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Constantiou, Ioanna; Mukkamala, Alivelu Manga ; Sjöklint, Mimmi; Trier, Matthias

Document Version
Accepted author manuscript

Published in:
European Journal of Information Systems

DOI:
10.1080/0960085X.2022.2081096

Publication date:
2023

License
Unspecified

Citation for published version (APA):
Constantiou, I., Mukkamala, A. M., Sjöklint, M., & Trier, M. (2023). Engaging With Self-tracking Applications: How do Users Respond to Their Performance Data? *European Journal of Information Systems*, *32*(6), 941-961. https://doi.org/10.1080/0960085X.2022.2081096

Engaging with self-tracking applications: How do users respond to their performance data?

Ioanna Constantiou[a], Alivelu Mukkamala[a], Mimmi Sjöklint[a] and Matthias Trier[b]

[a]Copenhagen Business School, Frederiksberg Denmark; [b]Universität Paderborn, Paderborn, Germany

To cite this article: Ioanna Constantiou, Alivelu Mukkamala, Mimmi Sjöklint & Matthias Trier (2022): Engaging with self-tracking applications: how do users respond to their performance data?, European Journal of Information Systems, DOI: 10.1080/0960085X.2022.2081096 **To link to this article:** https://doi.org/10.1080/0960085X.2022.2081096

Abstract

Self-tracking devices and applications have become popular in recent years and changed user behaviour. Previous research has primarily focused on the adoption of self-tracking devices and their effects on self-assessment. As adoption increases, user engagement becomes prominent for the continuous use of the devices and the applications. In this study, we focus on user engagement with activity tracking applications, e.g. Fitbit Flex and Jawbone Up that offer data on user performance. We collected data from semi-structured interviews with 54 participants. We propose a process model comprising four stages which involve distinct user interactions with data: review, react, reflect, and respond. To advance research in this domain, the process model explicates user engagement in two cases: when the user encounters satisfactory or unsatisfactory results. In particular, we observe four response tactics when users are confronted with unsatisfactory results.

Keywords: Activity tracking applications; Personal data; User engagement; process model, response tactics

Introduction

The use of self-tracking devices and applications has increased in recent years (Llamas *et* *al.*, 2019). Viewed as wearable information systems (Benbunan-Fich, 2019), self-tracking devices and applications constantly record data on mental and physical performance (e.g. exercise, sleep), individual state (e.g. mood, blood sugar levels), and consumption (e.g. food, air quality). Self-tracking involves activity tracking, mood-tracking, bio-hacking, and lifelogging (Doherty *et al.,* 2011; Sellen & Whittaker, 2010). For device vendors (e.g., Fitbit) and application providers (e.g., Strava Inc), the data from activity tracking is an invaluable resource for new service development (Curtiss & Ussery-Hall MPH, 2020).

We focus on activity tracking applications, which are means of evaluating, reflecting on, and understanding aspects of *the self*, related to daily physical activity and enabling self-quantification (Li *et al*., 2010; Swan, 2012; Sjöklint *et al*., 2013). They also increase self-awareness, which may lead to changes in attitude and behaviour (DiClemente *et al.,* 2001; Fritz *et al*., 2014). Activity tracking applications provide data for self-quantification and differ from data-driven mobile services providing generic data, e.g. location tracking, time spent on transportation. In view of such profound implications for users, it is important to understand how users engage with and respond to personal performance data in order to maintain continuous service use and data generation.

While the literature suggests that the use of self-tracking devices and applications is a complex and dynamic process (Baumgart & Wiewiorra, 2016; Prasopoulou, 2017; Abouzahra & Ghasemaghaei, 2021; Zakariah *et al*., 2021), empirical studies mainly build their analyses of user behaviour on variance models (De-Moya *et al*., 2019; Buchwald *et al*., 2018; Ferreira *et al*., 2021) that focus on static relationships between variables predicting consumer behaviour. In addition, existing theoretical conceptualizations in the Information Systems (IS) literature do not yet sufficiently capture the inherent complexity of activity tracking (Abouzahra & Ghasemaghaei, 2021) and, in particular, the evolving user reactions to different personal performance data. These reactions may not be easily captured by models assuming rationality and focusing on user perceptions of technology features (Chuah *et al*., 2016; Jung *et al*., 2016; Kalantari, 2017). Performance data and results of activity tracking offer users quantifications about themselves that evoke subconscious reactions which could influence user engagement with an application and thus use continuance. Exposure to this data has been mainly investigated in relation to behavioural reactions (Li, 2012; Fritz *et al*., 2014; Epstein *et al*., 2015), but questions arise about the cognitive and emotional reactions that might be triggered.

A user's interactions with activity tracking applications and performance data have been viewed as an engagement process (Ameen *et al*., 2021). User engagement is a key determinant of use continuance (Hollebeek *et al*., 2014) and value creation (O'Brien & Toms, 2008; Brodie *et al*., 2013) through data leveraging for innovation on data-driven services (Blasco-Arcas *et al*., 2016; Viglia *et al*., 2018; Hollebeek & Macky, 2019). We investigate user engagement with activity tracking applications by focusing on performance data and user reactions to results. We unpack user engagement with activity tracking applications and performance data and offer novel insights that contribute to the research discourse on user behaviour (e.g. Abouzahra & Ghasemaghaei, 2021, Ferreira *et al*., 2021). The engagement perspective foregrounds user interactions with the application instead of considering user characteristics and perceptions about the application's features. Our approach answers the call of Ameen *et al*. (2021) for interdisciplinary research on consumer interaction and engagement with wearable technologies at the intersection of the IS field and marketing.

To advance our understanding of the complexities of activity tracking, we apply a *process perspective* (evolved in Markus & Robey, 1988; Rescher, 1996; Shaw & Jarvenpaa, 1997; Langley, 1999; Burton-Jones *et al*., 2015) and derive a process model of user engagement with activity tracking applications. This theory-building perspective

(Burton-Jones *et al*., 2015) enables us to capture complex emergent phenomena that evolve over time (Langley, 1999) by focusing on changes of state rather than ranges of variables (Markus & Robey, 1988), with decisions made with contingent and even shifting outcomes (Shaw & Jarvenpaa, 1997). We decompose activity tracking into individual, distinct, sequential stages that sustain or reduce user engagement. To capture the complexities of user engagement in a process model, we follow Shaw and Jarvenpaa (1997) and adopt a qualitative research approach that addresses the following research question:

How do users engage with activity tracking applications and respond to performance data?

This study contributes to the domain of self-tracking technologies in the IS field in three important ways. First, we depict user engagement with activity tracking applications as a process model that goes beyond current empirical studies (Markus & Robey, 1988; Crowston, 2000), explicating different stages users go through when tracking their personal data and comparing it with their predefined goal. The process model offers a deeper understanding of how users engage with activity tracking applications, as well as how specific performance data, i.e. satisfactory and unsatisfactory results, influence user engagement. Following Burton-Jones *et al.* (2015), we combine existing insights from variance studies with a process model to dig deeper into the theoretical concepts and their relationships. The proposed model is tied to activity tracking applications as it is rooted in Personal Informatics (Li *et al*., 2010; Rapp & Cena, 2016; Epstein *et al*., 2015) and studies of self-tracking technologies and behaviours. Second, we unpack the concept of user engagement by focusing on its underlying dimensions, i.e. emotional, cognitive, and behavioural. This extends our theoretical understanding of user engagement, which in most empirical studies is limited to the behavioural dimension (e.g. Chen & Cheung, 2019; Ameen *et al.,* 2021). Third, by focusing on both satisfactory and unsatisfactory results, we reveal four user response tactics when encountering unsatisfactory results in performance data. These tactics are the outcomes of user engagement process with activity tracking applications and they influence future engagement.

The remainder of this paper is structured as follows. In the next section, we offer an overview of related research on self-tracking and activity tracking, as well as user engagement. Then, we describe our research method. In the subsequent section, we present the process of engaging with self-tracking applications and identify four tactics that users employ when they encounter unsatisfactory data. We then discuss the findings and develop a user engagement process model with response tactics. Finally, we offer conclusions and propose future research directions.

Theoretical Background

A number of studies on wearable IS adopt a variance perspective (Buchwald *et al*., 2018; De-Moya *et al*., 2019; Feng & Agosto 2019; Ferreira *et al*., 2021). The resulting theoretical focus on covariation among properties in invariant (static) relationships[1] (Markus & Robey, 1988; Rescher, 1996; Shaw & Jarvenpaa, 1997; Langley, 1999; Burton Jones *et al*., 2015) may be a reason why complex self-tracking activity is not yet fully understood. A notable exception is a qualitative study by Abouzahra & Ghasemaghaei (2021) that advances the established view on adoption by explaining use via interlinked sequences of affordances[2] and argues for the suitability of qualitative research and a focus

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[1] For example, the link between covarying 'user engagement' and 'continuance intention' can be identified in a regression analysis. This perspective presumes an invariant static (i.e. not evolving, Langley, 1999) relationship, which does not account for contingencies such as goal attainment or situational challenges (such as long work days with not enough time to reach the goal) that might have affected how the relationship changes.

[2] For example, for the activity planning goal, the 'activity recording' affordance is related to the 'comparative analysis' affordance, which is then related 'recommending activity level'

on linked stages of self-tracking. We build on this research approach and adopt a process perspective on activity tracking.

Process theories link an emergent perspective on change that accepts the complexity of the phenomenon being investigated to a belief in regularity and predictability (Markus & Robey, 1988). The outcomes are not variables that take on a range of values but changes of state (Markus & Robey, 1988; Langley, 1999). A process view's inherent acceptance of change may enable us to understand contingent, perhaps even shifting, outcomes; conversely, 'a variance model cannot explain how resistance from users changed' (Shaw & Jarvenpaa, 1997, p.79). This is particularly relevant to our investigation of user reactions to different performance data and repeated user decisions about whether to engage with the data.

The underlying process bears a complexity that, when broken down into individual sequential stages, allows us to understand how the outcome of user engagement emerges and is sustained. Black-boxing any intermediate steps is likely to oversimplify explanations of evolving behaviour. Consequently, we investigate activity tracking as a process that consists of a series of stages in which a user is affected by events over time that change the state and affect the unfolding process trajectory. In turn, this resonates with the focus of process research on 'how things evolve over time' (Langley, 1999, p.692) based on sequential activities, events, or choices. In line with the approach of Langley (1999, p.703), we identify these stages as a way of structuring the unfolding of a process that depicts the user reactions to events and leads to the outcome state. We note stages which are actually initiated by distinct events, such as reviewing the data. These

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affordance, which then feeds the 'activity planning' affordance (Abouzahra & Ghasemaghaei, 2021) events constitute a certain contingency, in that they affected the subsequent process trajectory.

Activity tracking and self-tracking

Viewed as cutting-edge, self-tracking technologies have been introduced to measure and record various aspects of individuals' everyday lives (Ameen *et al*., 2021), mainly associated with healthcare (Ferreira *et al*., 2021). Research on activity tracking has mainly investigated the adoption and use of devices (Buchwald *et al*., 2018). Some recent studies have focused on affordances (Rockmann & Gewald, 2018; Jarrahi *et al*., 2018; Rieder *et al*., 2020; Abouzahra & Ghasemaghaei, 2021). Benbunan-Fich have found that lack of affordances in a minimalistic design of the activity tracking device offers simplicity but may result in complexity of use (2019). Gimpel *et al*., have focused on user motivation for self-triggered monitoring of performance data and found as key categories self-entertainment, self-association, self-design, self-discipline, and self-healing (2013). James *et al*. have found that the use of device's features depends on the intrinsic and extrinsic motivation of a user and data management features could support well-being outcomes (2019).

Activity tracking applications are part of this research domain, which also includes 'Quantified Self' movement (Lupton, 2016; Kersten-van Dijk *et al.*, 2017; White *et al*., 2019), and contribute to self-quantification studies. Self-quantification practices go 'beyond remembering information about oneself; they focus on collecting data for the purpose of gaining self-knowledge through reflection' (Pirzadeh *et al*., 2013, p.1980). Self-tracking 'augments a person's self-knowledge by breaking down human barriers to personal data management' (Khovanskaya *et al*., 2013, p. 2). According to Zakariah *et al*. there is a continuous process of (re)configuration of the self, as users move between two sets of self-surveillance contrasting principles: ‘health and indulgence’ and ‘labour and leisure’ (2021).

Self-tracking data, such as step count or the number of hours slept during the night, reveals information about the user’s goal achievement (Munson & Consolvo, 2012; Niess & Woźniak, 2018; Schroeder *et al*., 2019). It may encourage changes in behavioural patterns towards an intended goal (Bentley *et al*., 2013; Rieder *et al*., 2019; Rieder *et al*., 2020), activate self-management (Fitzgibbon & Reiter, 2003) and support more effective decision-making (Cosley *et al*., 2012). This research area has been recently described as Personal Informatics (Li *et al*., 2010; Rapp & Cena, 2016; Epstein *et al*., 2015), focusing on how technology, e.g. self-tracking technologies, systematically tracks, organizes, analyses, and represents relevant data for an individual.

A few studies have adopted a process perspective (Karapanos *et al*., 2009; Li *et al*., 2010; Pirzadeh *et al*., 2013) and depicted the different stages users go through while making decisions about their personal performance based on observed data. A stage-based process model was proposed to depict user transitions between preparation, collection, integration, reflection, and action, aiming to acquire knowledge supporting behavioural change (Li *et al*., 2010). The model was extended by dividing the reflection stage into sub-categories: discovery and maintenance (Li *et al*., 2011). A more recent model depicts the process of ‘deciding to track and selecting tools, tracking and acting as an ongoing process of collection, integration, and reflection, and lapsing of tracking that may later be resumed’ (Epstein *et al*., 2015, p.735).

The proposed models focus on how users reflect and change behaviour (Lin *et al*., 2006; Li, 2012; Fritz *et al*., 2014; Epstein *et al*., 2015). Through exposure to personal data, the user becomes aware of undesirable behaviour, i.e. too little physical activity or poor quality of sleep, and is prompted to change it. Hence, self-tracking devices are viewed as commitment devices promoting lifestyle change (Fritz *et al*., 2014; Feng & Agosto 2019; Abouzahra & Ghasemaghaei 2021). However, these models do not fully capture the nuances in user interactions with the application and, in particular, with performance data displaying satisfactory or unsatisfactory results.

Despite its importance, research on user interactions and user experience with activity tracking applications is still limited in the field (Pfeiffer *et al*., 2016; James *et al*., 2019), suggesting a need for more research on the complexities of self-tracking processes (Rieder *et al*., 2019; De-Moya *et al*., 2019) and, in particular, on the subconscious reactions of the user when viewing personal performance data (Sjöklint *et al*., 2015) that may lead to behavioural changes on the physical activity (Lehrer *et al*., 2019). This requires advancing theory beyond the notions of adoption and use continuance. Against this backdrop, we draw on the concept of user engagement, which has been identified as a key determinant of continuous use (Shiau & Luo, 2013; Lin *et al*., 2014; Ameen *et al*., 2021). We propose a process model, following the sequential, staged approach (Li *et al*., 2010; Li *et al*., 2011) and unpack user engagement, which we view as a multidimensional concept that includes cognitive, emotional, and behavioural aspects. This model allows us to understand how user engagement with performance data influences the use continuance of activity tracking applications.

User Engagement

User engagement refers to users' interactions with technology (O'Brien & Toms, 2008) as individuals become captivated by technology (Attfield *et al*., 2011), for example, in case of social media, eLearning applications, or search systems (O'Brien & Cairns, 2016). It is a context-dependent psychological state characterized by fluctuating intensity levels within dynamic, iterative engagement processes (O'Brien & Toms, 2008, p.107). These studies provide input to the technology design process and especially the technology interface (Gouveia *et al*., 2015; O'Brien *et al*., 2018) in relation to user actions and behaviour (Chen & Cheung, 2019). User behaviour is commonly used to measure engagement with self-tracking applications (Gouveia *et al*., 2015).

We investigate user engagement to shed light on the user's interactions with self-tracking applications and build on insights from marketing, where user engagement has been intensively studied (Hollebeek, 2011; Brodie *et al*., 2013; Hollebeek *et al*., 2014). We view user engagement as a user's technology-related state of mind, characterized by specific cognitive, emotional, and/or behavioural manifestations in interactions with technology. This conceptualization offers a comprehensive view that goes beyond the behavioural dimension and allows us to observe the multidimensional aspects of user interactions with an application, as well as with performance data about personal results.

The cognitive dimension of user engagement refers to users' positive or negative considerations about technology and reflections on specific interactions with it. Adapted by marketing studies (Hollebeek *et al*., 2014), cognitive engagement refers to cognitive processing, that is the user's level of data-related thought processing and elaboration in a particular interaction with data displayed in the activity tracking application. In our study, this describes the mental state experienced during such an interaction (Hollebeek, 2011; Hollebeek & Chen, 2014). Emotional engagement refers to users' positive or negative emotional reactions to technology-related interactions (Hollebeek & Chen, 2014), for example, positive feelings such as pride (Hollebeek & Chen, 2014) or negative feelings of anxiety or guilt (O'Brien & Toms, 2008). Finally, behavioural engagement involves manifestations of user behaviour, such as energy, effort, and time spent on technological interactions (Hollebeek & Chen, 2014). For self-tracking applications, this can be captured through the frequency of visits or time spent using the application (Gummerus & Pihlström, 2011; Hollebeek & Chen, 2014).

User engagement is an appropriate theoretical conceptualization for a complex, multi-stage process (Brodie *et al*., 2013) in which the user experience involves interacting with self-tracking data. We unpack user engagement in relation to activity tracking and introduce a process model to identify the different outcomes that contribute to use continuance (Hollebeek *et al*., 2019).

Research Method

To address the research question and unpack the complex process of user engagement with activity tracking applications, we conducted a qualitative study.

Research Context

The activity tracking devices for this empirical study are Fitbit Flex and Jawbone UP. These two devices were selected as they are designed to be worn all day, except during activities that could harm the device, such as swimming. When worn, each device measures the individual's activity in terms of steps and sleep, as well as other activities (see the Appendix for a detailed comparison of the two devices' features). The user can also add manual data, such as food consumed, perception of mood, and workouts. Manual data can be added through the corresponding mobile application or dashboard. Both devices measure the daily number of steps and overall active, as compared to idle, time. Though many different devices are available (such as wristbands or clips attached to clothing), only users of the wristbands Fitbit Flex and Jawbone UP were chosen for interviews. Those devices shared the same functions as most of the devices in the market at the time of the study[3].

Sample

We used purposive sampling to select the study participants. This sampling technique is customary for qualitative research into a very specific phenomenon, e.g. user engagement with activity tracking applications (Patton, 1990). This technique involves the identification and selection of individuals or groups of individuals that are highly experienced with self-tracking applications (Creswell and Plano Clark, 2011). We followed the maximum variation strategy by targeting information-rich cases (Patton, 2002) to document variations in user engagement processes and response tactics to performance data that emerge when adapting to different conditions (Patton, 2002). The maximum variation strategy allowed us to look for shared patterns that cut across individual cases and have significance due to emerging from heterogeneity (Patton, 2002).

We looked for participants able to communicate their experiences and opinions with activity tracking applications in a reflective manner (Etikan *et al.*, 2016). Recruitment took place in several different settings, such as online forums, physical *Quantified Self* meetup groups, conferences, social media (especially Facebook university groups), and university email distribution lists. The sample consists of 30 men and 24 women of ages between 20 and 50. The participants mainly resided in North America and Northern Europe, which had a high diffusion of the activity tracking devices used in the study. Among our sample, 42 participants used Jawbone UP and 12 used Fitbit. Participants were expected to have used the activity tracking application for at least 6 months prior to

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[3] https://www.gearpatrol.com/tech/a106994/survey-best-wearable-devices-2014/

the interviews (this period has been used in other related studies, e.g. Rieder *et al.,* 2020; Lehrer *et al.,* 2021). Users over shorter periods were excluded, as were individuals that did not use the application on a daily basis.

The Interviews

Our empirical study took place in 2014 and was based on 54 in-depth, semi-structured telephone interviews. The interview guide included open-ended questions and covered topics such as self-tracking goals, motivations, application use, and user experiences (Epstein *et al.*, 2015; Abouzahra & Ghasemaghaei, 2021), which were identified as key topics in empirical studies of user behaviour and self-tracking applications. We expected to elicit users' considerations about and reactions to self-tracking applications and personal data to better understand the engagement process. The interviews ranged from 25 to 50 minutes. Interviews were conducted in Swedish, Danish, or English, to allow the participants to feel comfortable and express themselves in their native language. The interviews were audio-recorded, transcribed, translated into English, and imported in the software MaxQDA. This yielded 420 pages of transcription. Data were anonymised before analysis.

Data Analysis

Our research approach involved first focusing on individual responses from the interviews, to examine the user engagement process with the activity tracking applications. While there is some prior research on the process that users go through while using self-tracking applications (Karapanos *et al*., 2009; Li *et al*., 2010), this part of the analysis was largely data-driven, to understand users' engagement through their interactions with the application and uncover their reactions to satisfactory and unsatisfactory results. The exploration of the process was followed by a consideration of how it contributes to the user engagement literature, extending the understanding of user engagement with activity tracking applications. In order to do this, we took a broader perspective on the data and looked at how the specific dimensions of user engagement, i.e. emotional, cognitive, and behavioural (Hollebeek, 2011), are enacted in the different stages of the process model.

Three researchers were involved in the data coding and analysis. A fourth researcher, with expertise and knowledge of the domain, took a fresh look at the data and the coding, and helped resolve differences in data coding and interpretations. Our data analysis involved three steps (See Figure 1).

<<INSERT FIGURE 1>>

In the *first step*, we looked for how the study participants described situations and 'talked about' the self-tracking application and their reactions to data. We used descriptive coding (Myers, 2009) to compare and contrast similar and different situations, examine interactions and reflections evident in our data, and group similar elements into the same stage. This step was iterative, with three researchers working independently (each researcher coding every interview transcript) to identify the process stages, discuss them, refine them, and return to the data to corroborate them with examples. While we considered existing models of sequential stages in our analysis as 'guidance in approaching empirical instances' (Blumer, 1954, p.7), we also allowed categories to emerge from the data, as the process models in the literature did not yet consider user engagement a focal phenomenon (focusing instead on self-assessment). We therefore began our analysis of the user engagement process in an open manner. Through this process of linking specific categories of user interaction with performance data to stages (i.e. sub-themes in patterns of user interaction with data), we were able to abstract and identify the main stages of the user engagement process with self-tracking applications (i.e. themes). Examples of the data analysis are available in the Appendix.

The *second step* of our analysis involved identifying the three user engagement dimensions in our data. This entailed another round of data coding, looking specifically at how we could observe the user engagement dimensions adopted from the literature—emotional, cognitive, and behavioural (Hollebeek, 2011)—in the different instances of user interactions with performance data. The three dimensions of user engagement were linked to these instances of each stage of the user engagement process.

The *third step* entailed re-organizing the data on user engagement stages that depend on perceived satisfactory or unsatisfactory results, which were associated with particular performance data. We examined how the user engagement process was influenced by satisfactory or unsatisfactory results. In particular, we focused on the response stage to refine how people respond to different types of results. We used descriptive coding (Myers, 2009) to compare similar and different descriptions of reactions. We then applied interpretive coding (Myers, 2009) to further group conceptually similar sequences. For unsatisfactory results, these coding processes enabled as to uncover the main response tactics.

Findings

In our interviews, we first investigated general use and data-related practices. We noted that activity tracking devices have become part of daily life: '*It's just a part of me. I got used to that. If it breaks, I will just buy another one. Just like a toothbrush*' (Female 30, business analyst). While the devices are constantly present, users interact with data less frequently, e.g. twice a day: '*In the beginning, I would check it like four to five times a day. But the focus would be morning and evening*' (Male 29, account manager).

There were different motivations and lifestyles behind the use of self-tracking applications. Some users followed an active regime prior to using self-tracking devices, others aspired to have an active lifestyle and wanted to increase physical activity, while a few used the device for fun or as a gadget. Despite different lifestyles and motivations, the user engagement process for activity tracking applications and performance data does not differ among the participants. Our data analysis revealed that all participants followed the stages of the proposed model with different reactions and outcomes based on contingencies related to goal attainment.

Upon installing activity tracking application for the device on their smartphone, users opened it and manually approved the step and sleep goals. The application offers a recommendation to set the daily steps at 10,000. A user said, '*I had 10,000 steps and always the eight-hour sleep. I did consider changing it but then it said 10,000 steps was recommended from some American federation*' (Male 29, account manager). Another user explained, '*I stuck with 10,000 and 8 hours a night. Even if I don't ever make 8 hours of sleep, I haven't changed them because I still think they are ideal numbers, even if I can't make them*' *(*Female 29, designer).

The majority of the participants chose the recommended 10,000 steps as the daily step goal; only a handful chose above or below this figure. A participant explained, '*I never considered changing them ... Even if I didn't reach my goal I saw it as a motivator*' (Male 23, student). Even if the participants failed to reach the daily goal, they did not consider adjusting it either upward or downward. One user argued, '*it's a tool, just a tool, to move more. It doesn't have to be a precise or exact 10,000 steps, just as long as I get up there*' (Female 24, sales assistant).

In the following, we depict the four stages of user engagement with the activity tracking application while observing how users respond to performance data.

Review

The review starts with users' exposure to personal data in the dashboard, which stimulates behavioural engagement. Data is visualized in simplified graphs. The review process is short; it mainly consists of opening the dashboard and browsing data. Users look at the main page to get an overview of the performance data in a bar chart. User review data occasionally—mainly in the morning and evening. '*Usually closer to the evening time because I want to see how many steps are left, like if I am close to my goal or if I am far away, so I need to walk a little bit more or exercise or something like that*' (Female 30, business analyst).

React

The user reaction to data mainly involves emotional engagement—an immediate reaction—to their success or failure in attaining the goal. When the goal is reached, users experienced satisfaction: '*It makes me feel I'm a good person. An active person taking care of my health*' (Female 26, digital manager). '*It's a little victory when you do well … nobody can alter it or fake it: you've done those 10,000 steps and that's a good feeling*' (Female 28, researcher).

Exceeding their goals makes users happy and satisfied with themselves: '*I'm happy when I've reached my goals, especially when I have far outreached my goals*' (Female 30, geologist); '*it's when I go way beyond that, I'm happy*' (Female 35, researcher).

When a goal is not reached, users feel stressed. This is a strong sensation and a source of anxiety: '*a little irritated actually. It makes me feel lazy and I feel self-conscious about it*' (Female 26, store clerk).

When a goal seems difficult to attain, behavioural engagement is reduced to checking the app once a day. As a user explained, '*If I'd look at it more often, I'd just get stressed and feel that I have to perform more*' (Male 29, researcher). Users are motivated when viewing data in real time, as one respondent described: '*I like spot checking … when you use a Fitbit, then you can see the steps moving as you move. It's very self-reinforcing!*' (Male 36, PhD student).

Access to personal data makes users feel in control of their lives: '*It is a form of internal control. It is journal, a diary of behaviour. Behaviour can be adjusted and getting insights about behaviour … I have always had a certain control need and a wish to go back and check data to see how I've done with the goals I've intended to reach*' (Female 25, nutritionist). Yet, for some users, the data has no implications or significance for their well-being. A user claimed, '[it] *affects me for two seconds but not long term effects*' (Male 29, entrepreneur).

Reflect

The immediate emotional reaction stimulates cognitive engagement as the user evaluates their personal data. The user puts personal data into context by considering various aspects, such as whether the results are probable and reasonable, as well as if they are satisfactory.

Data visualization becomes an opportunity to self-reflect: '*It made me more knowledgeable about myself*' (Male 29, account manager). The device is '*a type of consciousness. I'm just conscious of what I am doing*' (Female 30, business analyst). Another user explained, '*You can get some statistics on yourself, so it's not just the feeling of "I've done something this day," but I can actually see that I've done something*' (Male 23, student).

This self-awareness often leads to the desire to make behavioural changes: '*If I don't reach my goals, yeah, I kind of think about it. But then I just think that I'll do something about it the next day instead to get the steps. I guess it's important to get a good average*' (Male 45, teacher).

By gaining self-awareness, users are able to reflect on problematic daily patterns. For example, a user described '*seeing how little I actually move when I am in the office. I mean, I spend a lot of time there and when you can see that you are only getting 2,000–3,000 steps in a day it's really a little scary. You should be moving more!*' (Female 28, researcher). Reflections on unsatisfactory results may lead to disappointment: '*Even if it is one day where I am on a good track and hitting my goal and [then] one day short, [I feel] disappointed, like you weren't good enough*' (Female 29, project manager).

Respond

Responses to the data mainly involve behavioural engagement, through actions such as taking an extra walk to get more steps or cognitive reactions such as rejecting the data for various reasons.

When users consistently reach their goals over a period of time, they attempt to go beyond the preset goal, as a user described: '*... I went with the recommended values but after a while I realized that I am moving more than what they recommended so I upped the amount of steps…to push myself beyond my limits*' (Male 29, account manager). Meeting the goal motivated further increase; '*My goal was at first 10 000 steps and I would make an effort to reach that. I quickly found out that I got a little lazy once I had reached my goal so I put it up to 12000 steps... and once I had reached that, a bunch of times then I set it up to 15000 steps per day*' (Female 26, store clerk*)*. For these users, reaching satisfactory results has contributed to behavioural change: '*My lifestyle pattern* *has changed. I'd never ever go all these extra walks if it wasn't for my Jawbone goals*' (Male 29, researcher).

When the user is exposed to data representing unsatisfactory results, the goal is treated in an arbitrary manner. Thus, the user debates the validity and importance of the goal. Users do not always accept the result (i.e. goal attained or not attained), but instead come to new conclusions and justifications based on response tactics.

The response tactics

Users mitigate negative impact from exposure to unsatisfactory results through four response tactics: dismissal, procrastination, selective attention, and intentional neglect.

Dismissal

The most common response tactic is dismissal, where the user does not acknowledge the information the application provides. This tactic involves cognitive engagement with the unsatisfactory results indicating an unattained goal, which is then attributed to some external reason.

Users choose not to attribute the results to themselves. Instead, the goal is not achieved because of specific circumstances: '[I] *did not have the possibility to change it, because you do not have more time in the course of a day, just because you now know that you are not moving enough*' (Male 23, student). Another user explained, '*I couldn't have changed that anymore because of my lifestyle*' (Female 28, account manager).

Some users are not able to reach satisfactory results because of time constraints or other context-specific reasons: '*I know I can't reach the goal because I was in the* *office in a meeting all day*' (Male 30, entrepreneur). However, users do not decrease the preset goal, despite a failure to meet it.

Dismissal is also influenced by how far the user is from the goal. One user explained, '*The days I don't reach my goals, it all depends on how far off my target I am. If it's only a few steps then I don't mind*', and then further elaborated, '*If I know the reason I haven't reached the goals, then I don't mind*' (Female 25, nutritionist).

Arguments sometimes involved the application's features: '*I could perform much better if the dietary functioning was better*' (Male 23, student). Users distrusted certain features and dismissed the results. One user argued, '*[it] really annoys me that the device can't understand that you are lifting weights ... I've had sessions where I'm almost throwing up and it only shows you had a little bit of activity. Then I would just look away from it*' (Male 27, lawyer).

Procrastination

Procrastination sees the user consider changing unsatisfactory results via future plans. This tactic activates cognitive engagement by focusing on the circumstances around the unsatisfactory results and considering how to change them. However, the user procrastinates rather than acting on the considerations. Procrastination is the opposite of dismissal, where the user automatically places the blame on their circumstances and voices no aspirations for the future. The user reverts to seeking behavioural change by stating future plans: '*...if I walked 4,500 steps one day, I knew I wouldn't allow myself to walk any shorter distance the next day.*' (Male 29, account manager), or '*I'm thinking then you just pull yourself together tomorrow*' (Male 23, student).

However, planning a change does not always lead to one. As a user described, '*I have considered whether it wouldn't be a great idea to take a little evening walk when* *you have not achieved your own goal. But I haven't really done it yet*' (Male 23, student). Another user explained, '*I will probably deliberately miss my goal, or know I haven't made it, half of the time. Maybe half of the time, I will do something about it. Like twice a week I will aspire to do something about it*' (Female 29, designer).

The procrastination tactic is more common when the user has already practiced it for a longer period of time. A user argued while viewing weekly personal reports, *'I can't change the past anymore so I just see it as a way to get an overview of my behaviours and maybe change them in the future but not thinking about the past'* (Male 29, designer).

Selective attention

The response tactic of selective attention is observed when the user response is an increased focus on more achievable goals rather than on those that are more difficult to attain. This tactic involves cognitive engagement with favourite services in the self-tracking application.

Most users have a favourite category, one where they perform well. For example, a user said, '*I know that I will do well on [stairs]. Stairs are thus important to me. It gives me a boost*' (Female 28, researcher). The same user explained, '*[it is] what I will look at most.*' Through selective attention, the user's cognitive engagement bypasses unsatisfactory results and merely focuses on attainable outcomes. The user might even adjust the interface to prioritize viewing their favourite categories. For example, a user described how '*You can switch up what you look at in the dashboard, so you can prioritize and see what you primarily look at up top. That thing with how much I've lost and how far from my goal I am, I keep that at the bottom, I don't even look at that*' (Female 45, housewife).

Through selective attention, the user may change behaviour to excel in a favourable category, which reinforces the initial departure point. A user explained, '*As long as I ran instead of lifting, I could measure how much I ran. It ended up being that I would rather run than lift because I wanted the result to look as good as possible*' (Male 29, account manager).

Intentional neglect

The response tactic of intentional neglect is observed when the user intentionally ignores unsatisfactory results. This tactic mainly involves behavioural engagement that influences the frequency of interaction with the self-tracking application. However, this is triggered by emotional engagement at the reaction stage.

Some users checked the data only when they had carried out a significant number of activities. For example, one user checked '*every two days. Especially, I check when I do sports. Then I want to see my data, but if I don't do sports I tend to not look at it, because I feel guilty*' (Male 27, lawyer). Another user also felt 'g*uilty. That is also one of the reasons I haven't been using it lately. I sometimes got upset about the fact that I couldn't always achieve my goal*' (Female 27, student). Because of negative emotional engagement such as guilt, users checked data less frequently, and often only in relation to activities expected to provide satisfactory results.

Similarly, users would intentionally not lower an unattainable goal: '*maybe my goal is too high, maybe I should lower it to 9,000, but I would feel like a wimp*' (Male 35, researcher).

Intentional neglect was also observed when the user avoided responding to certain parameters of the data because they were rarely or never satisfactory, even though the performance data were. For example, one user neglected calorie counting at all times: '*I* *never reach my calorie count even though I go on a 10km run. It never comes up there*' (Female 28, researcher).

Discussion

Our empirical study reveals activity tracking as an ongoing, complex process of user engagement. It is conceptualized as a process model grounded in four sequential stages of review, react, reflect, and respond. Through these stages, we track users' interactions with data about themselves and reveal the cognitive, emotional, and behavioural dimensions of user engagement with activity tracking applications. The process view offers a comprehensive picture that unpacks user engagement, allowing us to depict the consecutive stages leading to user behaviour in response to satisfactory and unsatisfactory results, thus contributing to a better understanding of service use continuance. We note that, in contrast to other data-based mobile services, this process characterises users' engagement with data about themselves, which gives rise to specific response tactics that aim at maintaining a positive self-image. The proposed model contributes to Ameen et al.'s (2021) call to advance the theory and knowledge of consumer interactions with activity tracking applications through interdisciplinary research at the intersection of information systems and marketing. In the following, we present the proposed process model of user engagement with performance data. The model builds on goal-related contingencies which lead to a bifurcation of satisfactory and unsatisfactory performance data. We also highlight the response stage to the engagement process, which allows us to capture a diversity of response tactics. Finally, we address practical implications.

<<INSERT FIGURE 2>>

Theoretical Implications: A model of user engagement with activity tracking applications

The proposed model (Figure 2) advances the extant view of activity tracking application use (Shiau & Luo, 2013; Lin *et al*., 2014; Ameen *et al*., 2021) by explicating how the cognitive, emotional, and behavioural dimensions of engagement (Hollebeek & Chen, 2014) influence user interactions with self-tracking applications and performance data. It goes beyond the variance approach of the adoption and use continuance models in the IS field (Ferreira *et al*., 2021); it allows us to understand the effects of the non-rational (e.g. emotional) dimensions of user engagement and investigate the dynamic nature of the drivers of self-tracking application use continuance. The model reveals user engagement as a complex process influenced by contingencies such as goal attainment, prior performances, or situational exceptions. This explains why outcomes such as sustained or reduced engagement cannot be described by a simple static relationship with the use of the activity tracking device. We find user engagement to be better understood via a process approach (Markus & Robey, 1988; Burton-Jones *et al*., 2015) that emphasizes subsequent stages depending on contingencies and user decisions. The process perspective of the study enables a better understanding of the response to specific performance data, as it allows us to shed light on how ‘decisions are made’ (Shaw & Jarvenpaa, 1997, p.83).

The proposed model also allows us to capture user reactions to activity tracking applications and performance data at a micro level while the user moves between contrasting principles such as ‘health and indulgence’ or ‘labor and leisure’ (Zakariah *et al*., 2021). This complements Zakariah *et al*. (2021), who argued that users’ movements between contrasting principles in self-tracking do not invalidate their engagement with self-tracking applications but instead enrich ‘their experiences of disciplining the body in an honest or savvy way’ (p. 9).

The proposed model (Figure 2) depicts user engagement with performance data as a process subject to goal-related results. The engagement process starts with the ‘review’ stage, which entails behavioural engagement with the applications, i.e. browsing data. There is a bifurcation of the remaining stages of the user engagement process between satisfactory and unsatisfactory results that depends on the performance data observed. The model suggests that the first emotional reaction to results will set in motion subsequent reactions, leading to either a behavioural change or a lack of one. We identify two trajectories for user engagement with performance data.

When users review *satisfactory* results, because they have attained their goals, they immediately feel content (reaction stage). Then, in the reflect stage, they contextualize the results in relation to their principles (Zakariah *et al*., 2021) by focusing on facts about problematic areas of their daily activities in order to gain personal awareness (Gimpel *et al*., 2013; Shin & Biocca, 2017). In the respond stage, the user may increase the goal or reduce their engagement with the activity tracking application, since the goal becomes part of their daily routine. Similarly, Lehrer *et al.* (2021) suggest that users who followed and internalized a predefined goal, by accepting it as their own, are more likely to reach satisfactory results. Hence this may lead to a change of behaviour and become more active (Lehrer *et al.,* 2021). The latter response reduces user engagement because of the decreasing importance of the information provided (Jarrahi *et al*., 2018).

When the users review *unsatisfactory* results, the reaction involves negative emotions and reflections on the reasons for not meeting the goal. The user’s reflections involve evaluations that contextualise the unsatisfactory results by considering the performance data relative to the predefined goal or assessing the importance of the specific results' distance from the goal (Sjöklint *et al*., 2015). In the reflect stage, the users increase their knowledge about themselves without invalidating their engagement with the data (Zakariah *et al*., 2021). The user's response to this assessment in the respond stage is enacted with four different tactics (dismissal, procrastination, selective attention, intentional neglect), which capture a variety of nuances of cognitive or behavioural reactions to the performance data, depending on specific goals, previous behaviour, and contextual elements leading to the unsatisfactory result. The proposed tactics build on the findings of Sjöklint *et al.* that identified user's coping tactics when faced with unsatisfactory results (2015). These tactics (Sjöklint *et al.,* 2015) are systematically introduced in the proposed process model, based on user engagement dimensions.

The investigation of the three engagement dimensions in each stage of the process model revealed underlying subconscious interactions with the data, which could be emotional or cognitive (i.e. based on heuristics). These dimensions enrich our understanding of the user response towards a specific result of goal attainment (Munson & Consolvo, 2012; Niess & Woźniak, 2018; Schroeder *et al*., 2019) or failure to do so (Sjöklint *et al*., 2015). This process explains how users change behaviour towards the continued use of activity tracking applications, as specific results lead to a response in one of many possible iterations of an ongoing engagement process.

The introduction of the response stage into the proposed user engagement process model contributes to Personal Informatics studies of wearables and user behaviour (Li, 2012; Fritz *et al*., 2014; Epstein *et al*., 2015) by explicating how the emotional and cognitive reactions to satisfactory or unsatisfactory performance data trigger specific responses that may change the level of user engagement, which in turn is a contributing factor to activity tracking application use continuance. The proposed model complements existing research focusing on user self-assessment and reflection after exposure to specific results (Karapanos *et al*., 2009; Li *et al*., 2010; Pirzadeh *et al*., 2013). These models depict reflection as the main stage and fail to consider what occurs afterwards. As a result, they do not distinguish between exposure to satisfactory versus unsatisfactory results, or the underlying nuances of user responses. We argue that the identified bifurcation of the user engagement process, according to the type of result reviewed by the individual, better explains future decisions in relation to use continuance of the device and should thus be investigated more systematically in future research.

The response tactics

As part of the respond stage of the user engagement process, we discovered four response tactics for users who encountered unsatisfactory results, as summarized in Table 1.

<<INSERT TABLE 1>>

The four tactics underline the importance of cognitive engagement when dealing with unsatisfactory results, which does not align with the logic of self-tracking applications as commitment devices that should lead to behavioural changes (Fritz *et al*., 2014). The user responds to unsatisfactory results with cognitive reactions that do not involve analytical thinking but rather a heuristic reaction with underlying cognitive biases. Unfolding the response to unsatisfactory results through the lens of engagement provides complementary insights about the micro-level reactions of the user and complements existing research in the domain that focuses on users' contradictory principles (Zakariah *et al*., 2021) or their consideration of goal attainment (e.g. Rieder *et al*., 2019; Lehrer *et al.,* 2021).

The proposed tactics unpack the complexity of user engagement and provide a specific outcome each time the user engages with data, which will feed the next iteration of the engagement process. For example, in the procrastination tactic, cognitive engagement involved time discounting (Sjöklint *et al*., 2015), and the user attributed more importance to planning for future behaviour. Because of this cognitive bias, the subsequent behaviour is never adjusted as planned; thus, the user acts upon the current confining circumstances and may not achieve satisfactory results in future iterations. In the dismissal tactic, cognitive engagement highlights the importance of competing activities when the goal is not met, which become the focus of attention; thus, the user's unsatisfactory results are ignored. In addition, we observed arguments related to the application's measuring accuracy, as in other studies (e.g. Rooksby *et al*., 2104; Feng & Agosto, 2019). Benbunan-Fich (2019) described the self-effecter paradox whereby data collection and display, despite the questionable accuracy offer awareness, and increase user motivation for physical activity. The dismissal tactic reveals another perspective of user's reaction to data accuracy when the gaol is not met, by underlining the role of user's cognitive engagement with the data. Similarly, the tactic of selective attention involves cognitive engagement, highlighting specific satisfactory aspects of the results that become more important for the user than the unsatisfactory ones (Sjöklint *et al*., 2015). Finally, in the intentional neglect tactic, the user disengages from self-tracking services that display unsatisfactory results.

Studies in the field identified a tendency to ignore the data (Lehrer *et al.,* 2021) because of a failure to meet individual goals. Our study goes deeper into the observed ignoring behaviour to reveal the different tactics of doing so as part of the user engagement process when responding to observed unsatisfactory results. This level of detail in a description of response tactics, focusing on users' cognitive reactions, is important for designing interventions or introducing new functionalities that could affect user response and potential future engagement with the application and data. We highlight the importance of user interactions with the data and application and argue that user motivations and personal goals are not the only determinants of user engagement. As users continue to use activity tracking applications, they may become less self-disciplined and their response tactics may adapt to the actual performance, rather than maintain the original motivations for self-triggered health monitoring as identified by Gimpel *et al.* 2013.

The identified tactics challenge the overall objective of introducing self-tracking devices as commitment devices that support user self-control (Sjöklint *et al*., 2015). In particular, the most common tactic of dismissal indicates that users attribute the unsatisfactory results, i.e. not meeting the goal, to external reasons and avoid taking action. In this case, activity tracking does not support self-control or increase the commitment of the user to the specific goal. Thus, we provide evidence against the 'normative view' of introducing activity tracking devices to improve user behaviour. These response tactics to personal data of activity tracking underline the focus on maintaining a positive self-image in contrast to other, mobile services collecting more general data.

Practical Implications

Our findings offer practical insights for activity tracking device vendors as they focus on user engagement while selling wearable devices. Even though the adoption rate is increasing, it has been argued that 'most of these devices fail to drive long-term sustained engagement for a majority of users' (Endeavour Partners, 2017). Activity tracking devices are positioned as a means of activating user commitment to externally predefined targets for health-related activities. This marketing strategy is not aligned with the value users perceive themselves as obtaining from activity tracking applications, and it may pose a challenge to the application's use. Our findings provide evidence that users may not engage with activity tracking applications as commitment devices but instead treat them as trackers or information providers that quantify aspects of daily physical activities. If this is the case, then the marketing strategies of vendors need to be revised to focus more on the utility of the applications for the users' daily routines (Ameen *at al*., 2021). By considering the proposed response tactics, vendors might better understand user reluctance to maintain a long-term engagement with activity tracking devices.

The proposed model of user engagement provides useful insights to service and feature designers who often focus on technological features instead of interfaces and the visualization of data (Patel *et al*., 2015; Rapp & Cena, 2016). This, in turn, may challenge user engagement, which is about the user's cognitive, emotional, and behavioural interactions with the data provided in the application. The designers may influence specific stages of the engagement process by the way performance data are presented and thus maintain user engagement. For example, unsatisfactory results for one day could be underemphasized if the user's running average for the week or month is above the predetermined goal. Thus, making visualization of weekly averages of performance data (already available in activity tracking applications) the default option for the user, could deter a negative affective reaction to the data observed. This in turn may also alter the response tactics of the user.

Overall, we view user engagement as a key determinant of value creation for application or device providers and, at the same time, point out that response tactics to unsatisfactory results may lead to reduced user engagement or even application use discontinuance and challenge the development of innovative, personalized data-driven services. Value creation from activity tracking applications builds on continuous service use and is paramount for device vendors aiming for service innovation or device upgrades. The more data are collected from users, the more information will be available for designers considering different use scenarios for service innovation to motivate users' physical activation.

Conclusions, further research and limitations

Our study introduced a process model of user engagement with self-tracking applications where every user goes through four stages—review, react, reflect, and respond—when observing results and engaging with performance data. The user engagement process differs depending on whether results are satisfactory or unsatisfactory. The findings revealed that users respond with tactics such as dismissal, procrastination, intentional neglect, and selective attention when they encounter unsatisfactory results. Since our findings involve user reactions to performance data about themselves, we argue that the proposed user engagement process, as well as the response tactics, are generalizable to other activity tracking applications, such as smartwatch applications. Thus, the findings of our study open up a number of avenues for further research into related areas, where data about the self is involved.

The proposed process model offers evidence that user engagement is a complex process that needs to be investigated through longitudinal studies to better understand its underlying stages. Accordingly, future studies can adopt a longitudinal research approach and examine specific trajectories of user engagement with activity tracking applications to reveal, for instance, how a particular response to performance data may influence the future engagement process or how the level of engagement changes over time in relation to satisfactory or unsatisfactory results. For example, reduced user engagement could be the outcome of a response tactic to persistent unsatisfactory results, or it could be the development of habitual behaviour, where the user can easily attain satisfactory results. Another research topic involves the application of the proposed process model to study users who interchangeably observe satisfactory and unsatisfactory results and investigate how the different responses influence engagement in the long run. Related research could look into how engagement paths can shift from low engagement to high engagement, and the subsequent change in user behaviour.

Activity tracking applications have other features designed to motivate physical activity; their interactions with users should be investigated by drawing on perspectives such as the affordance lens (e.g., Benbunan-Fich, 2019) in relation to user motivation (Jarrahi *et al*., 2018). These studies would provide further insights into how designers can stimulate engagement along the process, especially when the user experiences negative results. Moreover, future research on users with different motivations is warranted to support or contrast the generalisability of our finding that differences in motivations for using activity tracking applications do not influence user engagement with performance data through a four stages process.

We identified a number of response tactics observed as a part of user engagement when the user is met with unsatisfactory results. These tactics should be further investigated in other self-tracking applications, e.g. food-related, mood-related, and especially health-related, where the effects could be more prominent and may lead to service discontinuance. Both experimental studies, testing the efficiency of specific interventions by the service provider to alter response tactics, and longitudinal studies, to see their long-term effects in user engagement, are required. Further, studies choosing user groups with similar motivations and needs would allow researchers to test whether social pressure or other forces alter response tactics and influence the user engagement process.

The study has certain limitations, as we focused on user engagement with performance data but did not investigate users who are not engaging with the data. We also investigated only two types of wearable devices that collect activity tracking data about physical activities and sleep. Another limitation is that the study did not focus on user groups in which social pressure and other factors could influence user engagement and response tactics. Finally, cultural differences were not taken into account, and further research in this direction could generate useful insights.

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Figure 1: Data Analysis process

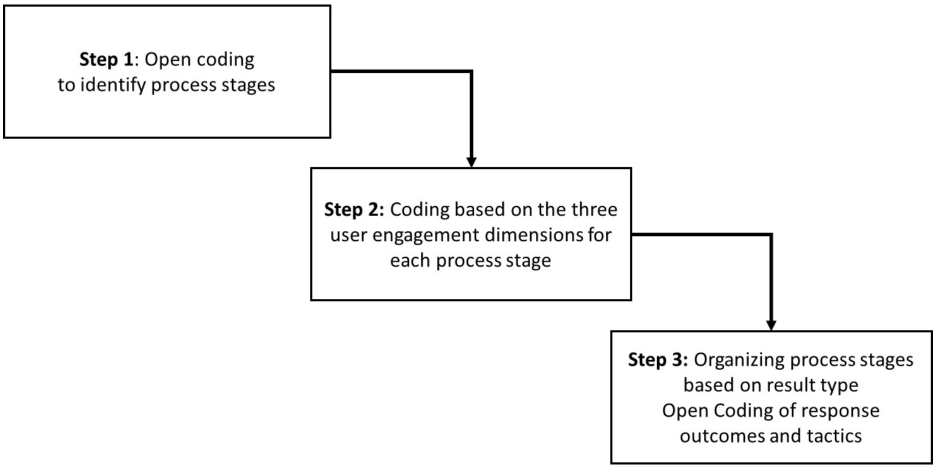

Figure 2: A Process Model of User Engagement with self-tracking Applications

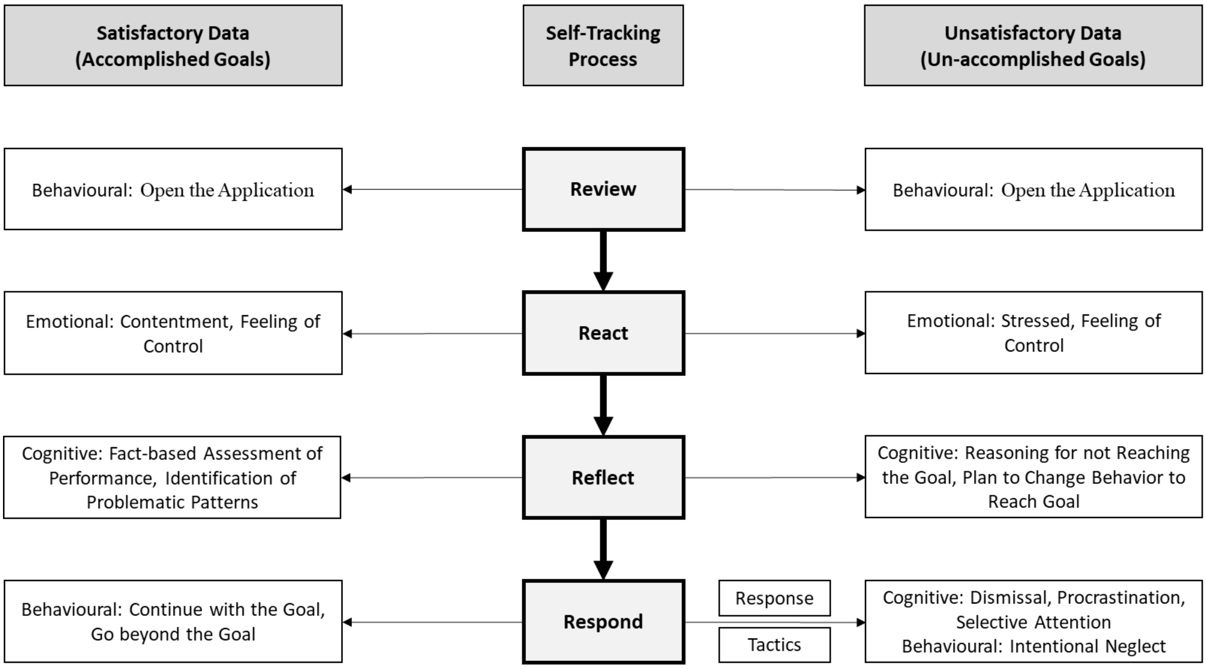

Table 1 Users' response tactics when they encountered unsatisfactory results

Response Tactic	**Definition**
Dismissal (cognitive engagement)	Users do not acknowledge the information provided by the application when a goal is not met.
Procrastination (cognitive engagement)	Users make plans to meet the goals in the future.
Selective Attention (cognitive engagement)	Users focus on more achievable goals and favour categories where they performed well.

Intentional Neglect (behavioural engagement)	Users only respond to results expected to be satisfactory, and avoid data representing unsatisfactory results.

Appendix

Comparison between Fitbit and Jawbone UP

Features/ services	**Fitbit Flex**	**Jawbone UP**
Step tracking	x	x
Sleep tracking	x	x
Food tracking	x	x
Mood tracking	x	x
Wristband display (no screen, colored signals when reaching goal)	x	
User owns personal data	--	x
Premium membership scheme	x	--
Social network	x	x
Bluetooth	x	-- (*)
Compatible with Android	x	x
Water resistant	x	x
Battery life > week	x	x

X = feature supported, -- = feature missing,

(*) this feature was added in the second version of the wristband

Table A: Examples of data coding and analysis

Quotes	Sub-themes*	User Engagement Dimension**	Themes*
'The Jawbone is quite simple. It put things into graphs so you can see things instantly so you don't have to sit and load that specific data. That makes it easy to see what's good and what's bad regarding you work out' (Male 23, student)	Monitoring data	Behavioural	**Review**
'I would look at the percentages that I have reached out of my goals. And how far I am from my goals from today. That's the first thing. And then I usually flicker down to see what others have done' (Male 29, account manager)			
'I would open the app, I would go in, I would look at the bars and then I would go in and tag activities that I did during the day. For example, if I would go into the gym I would tag those and put in what I did. That's basically what I would do' (Male 29, account manager)			
'numbers in the bar chart. That's absolutely the most important thing that I follow up on when I open the app' (Female 30, marketing manager)			
'the graphs that appear on the first page. I would click on them sometimes, but not always' (Male 29, account manager)			
'I would look at the home page and the two bars. Then I would look at weekly trends, daily trends. I would click in on the bars. Calories burned were never really interesting. I was mostly interested in steps. I would look at number of steps registered. Then I'd probably zoom out and look at weekly trends and across a couple of weeks' (Female 29, account manager)			
'Once or two times a day, usually when I sync it'(Male 23, student)	Data check in regular intervals	Behavioural	
'On average, twice a day. So I normally did it in the morning and I did it during the afternoon' (Male 29, academic degree)			
'Maybe 2–3 times per day. It's usually in the evening when I can see a full account of how many steps I have taken. Also in the morning to check how my sleep has gone' (Female 25, nutritionist)			
'Usually in the evening, I check how far I've gone during the day' (Male 45, teacher)	Data check in the end of the day	Behavioural	
'usually closer to the evening time because I want to see how many steps are left, like if I am close to my goal or if I am far away so 'so I need to walk a little bit more or exercise or something like that. So around 5 pm–6 pm' (Female 30, business analyst)			
'I always check the app in the afternoon for a status update. It is at that time I upload my data and see whether or not I have reached my goal for the day' (Female 47, administrator)			
'I checked every day but then after some time, like a few weeks, I stopped checking so often' (Male 29, entrepreneur)	Decrease in Data check activity	Behavioural	
'At first it would be every day, a couple of times a day, but then it would be around once every third day or so' (Male 29, marketing creative media)			
'I stopped checking so often. I kind of knew what was going on, and I got a little bored' (Male 29, entrepreneur)			
'It is a form of internal control. It is journal, a diary of behaviour. Behaviour can be adjusted and getting insights about behaviour … I have always had a certain control need and a wish to go back and check data to see how I've done with the goals I've intended to reach' (Female 25, nutritionist)	Feeling of control	Emotional	**React**
"I like spot checking … when you use a Fitbit, then you can see the steps moving as you move. It's very self-reinforcing!' (Male 36, PhD student).			
Satisfactory results ***			
'was a good feeling when you were reaching a goal' (Male 29, account manager)	Feeling positively	Emotional	
'Happy, refreshed, alert, good' reaction (Female 26, store clerk)			
'It makes me feel I'm a good person. An active person taking care of my health' (Female 26, digital manager)			

‘I’m happy when I’ve reached my goals, especially when I have far outreached my goals’ (Female 30, geologist)			
‘it’s when I go way beyond that I’m happy’ (Female 35, researcher)			
‘a stronger sensation than reaching your goal’ (Male 27, lawyer)			
‘It’s a little victory when you do well but it’s completely ridiculous, because it’s just your steps …. nobody can alter it or fake it: you've done those 10,000 steps and that’s a good feeling. So you kind of feel like “I've done good today”’(Female 28, researcher)			
‘affect me for two seconds but not long term effects’ (Male 29, entrepreneur)	Brief positive feeling	Emotional	
‘I feel satisfied at least. For me it doesn’t really last long, just for 5 min. Not even excitement but just, “Ok, I did well”’(Female 29, designer)			
Unsatisfactory results*			
‘very stressed from looking at my data, when it was bad’ (Female 27 consultant)	Feeling negatively	Emotional	
‘disappointing’ (Female 29, designer)			
‘it annoys me’ (Male 27, lawyer)			
‘A little irritated actually. It makes me feel lazy and I feel self-conscious about it’ (Female 26, store clerk)			
‘If I’d look at it more often, I’d just get stressed and feel that I have to perform more’ (Male 29, researcher)			
‘when I see that someone has totally surpassed their goal and I feel like “Oh god, I’m so lazy”’ (Female 29, project manager)			
‘I’m not that good at planning, so the Jawbone sets up some goals you have to reach and it’s quite annoying if you don’t reach them’ (Male 23, student)			
‘It made me more knowledgeable about myself’ (Male 29, account manager)	Self-awareness	Cognitive	**Reflect**
‘keeps me accountable’ (Female 29, project manager)			
‘a type of consciousness. I’m just conscious of what I am doing’ (Female 30, business analyst)			
Satisfactory results*			
‘I feel that internal competition, it's like when I run. I need to improve my results every time.’ (Female 47, administrator)	Positive self-assessment	Cognitive	
‘with Jawbone you are competing with yourself, which is the worst because if you go down you get angry with yourself’(Male 23, student)			
‘It was especially cool to see when you overpassed your previous goals: ‘today I played badminton this hard’. Good feeling. That’s cool. Because you are kind of fighting against yourself’ (Male 29, account manager)			
‘If I wasn’t able to track these things I would have absolutely no idea whether I was way doing the right amount or way over, and if I reached the right amount it would be pure luck’ (Male 23, student)			
‘You can get some statistics on yourself, so it’s not just the feeling of ‘I’ve done something this day’, but I can actually see that I’ve done something. It’s a little more factual, as you can prove it’ (Male 23, student)			
Unsatisfactory results*			
‘I really start to beat up myself about it. So I’ve definitely gotten down on myself. Especially if it’s two days in a row for some reason. Even if it is one day where I am on a good track and hitting my goal and [then] one day short, [I feel] disappointed, like you weren’t good enough’ (Female 29, project manager)	Negative self-assessment	Cognitive	
‘It makes me think. It does affect me. Makes me think of how I can improve. I would be upset if it would be continuous’(Female 35, researcher)			
‘So I go to analyse why I was more sluggish, I try to look at that day and to know not to have more days like that’(Female 35, academic degree)			
‘seeing how little I actually move when I am in the office. I mean, I spend a lot of time there and when you can see that you are only getting 2000–3000 steps in a day it’s really a little scary. You should be moving more!’ (Female 28, researcher)	Accepting the facts/reality	Cognitive	

'this is just not good enough [then] there is a contemplation about why I haven't reached the goal' (Female 25, nutritionist)			
'it was interesting to see how little I actually move when I'm at work. I felt a bit bad over that. It was a bit shocking' (Female 28, pharmacist)			
'I can always keep an eye on how much I actually burn and how many calories I take in… I don't take it as a defeat when I don't make it to 10,000 steps. More like a goal that I should reach. It still motivates me' (Female 45, housewife)			
'If I don't reach my goals, yeah, I kind of think about it. But then I just think that I'll do something about it the next day instead to get the steps. I guess it's important to get a good average' (Male 45, teacher).			
Satisfactory results*			**Respond**
'I increased the default step goal'(Male 29, academic degree)	Increase of the daily goal	Behavioural	
'My goal was at first 10,000 steps and I would make an effort to reach that. I quickly found out that I got a little lazy once I had reached my goal so I put it up to 12,000 steps... and once I had reached that a bunch of times then I set it up to 15,000 steps per day' (Female 26, store clerk)			
'My goal was at first 10 000 steps and I would make an effort to reach that. I quickly found out that I got a little lazy once I had reached my goal so I put it up to 12000 steps... and once I had reached that, a bunch of times then I set it up to 15000 steps per day' (Female 26, store clerk).			
'… I went with the recommended values but after a while I realized that I am moving more than what they recommended so I upped the amount of steps…to push myself beyond my limits' (Male 29, account manager).			
'before I went to bed I checked the data, it'd say how many steps I needed to reach my goal - and then I'd go out for a walk. I felt that I needed to finish it every day' (Male 29, researcher)	Provide extra effort to meet the daily goal	Behavioural	
'I went out for walks. I did that every time I hadn't reached my goal' (Male 29, researcher)			
'When you were not reaching a goal sometimes you were ok with it, sometimes you were like "No, I'm going to go for a walk now"' (Male 29, account manager)			
'My lifestyle pattern has changed. I'd never ever go all these extra walks if it wasn't for my Jawbone goals' (Male 29, researcher).			
Unsatisfactory results			
'did not have the possibility to change it, because you do not have more time in the course of a day, just because you now know that you are not moving enough' (Male 23, student)	Dismissal	Cognitive	
'I couldn't have changed that anymore because of my lifestyle' (Female 28, account manager).			
'I know I can't reach the goal because I was in the office in a meeting all day ' (Male 30, entrepreneur).			
'I don't really care that much about the daily goals' (Male 23, student)			
'It doesn't really mean much' (Female 30, business analyst)			
'It just told me that I was exercising various levels depending on my work schedule. It didn't really help me exercise more or become fitter, to be honest, so I didn't see the need in wearing it anymore' (Female 29, account manager)			
'I know I can't reach the goal because I was in the office in a meeting all day' (Male 30, entrepreneur).			
'The days I don't reach my goals, it all depends on how far off my target I am. If it's only a few steps then I don't mind'…If I know the reason I haven't reached the goals, then I don't mind' (Female 25, nutritionist).			
'I could perform much better if the dietary functioning was better' (Male 23, student).			
'[it] really annoys me that the device can't understand that you are lifting weights … I've had sessions where I'm almost throwing up and it only shows you had a little bit of activity. Then I would just look away from it' (Male 27, lawyer).			
'I need to move more tomorrow' (Female 28, designer)			

‘I would be disappointed that I didn’t get further and I guess it made me walk more. I would make more effort the next day. It got me to put my shoes on’ (Male 29, marketing creative media)	Procrastination	Cognitive	
‘I can't change the past anymore so I just see it as a way to get an overview of my behaviours and maybe change them in the future but not thinking about the past’ (Male 29, designer)			
‘I know that with myself that if I walked 4,500 steps one day, I knew I wouldn't allow myself to walk any shorter distance the next day. So for me it was a great way of keeping motivation up and to keep pushing myself’ (Male 29, account manager)			
I'm thinking then you just pull yourself together tomorrow’ (Male 23, student).			
I have considered whether it wouldn't be a great idea to take a little evening walk when you have not achieved your own goal. But I haven't really done it yet’ (Male 23, student).			
‘I will probably deliberately miss my goal, or know I haven’t made it, half of the time. Maybe half of the time, I will do something about it. Like twice a week I will aspire to do something about it’ (Female 29, designer).			
‘You can switch up what you look at in the dashboard, so you can prioritize and see what you primarily look at up top. That thing with how much I’ve lost and how far from my goal I am, I keep that at the bottom, I don’t even look at that’ (Female 45, housewife)	Selective attention	Cognitive	
‘I try to look at the stuff I’m good at, instead of bad stuff’ (Male 26, student)			
‘I know that I will do well on [stairs]. Stairs are thus important to me. It gives me a boost’…[it is] what I will look at most.’ (Female 28, researcher)			
As long as I ran instead of lifting, I could measure how much I ran. It ended up being that I would rather run than lift because I wanted the result to look as good as possible’ (Male 29, account manager).			
‘I don’t think I really follow it. I’m just using it for fun so I don’t react. It would totally be different if it recorded when I go to yoga’ (Female 27, assistant professor)	Intentional neglect	Behavioural	
‘every two days. Especially, I check when I do sports. Then I want to see my data, but if I don’t do sports I tend to not look at it, because I feel guilty’ about not doing sports (Male 27, lawyer)			
‘I don’t want to feel like I don’t conquer the new goal. I think it’s just my own mental sort of thing, that if I create new goals I am not going to achieve them and be disappointed in myself’ (Female 29, project manager)			
That is also one of the reasons I haven’t been using it lately. I sometimes got upset about the fact that I couldn’t always achieve my goal’ (Female 27, student).			
maybe my goal is too high, maybe I should lower it to 9,000, but I would feel like a wimp’ (Male 35, researcher).			
‘I never reach my calorie count even though I go on a 10km run. It never comes up there’(Female 28, researcher).			

**Data coding and Analysis Step 1, **Data coding and Analysis Step 2, ***Data coding and Analysis Step 3*