone apps rather than watches or bracelets (Xie et al., 2018). However, such watches had an accuracy over 80% for heart rate variability measures, indicating that common wearables may be beneficial for asthma or pulmonary disease, for example (Rahman et al., 2020).Thus, RPM can allow for earlier identification of symptoms, decreasing hospitalization costs and times without reducing the quality of care (Pekmezaris et al., 2012).

However, many sources recognize the ethical concerns involved with telemedicine and RPM. Telemedicine is more easily available to certain demographics, further increasing socioeconomic disparities. For example, telemedicine is less utilized by non-white people residing in poor areas and typically, elderly people. Due to the pandemic however, elderly people are increasingly using telemedicine measures of healthcare (Pierce and Stevermer, 2020). Nevertheless, elderly people are often inexperienced with modern technology and poor communities have access to fewer healthcare services, physicians, and internet availability, reducing the ability to receive equal care as others who are younger or of a higher economic standing (Pierce and Stevermer, 2020). In addition, those who prioritize their health are more willing to utilize telemedicine and RPM, resulting in others to miss out on health insights and preventative care (PHG Foundation, 2020). Many sources also argue that RPM reduces patients to their data and in a sense, objects (Clark et al., 2020). Health data does not describe a patient's mental or emotional state and the lack of in-person interaction in comparison to normal in-person appointments could be further detrimental to their wellbeing (PHG Foundation, 2020). Subjects of RPM could also change their actions based on their data and become more anxious of the health through constant monitoring of their devices (McCaldin et al., 2016). Effectively, patients could try to self-diagnose symptoms (McCaldin et al., 2016) or in the opposite scenario, over-rely on their data and miss diagnoses by their doctor (PHG Foundation, 2020).

Legal concerns are also present with the rise of telemedicine. Standardized legal frameworks remain elusive and differ from state-to-state as telemedicine is not yet clearly defined (Rita M. Marcoux, 2020). Although Congress passed the FDA Safety and Innovation Act which tasked the FDA with developing a regulatory framework for health information technology, reimbursement by payers to care providers is not clear (Rita M. Marcoux, 2020). In addition, many RPM devices or apps permit the sale of users' health data to third parties (PHG Foundation, 2020), allowing data to be shared inappropriately (Silvera-Tawil et al., 2020).

The benefits of RPM also depend on the accuracy of the data collected. However, due to conflicting evidence, it is not yet clear that commercial devices meet the same standards as current medical devices as they are known to be less accurate and less consistent (Silvera-Tawil et al., 2020). Patients are also less willing to share their mental wellbeing and behavior in telemedicine due to the difficulty to observe behavior through video (Betkus et al., 2020), potentially disproving the previously supported claim that patients will receive equal quality of care through telemedicine.

As evident, much of the literature on the topic of telemedicine and RPM clearly evaluates the proposed benefits, concerns, current regulations, and accuracy of wearable technologies, but emphasizes primarily on patients. The use of such technologies impacts not only the patients, however, but the physicians and the medical industry also. These impacts are not shown in current literature and provide opportunities for future research.

STS Frameworks and Research Method

Due to the importance of wearables in RPM, it is necessary to analyze the users of such wearables and their roles in the development of the technology. However, various stakeholders have different expectations for wearables and as a result, Pinch and Bijker's Social Construction of Technology (SCOT) will be utilized as it recognizes the interdependence of social and technical elements in technology.

The most influential relevant social groups are those who are most impacted by the use of wearable devices, doctors and those with health risks. Health vulnerable people will likely be the most prominent users of such devices due to the ability to track valuable health data in real time while doctors assess this data to provide appropriate care. As a result, both social groups are interrelated and have similar priorities in the design of wearables. Both groups are interested in a device that captures accurate data, lots of relevant data, and provides real-time data transmission in order to provide the best care as soon as possible.

Other relevant social groups are fitness lovers and tech-savvy people. Although each group may not utilize wearables for their intended purpose and thus share less power in the construction of wearables, they may represent many users of the devices. Fitness lovers purchase devices such as Apple Watches not for use by their doctors, but for self-monitoring of heart rate, calories burned, and more. Tech-savvy people, however, may not utilize any of these features, but others often found in wearables such as messages or music illustrated in the Apple Watch. Thus, fitness lovers may prioritize accurate and various types of data collection while tech savvy people emphasize affordability and style.

Due to these differences in interests, conflicts are present among the social groups. A partnership can be formed between doctors and those with health risks due to the similarity in interests, but other groups may disagree. Although all are in agreement for the collection of accurate data, factors such as the ability to share data in real-time, the price, functionality, and privacy of the data present potential issues. For example, doctors would like to see as much data as possible from their patients, but regular users of wearable devices may be concerned for the privacy of sensitive health data being shared. Thus, such interests are negotiated and are done so through discussions with the manufacturing company as well as the government for privacy regulations on health data. This could lead to standardization of health data by the government or continued protests. In addition, shared designs could be implemented as done by the Apple Watch, which is fashionable, inexpensive, provides data collection, and can be used for real-time data transmission due to its internet capabilities. Lastly, different models or types of devices can be marketed towards their respected social groups to provide closure.

The interdependence between the described relevant social groups and their desired implementation of wearables may significantly alter the social interactions between doctors and patients. Depending upon the data collected and privacy of the device, wearables may not provide enough valuable information or be utilized comfortably by the patient, respectively. Consequently, wearables may be limited in their practicality for use in the medical field. However, such design is dependent upon the power dynamics presented above and their ability to influence manufacturers.

As a result, users of wearable devices and telemedicine patients will be interviewed in order to determine their satisfaction with such technologies as well as technology companies to better understand how health data can be privately secured and their role in RPM. Due to the lack of analysis on the impact of RPM in the medical industry, I intend to interview physicians of various specialties to discover their concerns. Surveys will be utilized on these doctors and if permitted, their patients to establish whether my findings prove to be a common consensus. However, the sample size and the extent of the surveys may prove to be insufficient and unrepresentative of the medical industry and its patients. Due to differences in knowledge of technology, it will be difficult to acquire data from older patients and of various socioeconomic standings, creating bias towards the preferences of younger and wealthy patients. Quantitative data related to the accuracy of wearables will be acquired through further investigation of research studies as well as my technical study.

Timeline

To begin my research, I will continue to analyze STS related journals in order to improve my understanding of the implications of RPM and develop valuable questions for use in the following interviews. Then, I will interview doctors and patients-if provided permission- about the use of wearables, data privacy, accuracy, and the effect upon the doctor-patient relationship at the Strong Memorial and University of Virginia Hospitals. Otherwise, people not in the medical industry will represent patients and be chosen randomly. Once a consensus is reached, I will interview wearable technology and telemedicine-related companies such as Kilo Medical, a biomedical startup, to determine how they will accommodate the interests of the doctors and patients as well as their role in RPM in the future.

The previously mentioned steps can be expected to be completed within two months and will occur simultaneously to my work on the technical project. I will also work on the introduction of my thesis during this time and after completion of my research, I will describe my findings in my thesis which will be completed within the remaining weeks of the semester.

Conclusion

Despite the ability to provide preventative care and improve the health of more patients through RPM, many have suggested that RPM presents technical and ethical concerns for patients. However, I intend to contribute to this research by presenting the impact of RPM on the medical industry and doctors specifically, rather than solely the patients. Doctors may raise concerns for this new manner of medicine which will allow the medical industry to better understand the impacts of RPM on each stakeholder and provide valuable insights to wearable technology companies for use in their products.

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