Spring 3-20-2019

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Abstract. Discussion platform, Reddit, is the third most visited website in the US. People can post their questions on this platform to get varying opinions from fellow users, which in turn might also influence their behavior and choices. Wearables are becoming widely adopted, yet challenges persist in their effective long term use because of technical and device related, or personal issues. Therefore, by employing sentiment analysis, this paper aims to analyze how decisions of use or abandonment of wearables are influenced by discussions on Reddit. The results are based on the analysis of 6680 posts and their associated 50,867 comments posted between December 2015 - December 2017 on the subreddit (user created groups) on android wear. Our results show that sentiment of the discussion is majorly dictated by the sentiment of the post itself, and people decide to continue using their devices when fellow Redditors offer them workarounds, or the discussion receives majority of positive or fact-driven neutral comments.

Keywords: Reddit · Sentiment Analysis · (Non-)Use of Technology

1 Introduction

Companies nowadays often use social media as a marketing tool to engage customers and promote their products and services [7]. Users/customers also post their opinion on social media with the belief that they can influence public viewpoint and businesses. Participants in our preliminary survey-based study also pointed that social opinion influences their decision to use such devices or abandon them [6]. Therefore, this paper explores how people use social platform of Reddit to make decisions regarding continued use or abandonment of wearables such as smart watches and activity trackers.

Reddit is an online social system with attributes of a forum. It comprises of several user created and controlled subreddits, which are topical forums for content. Users of Reddit, frequently referred to as Redditors, can interact in these subreddits either by creating a self-post, or by commenting on the existing posts. The comments help sustain discussions on various subtopics initiated

[⋆] All the work was done during author's affiliation with Syracuse University through posts. We chose to explore our research questions through discussions on subreddit of r/androidwear because (1) the user community of smart devices on r/androidwear is very active, specifically on the topic of device use and adoption due to the dwindling popularity and sales of android wear, and (2) all postings, comments, and other meta data about users and their postings are publicly available.

While researchers have explored the sentiment aspect of product reviews (e.g., [17]), social media posts (e.g., [13]), and blogs (e.g., [10]), the role of discussions' sentiments on the decision-making process of using or not-using the devices have not been studied thus far. Our work aims to fill this gap by analyzing the sentiment of 6680 posts and corresponding 50,867 comments posted from December 2015 to December 2017 on r/androidwear. We found that majority of comments to positive posts also had a positive sentiment, negative posts had more neutral comments, and neutral posts had more positive comments. Further, the final decision of the person, who started the post, regarding continued use or abandonment of the device was dictated by the sentiment that was associated with the majority of the comments in the discussion thread. For example, if a Redditor started a discussion with a negative post owing to his/her frustrations of using a devices, but then received majority of positive or neutral (fact driven) comments, he continued to use his/her device due to the advise and workarounds offered to him in the discussion. Further methodological details and results will be discussed in the sections that follow.

2 Related Work

Our work is related to two broad streams of research: Technology (non-)use and sentiment analysis of social media's content. Therefore, first, we review literature that concentrates on exploring decisions of use or abandonment of wearables. Second, we review literature on sentiment analysis of social media's content that unpacks how sentiment analysis has been used to analyze users' opinions and decisions.

2.1 Use or Non-Use of Technology

Studies exploring use or non-use a technology focus on understanding the process and choices current users of any technology make to either continue using the technology or abandon it. Previous studies have employed observations, interviews, and surveys to understand the users' practices of continued use and the challenges users experience while using smart devices such as activity trackers and/or wearables [6, 9, 13, 18]. For example, survey-based study [6] found that increased control in daily activities, and competitive edge among peers and friends led people to continue using smart devices. Another study done with 26 participants, who were given physical activity trackers for 6 weeks, found that there are gender differences in use and adoption of wearable devices [18]. 65% of the participants stopped their devices within two weeks, because they felt device was very obtrusive and it was too difficult to manage and integrate data across multiple devices. In summary, existing research focuses mostly on the technical- or device-related challenges for long-term use. However, such studies are limited in terms of number of people who can be studied, and are based mostly on self-reported data from the participants who were using the devices only for the purpose of the study. In fact, researchers (e.g, [16]) have pointed out that behavior change is not just a possible outcome of using an individual technology, but is something that is achieved by people, potentially across various technologies that they interweave.

Additionally, previous research has shown that sentiment of online discussion forums or social media can be used to understand and predict public opinion [11], including that of technology use [6]. But, how people use platforms like Reddit to discuss their technology use, and how discussions on platform influence users' decision of technology (non-)use has not been studied so far.

2.2 Sentiment Analysis of Social Media's Content

Researchers in the past have studied how sentiment of the posts, tweets, and reviews affect the discussion, retweets, and emotional state or opinions of the participants. For example, [19] found that emotionally charged Twitter messages tend to be retweeted more often and more quickly compared to neutral ones. Another study on emotional contagion in social media highlighted the presence of a linear relationship between the average emotional valence of the stimuli users are exposed to, and that of the responses they produce [4]. A study on online health support groups, found that negative messages attracted a larger number of comments to reinforce positivity [20]. Finally, [17] concluded that consumer reviews with neutral polarity in the text are perceived to be more helpful. However, influence of posts' and comments' sentiment on the discussion that occurs on Reddit has not been yet investigated.

Therefore, motivated by these open issues our work is driven by two Research Questions (RQ). **RQ1:** Does the sentiment of posts influence the sentiment of following discussion? **RQ2:** What is the role of sentiment in influencing the decision of use or non-use of new technologies?

3 Sentiment Analysis

There are large number of models that have utilized machine learning to perform sentiment analysis across different domains such as product reviews, online health support, and twitter discussions. However, as users might use different words to express sentiment in different domains, sentiment analysis models developed for one domain can not necessarily be used for other domains [14]. Therefore, the following sections describe the method and results of supervised sentiment analysis model that we developed for the context of discussions on Reddit.

3.1 Dataset

r/androidwear gained popularity in December 2015 and has currently 44,866 Redditors or subscribers. We obtained comments and posts from December 2015 to December 2017 in r/androidwear from a public Reddit comment dataset [1] that also contains meta information such as ID of the author, date of comment, position in discussion thread. The information was retrieved using SQL commands on Google BigQuery[3], which is Google's low cost enterprise data warehouse.

We first retrieved all the posts (13,037) and the comments in response to each post between December 2015 and December 2017. Thereafter, we observed that there were few posts in the corpus that were related to troubleshooting steps or updates that Android released during that time period. In other words in this subreddit people not only share their opinion regarding android wear but also use this platform for troubleshooting any technical difficulties they face while using their devices.

Few examples of such posts are: "The preview of my watch, a Moto 360 V1 Silver, has disappeared from the blue space of the app..Any thoughts?", "good news for the Chinese Android wear users, soon they will have access to Google service, like play store..", and "I was wondering if you guys get perfect smooth scrolling through the menus or do you get a few jitters while doing it with the Huawei Watch?" Therefore such posts were removed from the corpus before conducting sentiment analysis. In the end approximately half of the posts (6680), with an average sentence per post of 8.01, contained opinions.

These 6680 posts and all the their corresponding 50,867 comments (average sentence per comment 2.86) were included in the analysis. Our final dataset included contribution from 27,136 Redditors. We preprocessed the screened data using NLTK library [2] as follows:
- Unwanted hyperlinks and html tags embedded in the comments were removed
- Unwanted characters, punctuations, numbers, e.g., 8n9lnxr, zw1, -, comma (,), and others were cleaned.
- Text was converted to lowercase and stemming was done to reduce words to their stem.
- Stop words were removed, excluding negation words such as not, never, or no.

3.2 Training Dataset

Our sentiment analysis model uses a supervised machine learning algorithm. Therefore, the first step involved creating manually labeled data. To this end, random 1026 posts and their corresponding comments were chosen from our dataset. To classify the training data set, first, both authors individually labelled each message into positive, negative, or neutral class. Then the authors worked together discussing and assigning final label (or class) to each message (posts and comments), with a Cohen's Kappa of 0.90.

[3] https://cloud.google.com/bigquery/

3.3 Sentiment Analysis Model

After labelling the training data, features were extracted from these posts and comments. Extracted features included n-grams (unigram, bigram, and trigram), tf-idf weights, and unigrams with negation tagging. For negation we followed the approach proposed in [12], which considers bigrams (and n-grams in general) to be an orthogonal way to incorporate context. Therefore we did not add negation tags to bigrams and trigrams, and only unigrams were included with negation tagging. [12] also suggested that a product review might begin with an overall sentiment statement, proceed with details about the product, and conclude by summarizing the author's views. Therefore, position of the word in comments were treated as an additional feature. Furthermore, for treating number of positive and negative words in a comment or post as a feature, we used domain specific positive and negative word lists [8] and [15] to count the words belonging to each category.

Using these features and our training dataset, we trained four different classifiers: Support Vector Machine, Logistic Regression, Random Forest, Multinomial Naive Bayes. The best accuracy (accuracy: 79.6%, F1-measure: 0.78) was achieved using logistic regression classifier. In order to avoid overfitting we employed 10-fold cross validation. Hence, this reported accuracy is the average accuracy of the model across all the 10-folds.

4 Results of Sentiment Analysis of Discussion on r/androidwear

The ability to automatically identify sentiment of messages allowed us to study the interrelations between sentiment of the posts/comments and sentiment fluctuations in discussion threads. Following sections illustrate our findings.

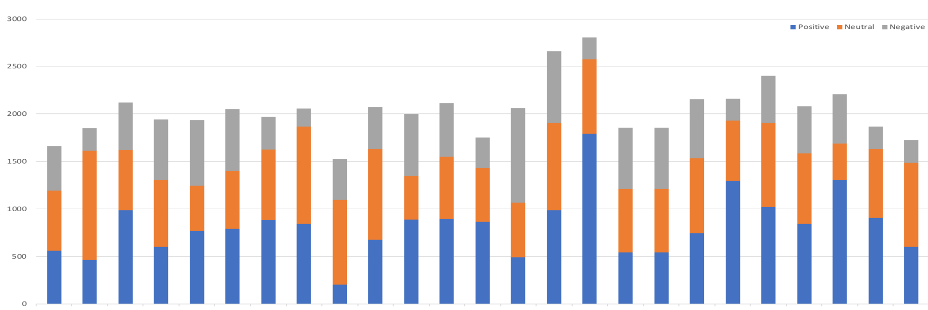


Fig. 1: Sentiment Distribution of Comments over Time

4.1 Sentiment Distribution for Discussions

Based on the sentiment label assigned by our model, 20478 positive (40.13%), 12218 negative (24.47%), and 18171 neutral (35.39%) comments were posted

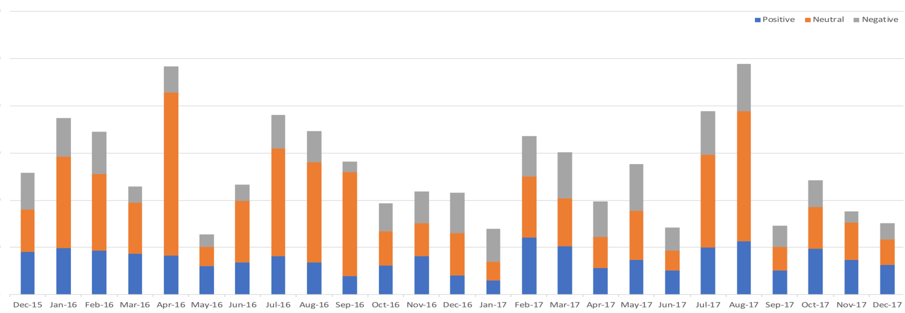


Fig. 2: Sentiment Distribution of Posts over Time

over the period of our data collection. The distribution of comments' sentiment over time can be seen in Figure 1. In general, majority of the comments posted in this subreddit were positive. In fact, majority of comments posted in months with highest number of comments also had positive tone. For example, 63.84% of comments made in March, 2017 (month with highest number of comments) were positive. Similar pattern in comments' sentiment exists in months of February and August, 2017 that had next highest number of total comments. Qualitative analysis of these comments revealed that excitement due to the release of new android wear (e.g., LG Watch Sport/Style (Feb, 2017), Q Venture (Aug, 2017)) in the market led to a peak in neutral or positive discussions. Even though, this euphoria did not necessarily increase the number of posts, it triggered long discussions amongst Redditors regarding their opinion about the newly released products in the market. The distribution of posts' sentiment over time can be seen in Figure 2.

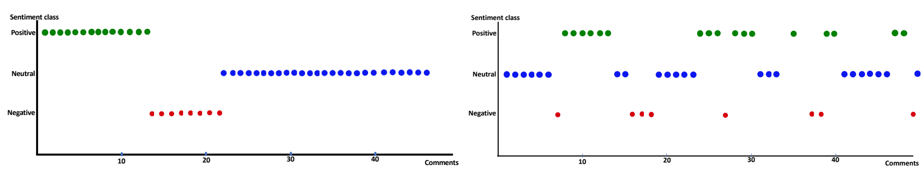
Table 1: Sentiment Distribution of Posts and Comments

Posts Count per Sentiment	**Comment Count per Sentiment**
Positive, 1889 (28.27%)	Positive 8128 (51.40%)
	Negative, 3405 (21.53%)
	Neutral, 4278 (27.05%)
Neutral, 3187 (47.67%)	Positive, 8084 (43.25%)
	Negative, 3598 (19.25%)
	Neutral, 7008 (37.49%)
Negative, 1604 (24.01%)	Positive, 4266 (26.06%)
	Negative, 5215 (31.86%)
	Neutral, 6885 (42.06%)

Furthermore, in terms of Redditors response to posts, the sentiment of the post indeed influenced the sentiment of the discussion that follows (cf. Table 1, RQ1). The majority of the comments (51.40%) in response to positive posts had a positive sentiment. At the same time the majority of responses (43.25%) to neutral posts had positive sentiment; however, there were also a significant number of neutral comments (37.49%) along with considerable negative comments (31.86%) in response to negative posts. The fact that most kinds of posts attract more neutral or positive comments indicates that Redditors tend to offer advice on how to improve or upgrade the devices, as opposed to just criticizing the technology or device under discussion.

4.2 Changes of Sentiment in Discussion Threads

As noted in the research questions, we are particularly interested in 1) identifying distinct sentiment patterns in comments within a discussion thread, and 2) to assess how such patterns impact the decision of (non-)use. To this end, Figures 3, 4, and 5 illustrate the two most commonly occurring patterns of sentiment changes in posts with positive, neutral, and negative sentiments respectively. For each sentiment pattern, posts with longest discussion (highest number of comments) were chosen for demonstrative purposes in these figures.



(a) Focussed Sentiment (b) Deviated Sentiment

Fig. 3: Patterns of Discussion Sentiment on Positive Post

Figure 3a presents a pattern of stable positive responses in response to a positive post, followed by a complete shift to a number of negative responses, and then discussion ending with neutral comments. Discussion in almost 44% of positive posts had such focussed sentiment pattern. Our qualitative investigation of such threads highlighted that Redditors try to help the fellow member (who started the discussion) to make an informed decision of either continuing to use the device (with the help of workarounds to their device issues through positive or neutral comments) or abandoning the device (due to lack of functionality or other issues in the device through negative comments).

For example, a Redditor posted: *I'm thoroughly enjoying my Moto360, except now when I say "OK google, play blah," it tries to find music on my phone that is potentially not even there. How do I fix this? I might have to stop using the device because of this.* Even though some people shared their frustrations of going through the same issue by posting comments such as *this is exactly what irritates me, my usage is going down because of that*, other Redditors through neutral and positive comments such as *I ended up disabling the Music app and that seems to have done the trick* or *Try to get app picker that will help, this is an amazing device I would not give up for that reason* offered workarounds that helped in continued use of the device.

In comparison, the continuous change of sentiment (illustrated in Figure 3b), which was seen in 32% positive posts indicated contentious discussion between

Redditors due to their different experiences of using such devices or awareness of the device's capabilities under discussion.

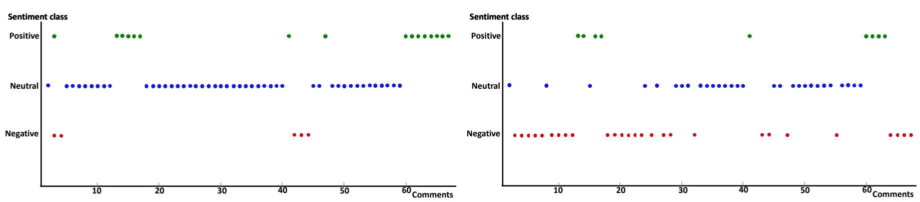
For example, in response to post: *I was using my Gear live for a LONG time. I loved it, especially the screen, thinking back, though, the watch broke 4 times, the charging cradle, the strap, and the contacts for charging on the back corroded away. Well, Best Buy has ASUS Zenwatch 2 on sale, this watch has the thing I wanted most: A square, AMOLED screen. It is phenomenal. However I need you opinion on the reliability problems before I get converted*, people commented with neutral comments that did not necessary answer the question posed but gave some factual information such as *It has a thinner, proper strap mounting claws, and a slightly curved screen vertically, which makes the light reflect off of it in a way that you might appreciate*. People also commented positively by giving their opinion on the issue under discussion *I recently got a Zenwatch 2, its my 2nd smartwatch and I think its a keeper, so reliable lasts for 3 days without charging again*. However, presence of argumentative negative comments such as *I don't believe people are not writing correct things about the watch, its so misleading. People like you are false sales men of such watches. It has been an utter disappointment. Watch sucks when I'm trying to show someone the watch and it doesn't work. It's even more frustrating when I'm taking 10x's the amount of time to look at a notification on the watch when I could have done it faster with the phone* made such threads end abruptly without offering any substantial help to the Redditor who initiated the thread.

Discussion on neutral posts was always driven by facts-based comments. Most of the neutral posts (∼40%) had relatively stable neutral discussion as illustrated in Figure 4a. This pattern of neutral discussion emerged specifically in response to posts that were explicitly seeking experience-based opinions on device use from fellow Redditors. Our investigation further revealed that such neutral comments motivated the person, who started the thread, to adopt a new device by providing him device alternatives that existed in the market.

For example, in response to the post: *I've been debating this with myself for weeks and I'm stuck between the Urbane 2 and the Huawei watch. Huawei has pretty solid battery life, good performance, and it looks nice. But every time I see a pic from an angle it looks really thick and makes me question whether I'd want it on my wrist all the time. I was pretty sure I was going to get the Huawei watch until I saw Urbane 2 demo a few days ago. So which of these would you guys get? Does anyone have any personal experience with them that should tip my decision one way or another?*, majority of people responded with fact-driven positive comments similar to: *Looks wise Huawei with black metal band is gorgeous. I'm not familiar enough with the urbane 2, but its uglier than the apple watch, and limited app wise. Personally got Huawei for very cheap, and planning to wait for the next Gen and get that as that is going to be brilliant*, or neutral comments such as *It doesn't look bad when on the wrist though. At least not in my opinion. I've only had it for a day so I haven't gotten a feel of the battery life yet. It was syncing music which killed the first 25% quickly. It's got the largest battery, and with the cellular not being used it should not have any more energy usage than* *anything else. But you may want to wait a few more days if you want a good review of the battery life.* These reviews helped the person to make the decisions in favor of Huawei Watch and was even satisfied with his choice based on his first few days of use.

The second most prevalent pattern, observed in ∼32% of neutral posts, was of deviated sentiment. Figure 4b illustrates this phenomenon with respect to one of the post - *Just curious what people think now that smartwatches have been around for a little while. Do you think you get a lot of value out of owning a smartwatch? Does it make your life easier? Or is it just an extra device to charge and an extra screen to distract you? Should I get one?* - that had highest number of comments. People responded with positive comments like *It is a life savior. You will have never to take out your phone outside your pocket in meetings*, negative comments like *the battery life is annoying so doesnt help at all*, or neutral comments such as *I just wish you could pair to multiple Bluetooth devices, so I could use my watch to control my Bluetooth headphones, and still answer calls.*

Analysis of several of such posts revealed that instead of being contentious, discussion with deviated sentiment in response to a neutral post validated the presence(absence) of the device-issue through negative(positive) comments. People also provided rationale for abandonment or continued use of the device through interleaved fact-driven neutral comments in the discussion.

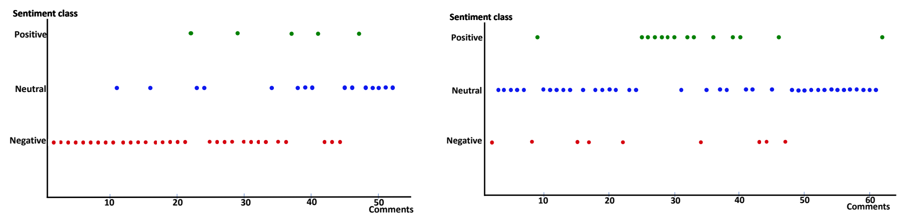


(a) Facts-driven Neutral Discussion (b) Facts-driven Deviated Sentiment

Fig. 4: Patterns of Discussion Sentiment on Neutral Post

Negative posts specifically represented the struggles of the users with their devices, which in turn led to change in usage pattern. Our further investigation of responses to negative posts revealed two patterns (cf. Figure 5a and 5b).

Majority of the people responded negatively by sharing a similar negative experience with the device in about 21% of negative posts. These comments reconfirmed problems with the devices, and towards the end of the discussion people started talking about either upgrading to a new device or stopping their use of the device altogether. For example, Redditor who posted: *Very frustrated with my watch at the moment. I feel with every update, the platform degrades more and more and I keep wondering if it's just me*, after reading several comments of following order: *I am totally with you. Seriously hoping that this gets fixed because my watch went from amazing to frustratingly useless in such a short time*, responded by saying: *I think it is better to save time and energy in bearing such issues and stop wearing the watch alltogether.*



(a) Majorly Negative Discussion (b) Fact-driven Neutral Discussion

Fig. 5: Patterns of Discussion Sentiment on Negative Posts

Redditors responded neutrally (sometimes even positively) using facts, workarounds, and other forms of informational support to around 18% of negative posts. These comments, are often longer (average length of 48 words), and they helped people know other people's opinion, troubleshoot the problems they had, and continue using their devices. For example in response to the post: *Strongly considering ditching Android wear. The watch can become incredibly slow even when connected to my phone. I'll say "ok Google show me my agenda" and the watch fails to respond. When it works, is wonderful. When it doesn't work, it is frustrating to no end*, other Redditors responded with: *I have the original LG G Watch and I have no issues like this at all. The watch is 99% working. I will say when something isn't working, there is always a reason (e.g., no data for voice recognition). So try checking your updates and connectivity.*

It is important to note, 61% of remaining negative posts did not seem to follow any specific sentiment pattern, particularly no common pattern of sentiment existed in more than 3% of those remaining posts.

5 Discussion and Conclusion

In this study we utilized sentiment analysis to understand how discussions on social media influence user-decisions of using or abandoning relatively newer devices such as wearables. The analysis was based on 6680 posts and their corresponding 50,867 comments posted between December 2015-2017 on the r/androidwear, a dedicated subreddit for discussions regarding Android Wear on Reddit. Our findings suggest that majority of the comments posted in response to positive and neutral posts are positive in sentiment. Furthermore, even though a lot of discussion with a negative sentiment materializes in response to negative posts, such posts also see fact-driven neutral discussions. The study also revealed connection between sentiment of discussion on the posts and its influence on the user's decision of using or abandoning devices. In general, discussions on Reddit prove to be of high assistance for the people to make such decisions, except for rare cases when discussions become contentious due to comments with negative sentiment. Future work may aim to investigate if similar patterns exist on other subreddits of the platform and their influence on user-decisions.

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