Investigating the Relationship between Data Literacy and Tracker Abandonment

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***Abstract*— We explore whether data literacy is related to tracker abandonment by comparing former and current users of wearable trackers on their data literacy skill. In an online survey, former and current users (*N* = 233) completed a data literacy scale and then interpreted a heart rate chart which described a person in a dangerous resting heart rate during sleep. We found that these two user groups had similar levels of data literacy on a self-reported scale but current users were better at recognizing the dangerous heart rate data and also better at effectively making use of their data than former users. We discuss the practical implications of our findings to support users' long-term tracker engagement.**

Keywords—wearable fitness tracker, tracker abandonment, data literacy, survey

I. INTRODUCTION

Users of wearable fitness trackers can enjoy numerous physical and psychological health benefits—they become fit [1], [2], they feel in control of their actions and report increased self-esteem and life satisfaction [3], and they become social as they compete with their social network on weekly goals [4], [5]. However, users can only enjoy such benefits if they continuously track their targeted behaviors. Unfortunately, numerous studies report many users abandon the tracker quickly, for diverse reasons: they forget to carry the tracker [6], they do not see the tracker as the true representation of themselves [7], and they already achieved their personal goals and no longer need to use the tracker [8].

Amongst these numerous abandonment reasons, we focus on users' data interpretation struggles and investigate the relationship between data literacy and tracker abandonment. Prior studies have shown user characteristics play a vital role in shaping user's experience with wearable fitness trackers. For instance, Li et al. [9] showed user variables such as age, exercise frequency, and education were strong predictors of long-term tracker use. Similarly, Faust et al. [10] found that user's personality was related to their short-term and long-term adherence to tracker. Given this, it is paramount to understand how the user characteristic that is most relevant to data interpretation (i.e., data literacy) is related to tracker abandonment. It may be that users with low data literacy level fail to make sense of the tracked data and subsequently feel negative emotions, leading to tracker abandonment. To achieve this goal, in this study, we compared former and current users of wearable trackers on their data literacy skill in two ways: one comparison involved their mean difference on a data literacy scale and another comparison involved their performance difference on a heart rate data interpretation task. If former users have lower level of data literacy than current users, we can infer data literacy as one possible contributing factor to tracker abandonment. We formally ask, "Do former and current users of wearable trackers have different levels of data literacy?"

Our contributions are two-folds: (1) we provide a direct comparison of how former and current users are different on their data literacy skill, and by doing so, (2) we provide practical recommendations on how the designers and developers of personal informatics can support current users when they interact with personal data, with the ultimate goal of facilitating their long-term tracker use. In what follows, we first review relevant work on data struggles, data literacy, and tracker abandonment. Next, we outline our study method and detail the survey design and measurements and participants. Then, we present key findings and conclude the paper by providing practical recommendations.

II. RELATED WORK

A. Data Struggles and Tracker Abandonment

Data from wearable fitness trackers provide multiple avenues for users to explore and learn about themselves and initiate behavioral changes. Fitbit's step counts, calories burned, and water intake data can be used to improve a user's life style. Garmin's heart rate variability (HRV) data allow a user to identify which particular days were stressful, so they can identify and eliminate stressors and improve their sleep quality. Despite this tremendous value of data to promote behavioral changes, users of wearable fitness trackers experience data-related struggles which in turn can lead to user disengagement and eventual abandonment. Shih et al. [6] found that participants cited data inaccuracy as one of the four main adoption challenges. They felt annoyed and frustrated by the tracker's inaccurate tracking of calories burned and its incapacity to track "non-traditional" physical activities such as weightlifting and treadmill walking. Coorevits and Coenen [11] also observed that their participants struggled with issues centering on the technicality of the tracker, including the tracker's limited capacity to integrate data collected from different tools and its inaccurate data tracking, as well as the limited metrics provided by the tracker.

Users also report their struggles over data interpretation. Specifically, they do not understand the meaning of complicated metrics (e.g., VO2 max) and they are confused by the visual representations of these metrics [12]. It is this latter type of data-related struggles (i.e., data interpretation) that is the focus of our study. Past studies did not differentiate between data interpretation struggles that are due to the limited capacity of the tracker versus those struggles that are due to the limited capacity of the user [12], [13], [14]. The former are struggles resulting from the tracker's technological limitations (e.g., a sensor that is not advanced to accurately track the user's sleep duration) and the latter are struggles resulting from the user's limitations (e.g., data illiteracy). Hence, we sought out to complicate the relationship between data interpretation struggles and tracker abandonment by introducing this particular user variable.

B. Data Literacy and Tracker Abandonment

In the context of personal informatics, data literacy can be defined as a user's capacity to understand and use data effectively to engage in self-reflection and initiate selfimprovement [15]. In general, people with high data literacy skill can analyze and infer relevant insights from data and they can plan and act upon necessary actions to initiate the process of behavioral changes. Not many studies have directly examined the relationship between data literacy and data interpretation struggles [16], [13], [14]. However, we can infer from some studies that users of low data literacy skill might experience greater difficulty than users of high data literacy skill. In these studies, a user's data literacy skill can be assumed based on their years of experience using the tracker (i.e., a user with longer years of experience supposedly has higher data literacy skill than a user with shorter years of experience). Rapp and Cena [16] showed that naïve users found data hard to understand which required a lot of cognitive effort to deduce any useful insights. As such, they wanted metrics that were intuitive, a summary of what metrics mean, and direct recommendations on what they should do. In contrast, other studies have shown that experienced users were highly motivated to explore with different data visualizations and test set of hypotheses between different metrics (e.g., "do drug and alcohol affect my snoring?") and they focused more on quantitative metrics and numerical feedback [13], [14]. Not only they were highly data literate, these experienced users created their own apps and tools to explore their data.

All these studies suggest that naïve users struggle more with data interpretation supposedly due to their low level of data literacy skill. In our study, we directly measured and compared former and current users' data literacy skill. This comparison allows researchers to see how these two user groups are different on key user behaviors, thoughts, and emotions and thus it allows researchers to infer why former users abandoned their trackers [17]. We can infer data literacy is related to tracker abandonment if former users show different levels of data literacy compared to current users. We formally state our research question as the following:

Research Question (RQ): Do former and current users of wearable trackers have different levels of data literacy?

III. Method

This study was part of the first author's larger project and we only present a subset of data that was directly relevant to address the study's research question.

A. Study Participants

We recruited former and current users of fitness trackers through social media, including Facebook and Twitter, word of mouth, as well as flyers displayed on a large Canadian University campus and at select municipal recreation facilities. For participants who completed the survey, we entered them into a draw to win one of two $50 gift cards. After 6 weeks of recruitment, we had unbalanced groups of current users (n = 160) and former users (n = 20). Thus, we recruited another batch of former users using Prolific, an online resource for participants for online surveys with a fair proportional compensation of $14 per hour. In the end, we had a total of 233 participants (female = 132; M_{age} = 37.01, SD_{age} = 12.40): 186 participants were active users and 47 participants were former users. Most participants resided in Canada (n = 79), USA (n = 59), and the UK (n = 23), with the rest residing in diverse countries (e.g., Australia, Germany, Pakistan, The Netherlands, Spain, Serbia, Singapore) (n = 25). Of the respondents, 84 indicated their highest level of education was 'postgraduate', 95 said 'undergraduate', while 38 said 'high school', with 16 saying 'other'.

Former users indicated they only used one device and used Fitbit series (n = 25), followed by Xiaomi Band (n = 9), Garmin (n = 2), Apple Watch (n = 2), and various other devices (n = 9); they used their reported trackers on average of 6.65 months before they abandoned it (median$_{months}$ = 4; range$_{months}$ = 35) and listed only one device when asked the name of the tracker they used. In contrast, current users reported that they used multiple trackers, with Garmin, FitBit, Apple Watch, Whoop, and Xiaomi Band being the most frequently mentioned devices. They reported that they have been using the tracker on average of 22.79 months usage (median$_{months}$ = 14; range$_{months}$ = 77).

B. Survey Design

Fig. 1. Heart rate data shown to study participants.

Participants completed a survey on Qualtrics. They first responded to general demographics questions related to themselves (e.g., age, gender) and the tracker (e.g., the names of trackers) and then responded to questions asking about their data literacy skill and general data habit (see more details under Survey Measurements). Then, participants saw a chart showing heart rate data that was directly adopted from a real incident from 2017. A man named Scott Killian who was an Apple Watch user woken up from his sleep by a 3rd party app that alerted him to an elevated heart rate [18]. He did not feel sick but went to the hospital where he was diagnosed with having a heart attack. His doctor told him that he would have died in his sleep without the alert.

As seen from Fig. 1, a resting heart rate of 121 BPM is dangerous while one is in sleep and this condition requires a doctor's immediate attention. For adults, a normal resting heart rate in sleep should be between 60 and 100 BMP and it can even be under 60 BMP if one is in deep sleep [19], [20]. We showed the man's heart rate data (Figure 1) to our participants and asked them the following question, "With the above data, what can you understand from the data? What might you do with this data?" Participants were informed that this data came from a man while he was sleeping.

C. Survey Measurements

1. Data Literacy Skill was measured using the following three items, "I can understand graphs well," "I can make a sense of physiological data," and "I can plan a course of action based on the results" on a 5-point Likert scale (1 = Disagree strongly to 5 = Agree strongly; Cronbach's $\alpha = .71$). Participants with higher means had better data literacy skill than those with lower means on this scale.

2. General Data Habit was assessed using one multiple choice question, "What have you done with the data generated by the fitness tracker?" Participants were provided with 6 response options and were free to choose more than one option: a) Changed behavior, b) Charted progress, c) Consulted with a trainer, d) Didn't do anything, e) Didn't know what to do, and f) Other (please specify).

IV. Results

We now present results demonstrating how two user groups are different from each other on data literacy skill, thereby responding to our RQ.

A. Data Literacy Skill Scale

Given the non-normal distribution of data literacy variable for former and current users, we used Mann-Whitney U test to compare the difference between the two user groups on this variable. We found that two groups were not significantly different from each other ($U = 3859.500$, $p = .27$). That is, former users ($M = 4.13$, $SD = .65$) and current users ($M = 4.23$, $SD = .68$) rated themselves similarly on their data literacy skill. Both groups perceived themselves favorably on their data literacy skill, as indicated by their means nearing 5.

B. General Data Habit Scale

We computed frequency tables for former and current users to understand how each user group generally used their collected data (see Table I and Table II; participants were allowed to choose more than one option and percentages reflect the number of participants who selected each behavior as a portion of all participants in that subgroup).

TABLE I. GENERAL DATA HABIT FOR FORMER USERS

Participant Behavior	**Total, *n* = 47 (%)**
Planned a course of action	6 (12.76%)
Consulted with a trainer	3 (6.38%)
Charted progress	23 (48.93%)
Didn't do anything	21 (44.68%)
Didn't know what to do	9 (19.14%)

TABLE II. GENERAL DATA HABIT FOR CURRENT USERS

Participant Behavior	**Total, *n* = 186 (%)**
Planned a course of action	72 (38.70%)
Consulted with a trainer	28 (15.05%)
Charted progress	148 (79.56%)
Didn't do anything	22 (11.82%)
Didn't know what to do	12 (6.45%)

As seen from Table I, almost half of former users used the data to chart progress (48.93%) just as almost half of them did not do anything with the data (44.68%). Also, only a few indicated they planned a course of action based on their data (12.76%). As seen from Table II, the majority of current users used the data to chart progress (79.56%), some of them used the data to plan a course of action (38.70%), and only a few of them did not do anything with the data (11.82%). Moreover, the percentage of former users who indicated they did not know what to do with their data (19.14%) was almost the double of that of current users (6.45%).

C. Heart Rate Data Task Performance

We coded participants' responses to an open-ended question asking what they would do with heart rate data into 5 categories. These categories are dispalyed in Table III. These five categories are Medical situation, Basic reading, Causal reading, Clueless reading, and No response. Each category's definition is provided in the table.

TABLE III. DATA USAGE BEHAVIORS FOR CURRENT USERS

Category	**Definition**
1. Medical reading	Participants mentioned the person should see a doctor / specialist.
2. Basic reading	Participants mentioned basic data reported on the graph without engaging in deeper interpretation.
3. Causal reading	Participants recognized the data were unusual and tried to figure out events to explain the data.
4. Clueless reading	Participants mentioned they did not know what to do with the data or they provided incorrect interpretation.
5. No response	Participants did not provide any answer.

To understand if there was a significant relationship between data literacy skill and heart rate data task performance, we conducted a 2 (user status: former vs. current) x 5 (heart rate data task performance: Medical reading vs. Basic reading vs. Causal reading vs. Clueless reading vs. No response) 2-way Chi-square test of independence. The Chi-square test was significant, $\chi^2(4, N = 233) = 2.35$, $p < .05$. There were similar numbers of former and current users who showed basic reading, causal reading, clueless reading, and no response. However, for medical situation reading, fewer former users than we would expect provided responses that belonged to this category (the standardized residual of -2.1).

In line with above results, when looking at former users (Table IV), it is quite surprising that only one of them recognized the man in the story needed to see a doctor and specialist (2.1%). This contrasts sharply with 15.6% of current users who recognized the man's condition as an emergency and indicated the man needed to see a doctor. Interestingly, a few of current users in this Medical reading category mentioned the man might be suffering from apnea and tachycardia, which demonstrate their knowledge on sleep disorder and heart condition that affect one's heart rate. For both user groups, Basic and Causal readings were most frequently coded responses. While participants in the Basic reading category simply repeated the heart rate data that they saw on a chart or mentioned there was a high variability in the data, those in the Causal reading category recognized the person's heart rate was unusually high for someone who was sleeping. Thus, these participants attempted to identify some triggering events that could have caused such a high elevated heart rate, demonstrating they had better knowledge of what an average resting heart rate looks like than those in the Basic reading category but at the same time they failed to recognized the urgency of the man's condition. Some of the frequently mentioned events were alcohol, exercise, intimacy, and nightmare.

Lastly, there were similar percentages of former (12.8%) and current users (13.4%) who provided clueless interpretation of the data: some participants were confused by the data and other participants incorrectly suggested the man should plan for a better workout plan and the person had a healthy resting heart rate.

TABLE IV. HEART RATE DATA TASK RESPONSES OF FORMER USERS

Category	Total, *n* = 47 (%)	Example
Medical reading	1 (2.1%)	(S8) He has a high resting pulse and should probably consult a physician. It could be normal for him, but seems awfully high.
Basic reading	17 (36.2%)	(S15) That man had 49 min and 121 max heart rate; (S37) Range of heart rate during different time intervals for each day; (S89) Heart rate was highest on the Friday and lowest on Wednesday; (S111) I can understand how high and how low his BPM got. But I sincerely don't know if they are good or bad.
Causal reading	21 (44.7%)	(S21) On Friday he had an elevated heart rate. Maybe... I'd wonder what happened that day that was different to other days; (S9) That most of the week he slept well, relaxing especially on Weds but that on Friday and Saturday something was disturbing his sleep e.g., alcohol, staying up late, excitement; (S8) His heart rate was high overnight on Friday. I might ask what he was doing before he went to bed on Friday that caused his heart rate to go so high, or what happened overnight, maybe he had a bad dream.
Clueless reading	6 (12.8%)	(S33) You can see that his heart rate is in a healthy range; (S25) I might make better workout plan.
No response	2 (4.3%)	-

V. DISCUSSION

In response to our research question "Do former and current users have different levels of data literacy?" our results indicate the answer is they are somewhat different. Focusing on their self-rating of data literacy skill on a 5-point Likert scale, we found that two user groups rated themselves similarly on the scale and they felt confident in their skill to interpret and make use of their data. In fact, both groups had means that were nearing 5. However, when we examined how two user groups made use of their data in general, current users were better at effectively making use of their data, for instance, by planning courses of actions and consulting a trainer. In contrast, we saw that almost half of former users indicated they did not do anything with their data. This indicates that former users might understand what data mean but they do not understand how they should adjust their subsequent behaviors based on the data. This line of finding suggests that former users may place greater agency in the tracker rather than themselves [21] and could have benefitted from receiving tailored recommendations from the tracker when they were still using the tracker. There was also a difference between two user groups on their heart rate data task performance. There was a higher percentage of current users (vs. former users) who indicated the man in the story should visit a doctor. This implies that these users had a firm understanding of what an average resting heart rate looks like for a person who is sleeping. Without this understanding of average body metrics, these users could not have referred the person to see a specialist. This firm understanding was somewhat present in those who were placed in Causal reading category. These users also recognized abnormality in the man's heart rate but they may not have an in-depth understanding of what an average resting heart rate should look like in sleep or they may have lacked confidence to classify the data as an emergency. Lastly, the percentages of two user groups who provided Basic, Causal, and Clueless reading were similar. These data indicate that former and current users might differ only in certain aspects of data literacy, mainly on their capacity to initiate and plan actions and their understanding of what body metrics should look like, specifically a resting heart rate, for an average person.

TABLE V. HEART RATE DATA TASK RESPONSES OF CURRENT USERS

Category	Total, *n* = 186 (%)	Example
Medical reading	29 (15.6%)	(S17) The man's average heart rate is around 90, he has a high heart rate for sleeping and needs to see a doctor about that; (S162) Figure out why my heart is exploding at rest, check with my doctor what could cause this; (S61) Well, if he has had a night with a resting heart rate of 121 then either his wearable has the wrong data or he should schedule a doctor's appointment.
Basic reading	38 (20.4%)	(S15) Heart rate range during sleep. Not sure what to do with the data though; (S123) I see what my heart rate zone is while sleeping. I don't know how I would use the data.
Causal reading	78 (41.9%)	(S21) a few outliers are likely, but the concern for the high heart rate would warrant further questions, did the person have a nightmare, did they get up in the night, etc?; (S130) During peak hours while sleeping, if there's a lot of movement heart rate would increase. With this data you could try and pinpoint what happened during the day to cause a higher heart rate at night (i.e., a more stressful day than normal); (S183) Assuming a good sleep is a low variance heart rate at the true resting heart rate, I would make notes about what I did (sleep, eat, exercise) only during the nights of bad sleep and avoid those things in the future.
Clueless reading	25 (13.4%)	(S33) This chart seems confusing to me...I have no idea; (S231) He has a healthy resting heart rate (S213) The Friday night data is wrong.
No response	16 (8.6%)	-

Although current users were better at recognizing the dangerous heart rate data, it was disappointing to see that less than quarter of them showed such capacity. While not everyone has background knowledge in heart rate, it is a core feature of fitness trackers. This suggests that perhaps current users are not as knowledgeable about heart rate as the designers of personal informatics might assume. It also suggests a deeper issue, which is that it is easy to overestimate our abilities. Known as the Illusion of Explanatory Depth, most people feel they understand the world with far greater detail than they actually do [22]. Current users may believe they are better at interpreting data than they actually are and the concern is that they may misinterpret data. If and when users are having a serious physical episode and their wearable indicates there is something wrong, will these users be able to interpret the data and react accordingly? Similarly, this self-inflated view applies to former users who had similarly high mean on a data literacy skill scale.

Altogether, based on these results, we can conclude that there is some relationship between data literacy and tracker abandonment: former users' incapacity to effectively make use of their data after interpretation, as well as their basic understanding of the data could have contributed to their discontinuation of using the tracker.

A. *Design Recommendations for Wearables*

We can make several recommendations to the designers and developers of personal informatics. First, they should **provide options of what users can do with data**. Our results showed that a half of former users did not know what to do with the collected data and this implies this particular user group needs a personalized guidance on what they can do with the data. For instance, the tracker system can show them how users of high data literacy skill plan for their subsequent actions based on their data. Currently, Fitbit and Apple Watch manuals merely explain the logistics of the tracker (e.g., how to set a daily goal, how to change a battery) without explaining what users can do based on their understanding of the metrics. Such guidance can facilitate many users' self-reflection. Second, they can **consider introducing a gamified tutorial to improve users' data literacy skill**. Prior research has incorporated gamification as a way to engage users with personal informatics. For instance, Zhao et al. [23] incorporated avatars to represent the users in a running game. Similarly, Gawley et al. [24] created BitRun that connects to Fitbit devices and users play as a ship/object, avoid obstacles, and collect golden rings. Gamification could also be a fun way to improve users' data literacy skill. Perhaps a company could embed an assessment to establish when a user has mastered an understanding of the data. New features would be unlocked once this assessment had been passed, ensuring users are prepared for the new data. Finally, **a short, mandatory tutorial could then expose them to the data visualization**, with pop-ups offering explanations. The designers and developers could introduce several levels like Beginner, Intermediate, and Advanced user. This tutorial would be especially important for current users who show Basic and Clueless reading of data who might place their own and others' health in danger for incorrect reading of data.

B. *Limitations and Future Work*

Despite the contributions we make, our study is not without limitations. First, our sample size of former users made up only 20% of total respondents as it was more difficult to recruit former users than current users. We recommend future researchers to create more balanced user groups to get as diverse response patterns as possible. Second, we based much of our analysis on one graph featuring heart rate data and not everyone is deeply familiar with heart rate data so a more thorough assessment featuring multiple visualizations with multiple domains of content would reveal more conclusively how literate former and current users truly are. For instance, future studies can adopt stimulus sampling approach where participants are shown heart rate data, calories burned, counted steps, and more. Third, while we conducted a user study dedicated to examine the relationship between data literacy and tracker abandonment, we made limited technical contributions to wearable system community. Future work can consult our design suggestions to create personal informatics that consider the users of all data literacy levels. Lastly, given the online nature of the study, some participants might not have been fully engaged with the study. This lack of engagement was clearly present in a few participants who did not provide their response to an open-ended question for the heart rate data interpretation task (18 in total). Future researchers can consider ways to increase participants' engagement with online studies, such as higher monetary compensation.

In sum, this study generated many new exciting questions to be explored including:

- How should data be presented to users of different data literacy levels?
- Given the possibility that users think they are more data literate than they actually are, how do we proceed? How can designers and developers help users accept their weakness and improve?
- How do we ensure users maintain their data literacy levels once improved?
- Where and when should data literacy education be introduced without causing additional frustrations on users?

VI. Conclusion

It is without a doubt that wearable fitness trackers can bring a host of psychological and physical health benefits to users. To support users' long-term tracker engagement, we must understand adoption barriers associated with tracker and user characteristics. We contribute to an understanding of how user characteristic—data literacy—is related to tracker abandonment and consequently we provide practical implications for how Human Computer Interaction and Digital Media researchers, designers, and developers can create newer devices with better interfaces to creating more meaningful experiences.

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