WEARABLE MOTIVATION: THE EFFECTS OF MOBILE HEALTH SENSING ON USERS

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By

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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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THE WEARABLE DEVICES REVOLUTION

The rapid expansion of the fitness wearable market means more people are using wearable technology than ever. As shown in figure 1, over the last decade wearable units shipped worldwide has grown to an estimated 222 million by the start of 2020. Of these devices, a significant number include some level of health or fitness application. According to a recent Gallop Poll, one out of every five American adults uses a fitness wearable or smartwatch with fitness applications and one out of every three have at least tried these technologies (McCarthy, 2019). As more consumers adopt these devices, questions arise as to whether these devices are benefitting users' health. Scientists and journalists have taken an interest in the health benefits of these devices, and this research in particular aims to understand if these devices are benefiting user's health and, if so, in what ways.

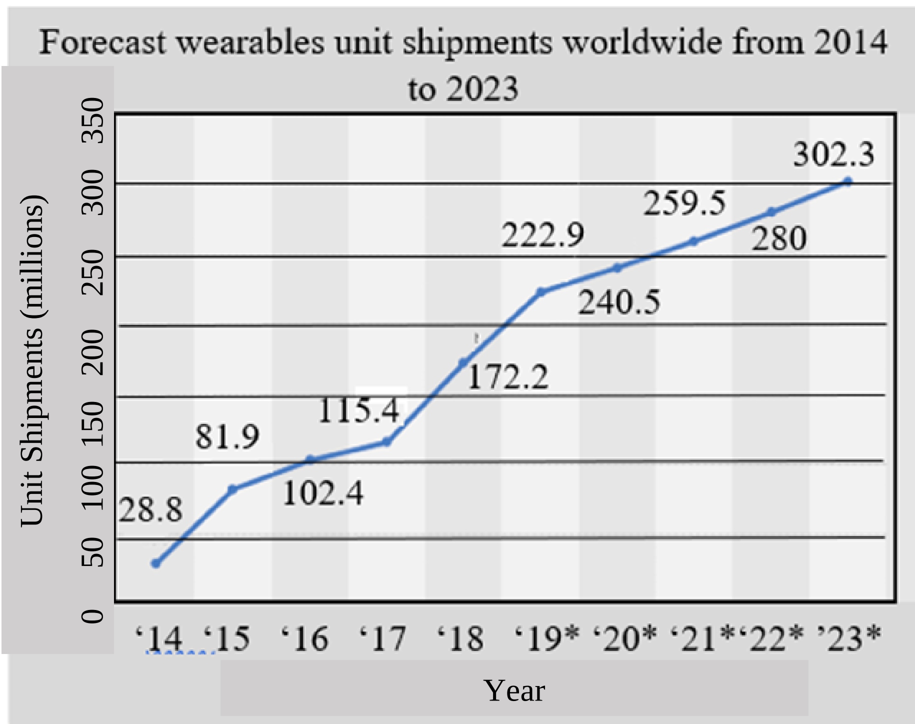

Figure 1. Forecast wearables unit shipments worldwide from 2014 to 2023. The figure shows the growth of the wearable devices market worldwide in terms of millions of units sold; years with '*' markings indicate projected units shipped. (Formatted by Nelson from Statista, 2019)

An understanding of the current state of consumer wearable devices is also essential to the technical project. One area in particular wearable sensors can improve is in predictive analytics. Predictive analytics is the use of data to develop computational models and estimates of metrics that give information about future events or behavior (Abdullah et. al., 2016). The technical team, led by Afsaneh Doryab, aimed to accurately predict an individual's biological rhythms and translate these rhythms into useable, beneficial information over the course of the 2019 to 2020 academic year. The Oura Ring and the Empatica E4, a consumer-grade and research-grade wearable respectively, were used to gather data, and applied rhythm analysis toolkits to study gathered data. This creates a strong link to the science, technology, and society (STS) investigation because researching how current devices benefit users can impact the approach of the technical project and what functionality the technical project should explore for these devices. The link between these projects enables two focused attempts at the improvement of fitness wearable devices.

WHAT YOUR WRIST CAN TELL YOU

Consumer fitness wearables right now focus on measuring and analyzing two factors of human health, activity tracking and sleep analysis. Activity tracking came first, popularized by the first of the Fitbit line of products, and is the most commonly included in wearables (MobiHealthNews, 2015). Activity tracking employs accelerometers, heart rate monitors, and sometimes GPS data to calculate how much a user is moving, or how "active" they are, throughout the day (Peake, Kerr, & Sullivan, 2018). This is often represented by a step count, measure of miles or kilometers walked, or calories burned. Sleep analysis, as it currently functions, is a much newer measure of human health for consumer wearables. Some sleep tracking capability was introduced as early as the first Fitbit model in 2009, however that only used activity during evening hours for data, using that as measure of restlessness during sleep (MobiHealthNews, 2015). Sleep tracking uses measures of heart rate and accelerometer data to create computational models of stages of sleep, restless time and time awake (Coughlin, & Stewart, 2016). As defined by the National Institute of Biomedical Imaging and Bioengineering, "computational modeling is the use of computers to simulate and study the behavior of complex systems using mathematics, physics and computer science" and "results of model simulations help researchers make predictions about what will happen in the real system" (National Institute of Biomedical Imaging and Bioengineering, 2016). There is a distinct lack of transparency on how step count, heart rate, and other computational models actually work in consumer wearables. This secrecy is generally due to competition between businesses and a wish to hide valuable trade secrets (Bridges, 2018). Additionally, research into sleep analysis is complicated by it's more recent introduction to consumer wearables. The relative novelty of sleep analysis means there is a limited amount of scientific research publicly available on the subject. At the time of writing, if activity tracking in fitness is searched for on Google Scholar, roughly 4,600 entries can be found, however if sleep analysis in fitness is searched for roughly only 140 entries can be found.

THE EFFECTS OF MOBILE HEALTH SENSING ON THE USER

Questions of efficacy clearly surround fitness wearables. Concerns about the benefits of fitness wearables exist not only in sleep analysis, but also the better researched area of activity tracking. The questions this investigation hopes to answer is, do users of wearable fitness trackers see significant improvement in their own health? This will be explored through the two broad categories of services fitness wearables provide; activity tracking and sleep analysis. Activity tracking will be defined as sensor data and models that relate to exercise and physical activity, such as step counts, distance walked, calories burned, and heart rate. Sleep analysis will be defined as sensor data and models that relate to duration of sleep, time spent awake, the stages of sleep, and sleep efficiency. Sleep efficiency is essentially using sensor data such as heart rate and accelerometer data to estimate the quality of a users' sleep (Buysse, 2014). These two functions of fitness wearables will enable a focused investigation of these devices and their efficacy for consumers.

THE MOTIVATIONAL WRISTWATCH

This investigation will require the use of several STS frameworks and theories. One of the most important STS tools to be used will be Actor Network Theory. Actor Network Theory (ANT) was developed by Bruno Latour in 1990 as an attempt to explain the interactions of different groups in the development of a technology (Latour, 1990). It will be used to explore the pressures on the engineers who create computational models for fitness wearables. Two of the biggest issues with fitness wearables stem from secrecy and motivation. The authors of a study conducted at George Washington University asserted that step count could vary between different devices “by as much as 26%” when worn by the same person (Bender, Hoffstot, Combs, Hooshangi, Cappos, 2017, p. 1). This clearly indicates differences in the models used by different companies; however, these differences cannot be truly examined because these companies keep their computational models as trade secrets. Along with secrecy, there are additional pressures on model developers that can impact model quality, best established by Katherine Bridges in her undergraduate thesis as innovativeness and timeliness. Innovativeness is the pressure to create something new, oftentimes at the expense of reliability of the model (Bridges, 2018). Timeliness is the pressure to deliver a model in the specified timeframe, which may lead developers to not run through every check for errors or efficiency possible (Bridges). These pressures are shown graphically in figure 2. There are also issues with the pace of innovation with regards to secrecy. When there has been enough time to compare consumer devices to medical equipment in studies, the

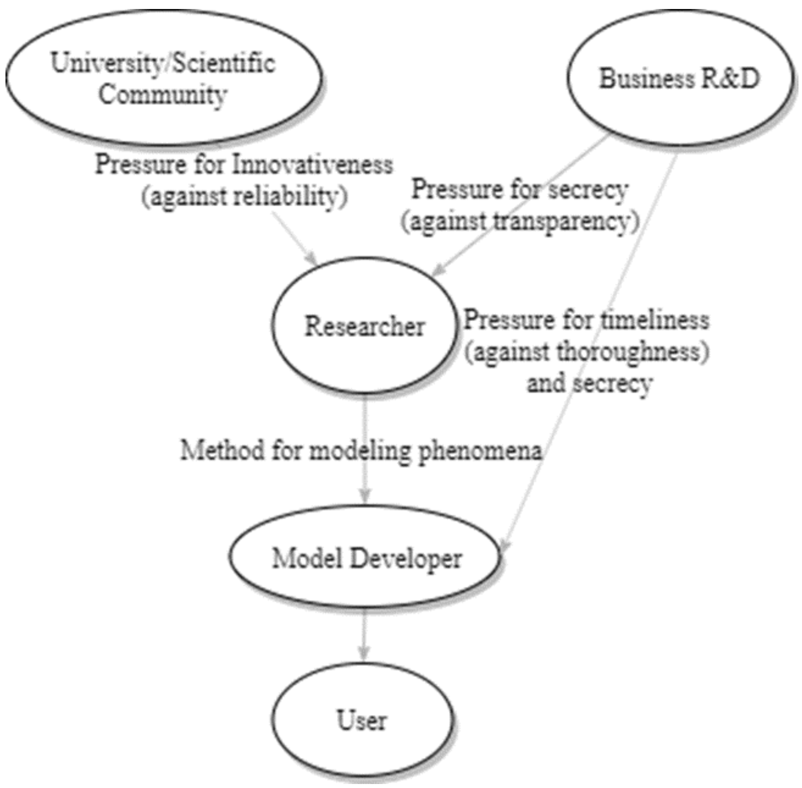

Figure 2. The Network of Actors and Influences in Model Development. This network illustrates the set of actors that influence model development and the pressures they exert on model designers themselves (Adapted by Nelson from Carlson and Barituad, 2019).

example for sleep analysis is polysomnography (PSG), a new update or enhanced model has already been pushed to devices, rendering the comparison outdated (Zambotti, et. al., 2016).

When examining the two key approaches of fitness wearables, activity tracking and sleep analysis, one aspect of their efficacy becomes immediately apparent. Canhoto and Arp rightfully claim in their examination of fitness wearables that while these devices can have a positive impact on users' health "these benefits will only materialise, however, if users adopt and continue to use these products, as opposed to abandoning them shortly after purchase" (Canhoto and Arp, 2017, p. 1). The benefits gained from these devices are motivational in nature, as the data displayed encourages users to continue exercising or making positive alterations to their sleep patterns. Canhoto and Arp assert that there is a large population of fitness wearable adopters originally obtain a device when they have a specific fitness goal in mind (Canhoto and Arp, 2017). These users benefit the most from fitness wearables as the data they receive from their devices can be compared against a set goal and milestone.

There is also some evidence that activity tracking is promoting healthier living overall according to literature reviews. One conducted by Steve Coughlin and Jessica Stewart in 2016 for the Journal of Environment and Health Sciences (Coughlin & Stewart, 2016). Another, conducted for the International Journal of Behavioral Nutrition and Physical Activity by Kelly Evenson, Michelle Goto, and Robert Furberg, found similar results when examining 22 studies, and found step counting metrics from Fitbit in particular was very accurate when compared to manually counted steps and accelerometer data. They also found that when comparing true distance traveled and calories burned to empirical measurements, Fitbit devices were less accurate, and in particular under-estimated calories burned (Evenson, Goto, & Furberg, 2015).

However, there is some evidence that wearing fitness wearables for long periods of time may actually introduce unnecessary stress into fitness routines. This effect occurs when users note the changes in their data, like calories burned or steps taken, on a day to day level and focus on micro changes in their behaviors rather than macro ones (Ducharme, 2019). Focusing on minutia develops stress that may make users less healthy than they were before they began using the fitness wearable in question. These pressures are demonstrated by a System in Context Diagram shown in figure 3.

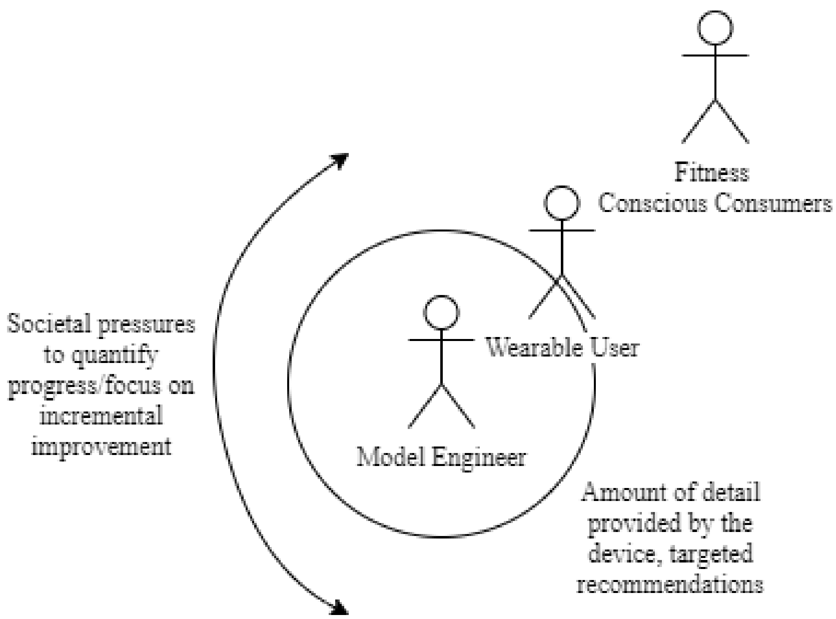

Figure 3. Pressures of detail in wearable recommendations in context. This diagram demonstrates the pressure on users generated by society for improvement and quantification of fitness progress and the place model engineers have in this system (Adapted by Nelson from Carlson and Barituad, 2019).

While research on sleep analysis in consumer wearables is limited, fortunately there are some studies examining their efficacy from the last five years. These studies have compared a variety of consumer wearables such as the Neuroon eye mask, which is a consumer electroencephalogram (EEG) for tracking brain electrical activity (Liang & Martell, 2018), the Basis Health Tracker, several Fitbit models including the Fitbit Ultra, FitbitChargeHr, and Fitbit Flex, and other devices (Mantua, Gravel, & Spencer, 2016). One such study, conducted by Mantua, Gravel, and Spencer at the University of Massachusetts, compares the Basis Health Tracker, Fitbit Flex, and several other consumer wearables to PSG readings of the same subjects using Wilcoxon Signed Rank tests. The Wilcoxon Signed Rank test is a statistical test that compares samples' population mean ranks. They found that total sleep time did not differ across the consumer devices and PSG, however they found that no consumer device accurately compared to PSG for all other measures evaluated, specifically sleep efficiency, light sleep, and deep sleep (Mantua, Gravel, & Spencer, 2016). Another study, conducted by Zilu Liang and Mario Martell for the Journal of Healthcare Informatics Research, produced similar findings for the Fitbit Charge 2 and the Neuroon eye mask (Liang & Martell, 2018). However, Liang and Martell reach the conclusion that these devices are only unsuitable for clinical use, but they are "reasonably satisfactory for general purpose" (Liang & Martell, 2018). The main challenge these studies highlight is the lack of standard measurements for what makes a satisfactory consumer device. This is both due to the commonplace secrecy of fitness wearable companies, and due to a lack of government regulation over these devices. As these devices are meant for daily life recommendations, and are not explicitly designed for a clinical setting, the government of the United States provides little regulation over these devices (Liang & Martell, 2018). This is one of the key sources of standards in electronics, without government mandated standards, it may prove difficult to convince companies to create standards amongst themselves.

Data, while it can be quite valuable, is no substitute for action. Fitness wearables can only give users information, wearables cannot force users to exercise or get more sleep. Even if computational models are developed robustly, thoroughly, and with transparency the information these models create is only as useful as its application to everyday life.

As a result of this investigation, several key takeaways about fitness wearables have come to light. The first, is that the lack of independent validation of consumer fitness wearables creates major issues in evaluating their efficacy (Peake, Kerr, & Sullivan, 2018). If fitness wearable companies are going to build trust among the scientific and consumer communities, then they need to be more transparent in their computational model development and about the sensors they use to collect data. However, based on the information that can be gathered through comparison to medical grade devices, many consumer wearables perform well enough in data collection and analysis to provide general wellness insights, even if they do not perform as well as medical grade devices. This was demonstrated for both activity tracking and sleep analysis. Another important consideration to note about these wearables is that the information they provide is only as valuable as the user wants it to be. If users do not value the insights generated as motivation the information generated is worthless. Taken too seriously however, the details created by these devices can cause undue stress and loss of satisfaction. In essence, information will not provide a benefit to every person.

Looking to the future, much work needs to be done in order to improve the efficacy of consumer wearables. Researchers should continue to monitor the development of fitness wearables as the industry grows, and should pay special attention to the rapid pace of change in regards to computational models and devices. The scientific community should also attempt to partner with the businesses that make these devices in order to create standards of reliability for both the sensors used in these devices and the models these devices use for their recommendations. A set of standards would make comparing these devices easier for consumers and would make it easier for the scientific and medical communities to determine what should be used for research and clinical settings. All of this will require cooperation from private and public businesses that may be slow to materialize, however without their cooperation current methods of evaluating wearables will remain the norm well into the future.

Fitness wearables, while they can give valuable information, still require some work to be useful to every consumer. While some of their sensing capabilities are accurate in comparison to empirical methods, some, especially measures and models for sleep analysis, fail to measure up to clinical devices. However, with cooperation between wearable companies, researchers, and the government, there is potential to improve these devices through the application of a set of standards for models and sensors. Hopefully, in the future these standards could be implemented and these devices could produce an increased benefit for all consumers who use them.

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