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Drivers and Challenges of Wearable Devices Use: Content Analysis of Online Users Reviews

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Completed Research

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Abstract

With recent advancements in wearable device technologies, there is still a need to investigate drivers and challenges associated with the use of these devices. Following a content analysis approach, this study leverages recent “found large-scale” data to better understand the drivers and challenges that affect the adoption and use of such devices. Analyzing a total of 16,717 online reviews about wearable devices, the findings emphasized the importance of various functionalities (perceived usefulness), appeal, and a number of device design features as the most prominent drivers, while concerns about quality, credibility, and perceived value as potential challenges to wearable adoption and continued use. The findings could inform theoretical models for technology adoption and continued use and can also provide guidance to the design and development of wearable devices.

Keywords

Wearable devices, online user reviews, drivers, challenges, analytics

Introduction

Wearables devices are considered the next generation market after smartphones (Niknejad et al. 2020) and could be found in different form factors. Such devices, like smart watches, smart bands, and smart rings, became increasingly popular and play a significant role in the consumer's daily life as they offer a wide range of functionalities and wearing options (Seneviratne et al. 2017). Wearable devices are always turned on and interact with the surrounding environment, which in turn can sense, collect, and upload important data daily. As a result, such devices can provide a wide range of benefits and support for many domains, and perform many basic functionalities and micro tasks such as checking incoming messages (Seneviratne et al. 2017), generating reminders, capturing information (Popat and Sharma 2013), and supporting the user by providing time sensitive information (Popat and Sharma 2013; Seneviratne et al. 2017).

In addition, wearable devices have been used in various ways, such as measuring the vital signs of the human body (John Dian et al. 2020), behavioral change (Kinnunen et al. 2016), activity recognition and sports applications (John Dian et al. 2020; Park and Jayaraman 2021), tracking and localization (Hyndavi et al. 2020), monitoring stress, depression, anxiety, and insomnia (Ueafuea et al. 2021), healthcare tracking and rehabilitation (John Dian et al. 2020; Moulaei et al. 2021), and many others. Such interesting applications in different domains bring these devices a significant advantage compared to other devices such as smartphones (Oliveira and Nunes 2019).

Although many brands of wearables devices exist, the adoption and continuous use of such devices are still low compared to other well-established technologies, such as smartphones, (Cheung et al. 2019; Liu and Han 2020). While there is a number of studies that addressed factors influencing user adoption and use of wearables (Cheung et al. 2019; Dai et al. 2020; Kalantari 2017; Liu and Han 2020), there is a limited number of studies that attempted to leverage "found large scale data" on the web such as online reviews (Hasan and Stannard 2022; Michaelis et al. 2016) to understand drivers and challenges associated with wearable devices use. Furthermore, found data available on the Web provides opportunities for tracking and analyzing actual users' opinions about a phenomenon, such as wearable devices, and can provide better indicators of such devices' acceptance and use (Motiwalla et al. 2019).

With the advances of Web 2.0 technologies, consumers have the power to share experiences about services and products freely and easily, on an unprecedented scale, and in real time. Online user review provides one of the most powerful channels for extracting user feedback from actual use that can help enhance wearable systems design. They are considered the third most trusted format of consumers' opinion (Aerts et al. 2017). Consumers through online reviews play a critical role in conveying the needs and expectations from products, such as wearable devices (Hasan and Stannard 2022). Such online reviews are valuable resources for manufacturers and researchers as they shed light on consumers' preferences (Hasan and Stannard 2022; Michaelis et al. 2016).

In this paper, we performed a content analysis using online user reviews about wearable devices to better understand the drivers and challenges that affect the adoption and use of such devices. The paper extends the set of drivers and challenges associated with wearable devices using computational social science methods by analyzing large-scale "found data" (Engel 2021), online reviews, as opposed to "design data", survey and interview data (Enes 2022; Engel 2021) used in social sciences. From a theoretical perspective, the research could contribute to the development of more comprehensive theoretical models encapsulating an expanded set of factors associated with wearable adoption and use. From a methodological perspective, this study demonstrates the potential of content analysis approach for analyzing online reviews on a large scale compared to other studies in the literature (Hasan and Stannard 2022; Michaelis et al. 2016). With respect to practice, the findings could inform the design of wearables and the provision of innovative applications of these devices.

Background and Related Work

Wearables are devices that can range from large backpack computers to smart watches (Billinghurst & Starner, 1999). They can be categorized into accessories (such as smart watches and wrist bands), E-textiles (such as smart garments and hand/foot-worn), and E-patches (such E-tattoos and sensor patches). The number of users of wearable devices has been increasing and the literature has a growing body related to users' experience with these devices. According to the literature, a number of factors drive wearable devices use among consumers, these include, appeal and aesthetically pleasing (Dehghani 2018; Karahanoglu and Erbug 2011), personalization (Karahanoglu and Erbug 2011), ease of use and simplicity (Ahmad et al. 2020; Dehghani 2018), usefulness and benefits (Gupta et al. 2021; Pal et al. 2020), functional congruence and multifunctionality (Gao et al. 2015; Kalantari 2017), hedonic motivation (Gao et al. 2015; Pal et al. 2020), social support and social influence (Gupta et al. 2021; Kalantari 2017), perceived privacy, risk, and vulnerability (Gao et al. 2015; Kalantari 2017), self-socio motivation and battery-life (Pal et al. 2020), portability, reliability, flexibility, robustness, and interactivity (Karahanoglu and Erbug 2011), comfortability (Karahanoglu and Erbug 2011; Pal et al. 2020), and compatibility (Dehghani 2018). Further, a number of studies have identified challenges and barriers associated with wearable device use. These challenges include data accuracy (Maher et al. 2017; Patel et al. 2015; Shih et al. 2015), data privacy, security, and safety (Habibipour et al. 2019; John Dian et al. 2020), comfortability (Maher et al. 2017; Shih et al. 2015), battery lifetime and power consumption (John Dian et al. 2020; Maher et al. 2017), appeal and data integration (Shih et al. 2015), affordability and social support (Patel et al. 2015), regulation and data resolution (John Dian et al. 2020), and system support issues (Maher et al. 2017).

However, the literature is limited in terms of studies that utilized found data, such as online reviews, to determine drivers and challenges associated with wearable device use. Hasan & Stannard, (2022) mined users reviews of wearable devices for baby monitoring on Owletcare.com and Amazon.com and found that effort expectancy, price value, and performance expectancy played an important role to persuade user's adoption, continued future use and recommendation to others, whereas perceived privacy risk had the least importance. Another study by Michaelis et al. (2016) analyzed online reviews of wearable fitness devices and found that wearable drivers are related to tracking functionalities, data accuracy, accountability, comfortability, ease of use, notifications, battery life, and aesthetics. On the other hand, challenges of wearable devices were related to poor battery life, syncing issues, inaccurate information, not waterproof, uncomfortable, limited functionality, unclear instructions, device falls easily, and poorly designed charger. According to the literature and up to the knowledge of researchers, there is a limited number of studies that took advantages of online reviews to understand challenges and drivers associated with wearable devices. Compared to existing studies (Hasan and Stannard 2022; Michaelis et al. 2016) that relied on manual coding to analyze a few hundred reviews, focused on specific application such as fitness tracking (Michaelis et al. 2016), or specific product such as smart socks (Hasan and Stannard 2022), the current study extend the literature by analyzing online reviews on a large scale and address drivers and challenges associated with wearable devices in general.

Given the limitations associated with survey data, and with the advances in Web technologies, this study utilized online reviews that provide a rich source of information that could help understand consumers opinion about wearable devices on an unprecedented scale and in real time. Online reviews are important not only because they represent actual user experience but because they are perceived as a source of product information to guide consumers in their purchase decisions. Found data, such as online reviews, have different advantages over structured surveys. Online reviews can help get a more comprehensive picture of a phenomena (Strohmaier and Wagner 2014), such as wearable devices, by providing information on a large scale. They also help address the Hawthorne effect (Adair 1984), where survey participants may adapt their responses to being directly observed. Finally, online reviews can alleviate traditional research methods problems (Groves and Peytcheva 2008), such as the non-response biases.

Methodology

Figure 1 shows the methodology followed for analyzing online wearable devices reviews using a content analysis approach. The methodology starts with data collection using Brandwatch, a social media mining platform. A search query was developed to identify relevant reviews on Amazon and BestBuy Websites. Data were split into 1 and 2-star and 4 and 5-star rating reviews, where 4- and 5-stars reviews are considered positive reviews, while 1- and 2-stars are considered negative reviews. The 3-stars rating reviews are considered neutral reviews and are often ignored in different kind of analysis because of their ambiguity and lack of information (Al-Ramahi et al. 2017). Wearable use drivers and wearable use challenges and issues were identified by analyzing sample data using a qualitative coding approach. Results from qualitative analysis were used to automatically classify all the reviews using two separate classifiers for 1 and 2-star and 4 and 5-star rating reviews. The methodology is detailed in the following sub-sections.

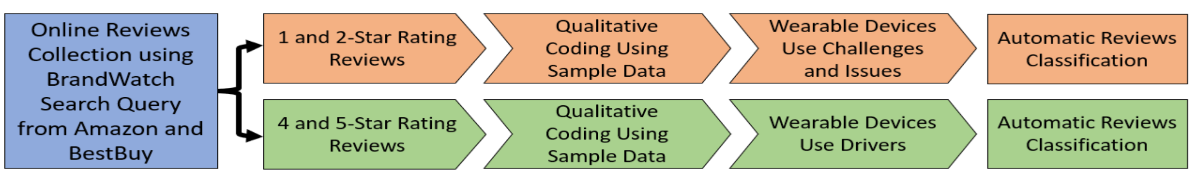

Figure 1. Research methodology

Data collection

Online reviews were collected using an extended version of the search query in (El-Gayar et al. 2019) in order to have comprehensive coverage of consumers wearable brands. The collected reviews were selected based on the criteria of having at least one of the search keywords. We have excluded reviews with certain words that are not context relevant as shown in Figure 2. We collected 16,717 reviews on Amzon.com and BestBuy.com from 12,451 unique users between Jan 01, 2020, and Dec 31, 2021. As a rapidly changing field, the timeframe was chosen to reflect recent advancements in wearable devices.

Qualitative Analysis – Manual Coding

Qualitative data analysis has been used due to its ability to understand a phenomenon from the participants point of view (Anderson and Aydin 2005). In this context, qualitative coding was utilized to identify wearable devices use drivers as well as challenges and issues by the public. The main feature of qualitative coding is that results are grounded in the collected and analyzed data itself (Kelle 2007). To identify drivers and challenges, we focused on high rating reviews (i.e., 4 and 5-star), low rating (i.e., 1 and 2-star) online user reviews, and removing neutral reviews (i.e., 3-star) from the collected data. The process of identifying drivers and challenges associated with wearable devices use started with a quasi-randomization process (Cochran 1946), where a random sample of 600 reviews (300 1 and 2- star rating for identifying challenges, 300 4 and 5-star rating for identifying drivers) were randomly selected for the purpose of manual analysis. A separate qualitative coding was completed for 1 and 2- star rating reviews and 4 and 5-star rating reviews. To ensure that the results obtained are reliable and consistent, we have established inter-rater reliability to avoid any bias in the coding process and ensure that both researchers will conclude with almost similar results. To do so, a random sample of 50 (1 and 2- star rating) reviews and 50 (4 and 5-star rating) reviews were selected and manually coded by two researchers.

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("Fitbit Ace" OR "Fitbit Charge" OR "Fitbit Verca" OR "Fitbit Ionic" OR "Fitbit Versa Lite" OR "Fitbit Inspire"
OR "Fitbit Versa" OR "Garmin Forerunner" OR "Garmin Fēnix" OR "Garmin Vívoki" OR "Garmin Vívofit" OR "Garmin
Vívoactive" OR "Garmin Vívomove" OR "Garmin Vívosmart" OR "Garmin Vívosport" OR "Garmin Venu" OR "Garmin Instinct"
OR "Garmin Luxe" OR "Garmin Darth Vader" OR "Garmin Captain Marvel" OR "Garmin Approach" OR "Garmin Lily" OR
"Garmin Swim" OR "Xiaomi Mi Band" OR "Xiaomi Mi Samrt Band" OR "Moov Now" OR "Moov HR" OR "Apple Watch" OR "Fossil
Gen" OR " Fossil Sport Smartwatch" OR "Fossil Hybrid Smartwatch HR" OR "Misfit Vapor" OR "Misfit Ray" OR "Misfit
Path" OR "Misfit Command" OR "Withings Steel" OR "Withings Move" OR "Withings Pulds" OR "Withings Move ECG" OR
"iHealth Watch" OR "Samsung Gear" OR "Samsung Galaxy Watch Active" OR "Samsung Galaxy Fit" OR "Polar A360" OR
"Polar A370" OR "Polar M430" OR "Polar M200" OR "Polar H10" OR "Polar Vantage" OR "Polar Ignite" OR "Polar Grit
X" OR "Polar Titan" OR "Polar OH1" OR "Polar H9" OR "Striiv Fusion" OR "Striiv Apex HR" OR "Striiv Dash HR" OR
"Huawei TalkBand" OR " Huawei Watch" OR "Huawei Band" OR "MyKronoz ZeWatch" OR "MyKronoz ZeFit" OR "MyKronoz
ZeSport" OR "MyKronoz ZeTime" OR "MyKronoz ZeFit" OR "MyKronoz ZeRound" OR "MyKronoz ZeNeo" OR "MyKronoz ZeTrack"
OR "Coros Apex" OR "Wyze band" OR "Letsfit Fitness racker" OR "Coros Pace" OR "Withings ScanWatch" OR "Amazon
Halo" OR "Timex Ironman" OR "Suunto Peak" OR "Wahoo Fitness") AND -(accessori* OR "gear VR" OR TV OR shoe OR
mountain* OR beach OR appltv OR show OR iphone OR appleevent OR express OR show OR shield OR Protection OR
"protective screen"  OR "protective case" OR "protective cover" OR "replacement bands" OR "replacement charger"
OR "screen protector" OR "case protector" OR "cover protector") AND - (RT OR http*) AND (site:bestbuy.com OR
site:amazon.com)
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Figure 2. Search query

Automatic Reviews Classification

Two separate classifiers, one for wearable drivers and another for wearable challenges and issues were created in Brandwatch using the ReadMe algorithm developed by Hopkins and King (2010). In contrast to existing computer science-based methods that focus on maximizing the percent of documents correctly classified into a given set of categories, the ReadMe algorithm emphasize social science goals where the focus is on broad categorization about the whole sets of documents (Hopkins & King, 2010). The algorithm is considered practical when the objective of the analysis is to show how reviews spread across the different topics and give an unbiased text classification compared to traditional supervised learning techniques (Hopkins and King 2010). In this research, we have trained two instances of ReadMe algorithm by manually coding a sample 1 and 2- star rating reviews and 4 and 5-star rating reviews in each predefined topic obtained from manual coding and used the trained models to classify the remaining 1 and 2- star rating reviews and 4 and 5-star rating reviews. A random sample of 50 (1 and 2- star rating) reviews and 50 (4 and 5-star rating) reviews were selected and manually labeled by two researchers to ensure the reliability and consistency of the manual training process for the ReadMe algorithm.

Results

The search query returned a total of 16,717 reviews, with 14,743 4 and 5-star reviews and 1,209 1 and 2-star rating reviews. The separate qualitative coding process for each group, 1 and 2- star group, and 4 and 5-stars results in Cohen's Kappa statistics of 0.82 and 0.84 for each group sample respectively, which reflects almost perfect agreement among different raters (Landis and Koch 1977). Appendix A describe the codebook used for labeling the categories.

Qualitative analysis using manual coding for 1 and 2- star rating reviews resulted in the identification of 8 categories that reflect wearable devices use challenges and issues, namely, *limited functionalities/features*, *connectivity issues*, *not user friendly*, *credibility support issues*, *perceived value*, and *quality issues* (*glitchy & faulty, battery & charging*, and *waterproof*). Figure 3 shows a high-level overview of the 1- and 2- star rating reviews. Manual coding for 4 and 5- star rating reviews resulted in the identification of 11 categories that reflect wearable devices use drivers, namely, *connectivity support*, *customizability*, *ease of use*, *appeal*, *perceived value*, *device features*, *motivating users*, *hedonic motivation*, and *perceived usefulness* (*tracking functions*, *notification/dialog support*, and *communication*). Figure 4 shows a high-level overview of the 4- and 5- star rating reviews.

To train the ReadMe classifiers, a sample of reviews were labeled by two researchers using the predefined categories. The process resulted in a Cohen's Kappa statistic of 0.80 for the 1 and 2- star rating sample and

0.84 for the 4 and 5-star sample, which reflects substantial agreement, and almost perfect agreement among the two raters (Landis and Koch 1977), respectively. The 1 and 2- star rating and the 4 and 5- star rating classifiers were able to identify 733 and 10,043 relevant reviews, respectively. The relevant reviews were classified by the corresponding classifiers into the identified drivers and challenges categories from the manual coding analysis.

Figure 3. 1 and 2-Star Rating Review Word Cloud

Figure 4. 4 and 5-Star Rating Review Word Cloud

As shown in figure 5, perceived value (28% of reviews) was a major challenge that affect the adoption and use of wearable devices followed by quality issues related to wearable devices being glitchy and faulty (19% of reviews) and battery and charging issues (15% of reviews). Connectivity support with respect to pairing and syncing and user friendliness were also reported as a major challenge (14% of reviews each). Finally, users reported issues related to wearable devices not being waterproof (5% of reviews), having limited functionalities and features (3% of reviews) and having credibility support issues (2% of reviews).

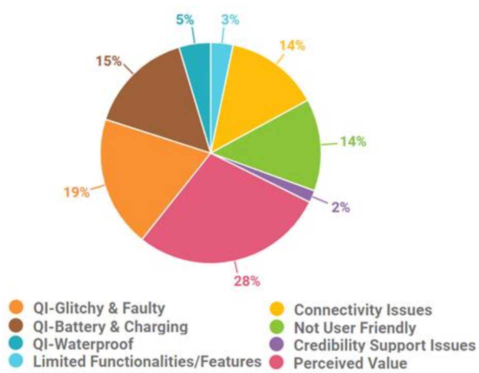

Figure 5. Distribution of Relevant 1- & 2-Star Reviews per Category

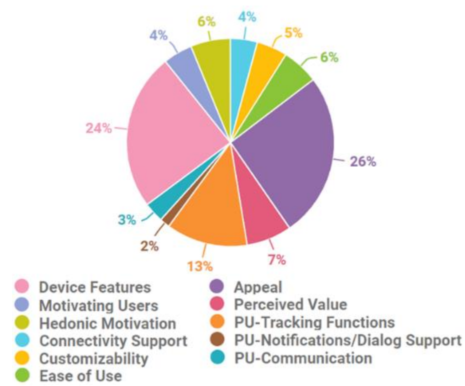

Figure 6. Distribution of Relevant 4- & 5-Star Reviews per Category

As shown in figure 6, the appeal of the wearable device (26% of reviews) and the device features (24% of reviews) were the major drivers behind the adoption and use of wearable devices followed by the perceived usefulness of wearable device tracking functionalities (13% of reviews). Users also reported perceived value (7% of reviews), hedonic motivation (6% of reviews), wearable device ease of use (6% of reviews), and customizability (5% of reviews) as the next set of drivers to adopt and use wearable devices. Finally, users reported adoption and use drivers related to the ability of the device to motivate users (4% of reviews), connectivity support (4% of reviews), perceived usefulness of wearable device to provide communication (3% of reviews), and notification/dialog support (2% of reviews).

Discussion

Data collection and analysis showed that online users' reviews of consumer wearable devices could help identify the drivers and challenges associated with wearable device use. The analysis of the collected data over the past two years showed that, overall, users are mostly satisfied with the wearable device they use, with 93.1% of the relevant reviews analyzed are 4- and 5- star rating reviews. Results revealed that non-functional characteristics (i.e., *device features)* such as screen size, weight, speed, and performance as major drivers for having and using wearable devices. In the literature, such drivers have been less frequently cited (Muller 2020) or have been collectively addressed as a part of the wearable device characteristics

(Kalantari 2017; Zhang et al. 2017). *Motivating users* was another driver reported by the users. In this context, motivating users relates to wearable devices' ability to keep users accountable and motivated to achieve their goals and remain mindful about their health. This is a critical driver when it comes to the role wearable devices play in self-care. Motivating users has been cited in the literature as health belief (Cheung et al. 2019; Zhang et al. 2017), self-motivation (Pal et al. 2020), and perceived health increase (Niknejad et al. 2020). This driver supports the "self-monitoring" persuasive design principle. In essence, a wearable device that keeps track of one's own performance or status supports the user in achieving goals (Oinas-Kukkonen and Harjumaa 2009).

Hedonic motivation has been reported as a driver behind wearable device with an emphasis on the fun and pleasure derived from such use. Hedonic motivation, sometime referred to as perceived enjoyment, has been widely addressed in the literature and had significant impact on the adoption and use of wearable device (Gao et al. 2015; Hasan and Stannard 2022; Niknejad et al. 2020). *Connectivity or integration support* is another driver that relates to wearable device abilities to connect, pair, and sync with other devices and services and having a single ecosystem for smart devices used by the user. This driver has been referred to as compatibility (Ahmad et al. 2020), the "degree to which a new technology works with other existing technologies without altering any functionalities". *Customizability* is another driver, which allows users to personalize and customize the wearable device settings and features. According to the literature and up to the knowledge of researchers, *Customizability* has been addressed by limited number of studies as personalization (Karahanoglu and Erbug 2011).

Ease of use is a well-known driver that relates to how easy the wearable device is and has an intuitive user-interface. Ease of use and "effort expectancy", respectively reflect the level of ease of use associated with the use of information technology. Ease of use has been widely addressed in the context of wearable devices and was a predictor of wearable device use (Ahmad et al. 2020; Dehghani 2018; Karahanoglu and Erbug 2011; Thong et al. 2006). Device *appeal* has been also reported as a major driver. It relates to the aesthetics of the wearable device in general and has been reported in the literature as aesthetically pleasing (Karahanoglu and Erbug 2011), perceived prestige (Li et al. 2016), and fashnology (Dehghani 2018). *Perceived value* is another reported driver that refers whether wearables devices worth their price in terms of their specifications and functionalities. Cost is a major factor that affect the users purchase decision. This driver has been addressed in the literature as perceived fee, which refers to the monetary expenses associated with wearable device use (Niknejad et al. 2020) and price value, which refer to "trade-off between the perceived value of the goods or services and the overall cost" (Hasan and Stannard 2022).

Perceived usefulness is a major driver of use. Perceived usefulness is the perception of the expected benefits when using a wearable device (Cheung et al. 2019; Gupta et al. 2021; Pal et al. 2020). In the context of this study, perceived usefulness is related to wearable devices' abilities to track different activities, provide notification, and dialog support, as well as ability to support basic smartphone functionalities. The literature reported some of these as separate factors that contribute to wearable device use, including the data accuracy aspect of perceived credibility (Ahmad et al. 2020) and functionality (Dehghani 2018).

On the other hand, users reported several challenges associated with wearable devices. A major issue was related to the *quality* of wearable devices that is related to issues like the wearable device being glitchy and faulty, quality issues with battery lifetime and charging, and not being waterproof. According to the literature, poor battery life (Michaelis et al. 2016) and wearable device being not waterproof (Michaelis et al. 2016) have been reported as issues associated with wearable devices. *Limited functionalities/features* were also observed as an issue of wearable device use. Another challenge reported was *connectivity issues* (i.e., ability to connect, pair, and sync with other devices and services). This challenge has been reported in the literature with respect to syncing issues (Michaelis et al. 2016). In addition, some users reported that wearable devices being *not user friendly*. Another crucial challenge mentioned is *credibility support*, which refers to wearable devices not being accurate in terms of information provided. This issue has been reported in the literature as perceived credibility (Ahmad et al. 2020; Zhang et al. 2017) and inaccuracy (Michaelis et al. 2016). This driver supports "trustworthiness" persuasive design principle (Oinas-Kukkonen and Harjumaa 2009). In essence, a wearable device that is viewed as trustworthy will have increased powers of persuasion. Finally, *perceived value* has been also reported as a challenge where users perceived the wearable device not being worth its price compared to features and functionalities. This challenge has been reported by (Hasan and Stannard 2022) as price values which refers to the "trade-off between the perceived value of the goods or services and the overall cost".

Limitations and Future Works

This study is not without any limitations. First, given the unstructured text available on social media, there is a probability that 1- and 2-stars rating reviews could address drivers of wearable devices and 4- and 5-stars rating reviews could address challenges and limitations of wearable devices. Second, the analysis completed using online reviews did not consider any bias within the reviews when it comes to the trustworthiness of the reviews, whether the reviews used are representable to the population of wearable devices users, as well as fake reviews from malicious users or competitive brands. Future works could include an empirical investigation to predict reviews ratings using the identified drivers and challenges as informative attributes. Such predictive analytics also has the advantages of cross-validation using holdout data. The findings could also allude to the relative importance (weight) of these factors and how such weights may differ in the context of wearables compared to non-wearables.

Conclusion

Using online reviews that reflect actual wearable devices use, this study attempted to explore the drivers and challenges associated with wearable device use. To researchers' knowledge, the study is one of the few studies that attempted to address wearable devices drivers and challenges using user reviews and content analysis approach for data analysis. In essence, this study takes advantages of "found large scale data" on the Web compared to behavioral studies, which usually use "small scale design data" collected from few hundreds of participants. Our findings provide mixed perspective when it comes to several drivers and challenges. These findings are related to ease of use, perceived value, and connectivity/communication. According to the analysis, these were mentioned as challenges and drivers by different users. One explanation for such mixed perspective is that these could be brand/model specific, where for example, one wearable device could be easy to use while another is not. Furthermore, the study emphasizes the importance of drivers such as connectivity support, customizability, hedonic motivation, and communication while highlighting concerns regarding user friendliness, perceived value, and quality. The findings of this study inform popular and well-known theoretical models from technology use, acceptance, and adoption like the unified theory of acceptance and use of technology (UTAUT) and persuasive design models. The findings can also have direct practical implications for wearable devices design and development by grounding and improving the driver in future wearable devices and mitigating and addressing the challenges associated with wearable devices. They can also be used to prepare and send feedback reports to wearable devices manufacturers.

REFERENCES

Adair, J. G. 1984. "The Hawthorne Effect: A Reconsideration of the Methodological Artifact," *Journal of Applied Psychology* (69:2), US: American Psychological Association, pp. 334–345. (https://doi.org/10.1037/0021-9010.69.2.334).

Aerts, G., Smits, T., and Verlegh, P. W. J. 2017. "How Online Consumer Reviews Are Influenced by the Language and Valence of Prior Reviews: A Construal Level Perspective," *Computers in Human Behavior* (75), pp. 855–864. (https://doi.org/10.1016/j.chb.2017.06.023).

Ahmad, A., Rasul, T., Yousaf, A., and Zaman, U. 2020. "Understanding Factors Influencing Elderly Diabetic Patients' Continuance Intention to Use Digital Health Wearables: Extending the Technology Acceptance Model (TAM)," *Journal of Open Innovation: Technology, Market, and Complexity* (6:3), p. 81. (https://doi.org/10.3390/joitmc6030081).

Al-Ramahi, M. A., Liu, J., and El-Gayar, O. F. 2017. "Discovering Design Principles for Health Behavioral Change Support Systems: A Text Mining Approach," *ACM Transactions on Management Information Systems (TMIS)* (8:2–3), ACM New York, NY, USA, pp. 1–24.

Anderson, J. G., and Aydin, C. E. (eds.). 2005. *Evaluating the Organizational Impact of Healthcare Information Systems*, (2nd ed.), Health Informatics Series, New York, NY: Springer.

Billinghurst, M., and Starner, T. 1999. "Wearable Devices: New Ways to Manage Information," *Computer* (32:1), pp. 57–64. (https://doi.org/10.1109/2.738305).

Cheung, M. L., Chau, K. Y., Lam, M. H. S., Tse, G., Ho, K. Y., Flint, S. W., Broom, D. R., Tso, E. K. H., and Lee, K. Y. 2019. "Examining Consumers' Adoption of Wearable Healthcare Technology: The Role of Health Attributes," *International Journal of Environmental Research and Public Health* (16:13). (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6650855/).

Cochran, W. G. 1946. "Relative Accuracy of Systematic and Stratified Random Samples for a Certain Class of Populations," *The Annals of Mathematical Statistics* (17:2), pp. 164–177.

Dai, B., Larnyo, E., Tetteh, E. A., Aboagye, A. K., and Musah, A.-A. I. 2020. "Factors Affecting Caregivers' Acceptance of the Use of Wearable Devices by Patients With Dementia: An Extension of the Unified Theory of Acceptance and Use of Technology Model," *American Journal of Alzheimer's Disease & Other Dementias®* (35), p. 153331751988349. (https://doi.org/10.1177/1533317519883493).

Dehghani, M. 2018. "Exploring the Motivational Factors on Continuous Usage Intention of Smartwatches among Actual Users," *Behaviour & Information Technology* (37:2), pp. 145–158. (https://doi.org/10.1080/0144929X.2018.1424246).

El-Gayar, O., Nasralah, T., and Noshokaty, A. E. 2019. "Wearable Devices for Health and Wellbeing: Design Insights from Twitter," in *Proceedings of the 52nd Hawaii International Conference on System Sciences*, p. 10.

Enes, A. 2022. *Opportunities and Challenges for Computational Social Science Methods*, IGI Global.

Engel, U. 2021. "Causal and Predictive Modeling in Computational Social Science," in *Handbook of Computational Social Science* (Vol. 1), Taylor & Francis. (https://library.oapen.org/handle/20.500.12657/51413).

Gao, Y., Li, H., and Luo, Y. 2015. "An Empirical Study of Wearable Technology Acceptance in Healthcare," *Industrial Management & Data Systems* (115:9), (D. Xiaojun Wang, Professor Leroy White, ed.), pp. 1704–1723. (https://doi.org/10.1108/IMDS-03-2015-0087).

Groves, R. M., and Peytcheva, E. 2008. "The Impact of Nonresponse Rates on Nonresponse Bias: A Meta-Analysis," *The Public Opinion Quarterly* (72:2), [Oxford University Press, American Association for Public Opinion Research], pp. 167–189.

Gupta, A., Dhiman, N., Yousaf, A., and Arora, N. 2021. "Social Comparison and Continuance Intention of Smart Fitness Wearables: An Extended Expectation Confirmation Theory Perspective," *Behaviour & Information Technology* (40:13), pp. 1341–1354. (https://doi.org/10.1080/0144929X.2020.1748715).

Habibipour, A., Padyab, A., and StÃ, A. 2019. "Social, Ethical and Ecological Issues in Wearable Technologies," *Twenty-Fifth Americas Conference on Information Systems*, p. 10.

Hasan, M. N.-U., and Stannard, C. R. 2022. "Exploring Online Consumer Reviews of Wearable Technology: The Owlet Smart Sock," *Research Journal of Textile and Apparel* (ahead-of-print:ahead-of-print). (https://doi.org/10.1108/RJTA-08-2021-0103).

Hopkins, D. J., and King, G. 2010. "A Method of Automated Nonparametric Content Analysis for Social Science," *American Journal of Political Science* (54:1), pp. 229–247. (https://doi.org/10.1111/j.1540-5907.2009.00428.x).

Hyndavi, V., Nikhita, N. S., and Rakesh, S. 2020. "Smart Wearable Device for Women Safety Using IoT," in *2020 5th International Conference on Communication and Electronics Systems (ICCES)*, , June, pp. 459–463. (https://doi.org/10.1109/ICCES48766.2020.9138047).

John Dian, F., Vahidnia, R., and Rahmati, A. 2020. "Wearables and the Internet of Things (IoT), Applications, Opportunities, and Challenges: A Survey," *IEEE Access* (8), pp. 69200–69211. (https://doi.org/10.1109/ACCESS.2020.2986329).

Kalantari, M. 2017. "Consumers' Adoption of Wearable Technologies: Literature Review, Synthesis, and Future Research Agenda," *International Journal of Technology Marketing* (12:3), p. 274. (https://doi.org/10.1504/IJTMKT.2017.089665).

Karahanoglu, A., and Erbug, Ç. 2011. "Perceived Qualities of Smart Wearables: Determinants of User Acceptance," in *DPPI*. (https://doi.org/10.1145/2347504.2347533).

Kelle, U. 2007. "The Development of Categories: Different Approaches in Grounded Theory," in *The SAGE Handbook of Grounded Theory*, 1 Oliver's Yard, 55 City Road, London England EC1Y 1SP United Kingdom: SAGE Publications Ltd, pp. 191–213. (https://doi.org/10.4135/9781848607941.n9).

Kinnunen, M., Mian, S. Q., Oinas-Kukkonen, H., Riekki, J., Jutila, M., Ervasti, M., Ahokangas, P., and Alasaarela, E. 2016. "Wearable and Mobile Sensors Connected to Social Media in Human Well-Being Applications," *Telematics and Informatics* (33:1), pp. 92–101. (https://doi.org/10.1016/j.tele.2015.06.008).

Landis, J. R., and Koch, G. G. 1977. "The Measurement of Observer Agreement for Categorical Data," *Biometrics* (33:1), p. 159. (https://doi.org/10.2307/2529310).

Li, H., Wu, J., Gao, Y., and Shi, Y. 2016. "Examining Individuals' Adoption of Healthcare Wearable Devices: An Empirical Study from Privacy Calculus Perspective," *International Journal of Medical Informatics* (88), pp. 8–17. (https://doi.org/10.1016/j.ijmedinf.2015.12.010).

Liu, Y., and Han, M. 2020. "Determining the Key Factors of Wearable Devices Consumers' Adoption Behavior Based on an MADM Model for Product Improvement," *IEEE Transactions on Engineering Management*, pp. 1–16. (https://doi.org/10.1109/TEM.2019.2960499).

Maher, C., Ryan, J., Ambrosi, C., and Edney, S. 2017. "Users' Experiences of Wearable Activity Trackers: A Cross-Sectional Study," *BMC Public Health* (17:1), p. 880. (https://doi.org/10.1186/s12889-017-4888-1).

Michaelis, J. R., Rupp, M. A., Kozachuk, J., Ho, B., Zapata-Ocampo, D., McConnell, D. S., and Smither, J. A. 2016. "Describing the User Experience of Wearable Fitness Technology through Online Product Reviews," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 60), SAGE Publications Inc, September 1, pp. 1073–1077. (https://doi.org/10.1177/1541931213601248).

Motiwalla, L., Deokar, A. V., Sarnikar, S., and Dimoka, A. 2019. "Leveraging Data Analytics for Behavioral Research," *Information Systems Frontiers* (21:4), pp. 735–742. (https://doi.org/10.1007/s10796-019-09928-8).

Moulaei, K., Malek, M., and Sheikhtaheri, A. 2021. "A Smart Wearable Device for Monitoring and Self-Management of Diabetic Foot: A Proof of Concept Study," *International Journal of Medical Informatics* (146), p. 104343. (https://doi.org/10.1016/j.ijmedinf.2020.104343).

Muller, C. 2020. "Wearable Activity-Tracking Device Feature Preference Amongst South African Generation Y Students," *International Journal of EBusiness and EGovernment Studies*, pp. 1–16. (https://doi.org/10.34111/ijebeg.202012101).

Niknejad, N., Hussin, A. R. C., Ghani, I., and Ganjouei, F. A. 2020. "A Confirmatory Factor Analysis of the Behavioral Intention to Use Smart Wellness Wearables in Malaysia," *Universal Access in the Information Society* (19:3), pp. 633–653. (https://doi.org/10.1007/s10209-019-00663-0).

Oinas-Kukkonen, H., and Harjumaa, M. 2009. "Persuasive Systems Design: Key Issues, Process Model, and System Features," *Communications of the Association for Information Systems* (24). (https://doi.org/10.17705/1CAIS.02428).

Oliveira, F. M. D., and Nunes, P. H. 2019. "Wearable Devices: Concepts and Applications," *INFOCOMP* (18:2), p. 7.

Pal, D., Funilkul, S., and Vanijja, V. 2020. "The Future of Smartwatches: Assessing the End-Users' Continuous Usage Using an Extended Expectation-Confirmation Model," *Universal Access in the Information Society* (19:2), pp. 261–281. (https://doi.org/10.1007/s10209-018-0639-z).

Park, S., and Jayaraman, S. 2021. "Chapter 1 - Wearables: Fundamentals, Advancements, and a Roadmap for the Future," in *Wearable Sensors (Second Edition)*, E. Sazonov (ed.), Oxford: Academic Press, pp. 3–27. (https://doi.org/10.1016/B978-0-12-819246-7.00001-2).

Patel, M. S., Asch, D. A., and Volpp, K. G. 2015. "Wearable Devices as Facilitators, Not Drivers, of Health Behavior Change," *JAMA* (313:5), pp. 459–460. (https://doi.org/10.1001/jama.2014.14781).

Popat, K., and Sharma, P. 2013. "Wearable Computer Applications a Future Perspective," *International Journal of Engineering and Innovative Technology* (3), pp. 213–217.

Seneviratne, S., Hu, Y., Nguyen, T., Lan, G., Khalifa, S., Thilakarathna, K., Hassan, M., and Seneviratne, A. 2017. "A Survey of Wearable Devices and Challenges," *IEEE Communications Surveys Tutorials* (19:4), pp. 2573–2620. (https://doi.org/10.1109/COMST.2017.2731979).

Shih, P. C., Han, K., Poole, E. S., Rosson, M. B., and Carroll, J. M. 2015. *Use and Adoption Challenges of Wearable Activity Trackers*, p. 12.

Strohmaier, M., and Wagner, C. 2014. "Computational Social Science for the World Wide Web," *IEEE Intelligent Systems* (29:5), pp. 84–88. (https://doi.org/10.1109/MIS.2014.80).

Thong, J., Hong, S.-J., and Tam, K. Y. 2006. "The Effects of Post-Adoption Beliefs on the Expectation-Confirmation Model for Information Technology Continuance," *International Journal of Human-Computer Studies* (64:9), pp. 799–810. (https://doi.org/10.1016/j.ijhcs.2006.05.001).

Ueafuea, K., Boonnag, C., Sudhawiyangkul, T., Leelaarporn, P., Gulistan, A., Chen, W., Mukhopadhyay, S. C., Wilaiprasitporn, T., and Piyayotai, S. 2021. "Potential Applications of Mobile and Wearable Devices for Psychological Support During the COVID-19 Pandemic: A Review," *IEEE Sensors Journal* (21:6), pp. 7162–7178. (https://doi.org/10.1109/JSEN.2020.3046259).

Zhang, M., Luo, M., Nie, R., and Zhang, Y. 2017. "Technical Attributes, Health Attribute, Consumer Attributes and Their Roles in Adoption Intention of Healthcare Wearable Technology," *International Journal of Medical Informatics* (108), pp. 97–109. (https://doi.org/10.1016/j.ijmedinf.2017.09.016).

Appendix A: Codebook for labeling categories

Drivers Categories & Description	Example
Connectivity Support: Relate to abilities to connect, pair, and sync with other devices and services	"I switched to Apple to sync all of my other smart gadgets together. The Apple watch sync perfectly with my Strava app and google map app"
Customizability: Relate to abilities to personalize and customize the wearable device settings and features	"Love my Apple Watch, very convenient. And so many options to personalize"
Ease of Use: Relate to wearable device interface being simple and easy use	"My first watch and love it; it's handy and easy to use"
Appeal: Relate to the aesthetics of the wearable device	"Love my Apple Watch in gold, Such a beautiful color. Matches my phone"
Perceived Value: Relates to wearables devices being worth the price compared to specs and functionalities	"Quality product at a low price" and "The Apple Watch is amazing and worth the price! I love it!"
PU - Tracking Functions: Relate to wearable device ability to track and monitor multiple exercises and tasks	"Fitbit - Charge 2 Activity Tracker + Heart Rate has been one of the best items I have purchased for tracking my daily activities"
PU - Notifications & Dialog Support: Relate to wearable device ability to capture interaction and feedback via notification and reminders	"Apple Watch works great. Easy notification access and other app access without taking out your phone. Fitness app is easy to use with daily reminders"
PU – Communication: Relate to wearable device ability to perform basic smartphone functionalities	"I love my Apple Watch. I can answer calls, receive messages, news and find my phone with it."
Device Features: Relates to non-functional characteristics of wearable devices	"It feels lighter and thinner. It is much faster, and the screen is much more usable!"
Motivating Users: Relate to wearable device ability to keep users accountable and motivated to achieve goals	"Love my apple watch, I use it to set goals and keep myself motivated throughout the day"
Hedonic Motivation: Relate to users having fun and pleasure using the wearable device	"Enjoying my Apple Watch. The walkie talkie is fun to use"
Irrelevant: The review is not related to the device itself with respect to the above categories	"Awesome Apple Watch protector. Easy to install and prevent watch from getting scratches"
Challenges Categories & Description	**Example**
Connectivity Issues: Relate to issues with wearable device abilities to connect, pair, and sync with other devices and services	"I can't receive text messages or make calls from my watch"
QI – Waterproof: Relates to wearable device functionalities not being waterproof	"It is not "water resistant" and Samsung will not fix for you! Stay away!"
QI - Battery & Charging: Relates to problems about battery life and charging issues	"The charge doesn't hold for more than a few days"
QI - Glitchy & Faulty: Relates to wearable device functionalities being inconsistent and having software issues	"This is my third Fitbit. Same experience with all three of them. They work for about 6 months and then become so glitchy"
Not User Friendly: Relate to wearable device interface being not easy use and non-intuitive	"It was pretty good watch except ease of use was not as friendly as apple watch"
Credibility Support: Relate to wearable device not being accurate in terms of information captured	"Bought a Fitbit versa to save money but it was horrible and completely inaccurate"
Limited Functionalities & Features: Relate to wearable device having limited or missing important functionalities	"My husband bought me a Galaxy Active 2 and I have been using it a while, but it doesn't track calories
Perceived Value: Relates to wearables devices not worth the price compared to specs and functionalities	"Not worth the price. Wish I bought the Apple Watch"
Irrelevant: The review is not related to the device itself with respect to the above categories	"Installed this to my Apple Watch. After a couple of weeks, I realized it fell off. Waste of money"