Why Do People Abandon Activity Trackers? The Role of User Diversity in Discontinued Use

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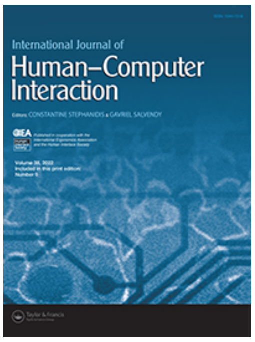

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Why Do People Abandon Activity Trackers? The Role of User Diversity in Discontinued Use

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ABSTRACT

Activity trackers are promising tools to increase the motivation to be physically active, thus strengthening users' physical constitution and potentially preventing cardiovascular diseases. To establish behavioral changes with such beneficial consequences, prolonged continuous use of trackers seems to be necessary. However, the usage behavior of many tracker users is characterized by interruptions or complete discontinuation after only a few months. Which factors determine individual usage trajectories is still unclear. This research sheds light on user diversity to investigate how inter-individual differences are related to reasons for usage interruptions and permanence of abandonment. Results based on a survey of $N = 159$ former users revealed that usage motives regarding self-determination theory, domain-specific personality traits (affinity for technology interaction), and interaction variables (dependency effect, trust in activity tracker measurement) were related to specific reasons for usage interruptions. Moreover, highly autonomous usage motivation and high trust were linked to more fragile abandonment decisions.

1. Introduction

Wearable activity trackers (i.e., fitness trackers or smartwatches) are increasingly widely used devices for monitoring various personal activities, fitness, and health parameters (e.g., step count, heart rate, energy expenditure, sleep cycles). Because of their broad functionality, they are used by different user groups with individualized goals. For instance, athletes use activity trackers to check their training progress and customize their workout routine (Wiesner et al., 2018) or people with many sedentary activities use activity trackers to enhance their everyday movement (Alley et al., 2016). The latter group might profit especially from activity tracker use (Chandrasekaran et al., 2020), as pronounced sedentary behavior is associated with poorer metabolic and cardiovascular health (Owen et al., 2010; Warren et al., 2010). Even moderate physical exercise such as walking is associated with increased fitness and cardiovascular health (Murphy et al., 2007). However, for substantial and sustained health effects to manifest, regular physical exercise is necessary (Wei et al., 2015).

Activity trackers can help to incorporate regular exercise into users' lives by providing external motivation through quantified behavioral feedback which can increase goal focus and anticipated motivation (Pettinico & Milne, 2017). This mechanism might be especially beneficial for users who have little intrinsic motivation for exercising. For this user group, physical activity might be dependent on wearing the tracker (Attig & Franke, 2019). Hence, a prolonged activity tracker use might be crucial for achieving positive health effects (Hancı et al., 2020), particularly for users with low intrinsic motivation for exercising.

Research on wearable activity tracker abandonment has shown that between 30 and 70% of users discontinue tracking after a few months (e.g., Alley et al., 2016; Hermsen et al., 2017; Lee & Lee, 2017). Reasons for abandoning the device are extensive and cover factors related to the tracker itself (e.g., perceived measurement reliability issues), the user (e.g., changes in life circumstances) or user-tracker interaction outcomes (e.g., obsessive tracking; see Attig & Franke, 2020 for an overview of abandonment factors). However, discontinuation does not necessarily mean abandoning self-tracking altogether (Attig & Franke, 2020; Epstein et al., 2015; Gorm & Shklovski, 2019; Meyer et al., 2017; Trace & Zhang, 2019). In fact, episodic use might even be inherent to self-tracking as it might serve as a mechanism for coping with tracker-related stress (Gorm & Shklovski, 2019). Hence, while some users decide not to self-track anymore, others simply forget tracking from time to time, and others consciously interrupt continuous tracking as a means of keeping self-control (Epstein et al., 2015; Gorm & Shklovski, 2019). What is yet little understood is which factors contribute to abandonment decisions, lapses, and episodic tracking, that is, why users differ regarding their temporal usage patterns. However, this knowledge is necessary to optimally support different user groups regarding beneficial tracker use with the aim of ensuring

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long-lasting motivation for physical activity. Consequently, to enable such support, a sound understanding of user diversity in tracker abandonment is essential. In fact, scholars have repeatedly argued to place more focus on the role of user diversity regarding research on human-centered technology development (Franke et al., 2019; Pozzi & Bagnara, 2013; Szalma, 2009). Nevertheless, research on the role of user diversity variables in activity tracker usage and abandonment is scarce.

The objective of the present research is therefore to advance understanding of user diversity factors that predict discontinued use (i.e., abandonment) of activity trackers. To this end, we seek to take domain-specific user diversity variables into account which have already been identified as relevant to tracker use in past research but have not been connected to tracking attrition so far. Specifically, we intend to examine the relationships of inter-individually differing usage motives (i.e., level of autonomy regarding usage motivation), domain-specific personality traits (i.e., affinity to technology interaction), and interaction variables (i.e., dependency effect, trust in activity tracker measurement) with reasons for abandonment and permanence of abandonment decisions. With this study, we consider domain-specific user diversity as a possible predictor for differences in usage trajectories, which constitutes a novel approach in the field of activity tracker research.

2. Background

2.1. Reasons for activity tracker abandonment

Several qualitative and quantitative empirical studies have examined the reasons for interruption and termination of activity tracker usage (e.g., Clawson et al., 2015; Hermsen et al., 2017; Lazar et al., 2015; Maher et al., 2017). However, the different survey methods and questionnaires used in these studies make it difficult to compare the available research results as they differ greatly in the level of detail regarding assessed reasons for abandonment (e.g., open interview questions vs. quantitative assessment of preselected abandonment reasons). Moreover, given the large proportion of qualitative studies in this field of research, quantified results (e.g., regarding the relative importance of the abandonment reasons) are scarce, impeding the deduction of robust findings regarding possible causal chains of activity tracker adoption, usage, and (dis)continued use.

Based on a systematic literature review that condensed the multitude of studies, Attig and Franke (2020) developed a questionnaire for assessing reasons for wearable activity tracker abandonment. Using this questionnaire in a quantitative study with former users of activity trackers, the authors were able to group abandonment reasons based on a factor-analytical approach into six broader factors (Attig & Franke, 2020; see Table 1). Thus, this factor analysis enabled insights into which abandonment reasons likely occur together and condensed these various reasons in preparation for subsequent correlational analyses. First, data inaccuracy/uselessness depicts tracker abandonment because of perceived measurement issues or perceived irrelevance of presented data (e.g., Yang et al., 2015). Privacy concerns/switch to alternative reflects users' concerns about data transfer to third parties that might lead to abandoning the device or to using an alternative, more convenient tracking device (e.g., standalone smartphone app; e.g., Fietkiewicz & Ilhan, 2020). Design/discomfort refers to tracking discontinuation because the device was considered unaesthetic, uncomfortable, or annoying (e.g., Harrison et al., 2015). Motivation loss depicts tracker abandonment due to demotivating negative feedback, tracker-related stress, and lost interest in the data (e.g., Epstein et al., 2016). Loss of tracking feasibility/necessity comprises changes in health status, priorities, life circumstances, and fitness goals that make tracking redundant or impractical (e.g., Clawson et al., 2015). Finally, habit formed refers to "happy abandonment" (Clawson et al., 2015), that is, stopping to track because the activity has become habitual, or the long-term goal was attained.

To comprehensively understand (dis)continued activity tracker usage, however, it is essential not only to examine the role of different abandonment reasons but also to take the duration of tracking interruptions into account. Given that some users tend to interrupt tracking as a means for keeping self-control (Epstein et al., 2015; Gorm & Shklovski, 2019), it is reasonable to ask which factors contribute to implementing lapses into one's usage routine. As a first step to shed light on this question, Attig and Franke (2020) showed that the six broad abandonment reasons differed with respect to permanence of abandonment: Motivation loss was significantly positively linked to permanence of abandonment and negative attitudes towards personal quantification, making it the most detrimental factor for beneficial long-term usage of activity trackers. However, the effect sizes of these correlations were no more than medium, indicating that, for instance, not every user who experiences motivation losses decides to stop tracking altogether. Taking user diversity variables into account might therefore be advantageous to shedding light on the causal chain between activity tracking adoption and discontinuation.

2.2. Activity tracking and user diversity

User diversity research indicates that inter-individual difference characteristics affect how digital technologies are accepted and used (Burton-Jones & Hubona, 2005; Svendsen et al., 2013). In the case of self-tracking, personal variables (i.e., traits, states, interaction variables) are still understudied (Hermsen et al., 2016; Jin et al., 2022). However, some personal variables which shape tracker use have been identified. These are rather domain-specific as the bandwidth-fidelity dilemma (Cronbach & Gleser, 1957; Salgado, 2017) suggests: Broad and theoretically well-established personality dimensions like the Big Five tend to show little explanation of variance with respect to specific behavior whereas domain-specific personal variables tend to show higher explanation of variance but are typically less theory-driven and sometimes conceptually overlapping (see also Kraus et al., 2020). In the case of fitness tracking, findings regarding

Table 1. Abandonment reasons and higher-order factors as identified in prior factor analysis.

Higher-order factor	Single abandonment reason	Item text I stopped using the activity tracker because …
Data inaccuracy/ uselessness	Perceived measurement inaccuracy	… I felt that the tracker wasn't measuring accurately.
	Measurement distrust	… I didn't trust the results of the measurements.
	Incorrect activity tracking	… I experienced that the tracker wasn't correctly registering my activities.
	Useless data/data interpretation	… I had no use for the data, or the data was ambiguous.
	Tracker did not assess relevant data/activities	… the tracker didn't register activities which were relevant to me.
Privacy concerns/ switch to alternative	Uncertainty regarding personal data transfer	… I didn't know what would happen to my data.
	Privacy concerns	… I had concerns regarding the circulation of my personal data.
	Switch to a more time- or cost-effective alternative	… I found an alternative which used less time or cost less.
	Tracking per smartphone more convenient	… tracking with my smartphone is more convenient, because I have it with me anyway.
Design/ discomfort	Tracker discomfort/annoyance during exercise	… the tracker was uncomfortable or bothered me during my activities.
	Tracker no longer aesthetically appealing	… I didn't like the visual appearance of the tracker (anymore).
	Charging discomfort	… charging the battery was inconvenient.
	Forgot to wear tracker	… I forgot to wear my tracker.
	Allergic reaction to wristband	… my skin under the wristband became irritated or had an allergic reaction.
	Usage of tracker/app too inconvenient/demanding	… I found the use of the tracker and/or the companion app complicated, wearisome or cumbersome.
Motivation loss	Obsessive tracking	… I had the feeling that I was no longer doing activities for myself, but rather for a satisfying result on my tracker.
	Oversaturation of social comparison	… I was no longer interested in comparing myself to other users.
	Demotivation through negative feedback	… I was demotivated by seeing my failures.
	Intrinsic tracking motivation loss (i.e., loss of interest/fun)	… I didn't have any further interest in tracking my data and/or I no longer had fun tracking.
	Tracker broken/could not be charged	… my tracker was defective, or the battery wouldn't charge anymore.
	Tracking took too much temporal effort	… tracking meant investing more time than I wanted to.
Loss of tracking feasibility/ necessity	Tracking routine disruption	… I paused my tracking routine (e.g., because of vacations or sickness) and didn't start again thereafter.
	Health status change	… my state of health had changed, and tracking was no longer meaningful and/or possible.
	Loss of motivation for physical activity	… I lost interest in physical activity.
	Tracker unable to support new activity goals	… my activity goals had changed, and my tracker could no longer support me in achieving these.
	Change of priorities/life circumstances	… my priorities/life situation had changed, and tracking my activities was no longer important.
	Tracking did not fit into daily routine	… I couldn't integrate tracking into my day-to-day.
Habit formed	Activity has become habitual	… my activities were now a habit and I no longer had to control them.
	Long-term goal attained	… I reached the long-term goal that I had wanted to achieve with the use of the tracker.

relationships between broad personality traits and usage variables are thus unsurprisingly inconsistent. For instance, Maltseva and Lutz (2018) found, contrary to their assumptions, only conscientiousness and neuroticism to be related to self-tracking practices. Attig and Franke (2019) did not find any significant relationships between Big Five dimensions and intrinsic tracking motivation. These findings indicate that broad personality traits might have an indirect effect on tracker use (Jin et al., 2022), that is, the relationship between traits such as extraversion and tracker usage intention might be mediated through interaction variables such as device usability (Rupp et al., 2018). Being the first quantitative study to investigate user diversity regarding discontinued use of fitness trackers, the present research focused on domain-specific variables which might explain variance more directly. To this end, we selected four user diversity variables (motivation for tracker usage, affinity for technology interaction, the dependency effect, trust in activity tracker measurement) covering three categories of factors (usage motives, personality traits, and interaction variables) which were identified as related to tracker use in past research. These user diversity variables are described more closely in the following paragraphs.

First, when examining inter-individual differences in motivated behavior such as activity tracker use, it is reasonable to start at a fundamental level such as usage motives (Lee et al., 2015). Activity tracker users have been shown to differ regarding their usage motives. Broadly, they might use their tracker because it is inherently interesting and fun (Lazar et al., 2015) or because it supports achieving an external, usually health-related goal (Day, 2016), or both (Attig et al., 2019). In terms of self-determination theory (Deci & Ryan, 1985), motivation can be characterized in terms of perceived locus of causality as well as level of autonomy, and vary from highly autonomous motivation (intrinsic motivation, integrated, and identified regulation) to external and controlled motivation (introjected and external regulation). Prior research has found that autonomous motivation is positively related to intense and continuous tracker usage (Attig et al., 2019; Rupp et al., 2018). The relevance of motivation for discontinued use and abandonment is unclear so far. Hence, we propose that motivations with varying levels of autonomy are linked to different reasons for abandonment (e.g., highly extrinsic motivation might be linked to tracker abandonment due to demotivation) but follow an explorative approach for answering this research question (RQ1). Regarding permanence of abandonment, we propose autonomous motivation to be linked to less permanent abandonment decisions (i.e., lapsing instead of abandoning; H1).

Second, on the level of personality traits, domain-specific constructs, rather than broad personality dimensions such as the Big Five personality traits (e.g., Costa & McCrae, 2009) have been shown to explain substantial amounts of variance regarding technology use (Attig et al., 2017; Kraus et al., 2020). One such domain-specific variable with robust connections to technology use in various fields is affinity for technology interaction (ATI; Franke et al., 2019). ATI is defined as a domain-specific personality trait that is rooted in need for cognition (Cacioppo & Petty, 1982) and determines an individual's tendency to engage in intensive technology interaction (Franke et al., 2019). It has repeatedly been shown to be related to a variety of technology interaction scenarios, for instance, to a greater variety of learning strategies for information technology use (Wensing et al., 2019), to greater trust in intelligent systems (Tolmeijer et al., 2021), to greater trust in automation and acceptability of automated vehicles (Kraus et al., 2020), and to a greater use intention of care and production robots (Biermann et al., 2020). Regarding activity tracker interaction, ATI has been found to be positively related to intrinsic tracker usage motivation, i.e., high interest in the gathered data (Attig et al., 2019; Attig & Franke, 2019). Hence, we propose ATI to be related to abandonment due to perceived data uselessness (H2). For instance, users who enjoy intensive interaction with the device may appreciate access to comprehensive data, thus, if the tracker does not provide the desired data richness, dissatisfaction and abandonment might emerge. Additionally, having attained a personal health goal should not be connected to tracking abandonment in high-ATI individuals as they are likely inherently interested in their data, regardless of their health goals. Thus, we propose ATI to be negatively related to abandonment due to a formed habit (H3). Moreover, as high ATI should translate into high interest in technology, we propose ATI to be negatively linked to permanence of abandonment (H4). That is, high-ATI users might start tracking again at some later point, possibly with another device, because they are inherently interested in technology.

Third, interaction variables (i.e., characteristics of the interaction between user and technology) are shaped through the interplay between dispositional factors (e.g., personality traits) and experience with technology in general or handling specific technological devices (e.g., computer self-efficacy; Gist et al., 1989; attitudes towards technology; Davis et al., 1989; trust in technology, Li et al., 2008). Therefore, they are more dynamic across situations and technologies than domain-specific personality traits (Gist et al., 1989). Regarding activity trackers, two interaction variables have been identified in past research that can predict usage motivation and intention to use and might therefore also be linked to (dis)continued use: (1) the dependency effect and (2) trust in activity tracker measurement. First, based on self-determination theory (Deci & Ryan, 1985), it has been argued that external rewards such as quantified feedback provided by the tracker might undermine motivation to track, which manifests particularly in situations when the tracker is not at hand (Attig & Franke, 2019). Moreover, this effect, which was termed dependency effect because of a proposed dependency of tracking motivation on the presence of the tracker, can manifest itself on three levels: (1) On a behavioral level (e.g., less effort during physical activities without the tracker, not starting physical activities at all without the tracker), (2) on a cognitive level (e.g., cognitive occupancy with tracker-related thoughts, devaluation of not correctly tracked activities), and (3) on an affective level (e.g., less fun during physical activities without tracker, feelings of disappointment with oneself when the activity goals were not met). At the heart of the dependency effect is a reattribution of one's activity on the tracker (e.g., having the impression that steps are only collected for the tracker and not one's health) which is related to stress and obsessive tracking (Rieder et al., 2020). Past research has shown initial motivation for tracker use and physical activity to be linked to the experience of this effect, that is, the more that users are extrinsically motivated for tracker usage and physical activity, the more they are inclined to perceive the interaction with their tracker as controlling and stressful, ultimately harming tracking motivation (Attig & Franke, 2019). First research suggests that this kind of obsessive tracking (i.e., extensive focus on the device) is related to abandonment (Coorevits & Coenen, 2016; Maher et al., 2017), but it is still unclear how robust and strong this relationship is. Thus, we propose a positive link between the dependency effect and abandonment due to demotivation (H5). In addition, we propose a positive link between the dependency effect and permanence of abandonment (H6) because demotivation has been shown to be an important factor for particularly strong abandonment decisions (Attig & Franke, 2020). Second, tracker users might differ regarding how much they perceive the measurement sensors and algorithms to be trustworthy, probably affecting usage intention (Rupp et al., 2016). Measurement accuracy of fitness trackers is a topic that has received much scientific attention, and review articles show that measurement inaccuracy is indeed a problem, particularly in relation to energy expenditure (Feehan et al., 2018; Fuller et al., 2020). Generally, diminished trust might compromise perceived usefulness and intention to use (e.g., Pavlou, 2003). First research in the field of self-tracking showed that this effect probably also applies for fitness trackers (Rupp et al., 2016; Trommler et al., 2018). Given that measurement inaccuracy has repeatedly been named as a reason for tracking attrition, we propose low trust in fitness tracker measurement to be linked to abandonment because of measurement inaccuracy (H7). Moreover, based on the relationship between trust and

Table 2. Hypotheses of the present study.

User diversity variable		Hypothesis
Motivations for fitness tracker usage	RQ1	How are usage motivations linked to specific reasons for abandonment?
	H1	More autonomous motivations (i.e., intrinsic and autonomous motivation) are linked to less permanent abandonment decisions.
Affinity for technology interaction (ATI)	H2	ATI is positively linked to abandonment due to data inaccuracy/uselessness.
	H3	ATI is negatively liked to abandonment due to a formed habit.
	H4	ATI is negatively linked to permanence of abandonment.
Dependency effect	H5	The dependency effect is positively linked to abandonment due to demotivation.
	H6	The dependency effect is positively linked to permanence of abandonment.
Trust in fitness tracker measurement	H7	Trust in activity tracker measurement is positively linked to abandonment due to data inaccuracy/ uselessness.
	H8	Trust in activity tracker measurement is negatively linked to permanence of abandonment.

intention to use, we assume trust in fitness tracker measurement to be negatively linked to permanence of abandonment (H8). See Table 2 for an overview of the proposed hypotheses.

3. Materials and methods

3.1. Participants

The present research represents the second part of the online study by Attig and Franke (2020). Former users of wearable activity trackers were recruited through German-language interest groups on social media websites (Instagram, Facebook, Twitter) regarding activity tracker usage, fitness, and weight loss. Additionally, a press release was published to recruit further participants (Technische Universität Chemnitz, 2018). The online study was realized on the LimeSurvey platform (LimeSurvey GmbH, 2018) where the participants also gave their informed consent. Data acquisition occurred from September to November 2018.

To estimate the required sample size, we performed an a priori power analysis using G*Power (Faul et al., 2009). We calculated the necessary sample size for a mean correlation of $r = 0.24$ (one-tailed), $\alpha = 0.05$, with a power of 90% (since no comparable analyses were reported in the literature, we took this medium effect size as a basis; based on empirically-grounded effect size magnitude estimates; Perugini et al., 2018). The required sample size for this analysis was $N = 144$. To have some buffer for possible missing or implausible data, we allowed data collection to continue until 15% more complete records (i.e., $N = 167$) were obtained.

A total of 167 participants (who were not compensated) completed the questionnaire. Four participants were excluded from the analyses because they still used their activity tracker, whereas four additional participants were excluded because of poor data quality (i.e., repeated implausible answers). Thus, the final data set included data from 159 participants. The sample had a mean age of $M = 32.4$ ($SD = 11.2$, Min = 18, Max = 80), the majority were female (74%), and their educational level was rather high (11% not yet with a vocational qualification, 25% completed vocational training, 64% bachelor's/master's degree).

The participants had been using their *last* tracker for $M = 10.8$ months ($SD = 0.6$) with a comparatively large range of 36.3 months (25th percentile = 4 months; 75th percentile = 14.0 months). On average, they had been using activity trackers *in general* for $M = 17.1$ months ($SD = 23.6$) with an even larger range of 260.0 months (25th percentile = 6.0 months; 75th percentile = 22.0 months).

The online study was carried out in accordance with relevant national guidelines and regulations (DGPs, 2004) and with the principles expressed in the Declaration of Helsinki (World Medical Association, 2018). Formal approval of the study by the Ethics Committee of Chemnitz University of Technology was not mandatory, as the study adhered to all required regulations. Participants' data was anonymized and confidentiality was ensured. The participants were informed about the study's objectives, the procedure of the survey as well as about their right to withdraw from the study at any time without reasons and any negative consequences. All participants gave their informed consent online in accordance with the guidelines of the Ethics Committee of Chemnitz University of Technology by ticking a checkbox.

3.2. Scales and measures

As an indicator of reliability Cronbach's alpha was used to assess internal consistency and interpreted according to common practice (see e.g., Cripps, 2017) as poor ($.5 \leq \alpha < 0.6$), questionable ($.6 \leq \alpha < 0.7$), acceptable ($.7 \leq \alpha < 0.8$), good ($.8 \leq \alpha < 0.9$), or excellent (≥ 0.9). All Cronbach's alpha values are depicted in Table 3. Participants provided their responses (if not stated otherwise) on 6-point Likert scales (completely disagree, largely disagree, slightly disagree, slightly agree, largely agree, completely agree; coded as 1–6).

3.2.1. Motivation for tracker usage

To assess motivation for tracker usage according to self-determination theory, we presented 13 items based on the Treatment-Self Regulation Questionnaire (TSRQ; Levesque et al., 2007; Ryan & Connell, 1989), which were translated into German and linguistically modified for past activity tracker usage (for a similar approach see Attig et al., 2019). Two items assessed intrinsic motivation (e.g., "I used my activity tracker because it was simply fun to deal with my

Table 3. Descriptive statistics of the assessed variables.

Variable	*M*	*SD*	25th Percentile	50th Percentile (Median)	75th Percentile	Cronbach's alpha
Data inaccuracy/uselessness	2.46	1.27	1.20	2.20	3.40	.88
Privacy concerns/switch to alternative	1.88	1.01	1.00	1.50	2.50	.72
Design/discomfort	2.48	1.08	1.50	2.33	3.33	.70
Loss of motivation	2.38	1.07	1.60	2.20	3.20	.70
Loss of tracking feasibility/necessity	2.18	0.92	1.33	2.00	2.83	.68
Habit formed	2.31	1.32	1.00	2.00	3.50	.65
Intrinsic motivation for tracker usage	5.61	1.06	5.00	6.00	6.50	.55
Autonomous motivation for tracker usage	4.54	1.23	4.00	4.67	5.33	.85
Introjected motivation for tracker usage	2.20	1.51	1.00	1.50	3.00	.76
External motivation for tracker usage	1.81	1.07	1.00	1.50	2.25	.75
Affinity for technology interaction	4.17	1.13	3.44	4.22	5.11	.93
Dependency effect	3.30	1.16	2.38	3.38	4.15	.93
Trust in activity tracker measurement	4.15	1.14	3.20	4.40	5.00	.95
Permanence of Abandonment	2.63	1.40	1.33	2.33	3.67	.91

Note. Responses for almost all scales were provided on Likert scales from 1 to 6, except motivation for tracker usage variables, which were provided on a Likert scale from 1 to 7.

data."), six items assessed autonomous (i.e., identified and integrated) motivation (e.g., "I used my activity tracker because I personally believed that it was the best for my health."), two items assessed introjected motivation (e.g., "I used my activity tracker because I would have felt guilty or ashamed if I didn't do it."), and four items assessed external regulation (e.g., "I used my activity tracker because others would have been disappointed with me if I didn't do it."). The factor amotivation was not assessed. Responses were provided on a 7-point Likert scale ranging from 1 (*not at all true*) over 4 (*somewhat true*) to 7 (*very true*; all other scale positions without verbal label). Internal consistency varied from poor to good.

3.2.2. Personality and interaction variables

We assessed affinity for technology interaction with the 9-item ATI scale (Franke et al., 2019). Internal consistency was excellent.

To assess the dependency effect, we used the 13-item scale (Attig & Franke, 2019) which measures demotivation on five dimensions: shift to external attribution, behavioral outcomes of not wearing the tracker, activity devaluation, affective outcomes of motivation loss, and cognitive occupancy. Items were rephrased into past tense. In the instruction, participants were asked to remember their active tracking phase and answer the items accordingly. Internal consistency was excellent.

To assess trust in activity tracker measurement, the 5-item facets of system trustworthiness (FOST) scale was used (Franke et al., 2015). Item texts were modified for activity data measurement (e.g., "The data measurement was precise."). Internal consistency was excellent.

3.2.3. Reasons for activity tracker abandonment

We assessed reasons for activity tracker abandonment with a self-constructed 31-item scale (for details on the scale development process and the final scale, see Attig & Franke, 2020). Abandonment reasons (i.e., single items) were grouped into higher-order factors using a principal axis factor analysis with oblique rotation (see Table 1 for results as reported in Attig & Franke, 2020). Two items could not be assigned to single factors and were thus deleted from further analyses. Internal consistency for the subscales varied between questionable and good.

3.2.4. Permanence of abandonment

Permanence of tracker abandonment was assessed with three self-generated items ("I imagine that I will resume tracking eventually." "I have ruled out ever resuming to track." "I have stopped tracking permanently"). Internal consistency was excellent.

4. Results

4.1. Descriptive analyses

Regarding usage motivation, most participants stated that they were more strongly motivated by autonomous than externally controlled forms of motivation when they started tracking their activities. Both intrinsic ($M = 5.61$, $t(158) = 19.22$, $p < 0.001$, $d = 1.52$) and extrinsic, but autonomous motivation ($M = 4.54$, $t(158) = 5.27$, $p < 0.001$, $d = 0.44$) were significantly above the scale midpoint 4.0. In contrast, the more externally controlled forms of extrinsic motivation, namely introjected motivation ($M = 2.20$, $t(158) = -15.05$, $p < 0.001$, $d = -1.19$) and external regulation ($M = 1.82$, $t(158) = -25.82$, $p < 0.001$, $d = -2.04$) were significantly below the scale midpoint. Dichotomizing participants' mean scores showed that 94% stated to have been intrinsically motivated when they started tracking and 76% extrinsically, but autonomously motivated. Introjected motivation was relevant only for 17%, and external regulation for 6% of the participants.

Our sample of former users had a rather high ATI; the mean score was significantly above the scale midpoint 3.5 ($M = 4.17$, $t(158) = 7.45$, $p < 0.001$, $d = 0.59$). Across all participants, the dependency effect mean score was significantly below the scale midpoint 3.5 ($M = 3.30$, $t(158) = -2.19$, $p = 0.030$, $d = -0.17$). Dichotomizing participants' mean scores revealed that 46% stated to be familiar with the effect from their usage phase. Trust in activity tracker measurement was significantly above the scale midpoint of 3.5 ($M = 4.15$, $t(158) = 7.22$, $p < 0.001$, $d = 0.57$).

Table 4. Correlations between abandonment reasons and user diversity variables.

		r (*p*) 95% CI					
Research question/hypothesis	Variable	Data inaccuracy/uselessness	Privacy concerns/switch to alternative	Design/discomfort	Loss of motivation	Loss of tracking feasibility/necessity	Habit formed
RQ1	Intrinsic motivation for tracker usage	.01 (.865) [−0.14, 0.17]	.06 (.454) [−0.10, 0.21]	.07 (.402) [−0.09, 0.22]	–.04 (.665) [−0.19, 0.12]	–.03 (.703) [−0.19, 0.13]	–.02 (.830) [−0.14, 0.17]
	Autonomous motivation for tracker usage	−0.12 (0.148) [−0.27, 0.04]	−0.02 (0.784) [−0.18, 0.13]	−0.09 (0.289) [−0.24, 0.07]	0.09 (0.253) [−0.07, 0.24]	**0.18 (0.026)** [0.02, 0.32]	0.13 (0.101) [−0.03, 0.28]
	Introjected motivation for tracker usage	0.10 (0.218) [−0.06, 0.25]	0.10 (0.219) [−0.06, 0.25]	−0.04 (0.663) [−0.19, 0.12]	**0.29 (<0.001)** [0.14, 0.42]	**0.24 (0.003)** [0.09, 0.38]	0.07 (0.361) [−0.08, 0.27]
	External motivation for tracker usage	0.11 (0.152) [−0.04, 0.27]	**0.23 (0.003)** [0.08, 0.38]	0.07 (0.370) [−0.09, 0.23]	**0.30 (<0.001)** [0.15, 0.43]	**0.26 (0.001)** [0.10, 0.39]	0.09 (0.241) [−0.06, 0.25]
H2/H3	Affinity for technology interaction	−0.01 (0.445)* [−0.17, 0.15]	**0.17 (0.036)** [0.01, 0.31]	0.03 (0.709) [−0.13, 0.19]	−0.08 (0.344) [−0.23, 0.08]	−0.05 (0.503) [−0.21, 0.10]	**−0.14 (0.038)*** [−0.29, 0.06]
H5	Dependency effect	0.13 (0.101) [−0.03, 0.28]	−0.02 (0.798) [−0.18, 0.14]	0.08 (0.920) [−0.15, 0.16]	**0.50 (<0.001)*** [0.37, 0.60]	**0.32 (<0.001)** [0.17, 0.45]	−0.10 (0.201) [−0.25, 0.06]
H7	Trust in activity tracker measurement	**−0.81 (<0.001)*** [−0.86, −0.75]	−0.06 (0.452) [−0.21, 0.10]	−0.09 (0.294) [−0.24, 0.07]	−0.15 (0.069) [−0.29, 0.01]	0.00 (0.973) [−0.15, 0.16]	0.05 (0.551) [−0.11, 0.20]

Note. Significant correlations ($\alpha = 0.05$) are boldfaced, $N = 159$. * = one-tailed tests because of directed hypotheses; all other tests were two-tailed.

Table 5. Correlations between permanence of abandonment and user diversity variables.

		Permanence of abandonment		
Hypothesis	Variable	*r*	*p*	95% CI
H1	Intrinsic motivation for tracker usage	**−0.22**	<0.001	[−0.36, −0.07]
	Autonomous motivation for tracker usage	**−0.29**	<0.001	[−0.42, −0.14]
	Introjected motivation for tracker usage	0.00	0.489	[−0.15, 0.16]
	External motivation for tracker usage	**0.14**	0.044	[−0.02, 0.29]
H4	Affinity for technology interaction	−0.04	0.302	[−0.20, 0.12]
H6	Dependency effect	0.06	0.245	[−0.10, 0.21]
H8	Trust in activity tracker measurement	**−0.19**	0.009	[−0.33, −0.03]

Note. One-tailed significant correlations ($\alpha = 0.05$) are boldfaced, $N = 159$.

Descriptive statistics of the higher-order abandonment reasons revealed that all mean scores were on the lower range (all $M < 2.50$), suggesting that participants on average did not tend strongly toward any of the abandonment reasons. However, these mean values were only limitedly informative, as the mean scores for the higher-order abandonment reasons did not represent latent factors consisting of multiple items but a clustering of the individual reasons with the aim of condensing information.

Permanence of abandonment was significantly below the scale midpoint of 3.5 ($M = 2.63$, $t(158) = -7.83$, $p < 0.001$, $d = -0.62$), indicating that many participants considered resuming to track at a later point. Dichotomizing the responses revealed that 74% of former users' abandonment decisions were rated as rather fragile.

4.2. Relationships between user diversity as well as interaction variables and abandonment reasons

To calculate Pearson correlations between user diversity variables and abandonment reasons, we computed mean scores for each of the six factors emerging from the factor analysis. Tests for the directed hypotheses were one-tailed; all other correlations analyses were based on two-tailed tests. Effect sizes were interpreted according to Cohen (1992). Results are depicted in Table 4.

Regarding RQ1, results from two-tailed Pearson correlations showed that the lower autonomous participants' initial motivation for tracker usage was, the higher the likelihood that relationships to particular abandonment reasons were found. Intrinsic motivation did not correlate significantly with any abandonment reason. Autonomous motivation correlated weakly positively with loss of tracking feasibility/necessity. Introjected motivation correlated weakly positively with loss of motivation and loss of tracking feasibility/necessity. External regulation correlated weakly positively with privacy concerns/switch to alternatives and loss of tracking feasibility/necessity, and moderately positively with loss of motivation.

ATI was uncorrelated to abandonment due to data inaccuracy/uselessness (H2 not supported) but weakly negatively correlated to abandonment due to a formed habit (H3 supported). Additionally, it was weakly positively linked to privacy concerns/switch to alternatives. Thus, the higher that participants' ATI was, the less likely they discontinued tracking because they reached their health goals and the more likely they discontinued tracking because of privacy concerns/switch to tracking alternatives.

The dependency effect was strongly positively linked to loss of motivation (H5 supported). Moreover, it was moderately positively linked to loss of tracking feasibility/necessity. This supports the assumption that the dependency effect not only reduces tracking motivation but might also lead to tracking discontinuation because of demotivating effects. As hypothesized, FOST was strongly negatively linked to data inaccuracy/uselessness (H7 supported), indicating the chain of causation that distrust in measurement might lead to tracker abandonment. No other significant correlations between FOST and abandonment reasons were found.

4.3. Relationships between user diversity as well as interaction variables and permanence of abandonment

All Pearson correlation analyses were based on one-tailed tests because of directed hypotheses. Results are depicted in Table 5.

The two highly autonomous motivations (i.e., intrinsic and autonomous motivation for tracker usage) were both significantly negatively linked to permanence of abandonment, whereas as the correlation between external motivation and permanence of abandonment was significant and positive (weak to moderate effects). No significant link between introjected motivation and permanence of abandonment was found. Hence, highly autonomous initial motivation for using the tracker was related to less permanent abandonment decisions, i.e., autonomously motivated users may be more inclined to interrupt usage rather than stop using completely (H1 supported).

No significant relationships between permanence of abandonment and ATI (H4 not supported) as well as the dependency effect (H6 not supported) were found. In contrast, trust in activity tracker measurement was significantly negatively related to permanence of abandonment (weak effect; H8 supported). Thus, the higher former users' trust was, the less likely later abandonment decisions may be cast in stone.

5. Discussion

5.1. Summary of results

The present study sought to advance understanding of user diversity factors that predict discontinued use (i.e., abandonment) of activity trackers in three areas of inter-individual differences: usage motives (i.e., level of autonomy regarding initial usage motivation), domain-specific personality traits (i.e., affinity for technology interaction), and interaction variables (i.e., experience of the dependency effect and trust in activity tracker measurement).

Participants were on average characterized by a strong initial autonomous motivation to track and a pronounced affinity for technology interaction, as well as trust in activity tracker measurement. Almost half of participants stated they were familiar with the dependency effect. Three quarters of them stated they would reconsider tracking in the future. The more controlled their motivation was, the more relationships with abandonment reasons were found (RQ1). The higher participants' ATI, the less likely they abandoned tracking due to achieving their health goals (H3 supported), and the more likely they did so because of privacy concerns/switch to alternatives. The proposed link to abandonment due to data inaccuracy/uselessness was not found (H2 not supported). Having experienced the dependency effect increased likelihood of abandonment because of motivation loss (H5 supported), and, additionally, loss of tracking feasibility/necessity. The lower participants' trust in measurement, the more likely they stopped tracking because of data inaccuracy/uselessness (H7 supported). The decision to stop using fitness trackers was rated as less permanent when initial motivation to use was highly autonomous and trust in activity tracker measurement was high (H1 and H8 supported). How high former users' affinity for technology was or whether they experienced the dependency effect did not indicate anything about the permanence of their abandonment decision (H4 and H6 not supported).

5.2. Implications

The present research provides insights into the user diversity of former activity tracker users. Comparing the presented descriptive statistics from former users to those of current users reveals that these user groups were, on average, very similar regarding user diversity variables. In comparison to a sample of current users (Attig et al., 2019), the former users in the present research are similarly characterized by higher autonomous and lower controlled usage motivation. Moreover, both current and former users had a rather high ATI (Attig et al., 2019; Attig & Franke, 2019) and trust in measurement (Trommler et al., 2018). Given that this is a pattern which has repeatedly been found in samples of activity tracker users, we have reason to assume that tracker users might generally be characterized by a highly autonomous tracking motivation, a higher mean ATI than the general population, and high trust in measurement accuracy. Consequently, it appears reasonable to conclude that the reported findings are not artifacts based on the specificity of the sample.

In contrast, experience of the dependency effect in everyday usage in the sample of former users (46%) was higher than in a sample of current users (36%; Attig & Franke, 2019). Hence, one could assume that experiencing the dependency effect (i.e., obsessive tracking behaviors and diminished motivation to track) likely leads to abandoning the device. However, an alternative explanation would be that the dependency effect and its related experience of stress are rather related to episodic tracking: Users who perceive the tracker's feedback to be demotivating and stressful might use deliberate lapses as a coping mechanism (Gorm & Shklovski, 2019). The missing link between the dependency effect and permanence of abandonment suggests that both explanations might be applicable, that is, the dependency effect might lead to behavioral adaptations, namely usage interruptions or abandonment.

More controlled initial tracking motivation (i.e., introjected and external motivation) was related to specific abandonment reasons, specifically loss of motivation and tracking feasibility/necessity. Moreover, autonomous motivation was linked to less permanent abandonment. These findings are in line with self-determination theory which proposes that controlled motivation elicits feelings of being pressured to behave in particular ways that might impede long-time persistence while autonomous motivation supports adherence (Deci & Ryan, 2008). Consequently, interaction with self-tracking devices such as activity trackers should underline users' autonomy to avoid external pressure and negative emotional outcomes (e.g., guilt, disappointment) that might stem from negative feedback (Shi & Cristea, 2016). Users, particularly those who are highly extrinsically motivated, should be able to anticipate the positive outcomes of activity tracker usage (e.g., awareness of exercise benefits, improvement of self-management skills; see also König et al., 2021). Possibilities to put this suggestion into practice could be to reward positive, albeit small, developments even if set activity goals were not met or to emphasize the relevance of the desired behavior for the user's personal goals. Importantly, user diversity must be taken into account when designing for high autonomy because different users with different personality profiles might be motivated through different strategies (Ramsey & Hall, 2016), for instance, high information density regarding the tracked parameters for intrinsically motivated users or clear statements regarding the status of goal achievement for extrinsically motivated users.

The higher users' ATI was, the more likely they would stop tracking because of privacy concerns, but the less likely they would stop tracking because of successful habit formation. This suggests, as proposed, that high-ATI users may continue tracking even when they attained their goal or might not even have had an external goal in the first place (i.e., tracking because of high intrinsic interest in technology and data). Research on different tracker user types suggests that "quantified selfers" are characterized by high usage rates and long usage periods, rooted in their strong desire to gather self-knowledge through highly specific quantified feedback (Jarrahi et al., 2018). Such users, who are likely tech-savvy, high-ATI users, have lower interest in motivational affordances and higher interest in numbers. Personal quantification is an autotelic behavior for them; hence, they should greatly appreciate high data quality. However, in our sample, ATI was unrelated to abandonment because of data inaccuracy/uselessness. Even though the participants had strong intrinsic tracking motivation and affinity for technology interaction, "quantified selfers" might not be included or at least underrepresented in our sample of ex-users, as they are defined by continually using tracking devices (Jarrahi et al., 2018; see also Maltseva & Lutz, 2018).

Finally, low trust in tracker measurement was strongly linked to abandonment due to data inaccuracy/uselessness and permanence of abandonment, suggesting a chain of causation from perceived inaccuracy to tracking attrition. Studies focusing on evaluation of objective measurement accuracy highlight the varying accuracy of tracker data types (e.g., step count, heart rate, energy expenditure; Alinia et al., 2017; Fuller et al., 2020; Beagle et al., 2020). Less clear is how users actually use measurement data to support their goal achievement and the extent to which inaccurate data prevents them from achieving their goals. For instance, it is conceivable that individuals with the external goal of losing body weight may use the indicated energy expenditure to adjust their intake of food calories. However, if the energy consumption is systematically overestimated by the tracker (as it is the case with Apple and Polar devices; Fuller et al., 2020), then the food energy supplied might also be too high to achieve the targeted weight reduction. Transparency regarding the accuracy of tracked data is essential (Yang et al., 2015) so that such a user does not falsely attribute the non-attainment of the target to their own failure. This could be realized by presenting a notice to the user if data could not be tracked correctly (e.g., because the sensors did not capture the data during an activity). To best support users in achieving their health goals, the complex interplay between data accuracy, trust, transparency, and tracking motivation needs more scientific consideration.

5.3. Limitations and future research

Our research utilized an online questionnaire to recruit a considerably large sample, but, based on the correlational design, causal inferences cannot be drawn. Hence, the presented results can only serve as a starting point for the investigation of user diversity variables related to the temporal progression of activity tracker use. Longitudinal data and quasi-experimental designs are needed to verify the proposed relationships between user diversity variables and usage patterns. Moreover, a closer look at tracking discontinuation is necessary to distinguish more clearly between involuntary lapses, deliberate episodic use, and ultimate abandonment (see e.g., Epstein et al., 2015). Furthermore, forced discontinuation of self-tracking practices may be an additional valuable method to examine cognitive, emotional, and behavioral responses to tracker loss that enables further insights into temporal usage patterns, for instance, the probability of resuming ("removal as a method"; Homewood et al., 2020).

In future studies, more diversity factors should be considered. The present sample was rather age-diverse but biased towards female and highly educated users. In light of findings indicating that persons with lower socio-economic status might particularly benefit from behavioral change interventions but have lower uptake (Patel et al., 2017) and higher attrition rates (Goode et al., 2016), the presented findings might not be generalizable across all socio-economic status levels.

Moreover, user types of self-tracking devices for physical activity (e.g., quantified selfers, recreational athletes, elite athletes) were not assessed. In addition, the sample was characterized by rather long tracker usage periods, that is, former users with very short periods of use (i.e., < 6 months) were underrepresented. Consequently, the findings regarding abandonment reasons could only apply to people with more usage experience (i.e., potentially less to people who try a tracker only for a short time and then quickly stop using it). Furthermore, the sample consisted of very few users who stated that their initial tracking motivation was externally regulated. This might be the result of self-selection as users with little tracking motivation of their own may tend to have little interest in taking part in self-tracking studies. This circumstance might restrict the generalizability of the findings as they might not apply for such former users with low autonomous tracking motivation.

For more robust findings, future research should incorporate more gender and education-diverse samples, different user types, and users with very short usage periods when investigating temporal patterns of activity tracker usage.

Moreover, it should be noted that motivational types may evolve (Ryan & Deci, 2017), i.e., the motivation that initially led to the use of the tracker may change during the use phase (e.g., a user may have started using the tracker in an externally regulated manner, but with continued use may have internalized a more enhanced personal significance of tracking; see e.g., Mullan & Markland, 1997). This intra-individual variance in tracking motivation is not accounted for in our analyses.

Finally, some scales showed low internal consistency values (e.g., intrinsic motivation, habit formed, loss of tracking feasibility/necessity; see Table 3). The used (sub-)scales are in general rather short (i.e., 2–6 items except ATI and dependency effect). Low internal consistency values of very short scales are not uncommon (Gosling et al., 2003; Romero et al., 2012), therefore the meaningfulness of Cronbach's alpha is limited for this case (see also e.g., Freudenthaler et al., 2008; Rammstedt & John, 2007). Nevertheless, the self-constructed scales should be validated for further investigation in the future.

6. Conclusion

Self-tracking device usage is characterized by high abandonment rates a few months after adoption. Past research has identified numerous reasons for tracker abandonment and highlighted that tracking discontinuation does not necessarily equal ultimate abandonment. However, why users differ regarding their stated reasons for tracking attrition and temporal usage patterns (e.g., permanent abandonment vs. episodic use) has not been thoroughly investigated yet. The present research was the first to take user diversity variables, which were previously identified as relevant to activity tracker usage, into account to gain first insights into this question. Results showed that types of controlled tracking motivation were related to tracking discontinuation due to loss of motivation and perceived tracking feasibility/necessity as well as more permanent abandonment, whereas autonomous motivation was linked to a higher probability of resuming tracking behavior. Affinity for technology interaction and trust in activity tracker measurement were related to specific abandonment reasons, but only trust was linked to strong abandonment decisions, making trust a critical factor for long-term adherence. Having experienced the dependency effect (i.e., problematic usage patterns such as obsessive tracking) was strongly related to tracking discontinuation due to demotivation, but the missing link to permanence of abandonment suggests that users might tend to deliberately interrupt tracking as a coping mechanism with tracker-related stress.

To conclude, for comprehensively understanding technology adoption and attrition, user diversity variables need to be considered. However, the present research constitutes only a small step in the long-term agenda of implementing user diversity factors into HCI research. Particularly, more follow-up research is needed to link user diversity variables to self-tracking practices for answering the question how self-tracking devices can be used in a beneficial manner to accomplish substantial and sustained health effects on individual as well as large-scale levels.

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