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Article

Motivation and User Engagement in Fitness Tracking: Heuristics for Mobile Healthcare Wearables

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Abstract: Wearable fitness trackers have gained a new level of popularity due to their ambient data gathering and analysis. This has signalled a trend toward self-efficacy and increased motivation among users of these devices. For consumers looking to improve their health, fitness trackers offer a way to more readily gain motivation via the personal data-based insights the devices offer. However, the user experience (UX) that accompanies wearables is critical to helping users interpret, understand, gain motivation and act on their data. Despite this, there is little evidence as to specific aspects of fitness tracker user engagement and long-term motivation. We report on a 4-week situated diary study and Healthcare Technology Self-efficacy (HTSE) questionnaire assessment of 34 users of two popular American fitness trackers: JawBone and FitBit. The study results illustrate design implications and requirements for fitness trackers and other self-efficacy mobile healthcare applications.

Keywords: fitness tracking; mobile healthcare; user engagement; motivation; self-efficacy; wearable technology; mHealth heuristics

1. Introduction

Mobile and wearable devices are a useful platform for the delivery of health behaviour interventions. Mobile health applications for fitness tracking are promising tools for engaging and motivating users in their own fitness levels -health care, because most people own and regularly use a smartphone, and mobile health (mHealth) can be an appropriate medium for delivering health-related information and self-knowledge [1–4]. The topics of exercise, fitness and wellbeing have gained increasing interest in the HCI community [5] with emphasis on designing technologies and tools to encourage people to engage in fitness and physical activity [6–11]. Current estimates suggest that there are approximately 40,000 mHealth applications [12]; however, there is little evidence for which precise factors contribute to user motivation and self-efficacy. Understanding these factors can help, designers understand how best to transfer the benefits of fitness tracking engagement to other consumer health applications.

This study leverages Self-determination theory (SDT, [13–15]) to detect motivational criteria in the design of user engagement for fitness tracking and mHealth apps. Guided by this theoretical approach, our research consisted of an in-depth global online diary study with 34 experienced Fitbit and Jawbone fitness tracker users who provided diary logs twice weekly over a 4-week period. The diary logs (open and context/usage collection data) measured reported motivation and self-efficacy over time, to determine what aspects of motivation were impacted by user experience factors or attitudes toward

Healthcare Technology Self-Efficacy (HTSE) [16]. The HTSE instrument was administered at the conclusion of the study and correlated to the results of user diary entries. In addition, throughout the data collection period, participants were instructed to communicate with our researchers to share photos of what aspects of the mobile tracking apps motivated them. An email exchange allowed researchers to gain context around responses, perceptions and reported data.

The goal of our diary study was to isolate motivational and engagement factors inherent with fitness tracking participants, across time. We propose a set of mhealth heuristics, based on research insights and analysis. The results of a study combining qualitative and quantitative data to address the following questions:

- What is the impact of self-efficacy and health technology factors on users' attitudes toward mobile fitness tracking apps?
- Which specific areas of UX directly impact motivation and self-efficacy?
- What are the design implications and requirements to improve fitness trackers and other m-health applications?

The contributions of this research to mHealth apps can be summarized as follows: (a) understanding what impacts user motivation in terms of self-efficacy; and (b) a general set of mHealth UX heuristics ready to be used with wearable applications for fitness and consumer health technologies where user motivation and engagement improve self-efficacy.

We begin with an overview of UX and fitness tracking apps, including details of the research study. The methodology section focuses on the situated online diary study and instruments used to collect user responses. The findings section is described next with quantitative results presented first followed by qualitative insights. After that, UX design propositions are described as well as future lines of work to be carried on mobile self-efficacy; and concluding remarks are discussed in the final section.

2. Fitness Tracking, UX and Self-Determination Theory

Commercial activity trackers for fitness, such as Fitbit, Polar, Apple Watch, Samsung Gear Fit, and Jawbone are increasingly popular with an estimated 19 million "connected wearables" purchased in 2014, compared to 5.9 million in 2013 [17,18] and substantial increase by 2019 [19]. Fitness tracking and wearable applications collect a broad range of data such as levels and quality of movement, sleep, steps taken, heartbeat, breath quality, water consumption, and even meditation and mood monitoring. In general, users use them to get feedback on movement, sleep and food. At the same time, some reports point out that approximately one third of devices are not used after a period within 6–12 months [20]. Specifically, [21] found that 50% of users who adopt a Fitbit, abandon it within the first two weeks of use, whereas [22] found that 62% of users who downloaded an activity tracking mobile app stop using it within the first two weeks or at best within six months after purchase [23]. In one of the few studies investigating the reasons for abandonment, [24] outlined barriers to engagement by reflecting on common user workarounds with an emphasis on tracking accuracy and rewards, social comparisons, and application customization. All users in our diary study were motivated, engaged fitness tracking consumers, and we did not study users who discontinued using their devices.

The majority of these wellness wearables provide users with immediate feedback and information associated with a variety of metrics related to broad goals, for example, step count, calories burned, stairs climbed, distance travelled, active vs. passive activity and sleep cycle and length. Some applications also offer users the ability to interact with and compete with others via "Duels" or social UX features, though social features do not always align with user motivation and intention [25,26]. Regardless, wearable devices and mobile apps have vast potential to enhance motivation and fun [27], and sustained engagement in everyday life [28]. In a recent study, [29] compared real-life experiences of 133 users of three popular wearable activity trackers: Fitbit, Jawbone Up and Nike+ Fuelband. Utilizing need fulfilment as a theoretical lens, the study revealed that UX is driven by the needs of *physical thriving* or *relatedness*. Moreover, activity trackers appear to enhance users' *feelings of autonomy* or *experience of relatedness* towards a healthier lifestyle and well-being.

Self-efficacy and motivation are central to user engagement in mHealth, with most of the studies highlighting principles from social cognitive theory (SCT) and cognitive behavioral theory (CBT) and their value to mHealth apps [30,31]. For example [32], describe a theoretical-based toolkit to support self-motivation and requirements for the design of rehabilitation technologies. At present, there is a keen interest to understand the elements that contribute to effectiveness of such apps [33,34]. With regard to feedback and user engagement mechanisms, [35] conducted one of the few in-the-wild studies to examine the long-term value and design of devices for monitoring fitness activities. As part of the respective study, 30 users adopted wearable activity-tracking devices of their own preference and had continued to use them for a total period of 54 months. The purpose of the respective study focused on the ways in which *metrics*, *data*, and *social networking features* provided by the devices influence people's *engagement* with their personal fitness goals and aims.

SDT is a suitable framework to collect and assess data related to motivation or persuasive design in software or mobile applications. According to SDT tenets, there are three needs that must be satisfied for intrinsic user motivation to be high: *autonomy, competence, and psychological relatedness*. SDT finds increasing acceptance and application as a fruitful approach to the study of interactive systems, e.g., to the motivational psychology of video games [36–38]. In our study, the concepts of autonomy, competence, and relatedness correspond to the user's perspective when interacting with fitness tracking applications, and provide the primary structure for analyzing the data and explaining the study findings.

Design requirements and recommendations for trackers have also been developed, early on by [39] and more recently by [34], however, these cannot easily apply to fitness tracking mobile applications or more generally to consumer health applications. Even more importantly, the benefits of mobile applications to effectively monitor and manage overall health are also challenged see [40] for sleep tracking apps due to low accuracy performance and limited supporting information/feedback provided to users. For instance, [34] point to critical UX issues of interest to human–computer interaction (HCI), including the design and everyday experience of activity trackers; wearability, user interface design, and interaction displays conveying data and information to the users. The study findings highlighted device capabilities for searching, analyzing and measuring on-screen data and information, when meeting specific user goals or milestones.

3. Methods and Study Design

Based on the discussion described in the previous sections, we explore self-efficacy and user motivations for fitness tracking mobile applications and their impact on UX, that are supported in a theoretical framework. To this end, we conducted an in-depth diary study [41] with experienced users of two popular fitness tracking applications: Fitbit and Jawbone. Specifically, each participant completed the study over a period of 4 weeks, involving 8 total online surveys sent at the beginning and end of each week, followed by the Healthcare Technology Self-efficacy (HTSE, [16]) questionnaire addressing both general motivational; self-efficacy and mobile wearable healthcare technology specific factors per [42], as well as earlier research by [43–45].

All items adapted from previous published studies with minor modifications in wording to fit into healthcare wearable device fitness context. Each item of the HTSE questionnaire was measured on seven-point Likert scales with 1 being 'strongly disagree' to 7 'strongly agree'. We invited two usability and healthcare professionals to examine the logical consistency, terminology, contextual relevance, and question clarity of the measurements. In addition, a pilot study with three users was conducted for collecting more feedback to improve the study design. The comments and suggestions from experts and the analysis of data collected from pilot study lead to minor modifications of the questions, including formatting of the questionnaire, and clarity for the items. We launched the main study after finalizing the questionnaire (see Appendix A).

The online diary study was carried out between March and April 2016 for a total of 34—Fitbit (17 users) and Jawbone (17 users). We recruited half who used their device for 12 months or less, and half over 13–24 months. Willingness to provide written informed consent and having the ability to communicate in English was also required. During the recruitment period, potential participants were provided with details of the study and screened to determine interest and eligibility to participate in the study. During recruitment, we also explained that all study activities were confidential and would not share their identity or other private information outside the diary study session.

Participants were encouraged to regularly track their data, capture screenshots of the applications and send feedback. Topics covered: reasons for wanting/using an activity tracker; reasons for choosing their specific one; physical activity habits and transport regime; activity tracking and barriers; motivation or demotivation concerning sustained use, needs and desires; impact of content that prompts motivational behavior, support for a personalized UX. Data from participant diaries were recorded, transcribed and thematically analyzed. The survey also included demographics, details of trackers used (e.g., type, ownership length) and specific questions which assess user motivation, reasons and barriers to motivation, quitting behavior and activity report for each week. Survey and questionnaire data were used to support qualitative and diary data analysis by providing comparable measures of physical activity, motivation—efficacy levels, and barriers for Fitbit and Jawbone use, respectively.

4. Findings

Thirty-four participants (13 females and 21 males) recruited globally (e.g., Kenyan, Brazilian) with the majority based in the U.S., took part in the situated diary study. Potential participants were recruited through Experience Dynamics, Inc. Participant Database, which called for current 100% active users of Fitbit or Jawbone devices. Eligibility criteria included being adult users of either Fitbit or Jawbone, and owning and using an activity tracker for more than a month. All participants were dedicated users of the device—they wanted to be using it (intrinsic motivation for use), though several reported receiving healthcare incentives form their employers for continued use of the device. Detailed demographics of study participants are presented (see Table 1).

Table 1. Demographics of diary study participants (n = 34).

Participant Demographics	Frequency	Percentage Frequency
Gender		
Male	21	61.76
Female	13	38.24
Age		
18 to 29	9	26.47
30 to 39	8	23.53
40 to 49	13	38.24
50 to 59	3	8.82
60 and over	1	2.94
Education		
High school	2	5.88
Some college	6	17.65
Bachelor's degree	13	38.24
Master's degree	10	29.41
Doctorate	3	8.82
Other	0	0
Computer experience		
None	19	55.88
Very little	11	32.35
Average	4	11.76
Quite extensive	0	0.00
Very extensive	0	0
Health technology experience		
None	10	29.41
Very little	13	38.24
Average	8	23.53
Quite extensive	3	8.82
Very extensive	0	0

Participants' ages ranged from 18–60. The majority (n = 31) had bachelor's and/or master's degree, and 3 a doctorate degree. Participants were rewarded with a $50 gift card for their participation. Participants tracked with Fitbit Flex model, and Jawbone UP. The most experienced participant reported having used a tracker for almost 3 years, while the least experienced had used it for one month. Over half (n = 28) reported using their tracker for more than 6 months. The majority of participants reported using other personal wellness tools in addition to activity trackers, including food journaling tools like MyFitnessPal and sleep tracking tools, such as Sleep Cycle. The analysis of diary study data and feedback was developed based on the SDT framework described earlier in this paper. The quantitative data were entered into STATA (version 13.0) statistical software for further analysis, respectively.

4.1. Descriptive Statistics

The majority of participants reported fitness tracking applications and devices to be useful for their motivation and behavior: enhance their motivation and willingness to undergo change in their fitness activities. We utilize Ordinary Least Squares (OLS) with robust standard errors regression (multicollinearity was not a problem as indicated by variance inflation factors (VIF) values) to explore the impact of the independent variables on the main dependent variable: attitudes towards health technology (AHT) for mobile fitness tracking. The dependent and the independent variables have been created by taking the mean values of the respective questions in the questionnaire answered by the participants.

The descriptive statistics of the study participants are described in Tables 2 and 3, respectively. Specifically, the following questions are included: application check (Did you look at your Jawbone app today?), access (How did you access Jawbone or Fitbit data in the past 48 h?), motivation (When looking at Jawbone data for the past 48 h, I feel), change (Did looking at your Jawbone data change your fitness activities since the last time you used it?), feeling (What is your overall feeling about the Jawbone data in the past 48 h?), and use (How long have you been using your Jawbone?) over 8 time periods (see Table 2).

Table 2. Means and standard deviations of diary study participants questions by application (n = 34, Observations = 272, 8 time periods, 2 applications).

Application	Check	Access	Motivation	Change	Feeling	Use
1 (Jawbone)	136 1.25 0.434614	136 1.470588 0.6433843	136 1.551471 0.5940427	136 1.47059 0.61993	136 1.316176 0.526374	136 2.772059 1.366081
2 (Fitbit)	136 1.073529 0.261968	136 1.455882 0.7969167	136 1.375 0.5434799	136 1.28677 0.45392	136 1.264706 0.611438	136 3.044118 1.327028
Total	272 1.161765 0.368914	272 1.463235 0.7229306	272 1.463235 0.5751058	272 1.37868 0.55006	272 1.290441 0.570024	272 2.908088 1.351099

Table 3. Means and standard deviations of diary study participants Healthcare Technology Self-Efficacy (HTSE) questions.

Variables	Obs	M	SD	Min	Max
General Self-efficacy (GSE)	34	5.85	1.11	2.85	7
Computer Self-efficacy (CSE)	34	4.20	0.63	2.66	6
Health Technology Self-Efficacy Technology (HTSET)	34	4	0.98	2	7
Health Technology Self-Efficacy Services (HTSES)	34	4.9	0.76	3	5.75
Health Technology Self-Efficacy Web (HTSEW)	34	6.19	1.10	3	7
Attitude toward Health Technology (AHT)	34	4.6	0.93	2.2	7

Moreover, we included means and standard deviations of the following variables adopted from the health technology self-efficacy (HTSE) questionnaire (see Table 3), namely general self-efficacy (GSE); computer self-efficacy (CSE); health technology self-efficacy technology (HTSET); health technology self-efficacy service (HTSES); health technology self-efficacy web (HTSEW); and attitudes towards health technology (AHT) modified for mobile fitness tracking.

4.2. Regression Analysis

A series of Regression analyses was conducted to explore whether self-efficacy and health technology specific-factors predict participants' attitudes toward mobile fitness tracking health technology. Moreover, we have used demographic information: gender, age, education, computer and health technology experience, respectively as control variables in the analysis. As can be seen in Table 4, health technology (Beta = 0.82, t = 6.53, p < 0.001) and health technology web-specific (Beta = 2.44, p < 0.002) factors levels explain a significant amount of the variance of attitudes towards mobile fitness tracking applications (F(10,23) = 123.83, p > 0.42, R^2 = 0.88).

Table 4. Linear regression model output for total sample of app 1 (Jawbone) and app 2 (Fitbit) participants.

Linear Regression Pooled Sample			Number of Obs	34
			F(10,23)	123.83
			Prob > F	0.0000
			R-squared	0.883
			Root MSE	0.38331
ahtmean	Coef.	Robust Std. Err.	t	$p > \|t\|$
htsewmean	0.248521	0.1018679	2.44	0.023
htsesmean	−0.03859	0.1344125	−0.29	0.777
htsetmean	0.828799	0.1270088	6.53	0.000
csemean	−0.00638	0.1935011	−0.03	0.974
gsemean	−0.06686	0.0939272	−0.71	0.484
Gender	0.114468	0.1513021	0.76	0.457
Age	−0.13972	0.0813213	−1.72	0.099
Education	0.024962	0.0947295	0.26	0.795
Computer experience	0.06789	0.1188585	0.57	0.573
Health technology experience	−0.10158	0.0988504	−1.03	0.315
_cons	0.542199	0.6659611	0.81	0.424

The results highlight that participants who have reported higher levels of self-efficacy when using health web-technologies specific apps believe that the use of fitness tracking would improve their well-being and general health quality levels. The qualitative analysis provided further insights that complemented and expanded the questionnaire study results.

4.3. Qualitative Data Findings

We recorded and transcribed the participants' notes and feedback from a special email account set up to communicate with the researcher, and analyzed them together with the diaries. During the analysis, we focused on the issues participants noted as part of their motivation in using the applications. Moreover, we sought to evaluate users' perceptions of satisfaction of autonomy, competence, and relatedness tracking, managing, visualizing, and using their data and feedback provided by the application. Fitbit and Jawbone participants reported walking as their main activity (80%) with a secondary or third activity (e.g., Weights, Yoga, Cycling) conducted by 40% of participants as a default activity. The focus on walking is likely to do to the fact that these trackers make gamification easiest with reaching the daily 'Step Goal'. Specific factors which impacted user motivation were as follows (a) Seeing if I met my goal (movement/sleep/calories count); (b) Look and feel good, improve mood and avoid sitting; and (c) Getting tips and recommendations from the app (Fitbit offers self-interpreted data, while Jawbone offers data interpreted by a SmartCoach).

From a UX point of view, using the application to work on a personal health or wellness issue (e.g., sleep, weight, mobility) is a driver for believing in the motivational power of the device as the following user quotes highlight:

> *"I can do exercise without Fitbit, but the actions would be less engaging with partial success—the feedback from Fitbit motivates and guides me to do better and keep going"* (USA).
>
> *"Each morning at look at the villages below and above my lodge to plan exercise and route"* (Kenya).

The apps provide users with an overview of their specific performance details and an overview of their general wellness; offering continuous positive reinforcement. The Dashboard enables users to both assess their level of competency (or self-efficacy) as well as their autonomy to better perform specific fitness activities. This is further supported by the overviews of motivating data (sleep, healthy eating, and exercise), that provide an instant "progress toward my goal" feature (see Figure 1). While the FitBit allows users to self-interpret, the Jawbone provides a rolling *interpreted summary and action recommendations as well as challenges* aka SmartCoach with trends and patterns of Steps and Sleep (toward a goal and average for that user's gender and age based on others data).

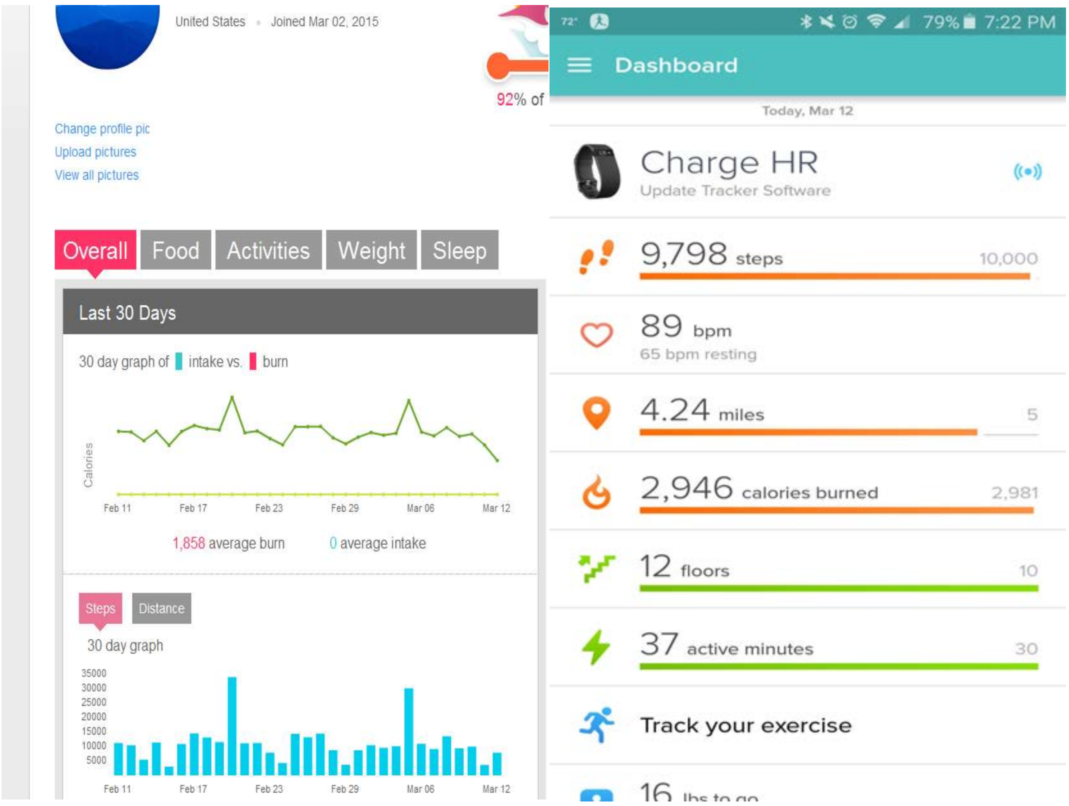

Figure 1. Fitbit screenshot of participant focusing on motivation metrics.

Users reflected positively on the use of the apps, with one user felt that the *autonomy-supportive style* was evident in terminology used. Users felt motivational value from seeing steps, styles and advice (Jawbone). User attitudes reinforced autonomy stating it made use of the device more engaging and positively influenced sustained or repeat use. Generally, users enjoyed the level of autonomy they were granted by the apps. However, some stated a need for apps to balance autonomy with more self-directed goal creation to support their engagement.

Participants regularly tracked their activity and habits and enjoyed the focus on goal fulfillment offered by Fitbit and Jawbone dashboards and email summaries (badges and praise). User's reported comments suggest, real-time percentage metrics to goal data is a powerful motivator for securing autonomy and competency of the activity tracked. Goal tracking seems to perpetuate motivation though it is important to note, fitness trackers do not make goal adjustment a dominant user experience (goals are typically defined at set-up and are too convoluted to alter over time—many users do not know they are "editable"). Attention to goal progress is highlighted by this user quote:

> *"This helps me try and use my Fitbit more and as much as I can, this only helps me to get better. The stats help me to see where I am in a bunch of areas - activity, sleep, food, calories,* etc. *These features are really inspiring and will help me to do better (USA)."*

Users reported using numerous *competence-supportive* strategies including affording users with the required skills, differentiation of exercise sequences, encouraging self-reflection, giving opportunities for receiving constructive feedback. These features include notes and comments, or competitions with other users, offering reflection on their own progress. Apps that can map users' awareness and their achievements allow them to provide targeted *competence support*. Fitbit users reported increased confidence and competence with using the app; however, they complained that they could not control the speed at which levels/sessions progressed. *Notifications* in the Fitbit app, and in Jawbone to a lesser extent - offers a component that allowed participants to track their progress and plan alternate or sustained activities, while reflecting on the impact of their actions. It can also be used for sustaining motivation over time: *'{It's a} nice, friendly reminder to keep me in check'* (quote by Fitbit user).

> *"I found that the sleep tracker really makes me want to sleep more and the fact that it is very accurate is quite good. Some days I wake up tired and never know why, but the Fitbit now tells me how much time I've been restless or awake, even if I am semi-conscious. I find that my reasons for being tired are really monitored well. Right now I'm having a very hard time sleeping so I know Fitbit will be tracking it as if I am awake!" (UK).*

Many users suggested a need to build trusting relationships with and between users, giving regular recognition and high-fives. Fitness tracker data is considered fun and often entertaining (JawBone SmartCoach uses some humor to cause self-reflection). Fitbit and Jawbone users expressed the need for relatedness with family and/or friends as they were interacting with the applications. A large number socialize their fitness data: 72% of Jawbone users said they shared their data (verbally) with others and 36% shared online. The majority of participants were motivated to interact with 'social' features, such as the FitBit Community or product Blog—feedback tips in order to *'learn more about my product and my fitness goals'* (quote by Fitbit user). In line with SDT, it appears that fitness tracking and health mobile apps users seek and remain motivated while satisfying relatedness needs.

> *"Really happy to see my weekly average of steps going up. Can't say that it is the prime motivator but it is NICE reinforcement!" (USA)*
>
> *"I have been a little stressed lately and my friend gave me these flowers to make me feel better and motivate me" (USA).*

In addition, participants were constantly checking the weeks' data to gain insight into the correlation between their fitness activities and wellness. However, both Jawbone and Fitbit did not provide an easy way to see trending or patterns to users, with a UX strategy that seems to focus on current fitness status data.

Although users generally felt motivated that they should be improving, FitBit did not provide *direction as to what users* should focus and improve upon. JawBone provided users with tips and hints as to how to respond to their activity tracking, but this caused more variability in their behavior over time (see Figure 2). FitBit users in comparison had more consistent motivation patterns over the 4-week reporting period.

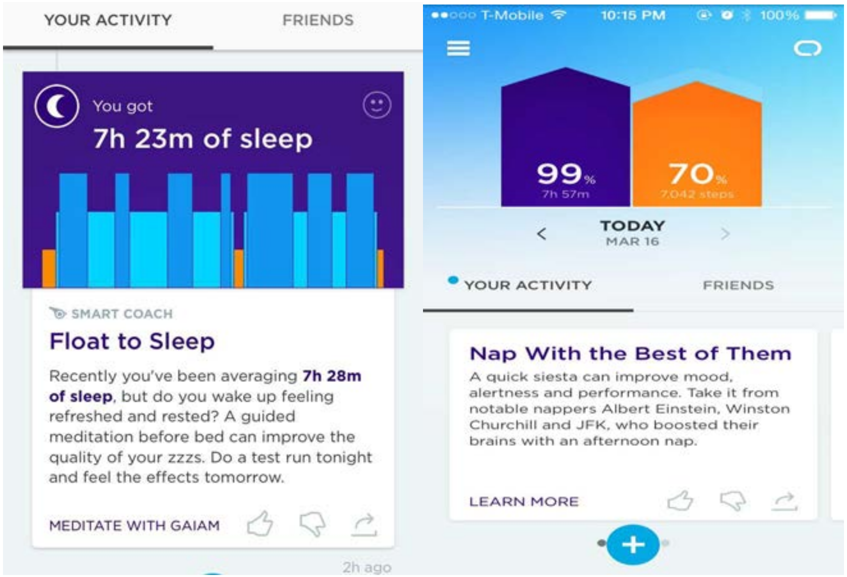

Figure 2. Tips and information provided by the app screenshot.

4.4. Summary

Overall, the findings revealed three key areas of UX that directly impact motivation and efficacy of users: data, gamification and content. In terms of *data* both devices seem to focus interfaces on statistics about movement and sleep. Goals are "pre-defined" meaning goals follow what the device can track, so goals are framed within the limitations of the UX. To change focus, a user has to manually define their own goals. Graphical visualizations are seen as useful, while Trend (mapping over time) interfaces are less usable and less useful for both devices. Fitbit users offered more praise to the desktop version of trending data with more manipulation of trend analytics. *Gamification* is primarily evidenced by real-time tracking and large infographic content of goals users are monitoring. Jawbone users have the added advantage of being coaxed with challenges by SmartCoach, which provides "challenges" to the user such as "go to bed earlier, at 11:30 p.m. tonight". Though as our 4-week diary study showed, motivation or reported behaviour change fluctuated, indicating that motivation is a dynamic and contextually driven phenomenon. Duels or competition (common in gamification) were evoked by a third or less of users, making fitness trackers primarily valuable for self-efficacy, not social cognition/motivation. *Content* is the most interesting centrepiece of self-efficacy and intention to adjust or change behaviour among users. What is clear is that motivational relevancy of content provided by wearables like the two chosen for our study, should support a users' immediate as well as overall intrinsic goals.

The majority of the participants reported STD principles of their exercise and use of app aligned with their exercise style and methods. Previous research suggests that providing action choice promotes self-determination and intrinsic motivation more than option choice. Further, the qualitative results highlighted the importance of combining *autonomy-support* with structure as participants felt uncomfortable when they were left to practice on their own with insufficient instructions. This study argues that exercise styles/UX which combine *autonomy-support* and structure are associated with improved learning, behavioural and motivational outcomes among users. It also highlights the importance of ensuring that UX interventions are able to help users balance these two SDT dimensions.

5. UX Heuristics for Fitness Trackers

In this section based on the participants' diary study insights and results yielded by our empirical work, we describe a set of plausible heuristics, intended as recommendations for the design of fitness tracking tools and mobile applications. Some general design guidelines are elicited from these results and a number of design implications to extend current approaches to fitness tracking of consumer health technology applications:

1. Level of personalization: Default goal-setting for most users/most occasions; let the user decide what is desirable without making necessary restrictions imposing a hinder for the desired outcome/activity performance level.
2. Navigation/input: Provide a starting point for personalization features; a clear way to show that there are options/further ways of personalizing single functions. Gamification of the process of navigating and personalizing is critical.
3. Positive Feedback: Provide feedback that motivation and/or self-efficacy level has changed through user-defined ratings and questionnaires; system to provide new goals based on the user reported or system-defined motivation level; *provide boundaries* for motivation and self-efficacy to support users in their activity and needs; expose users to positive and constructive feedback that seems to promote greater motivation—a finding contrary to [46] study.
4. Multi-activity motivation analysis: Users expressed a desire for features that enable them to better analyse relations between data/information—activities and motivation/self-efficacy behaviour, e.g., between sleep/diet and high or low motivation. Users may be able to categorize activities based on the motivation or self-efficacy improvements they see, as well as to explore behaviours that promote higher motivation or increased self-efficacy.
5. Context integration: Capturing reflections on life events and emotional [47] or social interactions during fitness tracking may be an important facilitator of motivation and self-efficacy. This can create an added sense of sociability [48] or social UX known to drive healing, motivation behaviour change in healthcare [49].
6. Provide intelligence to encourage more targeted behaviour change: Giving users a means to explore their gathered data to increase their self-efficacy and fitness levels, can make the experience more meaningful. Interpreted data can be helpful (like SmartCoach in the Jawbone app) but making sense of activity trends and patterns and tying those to "victories" or self-defined goals might improve self-efficacy.
7. Sustain user motivation by leveraging intrinsic motivation into a playful experience: Use game elements and small rewards to support different stages of self-monitoring; thus it is possible to meet user needs for autonomy, competence, and relatedness that support the development of intrinsic motivation [50].

This study demonstrates that usability and UX of consumer health applications can be enhanced by considering several individual trait dimensions including self-efficacy, motivation and usage patterns that facilitate interaction with mobile devices. Secondly, if we apply the finding that people have varying levels of healthcare IT self-efficacy and motivation, consumer health apps can be designed with this awareness; for instance, an app could include better management of goals/trends/motivational behaviours with descriptive content to guide users in their tasks. In this direction, research could also focus on post-adoption behaviour [51] *explicitly* including motivational and self-efficacy factors and their influence on the continued use of m-health apps. Future research is needed to understand the effectiveness of the proposed UX heuristics for mobile healthcare wearables from the design/evaluation of a fully-functional prototype for a mobile app and other consumer mHealth tools using this approach.

6. Conclusions

This research attempts to understand the complicated and context-sensitive topic of fitness tracking apps UX by examining the influence of user motivation and perceived self-efficacy during use. Our empirical analysis and findings demonstrate that users' motivation and self-efficacy are highly dependent on successful data, gamification, and content design of the apps as well as sensing context and providing appropriate motivational feedback to the user. The operationalization of the SDT framework in the context of mHealth applications can provide foundational guidance for future mHealth app design and development and UX guidelines that incorporate self-efficacy and serves consumer healthcare engagement.

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Appendix A.

Appendix Diary study questions

1. What did you do in the past 48 h?

Walking
training
Running/Jogging
Hiking
Team sports
Cycling
Nothing—I was too busy
Yoga
Other (please specify)

2. Did you look at your app today?

Yes
No

3. How did you access app data in the past 48 h?

Mobile (app on phone/tablet)
Desktop
Both phone and mobile

4. Have you ever owned another fitness tracker?

Yes
No
Other (please specify)

5. Do you know what model your app is? (Please state)

6. Which one did you own?

An older or different model
Other (please specify)

7. When looking at app data for the past 48 hours, I feel:

Extremely motivated
Somewhat motivated
Not motivated at all

8. What specifically is motivating to you in the past 48 h period?

Seeing how I rank (among others)
if I met my goal
information tips and suggestions
Other (please specify)

9. Did looking at your app's data change your fitness activities since the last time you used it?

Yes
No
Not sure

10. What is your overall feeling about the app's data in the past 48 h?

Good
Indifferent
Bad
Other (please specify)

11. How long have you been using your app?

1–3 months
4–6 months
7–12 months
13–24 months
2 years or more

Appendix Healthcare Technology Self-efficacy (HTSE) Questions

A. General Self-Efficacy

1. I can solve most problems if I invest the necessary effort.
2. When facing difficult tasks, I am certain that I will accomplish them.
3. I believe I can succeed at most any endeavor to which I set my mind.
4. I will be able to successfully overcome many challenges.
5. I am confident that I can perform effectively on many different tasks.
6. I feel insecure about my ability to do things. (R)
7. I give up easily. (R)

B. Computer Self-Efficacy

8. I have the ability to understand common operational problems with a computer.
9. I am very unsure of my abilities to use computers. (R)
10. I rely heavily on instructions and manuals to help me use a computer.
11. I am very confident in my abilities to use computers.
12. I find it difficult to get computers to do what I want them to.
13. At times I find working with computers very confusing.

C. Health Technology Self-Efficacy (Technology)

14. It is easy for me to use health technology.
15. I have the capability to use health technology
16. I do not feel comfortable using health technology (R) Adapted from
17. When using health technology, I worry I might press the wrong button and risk my health.

D. Health Technology Self-Efficacy (Service)

18. It is easy for me to receive service that uses health technology. Adapted from
19. I feel uncomfortable to receive service that uses health technology because the device can be risky. (R)
20. I am very confident in my abilities to receive service that uses health technology.
21. I would have difficulties receiving service that uses health technology

E. Health Technology Self-Efficacy (Web)

22. It is easy for me to use internet health services.
23. I feel uncomfortable to use internet health services. (R)
24. I am very confident in my abilities to use internet health services.
25. I would be able to use internet health services without much effort.

F. Attitude toward Health Technology

26. Using health technology is a good idea.
27. Using health technology may be harmful to my health.
28. Using health technology improve quality of my health
29. I believe that health technology is responsible for improving quality of healthcare.
30. Using health technology is risky.

Appendix Demographic information

31. Gender

    Male

    Female
32. Age

    18 to 29

    30 to 39

    40 to 49

    50 to 59

    60 and over
33. Education

    High school

    College

    Bachelor's degree

    Master's degree

    Doctorate

Other

34. How would you rate your computer experience?

    None

    Very little

    Average

    extensive

    Very extensive

35. How would you rate your health technology experience?

    None

    Very little

    Average

    extensive

    Very extensive

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