The Emerging Influence of Wearables on Adult Users in the Health Ecosystem

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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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Introduction

Wearable technologies, or "wearables," encompass a wide range of mechatronic devices that can be worn by or on a user. These include accessories, tools embedded in clothing items, or gadgets physically attached to—or implanted in—the users themselves. These devices aim to provide feedback to the user about their lifestyle and health through interconnected systems of sensors, controllers, and actuators. Through the advancements of these components and related systems over the past two decades, the wearable technology industry has grown to become integrated into the daily lives of millions. Commercially available devices allowed users to learn more about themselves and how their short-term decisions have led to specific habits or practices that compound over time. Wearable technology's ability to track physical activity, measure sleep activity, and directly help patients gain or regain control over their bodies have generated avenues through which individuals can prioritize their physical health and well-being.

The general public has been drawn to the benefits of wearables that display user health data as a consistent reminder of long-term goals. As wearables have grown in popularity and established a strong foothold in the healthcare space, it has become increasingly important to explore not only how these devices have influenced adult users, but also what concerns have arisen from excessive long-term use. I surveyed the literature on medical wearables before turning to a published account of a specific wearable device—Fitbit's smartwatch—to ground the group-level effects of wearables to a single richly described experience. While companies like Fitbit have created wearables with the intention of empowering users with a greater understanding of their health (De Moya and Pallud, 2020), the more subtle aspects of the data visualization techniques and the resultant impact on user behavior—along with inaccuracies in the data itself—justified an inquiry into just how trustworthy this industry is.

The Dissemination of Personalized Data from Wearables

Initially, the appeal behind these devices was simply their ability to collect health-related data and present it directly to the user (Hepworth, 2019). It was enough for the user to know that they had reached 10,000 steps, burned a specific number of calories, or accomplished some arbitrary marker of improved physical activity over time. Users monitored their activity voluntarily, but it was kept personal to the individual. Motivation and encouragement came from either the goals set by the device or the validation that the user maintained consistent levels of physical activity.

More recently, companies shifted to expand their scope by analyzing the data collected by the devices and integrating across multiple additional platforms. This integration created "personal health ecosystems" that seamlessly incorporated several interfaces to display more personalized information and more detailed visualizations (Hepworth, 2019). A prominent wearable technology company, Fitbit, has gained notoriety for its smartwatches that combine activity trackers and monitors to create a personalized fitness experience. The associated community page within the Fitbit app has juxtaposed users against their friends or patrons of a similar demographic according to their user profile. Email newsletters have similarly propagated charts and graphs that summarized the personal activity of those using the wearables. These devices no longer functioned solely as a personal tool for growth; rather, they became a new form of social media. Users experienced an unprecedented amount of information about themselves and how they measured up to peers. The data presented by the wearables continued to motivate the users to compete, but they were no longer simply compared to their past selves; they could now surpass other Fitbit consumers. Armed with the feedback dispensed by Fitbit's visualizations and data points that suggested they had achieved—or could soon achieve—a certain amount of physical fitness, users were subject to internalize the concept of the "quantified self," or an obsession with human self-knowledge and the intentional monitoring of one's own life (Lupton, 2013).

Larger institutions that want their employees or customers to meet specific physical requirements have initiated programs where biometric data could be shared not just among device users, but also with the organization itself. Fitbit's "employee wellness programs" allowed companies that distributed wearable devices to workers to promote what they perceived as healthy habits (Till, 2014). Through these programs, the aforementioned health ecosystem expanded beyond individual users, the Fitbit enterprise, and the employer; companies allowed the inclusion of health insurance companies and health care providers by giving them access to employee data. Some health insurance providers have offered premium discounts to workers involved in the programs (Wiegard and Breitner, 2019). Even select physicians and physical therapists have included wearables in the treatment plans that they recommend to patients (Hiremath et al., 2014). As an unfortunate result, however, participants that failed to achieve the required levels of physical activity have been strained by increased health insurance premiums or even denied medical treatment altogether (O'Neill, 2018).

These programs were all intended to help employees practice better lifestyle management (Dow Schull, 2016). Most in the labor force have even supported the concept of using wearables to encourage and engage in healthy behaviors at work (Mettler and Wulf, 2019). Fitbit and individual companies' dissemination of their users' data beyond just their employer remained unbeknownst to most supposedly consenting employees; this health ecosystem has shown its ability to harm the user overall as more groups have become involved. This theme was further explored later in this paper as both manifest and latent consequences of wearable devices inevitably mislead the user through strategies created by designers to impact user decision-making.

Mechanisms by Which Wearables Have Influenced User Behavior

Clear mechanisms have been built into the wearable devices themselves to target and drive user behaviors. Goal setting, prompts and cues, rewards, and social support were the most common strategies employed by fitness trackers (Lyons et al., 2014; Mercer et al., 2016). Each of these has shown its importance in its own respect. With that said, data visualization has been crucially implicated in the effective use of all the aforementioned strategies. Data visualization is characterized by how the device displays its collected and analyzed data to the user. Information presented by wearables has allowed the user to evaluate their behavior and draw conclusions about how they should achieve a goal, collect some reward, or perform better than a friend. In 2012, Gane said that devices like the Fitbit have successfully been "seducing rather than coercing (p. 622)" the user to monitor their own data with gamification techniques and finely-tuned visualizations.

To keep the audience invested in the data presented, Fitbit and other smartwatches employ rhetorical devices such as enthymeme and pathos. Enthymeme is a technique whereby authors choose to leave an important premise implicit; this allows users "to participate in its own persuasion by filling in that unexpressed premise" (Blair, 2004, p. 41). In Fitbit's visualizations, text descriptions of the data were either absent or intentionally vague to encourage the users to draw conclusions themselves. The wearable very clearly emphasized the intended interpretations through its graphics, but it left the explicit conclusion up to the user—a persuasive method to make the user feel more autonomous (Johnson et al., 2006).

The other critical element of the graphics—pathos—is integrated with the gamification of the wearables created by designers. The interface functionality of the fitness tracker ecosystem was specifically intended to elicit an emotional response from the user. The goal of the graphics was to appear objective and obvious to the user through the use of enthymeme described previously, but the aesthetics of the graphics enhanced the appearance of objectivity (Shen, 2019). The companies generated and disseminated data suggesting users were making decisions to adopt healthier habits, which led to a more consistent engagement. The subtle choices of rounded font styles, pill-shaped buttons, rounded data points, and saturated color schemes created a friendly visualization that still showed an objective conclusion without intimidating the user (Hepworth, 2019). The audience was captivated by viewing their data through the incorporation of those aesthetically pleasing appearances. As the user built more trust in the device over time, there was a greater sense of certainty and belief in the plots and progress bars that are displayed (Kostelnick, 2007; Skiba, 2014).

The data visualization and observation increased the efficacy of the larger-scale strategies listed at the beginning of this section. Whether it was the appealing progress bars of users trying to reach predetermined goals, the friendly and attention-grabbing prompts given by the device, the satisfaction felt when a new badge or reward was earned, or the anticipation when the user finally surpassed a friend in the rankings, the rhetorical devices and aesthetic decisions have all been user-tested to most effectively influence the viewer. The reality was, though, that these techniques masked the problems of the data itself.

The Potential Concerns of Extended Wearable Use

Users saw how well they had progressed towards the goals that the device set for them and the goals that the user established themselves based on the device community. Unfortunately, they were typically unaware of the statistical manipulations present within the images that appeared in front of them. The gamification and aesthetically pleasing experience were tactics used by companies to take advantage of the predictable nature of the user's cognitive processing strategies (Whitson, 2013). Companies intended for information given by the wearables to provide a clear image of the status of the user in terms of physical activity. It was not beneficial to these companies for the users to question where this data was coming from and how it was created. As a result, many online services that worked with personal data disincentive user understanding of what happened to their information behind the scenes; while long and extensive terms and conditions were available for the users to examine, the complex jargon included in them led consumers to rarely read them over. Users were expected and coerced into taking information at face value without further interrogation. This lack of transparency misled users into misunderstanding their own health and informed subsequent poor decisions intended to alter an individual's health outcomes without solid scientific justification.

By nature, big data has been relatively inaccurate even though it could be used for identifying certain patterns and trends from large samples. Many of the data visualizations generated from fitness trackers came to utilize big data automation and algorithms. What many users did not understand about the data shown in the visuals was that the automation and the algorithms determined potentially statistically significant patterns from insignificant ones through a sort of "smoothing out" process (Hepworth, 2019). The users were not informed about this process of what was deemed significant and, therefore, what was deemed insignificant when they were looking at the device ecosystem. Additionally, the margin of error was not explicitly stated on the beautiful displays, so the user interpreted that they were outside the mean and had to continue to change their behavior. If the users continuously found themselves outside of the "optimal" or "healthy" range without understanding the error and data processes involved, they were at risk of experiencing negative health effects or a sense of failure. It was also unclear who the user was being compared to when the graphics appeared on the screen. This lack of transparency relating to big data has been referred to as "dark data" that creates "dark patterns" (Ekbia et al., 2015; Crampton, 2015).

People saw the represented data as fact because statistics seemed objective by nature. It remained elusive to those users that the algorithms were not objective; they were created by people who had the ability to include factors without explanation. Regardless of the inaccuracies or explanation as to how the graphics were generated, the user was guided toward definitive conclusions about their health. Another inaccuracy stemmed from the lack of validity in their scientific techniques. The sleep data taken from the wearable has been widely considered to be invalid based on the method in which the device collected the data. The limited device sensors aimed to distinguish between awake and sleep states as well as time spent in specific sleep states and gave out a sleep score to the user (Peake et al., 2018). There is still debate in the medical community about how to accurately measure sleep and what is considered "restful sleep," which adds controversy to the legitimacy of the designer-produced visualizations that communicate to users if they were sleeping to their full potential. While the wearables displayed a lot of information about the user's sleep, there was reason to believe that the data was not meaningful or helpful in drawing any conclusions about sleep quality (de Zambotti et al., 2019).

The concerns stemming from wearable devices were often withheld when consumers looked at their own data and made choices based on the guidance of the device. As sociologist Deborah Lupton stated, “when notions of health, wellbeing, and productivity are produced via data drawn from self-monitoring, the social determinants of these attributes are hidden. Illness, emotional distress, lack of happiness, or lack of ‘productivity’ […] become represented primarily as failures of the individual” (Lupton, 2013, p. 27–28). While the devices were meant to promote better physical health habits, the information withheld from the viewer could have been damaging to their mental health and possibly gave them a false reading of their own body that could have led to physical harm.

An Exploration of a Fitbit User Experience

As discussed, wearables are attached to the user to constantly monitor their activity and present feedback to the consumer to promote improved health outcomes, motivate increased physical activity, and even encourage a healthy diet (De Moya and Pallud, 2020). Specifically, with smartwatches such as the Fitbit, the device has tracked user activities like step counts, the number of calories burned, detected heart rates, and monitored sleep patterns. The smartwatch has recorded and collected information from each of the parameters and displayed the information in an aesthetically pleasing manner such that it gave the user an idea of how their past performance compared to their current performance. The user could then easily interpret the feedback and make the necessary adjustments to improve performance (Mercer et al., 2016).

Fitbit markets itself to users as “help[ing] people become more active, exercise more, [and] sleep better,” by giving people the power to monitor several physiological data points (Fitbit Inc, 2016). Dr. Katherine Hepworth wrote about her own personal experiences while using a Fitbit device and interacting with the Fitbit ecosystem. Her article was cited multiple times throughout this paper when talking about the data visualization techniques that seduced and mesmerized her time as a Fitbit user. The large part wearables play in society and the influence they have on consumers has been documented, but a personal experience is important in validating why Fitbit's marketing slogan does not tell the whole story of the impact of the device.

Dr. Hepworth began by describing specific examples of Fitbit employing the data visualization strategies that she described as "embarrassingly thrilling (p. 8)." From the animated image of the heart pulsing to the beat of her own heart, to the saturated colors depicted on the formatted leaderboard design comparing her progress to her friends, and the sleep pattern bars informing her of how rested she should feel. She admitted how eager she was to see how her physical and sleep activity compared to that of those she was connected with through the Fitbit app. The line charts and the rankings evoked a sense of competitiveness to comply with the device in order to "beat" her friends. The horizontal bar chart along with the cumulative numbers on the right side effectively encouraged competition and comparison, so much so that she found herself wanting to "be better at sleep (p. 12)" than the other women that her device said were getting a higher sleep score. Dr. Hepworth's eagerness to improve her ability to remain unconscious led her to question how much influence this device was having on her and how the device was determining sleep patterns given the sensors involved.

It became clear to Hepworth that the Fitbit was presenting her sleep statistics confidently to her in a chart, but was not actually capable of collecting biologically relevant data. In order to more accurately track sleep states, probes would have had to be attached to the person's scalp to monitor brain activity (Gilmore, 2016). The Fitbit smartwatch instead used heart rate and movement sensors to predict the sleep state of the user. This prediction of sleep activity based on partial data is known as “activity-based intelligence” (Crampton, 2015). Not only was Fitbit claiming that it had the ability to monitor sleep with a level of certainty, but it also did so without clarifying the profiles of the other users in the comparison. As Dr. Hepworth astutely mentioned, the age range of those used to determine her comparison was unclear. Which women were represented? Were medications, health conditions, occupation, and stress neglected as factors that could have impacted the individual’s quality of sleep? The Fitbit visualizations appeared to violate the key rule of presenting information graphically, which is comparing like data with like data.

In doing so, users were striving for what Fitbit had determined as “optimal sleep,” but it was unclear if that goal was attainable given the flaws in the device ecosystem. Possible mental issues were introduced when the optimized goal was presented as achievable when, in reality, that was not necessarily the case. The user continued to comply with the device thinking that she could reach “optimal sleep,” but the fruitless effort exhausted the user and led her to feel as though she was failing. Fitbit did not intend for these concerning user outcomes; however, they failed to establish precautionary measures to avoid this situation. The company went to considerable lengths to take advantage of the predictable behaviors of consumers to encourage supposedly healthier habits, which made them culpable in precipitating detrimental consequences.

Conclusion

The wearables market size is approaching $50 billion and is expected to grow to over $100 billion by 2028 (Grand View Research, 2021). The devices will continue to advance and become more finely tuned to understand all different types of users and collect even more health parameters. Wearables devices, like smartwatches, are helping millions develop healthy behaviors and make physical activity a bigger part of their daily lives. The healthcare industry is coming around to including these devices in treatment plans and recommending them to patients. The benefits of these personal trackers are evident and necessary for a country struggling with obesity.

This paper is meant to explore wearables as they become a part of the health ecosystem and make users aware of the influence the devices can have after adults adopt them into their routine. Wearables devices are designed using specific mechanisms to promote behavioral change with rhetorical techniques and aesthetically appealing visuals. Those mechanisms hide important details about inaccuracies and clarifications that lead to potential concerns for users as they play a more active role in their health. For the few instances of users experiencing the harmful consequences of the device, there are countless others who have stories of improving their physical activity. The users should be conscious of the impact of wearables in the health ecosystem and on the users themselves.

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