Activity Trackers: Comparing Athlete Runners versus Health Runners through a Dedicated Technology Acceptance Model

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Abstract: The conducted study seeks to learn if, why and how two different groups of Activity Trackers users, Athletes and Health Runners, are utilizing these devices for their self-quantification. The study is based on the content analysis of 20 semi-structured interviews, 10 of which were with Athletes. To achieve its goals, the authors use a model based on the Technology Acceptance Model (TAM), a widely adopted technology acceptance theory. Amongst our findings, the construct Perceived Ease of Use showed that Athletes find it hard to program the settings for their training and Health Runners expressed that there is too much information involved. This paper contributes by showing that an all-purpose interface is not suitable and offers new knowledge for methodological discussions as it is, to the best of our knowledge, the first qualitative study to employ a TAM like model in order to qualitatively interpret the use of Activity Trackers.

1 INTRODUCTION

Activity Trackers have become mainstream gadgets for consumers in recent years. However, many people still do not achieve the recommended levels of activity for their age groups. For the activity of walking, it has been widely recommended that healthy adults should reach the goal of ten thousand steps per day in order to maintain or improve their health. The development and the commercialization of Activity Trackers have showed a positive effect in helping many users to reach this goal (Laranjo, 2021). Research has shown that users of Activity Trackers, when steadily checking their step count walk more (Carels, 2005), lose more body weight (Akers 2012), and are more in control of their actions (Burke, 2011). Nevertheless, a study on the adoption of a specific Activity Tracker found that half of the users stop using the device after two weeks (Shih, 2015).

Several models to describe and capture the use of Activity Trackers have been created since Li et al.'s seminal work of a model with five iterative stages: preparation, collection, integration, reflection, and action (Li, 2010). These authors later refined their model. Epstein et al. expanded that model by including the lapses and interruptions of tracking, and emphasizing the intricacy of integration, collection and reflection (Epstein, 2015). This model was also expanded to count for eudemonia and changing goals (Niess, 2018). However, these models are not quantitative, not dedicated exclusively to Activity Trackers, do not have a Health oriented component, and fall short in incorporating Data Control and Privacy issues. To address these shortages, a quantitative model was created, that has eleven factors that influence the acceptance and usage of Activity Trackers (Sol, 2016). Nevertheless, constructs as Subjective Norm or Attitude failed to be part of this model.

According to the International Data Corporation, worldwide shipments of wearables grew 9.9% during the third quarter of 2021 reaching 138.4 million units (IDC, 2021). Within these millions of users, one may be able to predict and identify that diversity can be found in types of use of trackers. Researchers have already noticed gender differences (Shih, 2015), differences between health runners and pleasure runners (Temir, 2016), others look to naïve users (Rapp, 2016) and yet others looked at extreme users (Sol, 2021). In our research we want to find and

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compare aspects that impact acceptance and use of Activity Trackers by Athletes whose focus are to better performance in competitions and Health or Recreational Runners whose focus is to be healthy.

The used model takes into consideration Data Control, unlike previous technology acceptance models in the field (Kim, 2012). This is a construct of importance, when only 31% of workers disagree to let their employer make use of wearable devices to monitor their performance at work, with 44% in favor (PWC 2021). Specially, when research shows that third-party vendors are collecting detailed data from users (Ho 2014).

We applied a quantitative model used to qualitatively elucidate why people are more or less likely to adopt and use all kinds of Activity Trackers. We propose recommendations about how that model can be supported to enhance analyses of Activity Trackers use.

2 LITERATURE REVIEW

In this section we review literature related to the use of Activity Trackers. We also investigate Technology Acceptance research to understand its associations, relevance and definitions. The acceptance and use of Activity Trackers is due to numerous reasons and motives, some of which appear to conflict. Individual users may start tracking their activity because they have a specific goal in mind (Epstein, 2014). These goals can be a healthier life or a beautiful physical appearance, or both, the later being an excuse to reach the former (Kay, 2013). Nevertheless, there are users who begin to use Activity Trackers having no objective in mind and use the device to help them set a specific goal. This goal becomes more defined as the usage moves from the discovery phase to the maintenance phase of pondering (Li, 2010). Others begin tracking simply moved by interest and curiosity in quantitative data (Lindqvist, 2011). Many users receive the device as a gift, but when having the chance to choose specific tracking devices they base their choices on online reviews, marketing campaigns, specific features, portability, or follow an advice given by friends or family members (Kaye, 2011). Goal setting is only one idea to support and persuade health-related behavior change, others include feedback, reminder notifications, and social comparison (Shih, 2015). To become aware of one's performance and to regulate performance concerning the defined objectives, users also tend to check the data as soon as it is gathered (Fritz, 2014). Users tend to change their habits, goals, and devices and the related applications or dashboards are unprepared to deal with this. When tracking, users tend to change devices frequently or use several devices at the same time, which leads to problems in assessing and consolidating data (Rooksby, 2014).

2.1 Technology Acceptance Model

The conceptual framework applied in this work is based on the Technology Acceptance Model (TAM), a widely adopted technology acceptance theory that can explain why different people have distinct levels of adoption and use of a specific information technology. TAM has its roots in Martin Fishbein and Icek Ajzen's Theory of Reasoned Action, a theory that comes from social psychology and illustrates the human behavior based on his intentions (Fishbein, 1997). TAM introduces two constructs: Perceived Ease of Use (PEoU) and Perceived Usefulness (PU), which determine Intention to Use through Attitude (Davis, 1989). Perceived Usefulness is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance", while Perceived Ease of Use is "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989). Further constructs used in this study are detailed as follows: Image: "the degree to which use of an innovation is perceived to enhance one's image or status in one's social system" (Moore, 1991). Self-Efficacy: "the judgment of one's ability to use a technology (e.g., computer) to accomplish a particular job or task" (Compeau 1995). Habit: "the extent to which people tend to perform behaviors automatically because of learning" (Limayem, 2007). Hedonic Motivation: "the fun or pleasure derived from using a technology, and it has been shown to play a key role in determining technology acceptance and use" (Brown, 2005). Perceived Privacy Invasion: "the degree to which a person feels that the monitoring is invasive of their privacy" (Dryer 1999). Perceived Data Control: "the degree to which a person feels they have control over the use of, and access to, the data collected" (Lindqvist, 2011). Perceived Severity of Disease: "the beliefs a person holds concerning the effects a given disease or condition would have on one's state of affairs". Health Threat: "abstract assessing the susceptibility and the severity, of disease- specificity" (Hochbaum, 1952). Perceived Susceptibility of Disease: "the perception of the likelihood of experiencing a condition that would adversely affect one's health". Health Consciousness: "the degree to which health concerns are integrated into a person's daily activities" (Jayanti, 1998).

3 METHODOLOGY

The study consisted of semi-structured interviews of participants that were informed and gave their free consent, recruited via convenience sample. In total, the participant group consisted of twenty activity tracker users. Of the 20 users interviewed for this study, 10 were female and 10 were male. To help ensure that there would be a variety of experiences amongst participants, interviewees were recruited from amateur running competitors and from the general public, being 10 self-identified competition-running athletes (4 females) and 10 self-identified health runners (6 females) how were not so easy to reach in our convenience sample. The athletes ranged in age from 22 to 45 (average 35.5, standard deviation 7.5, median 36), and had the devices from 1 to 150 months (Av=51.1, SD=52.9, M=30). The Health Runners ranged in age from 26 to 48 (Av=34, SD=8, M=31.5), and had the devices from 12 to 50 months (Av=24.5, SD=13.7, M=21). The participants were from Western Europe. The first author conducted 19 interviews face to face and 1 through Skype video call. From the 20 interviews 18 were made in the participants' native language. The interviews took off from 22 trigger questions. However, the interview protocol was used in a flexible manner according to the flow of the interview. The average time of the interviews was 18 minutes (12-34). Respondents were first asked for the activity trackers they knew and then asked for what purposes they used them. To make the interview more focused, next we asked participants to elaborate on their use of the device that they defined as the most frequently used for quantifying physical activity. In addition to finding out about general trends in activity trackers use and acceptance, we were interested in learning if activity trackers have changed user's attitudes. As part of the interview process, we asked the participants, for example, whether society recognizes activity trackers as part of the promotion of one's image. All interviews were digitally recorded using Word Audio Notes and then manually transcribed. The confidentiality and anonymity of all participants were safeguarded by making the names of study interview participants only known to the interviewer, using aliases for the interviewees in the transcriptions.

To analyze the transcripts, we employed the activity trackers acceptance model (Sol 2016) that conducted an extensive review and analysis of noticeable technology acceptance. Their resulting model confirms PU and PEoU as strong predictors of Behavior Intention to use. Although these kinds of models are usually applied to analyze and explain the quantitative data collected through a survey instrument, the current study has taken a different approach. To the best of our knowledge, this is the first qualitative study that deploys this quantitative model to study Activity Trackers use, which is an evolving line of research.

The results of our study are presented in the following sections. Firstly, we apply the model to analyze the interview data and compare with previous work. Next, we discuss its applicability to explain Activity Trackers use and make recommendations supported by the model. The concluding section summarizes the results.

4 EMPLOYING THE MODEL TO UNDERSTAND RUNNERS USE OF ACTIVITY TRACKERS

Here we apply an activity tracker Technology Acceptance Model to the interview data by examining each of the eleven constructs shown in Figure 1. In the following sections, we describe the participants as, for example: P9H12M18, meaning: Participant number (P1 to P10), runners' group (H = Health, A = Athlete), number of months using activity trackers, gender (F = Female, M = Male) and age.

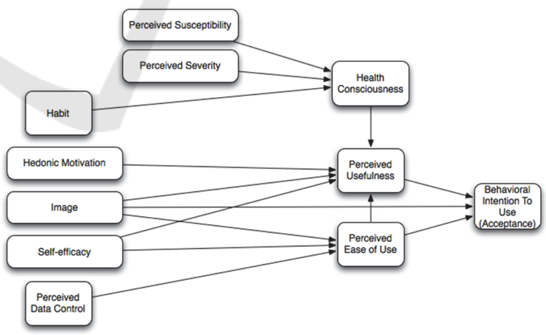

Figure 1: Activity Trackers Acceptance Model (Sol 2016).

4.1 Perceived Usefulness

When characterizing the Perceived Usefulness construct, we used statements such as: How using Activity Trackers was beneficial for you or not. All participants mentioned that being aware of the information collected by these kinds of devices was particularly useful and stated that they do not use all the information. Nevertheless, Athletes were focused on the immediacy for trainings, as said by P1A24F34: “I think it allows you to act on the spot and I think that's the relevance, knowing where you are and being able to correct it on the spot, or else correct it in the coming weeks.” We also noticed that the Athletes were inclined towards a perspective of near future actions when using the devices, as emphasized by the following quote by P1A24F34: “What changed the most was having more information and with it being able to plan my activity.” This confirms that the devices should facilitate more these plans and inclinations. Athletes also reported a focused experience, as expressed by P5A150M44: “It gives the necessary data to experience what I want. That's why I don't take full advantage of the program.” This points to the fact that some users are operating the technology in a limited way. Similarly, young Health Runners like P5H12M30 corroborate: “I don't think there's the need to buy dedicated device for activity tracking.” A few Health Runners were more concerned with using the devices for an assortment of situations, like P10H18F31 put it: “It doesn't have the possibility for me to record a group class. It’s got a set of activities, and it doesn't have what I need.” Overall, it was confirmed by this construct that these devices are useful, however it was also realized that there are specifics that are distinctive between the two groups. While both groups reported issues that are important, these issues are quite different and need specific design solutions.

4.2 Perceived Ease of Use

When characterizing the Perceived Ease of Use construct, we used questions such as: Which were the most difficult aspects when using Activity Trackers? All participants mentioned that the devices were easy to use. Nevertheless, Athletes find it hard to program the settings for their trainings, like P8A1F22 noted: “What is more complicated to do is, for example, the programing of the training scheme.” Which was corroborated by P9A60M41: “Not in the use part, but in the configuration.” Whereas Health Runners were more concerned, again, with using the devices for specific sports, like P1H36F28 put it: “If I want to ride a bike, I can't, I have to put the watch on my ankle otherwise it won't register my steps.” There were concerns about the understanding, meaning and clarity of the information provided, like P5H12M30 stated: “You don't know in practical terms what that means.” It is important to notice that users are not specialists in analyzing data, so the data displayed would need to be translated for the user. Overall, it was confirmed that these devices are easy to use, however some issues were reported, and these are different between the two groups.

4.3 Perceived Data Control

When characterizing the Perceived Data Control construct, we used statements such as: What do you think about your control of the information. In both groups there were users who did not care and there were users who were worried. The Athletes who cared were more concerned about the security perspective than with the data itself, as described by P1A24F34: “Hack the data, you can see what time the person is not at home. To rob houses is good.” This point was corroborated by P9A60M41: “Any person that follows me in the social app of the tool, easily finds out where I live, since my trainings start always in the same place. That's what worries me the most.” Most of the Health Runners stated that they knew that they were not in control of the data and that they did not introduce much personal information. Nevertheless, they did not care that this kind of data was available and exposed, except for participant P2H12M32 who said: “I know that the data is not locally stored and have access to the raw files. Especially in the case of Google fit, I knew that the data was in Google servers, and since they have everything, my email, my calendar, and from my physical performance, I felt a bit scared and stopped using Google Fit and GPS tracking.” To summarize, users are aware that their personal information can be seen, as found before, nevertheless overall most users in both groups are not overly concerned or worried about data control. The differences between the two groups did call our attention but were minor.

4.4 Self-efficacy

When characterizing the Self-efficacy construct, we used statements such as: How do you feel when managing the information. All users considered themselves quite efficient users of the devices, as stated by P7H15M33: “I'm not using it one hundred percent in all features. But the ones I use, I use it very well.” However, P3H24F40 noted: “I think there is too much information to manage.” Again, it is highlighted that information must be relevant for the users or it will be considered superfluous. To summarize, the major difference between the two groups is that Health Runners think there is too much information.

4.5 Image

When characterizing the Image construct, we used statements such as: What do you think about other people who use Activity Trackers. Both groups in our sample gave ordinary importance to Image. However, the idea of the device being an iconic trend was mentioned by P1A24F34: “Theoretically this turns out to be a cult.” The importance of the social aspect is underlined here. On top of this, for Athletes, one having a device was associated with a more competitive person, as expressed by P4A24F38: “They are people that have other goals, they are committed to progress in their training to reach one goal after another… improve their performances in the competitions they enter.” Similarly, Health Runners mirrored others, as expressed by P1H36F28: “They are smart like me and want to improve their health.” Nevertheless, P4H24F26 said: “I think the devices are ugly, I don't like to wear a black thing.” This denotes the importance of visual design and the consideration of gender differences or preferences. Overall, both groups are of the opinion that other people who use the devices have the same objectives as themselves.

4.6 Hedonic Motivation

When characterizing the Hedonic Motivation construct, we used statements such as: How do you feel using Activity Trackers. Participants felt good when using the devices. However, Athletes felt good when using but also before using the devices, as described by P5A150M44: “The more goals we reach, which are the data that the device also gives, the more desire to go training.” Whereas Health Runners felt well when running, such as P7H15M33 put it: “I find it more motivating during exercise. Not necessarily before doing the exercise.” This was corroborated by P3H24F48: “Not that it's going to make me get up one day and run-on purpose just because of the device.” This can indicate that Athletes are pre-motived to run while Health Runners need support to encourage behavior change. To summarize, there is a key difference between the groups.

4.7 Habit

When characterizing the Habit construct, we used statements such as: Using an Activity Tracker is or is not a habit for you. For Athletes using the device, this can be more than a habit they can be craving for it. Nevertheless, Health Runners who do not make use of the device as a habit blamed the recharging of the device batteries for their inconsistent use of the device, as said by P1H36F28: “What annoys me sometimes is putting the watch on charge, I don't want to get up without it counting those steps.” This point was corroborated by P4H24F26: “For me it's boring every three days to remember that the battery is going to fail.” This shows that the device needs to be able to encourage and give assistance in the implementation of habits. To summarize, the differences between the two groups are noticeable but were minor.

4.8 Perceived Susceptibility to Chronic Diseases/ Perceived Severity of Chronic Diseases/ Perceived Threat - Health Consciousness

In our interviews the three health related constructs were indistinctive. When characterizing the Perceived Susceptibility to Chronic Diseases construct, we used statements such as: What kind of injury have you had. When characterizing the Perceived Severity of Chronic Diseases construct, we used statements such as: How do you react to the possibility of having an injury. When characterizing the Perceived Threat-Health Consciousness construct we used statements such as: What kind of attitudes do you take concerning your health. All participants mentioned paying special attention to their diet, alcohol intake, and sleep. In both groups there were users with conflicting practices. Health Runners are more inclined not to think that they could have a health problem, most Athletes, on the other hand have this in mind all the time and consider how this can impact their occupation. As P3A36M45 noted: “I go to competitions carefully to avoid serious injuries. With care, with calm, because I see many competitors especially downhill, and I get scared to see them going downhill so fast. I'm often overpassed, because that scares me.” Similar attitude was viewed in a Health Runners, as described by P1H36F28: “In the gym there are exercises that I know I cannot do, I only do if I have someone next to me.” To summarize, the differences between the two groups grasped our attention but were minor.

4.9 Behavioral Intention to Use (Acceptance)

When characterizing the “Behavioral Intention to Use (Acceptance)” construct we used statements such as: In the long run do you think you will still use the device or not. All participants stated that they will continue to use the device, except P9H12M46: “If I can achieve a weight loss goal without needing to use, I will not use."

5 DISCUSSION

Our findings suggest that the model constructs revealed to be important in studying acceptance and use of Activity Trackers. The primary performance booster that participants saw in Activity Trackers was the ability to show data that one had never been able to see before. Other common useful practices of using Activity Trackers included motivational support and comparison with others and oneself.

We found that for this small sample population, Perceived Usefulness, Perceived Ease of Use, Image, Hedonic Motivation, and Habit were strongly associated with the acceptance and use of Activity Trackers and show significant differences between groups. Perceived Usefulness and Perceived Ease of Use constructs showed that Athletes experienced difficulties and problems with configuring the settings for their trainings, corroborating the design idea of facilitating micro plans (Gouveia, 2018) and that users are using the technology in a limited way (Didziokaite, 2017). It also showed differences among ages especially in young runners (Janssen 2020). Additionally, the study showed that Health Runners felt that they were faced with too much information or complex information and wanted the possibility to track different exercises. A similar issue with the volume of information has been described in previous work stating that users are not data scientists (Rooksby, 2014) and that the information is not in the user's language (Lazar, 2015). Perceived Data Control showed conflicting differences within the two groups, however generally speaking users are conscious that their personal information can be highly sensitive, as previously established (Lupton, 2017). However, most of our interviewees did not have many concerns in sharing their data. Self-efficacy construct showed that both groups are efficient users. Nevertheless, we have seen here the need of personal relevance of the data (Kim, 2016). Image construct showed that both groups in our sample gave ordinary importance to image and it is underlined here the long-viewed importance of the social aspect of these devices (Consolvo, 2006) (Clawson, 2015) (Patel, 2015), also the importance of aesthetics and form (Harrisson, 2015) and the significance of gender differences (Shih, 2015). Hedonic Motivation construct showed that both groups felt good when using the devices. Athletes find motivation before and during running, in accordance with previous findings (Rapp, 2020). The Health Runners denoted a previously identified need for behavior change strategies (Klasnja, 2011) and the two groups showed the need for egocentric design (Elsden, 2015). Habit construct showed that Athletes could be addicted to use while Health Runners use the battery recharge as an excuse. Thus, we have noticed the importance of the previously identified idea of implementing routines (Lazar 2015) and adherence (Tang, 2018). As for Perceived Susceptibility to Chronic Diseases, Perceived Severity of Chronic Diseases, Perceived Threat - Health Consciousness, and Acceptance showed no major differences between groups or conflicting differences within the groups.

By the end of conducting this research it was clear that an all-purpose interface is not suitable. The novelty of the findings suggests specific design considerations: designers should look at the ease of use and usability of the overall settings, the need for easy-to-use training plans and training settings. In order to accomplish this, we propose that the software has different modes that would be selected by different types of users: pleasure runners, health runners, athletes, etc. Other possibility would be to associate the modes to the three classes of tracker motivations: behavior change, instrumentation, and curiosity. One limitation of this work is that it does not make a clear split between intention to use activity trackers and the actual use. This is because most of the interviewees were users of at least one activity tracker. Finally, we anticipate that the establishment of specific models for each group may be a necessity to better explain the acceptance and use of Activity Trackers by these users.

6 CONCLUSIONS

There is an ample amount of studies looking into users of activity trackers. However, only a small part has compared different groups of users. This study was based on 20 semi-structured interviews with Health Runners and Athlete Runners. They offered us a diverse variety of information on how users are integrating Activity Trackers into their lives, their paybacks, difficulties, and future tendencies. This study shows that the Activity Trackers Acceptance Model can be employed in this context and makes suggestions for its future application. Participants that use Activity Trackers in their daily lives found them useful for emotional support, social parallelism and competition, and, surprisingly interesting for the data the device provides.

Our study revealed that there were significant differences regarding difficulties of the users experience, Athletes had issues with configuring the settings for their trainings whereas Health Runners found too much or complex information and wanted the possibility to track different exercises. There were also significant differences regarding motivation, the devices motivated Athletes before and during running while Health Runners were motivated by the devices only when running. Both groups thought that the people who use these devices had the same goals as themselves. Health Runners used the excuse of having to regularly recharge the device battery as the reason for not making the use of the device a daily habit in their lives. Even with a small number of users, and by utilizing the model constructs we have been able to gain new insight into the differences of how these two groups use and accept Activity Trackers in this initial investigation. This study brings to light the value of looking more closely at specific types of users and how their documented experiences and use of these devices can be analyzed and applied to the understanding of the use of Activity Trackers. Many more such studies need to be carried out in order to gain and maximize data pertaining to the abundant diversity that exists with regards to user experiences, which can then also impact future designs of Activity Trackers.

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