Data Protectors, Benefit Maximizers, or Facts Enthusiasts: Identifying User Profiles for Life-Logging Technologies

Abstract

Sedentary behavior and lack of exercise pose a threat to both individual health and the viability of health-care systems and societies. Portable fitness trackers as prominent persuasive technologies are seen as a way to increase the level of physical activity. Yet, despite their technical capabilities, their affordability, and their advantages in regard to increased physical activity, they are neither used across the population, nor for long periods of time. To understand if and how product design influences acceptance and projected use, we evaluated users' preferences of using wearables, using a conjoint analysis approach with 412 participants of a wide age spectrum. Besides different relative importances of product properties (*privacy design*, *perceived utility*, *accuracy*, *motivational design* are rated from most to least important), three user segments with distinct technical requirements were identified (*data protectors*, *benefit maximizers*, *facts enthusiasts*). The three segments differ not only in product preference but also regarding other user factors. We presume that a broader and more sustainable use of wearables can be achieved when tailoring information and communication strategies alongside with the requirements of these user segments.

Keywords: Life-Logging, Privacy, User Diversity, Consumer Health Information Technology, Technology Acceptance, User Modeling, Conjoint Analysis

1. Introduction

Digitalization and automation have changed the working life of today's societies tremendously. The majority of Western work nowadays includes the use of electronic devices, and, more often than not, that of computers. Therefore, eight or more hours a day are spend sitting in front of a monitor or hunched over a touchscreen. Not only does this have a negative impact on posture, but studies have shown that prolonged sedentary behavior plays a major factor in health issues such as decreased mobility, weight-gain or even obesity, and other cardiovascular impairments, see, e.g., [1, 2, 3].

According to Knight, physical activity is declining in North America and Europe, relates to several diseases, such as cancer, diabetes, hypertension, and coronary or cerebrovascular diseases, and therefore has a negative impact on life expectancy and – in the long run – the viability of health-care systems [4]. Yet, Mendes et al. show that regular medium-intense exercises have a positive effect on health [5]; especially for children, older adults, and people dealing with overweight or obesity. And although intensity, frequency, and duration of the exercises might be optimized to achieve the highest health benefits, some physical activity is always considered as better than none. Other benefits of regular physical activities include the mitigation of migraines [6], the reduction of symptoms of depression [7], as well as increased executive functioning and working memory performance for young children, young adults, as well as older adults.

Consequently, the World Health Organization (WHO) suggests for adults to engage in at least 150 minutes of moderately intense physical activity per week, [8]. Some studies suggest this can be roughly translated into a goal of 10,000 steps per day [e.g., 9, 10, 11].

As these issues are largely known, the importance of a healthy lifestyle, including a minimum of physical activity and also a balanced and nutritional diet, have increased [12, 13]. Resources to help achieve and maintain a healthy body and by extension a healthy mind include no longer just books and videos. With the ubiquity of mobile devices and computers, electronic resources have been added. These incorporate digitized copies of the previously mentioned resources but also new(er) materials such as websites and applications (apps) to instigate or at least keep track of one's daily activities and caloric intake.

An easy way to maintain one's weight or adhere to health-recommendations is to keep track of one's life, e.g., [14]. The so-called life-logging or quantified-self-movement is based on the assumption that you can only change or improve behavioral patterns if you know what they are. To do so, you have to keep track of whatever area in your life you want to either change or maintain.

Specialized devices such as pedometers, heart-rate monitors, or GPS tracking devices can offer support. With the ongoing digitalization the electronic market now also includes small devices that can record a multitude of data about one's daily life. This include pulse, steps, climbed stairs, GPS routes traveled throughout the day, active minutes, type of sportive activity participated in, and so on (cf. [15]).

Despite the evident benefits of using life-logging technologies to increase one's level of physical fitness, these technologies are either rarely used or usage declines quickly [16]. Several studies have addressed the reasons for this by means of technology acceptance studies, e.g., [17, 18, 19]. However, these models usually build on the evaluation of a single product and do not take multiple potential product configurations, individual user requirements, and the respective trade-offs into account.

The conjoint method is a well-suited approach for systematically examining these trade-offs in user requirements [20, 21, 22]. To the best of our knowledge, conjoint analyses have been rarely used for the study of wearable devices and their acceptance or use. Consequently, this study empirically investigates individual trade-offs regarding aspects of life-logging devices (privacy design, utility, motivational design, accuracy) and identify distinct target groups.

2. Related Work

A multitude of individual and system factors influence the acceptance as well as short- and long-term use of life-logging technologies. In a first step, the concept of technology acceptance is described, followed by the report of single factors that influence the acceptance.

2.1. Technology Acceptance: Approach and Models

Technology acceptance research aims at predicting individual and system factors that explain the adoption and long-term use of technology [23, 24, 25, 26]. Apart from the technical aspects of those tracking devices, namely accuracy, available sensors, etc., another large part of research is devoted to the users' perspective when interacting with these so-called consumer health information technologies (CHITs).

The Unified Theory of Acceptance and Use of Technology (UTAUT2) and its extensions, for example, show the impact that *performance expectancy*, *effort expectancy*, *hedonic motivation*, *habit*, the *price-value* trade-off, but also *social influence* as well as *facilitating conditions* such as knowledge or compatibility to existing devices have on the intention to use a technology (cf. [25]). Those factors still influence the intended and actual use of technologies, including health technologies. Wearables, even though mostly labeled life-style technologies, measure myriads of personal information, movement profiles, and vital parameters, and as a result, they enter into personal areas that are perceived as very sensitive. Therefore, other very important factors need to be taken into consideration as well when trying to understand user acceptance of these devices. While many technology acceptance models exist, usually developed for other applications or contexts, the majority can be adapted to CHITs as well. Acceptance of theses technologies is shaped by properties of the technical design, as well as individual perceptions.

2.2. Factors Influencing the Short- and Long-Term Use of Life-Logging Technologies

Perceived usefulness: If a consumer does not perceive any gain from its use, chances are the technology will not be accepted, i.e., adopted and used. This might either prevent the use from the get-go or it might lead to the cessation of use after a (short) period of use. The most obvious use of an activity tracker would be that of maintaining sufficient or increasing insufficient physical activity. As Bice et al. [27] could show, the use of activity trackers does in deed have the potential to increase physical activity, and thereby reduce the volume of negative repercussions of overweight, obesity, or sedentary behavior.

Perceived privacy: While e-commerce and social networks are well-studied areas in terms of privacy research, e.g., [28, 29, 30], the application in the area of fitness trackers has been lagging behind. Nevertheless, privacy concerns when dealing with mobile health apps has come into the focus for research. Despite the physical, or perhaps even medical, benefits life-logging offer, the multitude of different types of data one can track, can also prove to be a barrier to engaging with activity trackers or life-logging technologies: The type of data recorded by CHITs might be seen as a potential breach of privacy, as many users or potential users view medical or biometric data as highly sensitive, see, for example, [31, 32]. In the context of fitness trackers, Lidynia et al. [33] have found that, while there is a general interest in the data provided by those devices, their use is prevented by the perceived sensitivity of the data and the unknown access by third parties. While the perceived sensitivity might be influenced by the general privacy disposition or need for privacy of a person, [e.g., 34], the willingness to use life-logging apps and thus use online services for their data might be influenced by the so-called privacy concern, [e.g., 35].

Need for privacy: As life-logging is about the mass collection of data, there is — as with all technologies in which online data is disclosed — the question of data protection and the privacy needs of users. The construct *Need for Privacy* is independent of the concrete object and describes how willingly someone is to generally talk about him-/herself and lets other people invade his/her privacy [36]. According to [37, p.470], this is the case: "an individual's propensity to protect their personal space and minimize the disclosure of personal information". This, in turn, could be summed up in typologies to introduce the main characteristics of potential users in different contexts: Schomakers et al. [38], for example, could identify three types of internet users – the guardians, cynics, and pragmatists – differentiated by "their attitudes and behaviors regarding online privacy" (p.156).

Accuracy: Accuracy of consumer-based physical activity monitors is an important part of users' willingness to employ an activity tracker. A device that does not work accurately will be discarded after a while. Therefore, many studies exist that compare the accuracy of different commercially available fitness trackers. For a systematic review of existing studies, see, for example, [39]. In most studies, distinctions are made based on (1) the location of the tracker, that is, if it is worn on the wrist, clipped to the belt, on chest level, or even on the ankle; (2) on the different available brands or models that have been tested – not only against each other but also against clinical grade meters – and (3) based on different activities, from running on a treadmill, to outside, and also if the measured activity was of high or low intensity.

Competition and reinforcement: Fitness apps and, in extension, wearables can motivate or encourage their users to more activity in different ways [40]. Some apps offer narratives or encouraging texts if goals have been reached or are about to be reached. They all have in common that they utilize elements of gamification which means the integration of game elements such as scores or rules to non-game environments or contexts [41]. Acceptance research across different technologies and products has shown that not only system properties but also individual differences – such as age, gender, and technical self-efficacy – shape usage, evaluation, and also overall acceptance of products [24, 26, 25].

Age and gender: When investigating whether personality traits have an influence on the evaluation and use of life-logging devices, age must also be considered. Many studies have shown that age influences technology usage, e.g., [42], as the ability to interact with technologies decreases with age. In addition, older people feel that the ease of use and performance are lower when compared to younger users [43]. Usually, younger persons and men express a higher self-efficacy in interacting with technology ([44, 42, 45]). It is also known that gender differences in the use of technologies need to be taken into consideration, which applies to all age groups. Women and men differ in self-efficacy in interacting with computers and women usually show more anxiety towards computers[46][45][47]. Studies on the established technology acceptance models have also shown that there are gender differences in the intention to use the technology and in its use: While the perceived usefulness is more likely to motivate men to intention to use a technology, women are more likely to be motivated by ease of use [48].

Self-efficacy and motivation: Self-efficacy in interacting with technology also plays an important role as it has been shown in many studies that this influences perceived usefulness of a product (here a life-logging device), the efficiency, effectiveness, and user satisfaction as well as learning outcomes [49, 50, 42, 51, 46].

While the Motivation for Physical Activity (MPAM) scale included both intrinsic and extrinsic motivation factors, and it could be shown that intrinsic motivation factors are more important for long-term adherence to exercise schedules or programs [52], the motivation for physical activities was surveyed to understand if the use of so-called fitness trackers could be explained or facilitated by a generally higher willingness to engage in physical activities.

Summarizing: A multitude of individual and system factors influence the acceptance as well as short- and long-term use of life-logging technologies. Mostly, all these influencing factors have been examined in isolation. In reality, however, users might decide to use or not use life-logging technologies by evaluating combinations of factors given in the usage situation. In line with the approach of [53], who examined users preferences in wearables by conjoint analysis in the medical context, our study seeks to find out how personal and motivational factors to use life-logging technologies are weighted, whether this weighting is similar across all potential users of life-logging technologies, and if individual weightings are influenced by personality factors and user diversity.

2.3. Research Questions

To understand the interplay of different factors for the acceptance of life-logging technologies, we adressed the following exploratory research questions:

1. How are product properties of life-logging devices weighted and are some product properties perceived as more important than others?
2. Do the weightings yield a single best product or do users prefer several products with distinct product characteristics?
3. Do effects of user diversity (previous experience, personality, demographic variables) impact the preference judgments?

3. Method

We designed a survey to explore which aspects are most important for potential life-logging users. In this section, we first outline the concept of the conjoint analysis (CA) applied in this study. Next, we present the attributes and levels of the conjoint analysis as well as the selection of independent and dependent variables. Finally, we describe the data acquisition, the applied statistical procedures, and the sample of our study.

3.1. Conjoint Analysis

Conjoint Analysis is a quantitative empirical research method developed by Luce and Tukey in the 1960s in which consumer choices or preferences for complex products can be studied by decomposing the influence of individual product features [20]. In contrast to conventional survey approaches, participants evaluate configurations of a product that are combined from different attributes (e.g., color of a product and size of the packaging) with different attribute levels (e.g., blue and red, large and small). This enables the decomposition, analysis, and simulation of choices or purchasing decisions and enables the weighting of product characteristics, the analysis of trade-offs between different product characteristics, and the segmentation of users into groups with different preferences.

CA informs which attribute influences the decision of the participants the most (relative importance), which attribute levels are rated lower or higher (part-worth utilities), and whether an attribute level contributes positively or negatively to the decision [21, 54]. These preference ratings can then be interpreted as indicators for acceptance of a technology [22]. In a first step, part-worth utilities for the separate attribute levels are calculated using Hierarchical-Bayes (HB)-estimation. These part-worth utilities indicate how attractive the levels are in comparison to the other levels of the same attribute (cf. [55]). In the HB-estimation, the personal part-worth utilities are combined with the average of the overall sample to get part-worth utilities.The advantage of this process is that the calculated utilities are reliable even either the sample is small or the participants get few decision sets (as in this survey). The importances for the single attributes are also calculated through the part-worth utilities. A high importance indicates that the influence of the attribute for the selection of a device is strong. To calculate the relative importance, the range of the part-worth utilities of one attribute is divided by the total range of the part-worth utilities of all attributes.

In this survey, we use a Choice-Based-Conjoint Analysis (CBC). It mimics decision processes for or against complex products in which multiple attributes influence the decision [56]. In a CBC, participants repeatedly select one of several product concepts that are composed from multiple attributes and multiple attribute levels. Based on these decisions, a model for the selection probabilities is calculated using multinominal logit or probit models [56].

3.2. Identification of Usage Motives of Life-Logging

Subsequent to a literature review, interviews with life-logging users and non-users were carried out in order to identify important aspects that can influence the evaluation of life-logging devices. Persons answered to an advertisement in the local newspaper, in which we looked for both persons using life-logging technologies as well as those who are not using life-logging technologies. Participants were not gratified for their efforts but volunteered to take part in the interview study. Interviews were run during June and July of 2017. In the beginning of the interview session, a definition of life-logging was given as to create a common understanding of the topic of the interview. Also, two examples (water drinking behavior and step counter) were explained. Afterwards, users' motivation to use life-logging apps were thematized. Overall, the interviews were run individually and lasted between 30 and 50 minutes, depending on individual answering styles and engagment with the topic.

In the user group of life-logging devices, nine persons (six women, three men) reported to use life-logging technologies quite regularly for a period between seven months and five years. Also, seven persons had not used life-logging technologies so far (non-user group, five women, two men). All participants were asked for the key motivations and their reasons for (not) using life-logging technologies. In order not to restrict persons in their natural reporting motivation, interviews were kept quite open, still a semi-standardized interview guideline was used. The interviews were audio-recorded. From the verbal recordings, we identified eight motivational factors that were characterized as motivations to use life-logging in the short term usage as well as for longer periods of time by the interviewees within the user group. Also, six inhibitory factors have been identified that were reported as discouraging the use of life-logging devices (non-user group) (see Table 1). Accuracy of the measurement, perceived utility, and motivational design were the key motivators, but also the reasons for not using the devices. In addition, we also integrated privacy design, as the interviewees saw privacy as one of the most important inhibiting factors (mentioned by both, users and non-users). In Table 1, the mentioned reasons for and against using life-logging technologies are listed. The reasons in bold represented the most often mentioned factors that were selected for the subsequent conjoint study.

A closer look into the reasons for and against the usage of life-logging technologies shows that some of the reasons were referred to as pro- and, at the same time, as contra using motives. For example, usefulness turned out to be an argument which was mentioned as a pro-using motive, and, likewise, as a contra-using motive. The same applies for accuracy and the motivation which were seen as positive and negative. Similar findings have been revealed by [57], which explored the usage motives of information and communication technologies in different usage contexts (working vs. medical context). Authors introduced the term "janus-faced" categories" (p. 49), that deliver a relevant dimension for acceptance, but the relative weight of the dimension can fall either in the contra and the pro-using motive category. Apparently, human evaluations towards the overall utility of technologies as well as the final intention to use a technology are not guided by simple clear-cut decisions "yes" or "no". Rather, they reflect individual or situational combinations of the factors and usage contexts that need a closer look.

3.3. Attributes and Their Levels

On the base of the interviews, we selected the four most important attributes for the subsequent conjoint study. Each of the attributes was operationalized by means of different levels that will be introduced in the following section:

Perceived Utility: For the first attribute, the par-

	motivating factors	inhibitory factors
1	**perceived usefulness**	**perceived uselessness**
2	**high accuracy**	**lack of accuracy**
3	**motivational design (positive feedback)**	**discouragement (negative feedback)**
4	many functions/ individualization	**loss of privacy**
5	low user effort	high user effort
6	support	surveillance and heteronomy
7	perceived fun	
8	low commitment	

Table 1: Motivation and inhibition factors identified in the 16 interviews. Factors printed in **bold** are selected as key motives for the subsequent conjoint analysis.

ticipants should imagine that they usually walk 2,500 steps a day (level 1). In this scenario, the utility relates to the increase of daily steps due to the device: Users could either double (level 2), triple (level 3), or quadruple (level 4) their daily steps by using the device. We opted for an initial value of 2,500 steps because the current movement behavior should be perceived as poor so that the participants find it desirable to increase their daily number of steps. In addition, we wanted to divide the *perceived utility* attribute as well as the *accuracy* attribute into four levels with equal gradations. Another reason for the increase of 2,500 steps was that some studies show that the increase of 2,000 to 3,000 steps contributes to a significant improvement of health [58, 59].

To better visualize the above described effect, the participants were shown images indicating the (increased) number of steps per day. In order to ensure the comparability and to make statements about the importance of one level in comparison to another level, the levels varied by 2,500 steps, respectively. The participants were informed about the fact that 8,000 to 10,000 steps a day or 30 minutes of movement are recommended [10, 11, 60].

Privacy Design: This attribute consists of two dimensions: For one, there is the question where the data is stored and, for another, the question who can see the data or to whom it is available. The two dimensions were combined in the individual levels, so that the data is either stored in the device or in a cloud and is simultaneous visible for the user himself, a sports group, a fitness community, or in social networks.

Accuracy of the Device: The accuracy indicates how exact the device measures the outcome. It is 100% (level 1) if the results are absolutely precisely stated. The gradations to the next levels are similar to the perceived utility. The device can indicate the results with a deviation of 5, 10, or 20% percent which makes it 95% (level 2), 90% (level 3) and 80% (level 4) precise. For a better comprehensibility, we gave the participants the following example: "*If you walked for example 1,000 steps and the accuracy of* *the device was 80%, the device would show results between 800 and 1,200 steps.*"

Motivational Design: Different forms of competition were used to operationalize the motivational aspect of the device. Similar to the *privacy*-attribute, this last one contains two dimensions as well: The first dimension relates to whom the user competes with, which can be either himself, i.e., *me*, or *competition with others*. The second dimension describes how the results are illustrated: As feedback, the potential users get either a fictitious trophy; or a comparison with themselves, i.e., their previous achievements/performances; or a comparison with others in form of a leaderboard.

Figure 1 shows the attributes, their levels, and their visual representation used in the study.

We reduced the number of decision tasks to 9 per participant, as a full-factorial design would require 256 decision tasks ($4 \times 4 \times 4 \times 4$) and asking 8 to 15 decision tasks are recommended [61]. Consequently, the participants did not evaluate all possible designs and it is unlikely that multiple participants evaluated the same choice set. Still, the random distribution of the selection sets enables the results to be as good as the results of the full orthogonal design, despite the smaller number of selection tasks. In order to ensure the efficiency of the survey, the test design was previously tested in the Sawtooth software [62]. This calculated efficiency value indicates whether the design is as good as the fully orthogonal design. In this survey, 412 participants achieved values of almost 1 for all attribute values. This means that the test affirmed a median design of 99% and thus the results are of 99% comparable to an orthogonal test design. The design's standard error was below the limit of 0.05. The standard error indicates how accurate the main effects are and the smaller the standard error, the better. Based on studies already carried out, it is recommended that the standard error for the levels of each individual attribute should be less than 0.05. The standard error should be less than 0.05 for the levels of each attribute [63].

3.4. Structure of the Questionnaire

The survey consisted of three main sections and Figure 1 illustrates its structure.

The first section considered user characteristics and questioned demographics such as age, gender, and current life-logging usage (if yes, in which form and how often). In addition, we assessed several personality states and traits that we expect to influence the preferences for life-logging devices and the acceptance of life-logging in general:

Self-Efficacy in Interacting with Technology (SET): The subject's self-efficacy in interacting with technology was measured on a 4-item scale by Beier [64] with a good internal reliability ($\alpha = .876$). SET relates to how successful people interact with technology and if they are open to new technologies for both medical [65] and non-medical contexts [42]. The items used can be found in Table A.5.

Motives for Physical Activity (MPAM): We used a scale by Ryan et al. [52] to measure the subjects' general motivation for physical activity. Our reduced scale consists of 15 items and has a good to excellent internal consistency ($\alpha = .889$). The items used to answer the question "Why do you do sports?" can be found in Table A.6.

Need for Privacy (NfP): Next, to find out to what

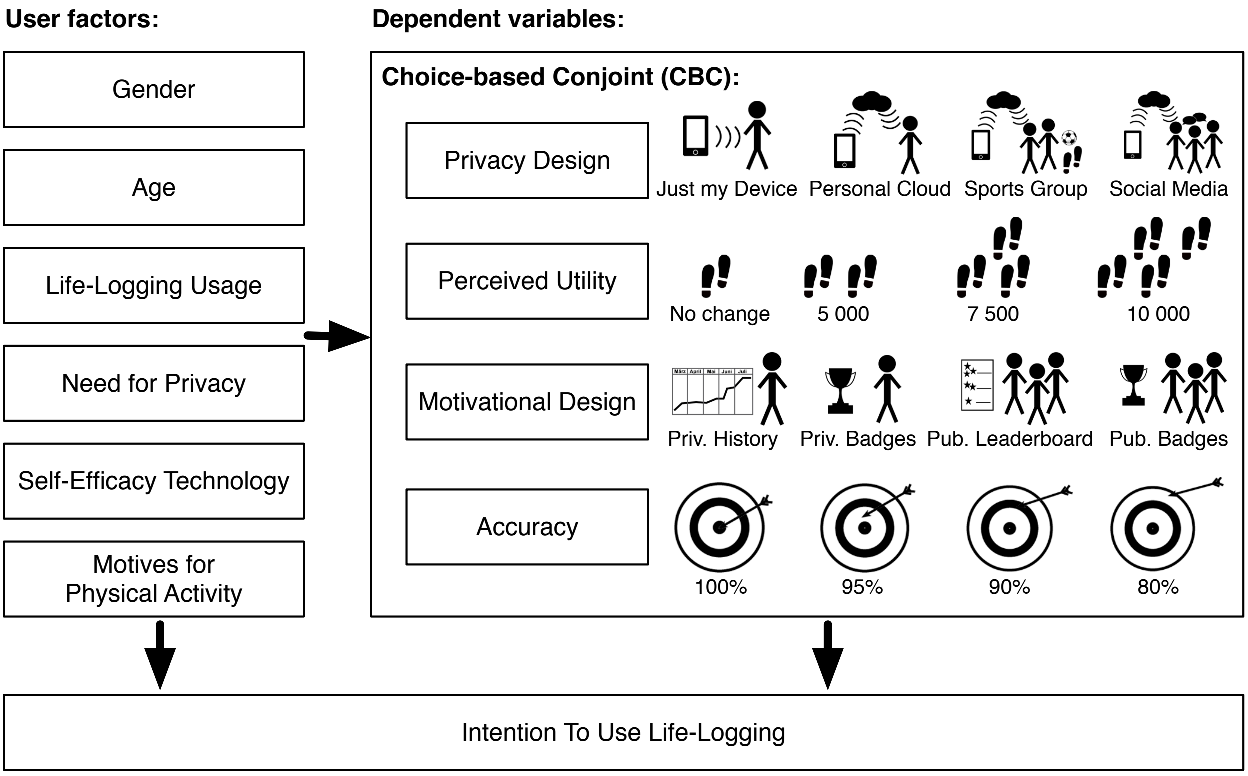

Figure 1: Research design with investigated user factors, attributes and levels of the conjoint analysis, and intention to use life-logging as dependent variable.

degree privacy as a personality trait influences intention to use life-logging, we measured the subjects' general attitude towards information disclosure with three items ($\alpha = .701$) on the *Need for Privacy* or *Disposition to Privacy* scale. The items used can be found in Table A.7.

The second section introduced the CBC and captured the participants preferences for different configurations of life-logging devices.

For the instruction, we informed the participants that life-logging devices can have different functions and features and that we would like to know which features are particularly important to them.

We then informed them that in the following part of the survey different fictitious devices with different device configurations will be displayed and selected by them. At the beginning of each selection task, the test persons were asked: "Which of these devices would you most likely use?"

The four attributes (*privacy design*, *perceived utility*, *motivational design*, *accuracy*) and their levels were introduced and presented textually and visually (see Figure 1). In each of the nine random choice tasks (consisting of products with all attributes and levels), the participants were asked to select their preferred product configuration. As a scenario that framed the decision task the participants should imagine that they usually walk 2,500 steps a day (see Section 3.3) and that they want to improve their daily step rate with the support of a fitness-watch, which was described shortly.

In the last section, we surveyed the participants' *intention to use life-logging* as dependent variable. This construct refers to Davis' Technology Acceptance Model that uses the intention to use a technology as predictor to the later actual use [66]. We measured this using two variables (see Table A.8).

Before distributing the survey, we checked everything – introduction, questionnaires, decision tasks (including the visualizations), and closing remarks – for legibility, comprehensibility, and clearness. Therefore, we previously sent the survey to several participants and incorporated the feedback from these pre-tests.

3.5. Data Acquisition and Analysis

Participants for the web-based questionnaire were acquired in the social environment via email and technology-mediated social networks (to attract a wide variety of potential users) as well as in specialist forums on the topics of life-logging devices, jogging and nutrition (to attract users with a specified usage motivation). Data were collected in October-November 2017.

All items besides the conjoint decision tasks were captured on six-point Likert scales. The results were analyzed with parametric and non-parametric methods, such as bivariate correlations (Pearon's r or Spearman's ρ) and uni- and multivariate analyses of variance ((M)ANOVA). The level of significance is set to $\alpha = .05$. If the assumption of sphericity is not met, Greenhouse-Geisser–corrected values are used, but uncorrected dfs are reported for better legibility. We used Levene's test to check for homogeneity of variance (homoscedasticity) as prerequisites for the (M)ANOVAs.

For the analysis of the decision tasks, we used Sawtooth Software using Hierarchical-Bayes (HB) estimation to first calculate the relative importances and the part-worth utilities of the attributes. Next, we used a latent-class-analysis (LCA) to identify user segments with similar decision behavior (cf. [67]). With latent-class-analyses, groups or types that are similar in some traits can be identified by some criteria. The participants are classified by specific variables so that homogeneous subgroups (latent classes) with persons with similar characteristics arise. For the classification, observed response patterns of the participants for various categorical (nominal or ordinal) questionnaire items are consulted (for example symptom present yes/no). Thereby item-connections can be revealed and explained through subpopulations or latent classes, which were unknown before ([68]). In the analysis underlying this work the attributes privacy, utility, accuracy and competition served for the classification.

Arithmetic means (M) are reported with the 95%-confidence intervals (denoted by $[lower, upper]$). The error bars in the diagrams show the 95% confidence interval.

3.6. Description of the Sample

Of the 412 participants, 214 (51.9%) were female and 198 (48.1%) male. The mean *age* was 36.1 (SD = ± 12,2 years) with a range from 17 to 78 years of age. This ratio indicates a heterogeneous sample with no correlation between age and *gender* ($r = .061$, $p = .213 > .05$).

In our sample, *age* and *motives for physical activities* correlate ($r = -.175$, $p < .001$) negatively, as do *age* and *self-efficacy in interacting with technology* ($r = -.099$, $p = .044 < .05$). *Gender* and *technical self-efficacy* correlate ($r = .312$, $p < .001$) positively, as do *gender* and *motives for physical activities* ($r = .163$, $p < .001$). Men reported a significantly higher *self-efficacy in interacting with technology* (82.3 ± 17.6%) and *higher motives for physical activities* than women (69.3 ± 21.6%). We did not find any correlations for need for privacy ($p > .05$). Table 2 gives an overview of the user factors' correlations.

225 (54.5%) participants of our study were users of life-logging technologies and 187 (45.4%) were non-users. Of the 225 users, 169 (41.0%) use smartphone apps for life-logging, 118 (28.6%) have an extra device, such as wristband, for life-logging, 32 (7.7%) use a fitness portal, and 18 (4.4%) record their behavior in a diary. In this article we only consider users of apps, portals or wearables as life-logging users and ignore the life-logging forms that are not electronically mediated.

4. Results

First, the relative importances and the part-worth utilities of the attributes for the overall sample are reported. Next, a comparison of the preference ratings of users and non-users of life-logging technologies is undertaken. In a third step, we use latent-class-analysis to segment user groups according to their demographic variables, personality factors and preference ratings.

4.1. Evaluations of Life-Logging Devices

We first show the preferences for a device (see section 3.4) and thereby outline what promotes the acceptance of a device or complicates it. There is one best combination of the four attributes, but we also illustrate which combinations are attractive if the best choice is not available and how important the individual attributes are for the participants.

As Figure 2 shows *privacy* with a relative importance of 42% affected the selection of a device clearly the most. There is a huge gap between the importances of *privacy* and the other three attributes, which are closer together.

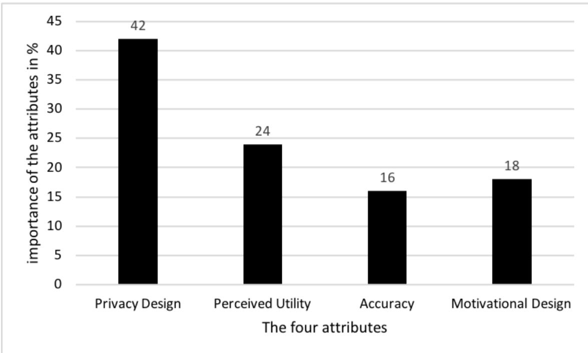

Figure 2: Relative importance of the four attributes for the whole sample.

For the interpretation of the part-worth utilities, it is important to consider that the values within one attribute are scaled to zero. Hence they show preferences inside of an attribute, but they do not enable comparisons between the attributes. Moreover, a high part-worth utility demonstrates that one attribute level is the most attractive of the eligible alternatives, but it does not show that the respondents rate it *good* on an absolute scale. Likewise, negative part-worth utilities do not indicate

	Dimension	Descriptives	2	3	4	5
1	Gender	214 female, 198 male			.312**	.152**
2	Age (range from 17–78 years)	M=36.1 SD=12.2	—		-.099*	-.175**
3	Need for Privacy	M=4.30 [4.20, 4.40]		—		
4	Self-Efficacy Technology	M=4.78 [4.68, 4.88]			—	
5	Motives for Physical Activity	M=4.30 [4.23, 4.38]				—

Table 2: Characteristics of the sample (Gender dummy coded as female=1, male=2). Numbers in square brackets indicate the upper and lower limit of the 95%-CI.

absolute refusal but only a worse evaluation relative to the attribute levels with positive values.

The part-worth utilities are highest for the highest *utility* (i.e., *10,000 steps* per day) and the highest *accuracy* (i.e., *100% accuracy*) (see Figure 3). Considering *privacy*, the participants prefer the device, on which *only themselves* can see the data and for the *motivational design* they favor the *historic comparison with themselves*.

Now, the differences between the individual part-worth utilities of one attribute are focused. Therefore the high distances between the levels show the high importance of *privacy*, whereas the distances of the other attributes are smaller. The two highest differences are within of the attribute *privacy*: 149.91 between *device, me* and *cloud, social media* as well as 130.13 between *cloud, me* and *cloud, social media*. There is one unwanted option of *utility* and one of *accuracy*, as the differences between *80% precise* to the next higher level *90% precise* with 29.92 and the difference between *no change* and *5,000 steps* with 56.46 are clear. In contrast, it seems to be less important for the respondents if the device is *90% precise*, *95% precise* or *100% precise* and if they walk *5,000*, *7,500* oder *10,000* more steps through life-logging. There is one favored level for the attribute *motivational design*, namely the *historical comparison*. The other levels have rather similar values, which means that the participants rate them similarly negatively.

4.2. Preferences of Users vs. Non-Users

A first insight into subgroups of the sample and a deeper understanding into the motives to use life-logging technologies regards the comparison between persons which already use life-logging technologies and those which do not. It was thus determined whether users and non-users attach different importances to the attributes, thus have different needs regarding *privacy*, *accuracy*, *perceived utility*, and *motivational design*.

To answer this question, we used independent sample t-tests (n = 225 users, n = 187 non-users). The analysis revealed (see table 3) that both groups did not differ significantly for *perceived utility* and *motivational design*, but only for *privacy design* and *accuracy* (see Figure 4). Outcomes in significance testings are given in Table 3. Obviously, the usage of life-logging technologies modulates the vulnerability of privacy concerns (users are less con-

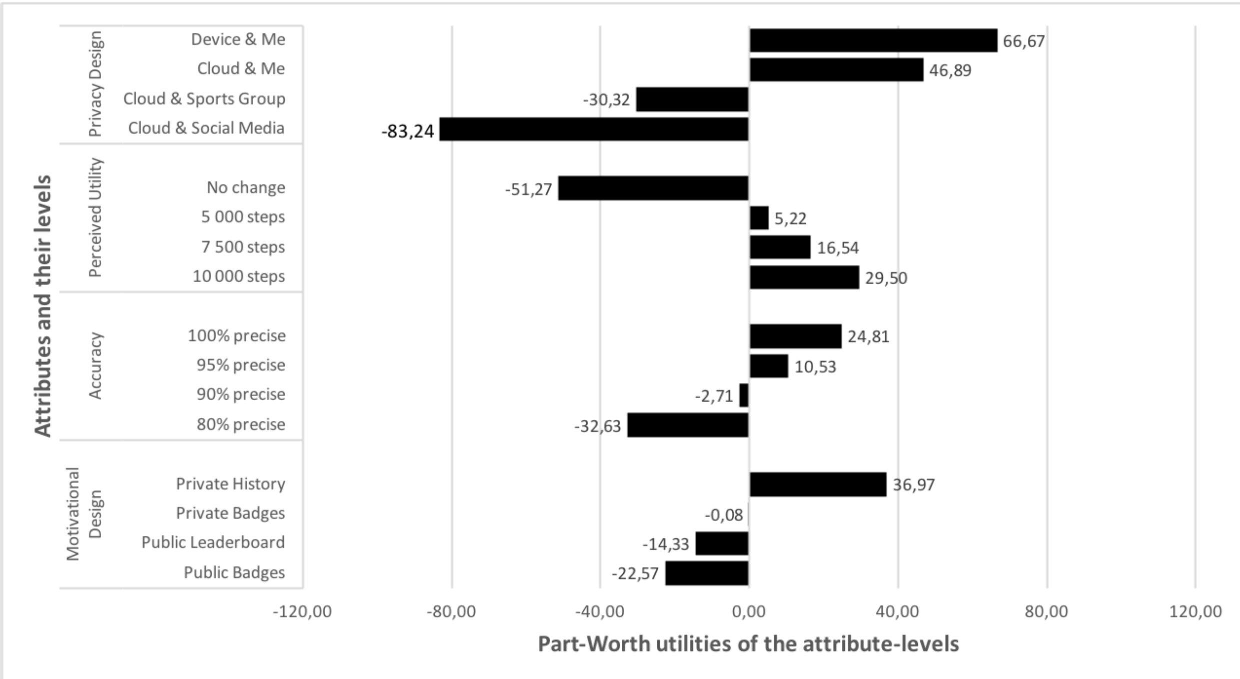

Figure 3: The part-worth utilities of the attribute-levels for the whole sample.

cerned about potential privacy issues in comparison to non-users) and the perceived importance of accuracy (non-users rate accuracy of measurements as less important in comparison to non-users). However, from the importance ratings no differences between usage motivation and perceptions of the usefulness of life-logging technologies can be found. Possibly, the simple dichotomization between “usage” and “non-usage” is veiling potential user profiles within the preference ratings. In a next step, we use a latent-class-analysis to identify more pronounced user segments that rely on more individual and personal user characteristics.

4.3. User Segments of Life-Logging Technologies

Based on the results of the CBC-analysis a typology of the respondents was created. The division was conducted with a latent-class-analysis and the four factors of the fictitious choice of a device *privacy design*, *perceived utility*, *accuracy* and *motivational design*. With the cluster-analysis the user segments of potential target groups of life-logging could be identified.

The cluster-analysis computed five different clustering and the 3-group solution turned out best based on the *Consistent Akaike Information Criterion (CAIC)* [69] of 5887.17. The significance of each attribute could be shown and all respondents can be categorized with 90% accuracy in only one of the three groups, which we have arbitrarily named from each other for clarity reasons.

For the biggest group, the *data protectors*, *privacy* is especially important, which reflects the total sample for which *privacy* is also most important. For one group (*benefit maximizers*), the *utility* is especially important, which reflects the total sam-

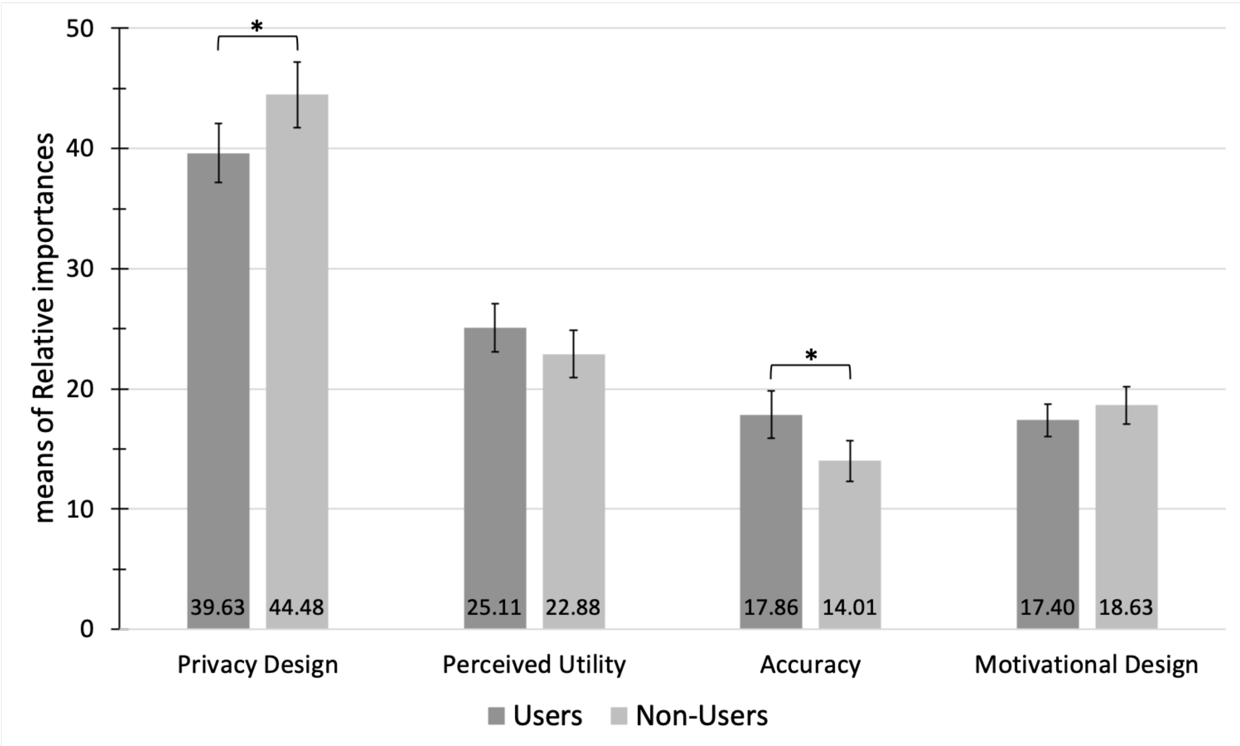

Figure 4: Importance of the four attributes for Users and Non-users. Error bars indicate the 95%-CI.

Attribute	**Levene's Test**		**T-Test**	
Privacy Design	$F(410, 394.162) = 1.44$	$p = .231$	$t(410, 394.162) = -4.85$	$p = .009$
Perceived Utility	$F(410, 407.810) = 10.68$	$p = .001$	$t(410, 407.810) = 2.23$	$p = .123$
Accuracy	$F(410, 409.236) = 4.99$	$p = .026$	$t(410, 409.236) = 3.85$	$p = .004$
Motivational Design	$F(410, 389.958) = 1.01$	$p = .316$	$t(410, 389.958) = -1.24$	$p = .234$

Table 3: T-tests for differences between users and non-users of Life-Logging for the four attributes

ple too, where *utility* is the second most important. The third group (*facts enthusiasts*) evaluates especially the *motivational design* and the *accuracy* as important. This reflects the total sample as well, because their the distances between these two attributes are lower than between the others.

We created a target-model for the *usage* of life-logging using the three groups described before. Thereby we can analyze which factors are motivating and inhibiting for each group. Following we describe the individual groups and their motivational and inhibiting factors.

4.3.1. The "Data Protectors"

For the *data protectors* (48%, 98 users), *privacy* is particularly important when using life-logging technologies. The relative importance of *privacy* reaches 62% (see Figure 5), while the other attributes, which only show relative importances up to 15%, are less important with a great space *Privacy* is not only very important for the *data protectors*, but more important than for the whole sample (r.i. = 42%).

We conducted a Welch's *t*-test for unequal variances (Levene's test: $F(2, 409) = 34.53$, $p < .001$) with the clusters as independent and the relative importance of *privacy* as dependent variable and found that at least two of the three groups differ significantly. We applied the Games-Howell test as post-hoc test and the results showed that *privacy* is significantly more important for the *data protectors* than for the *benefit maximizers* (34.85, 95%-CI [32.96, 36.74], $p < .001$) and for the *facts enthusiasts* (32.97, 95%-CI [30.57, 35.38], $p < .001$).

4.3.2. The "Benefit Maximizers"

For the *benefit maximizer* (23%, 59 users),there is one aspect which is especially important: the *utility* (see Figure 5) of using life-logging (r.i. = 51%). Compared to the whole sample, the *benefit maximizers* rate *utility* considerably more important (51% vs. 24%) and *accuracy* a little more important (20% vs. 16%) but *motivational design* (8% vs. 18%) and *privacy* (22% vs. 42%) clearly less important.

Because of unequal variances (Levene's test: $F(2, 409) = 149.67$, $p < .001$), we calculated a Welch's T-test with the user segments as independent variable and the relative importance of *utility* as dependent variable. According to this, at least two groups differ significantly in the relative importance of *utility* ($F(2, 157.41) = 946.60$, $p < .001$; $\eta^2 = 0.69$). In accordance with the Games-Howell test, *utility* is significantly more important to the *benefit maximizers* than the *data protectors* ($M = 30.68$, 95%-CI [29.01, 32.36], $p < .001$) and the *facts enthusiasts* ($M = 22.78$, 95%-CI [19.47, 26.08], $p < .001$).

4.3.3. The "Facts Enthusiasts"

Considering the *facts enthusiasts* (29%, 68 users), the relative importances of the four attributes are closer together compared to the other groups (see Figure 5). They rate *motivational design* the most important and more important than the total sample (r.i. = 37% vs. 18%). Also, the *accuracy* is important for them and more important than for the other groups (8%, 20%) and for the average (16%). In contrast *utility* (15% vs. 24%) and *privacy* (21% vs. 62%) are less important for the *facts enthusiasts* than for the whole sample.

A calculated Welch-test with the clusters as independent variable showed that *motivational design* (Levene's test: $F(2, 409) = 70.14$, $p < .001$; $F(2, 409) = 70.14$, $p < .001$; $\eta^2 = .36$) and *accuracy* (Levene's test: $F(2, 409) = 137.18$, $p < .001$; $F(2, 409) = 137.18$; $\eta^2 = .21$) are statistically proven more important for at least one of the two other groups. In accordance with the Games-Howell tests *motivational design* is significantly more important for the *facts enthusiasts* than for the *data protectors* ($M = 11.06$, 95%-CI [8.18, 13.93], $p < .001$) and for the *benefit maximizers* ($M = 16.73$, 95%-CI [13.90, 19.56], $p < .001$). Likewise *accuracy* is significantly more important for them than for the *data protectors* ($M = 14.00$, 95%-CI [9.44, 18.57], $p < .001$) and for the *benefit maximizers* ($M = 4.17$, 95%-CI [-.48, 8.81], $p = .041 < .05$).

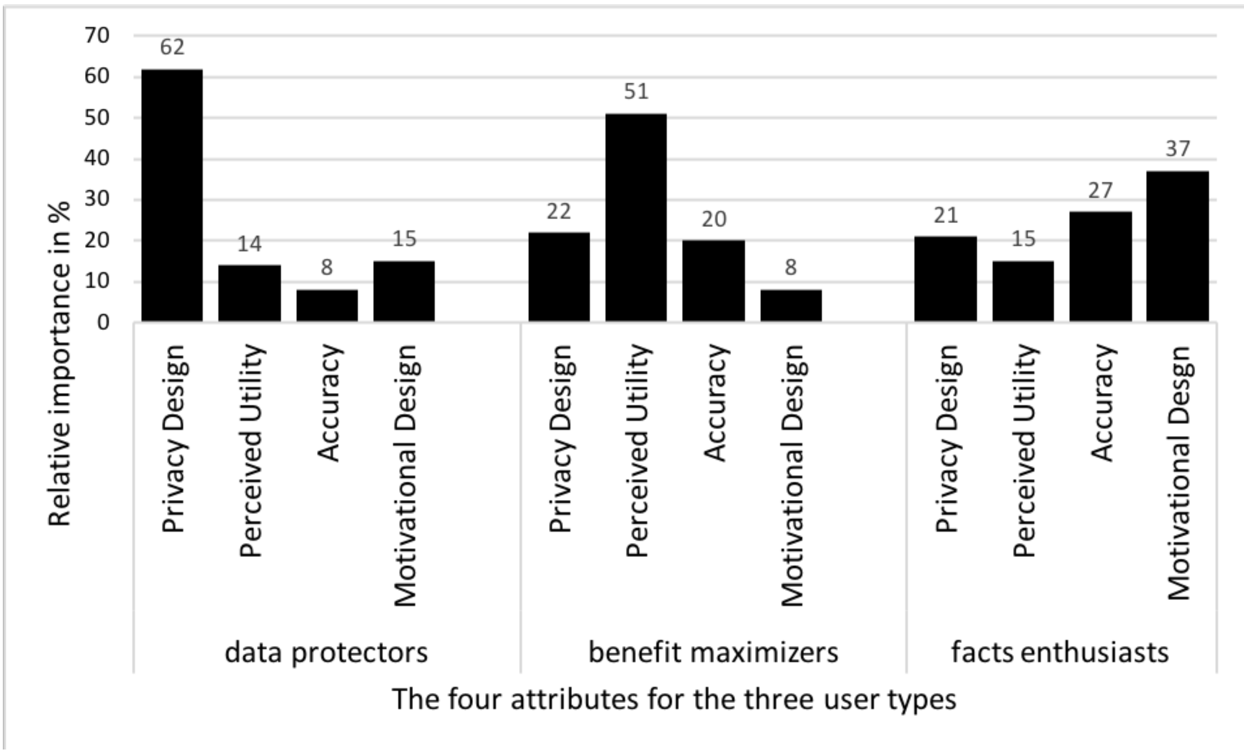

Figure 5: Relative importances of the four attributes for the total sample and for the three user types

4.3.4. User Segments and Personality Traits

So far we described the three user segments and their preferences with respect to the settings of life-logging devices. Following we illustrate if they differ in their user characteristics as well.

As Figure 6 and Table 4 show, the three target groups can be characterized by different personality traits: Unsurprisingly, the *data protectors* expressed the highest *Need for Privacy* whereas the *benefit maximizers* showed the lowest. In contrast, the *benefit maximizers* have the highest *self-efficacy in interacting with technology* and the strongest *motives for physical activity* while the *facts enthusiasts* have the lowest *SET* and the *data protectors* the lowest *MPAM*. On average, *benefit maximizers* are the youngest and *facts enthusiasts* are the oldest.

A MANOVA with the clusters as independent and the user characteristics as dependent variables found an overall significant difference between the three user segments (Wilk's $\lambda = 0.450$, $p < .001$, $\eta^2 = .33$). Specifically, the clusters differ in regard to *age* ($p < .05$), *SET* ($p < .05$) and *MPAM* ($p < .05$) as well as a effect with middle effective power on *Need for Privacy* ($p < .05$).

4.3.5. User Segments and Intention to Use Life-Logging

Besides the question if members of the tree target groups differ in their personality it is also interesting if the group sizes differ, if the intention to use life-Logging is higher for one group than for the others or if one uses it more frequently.

In the group of the data protectors are least users

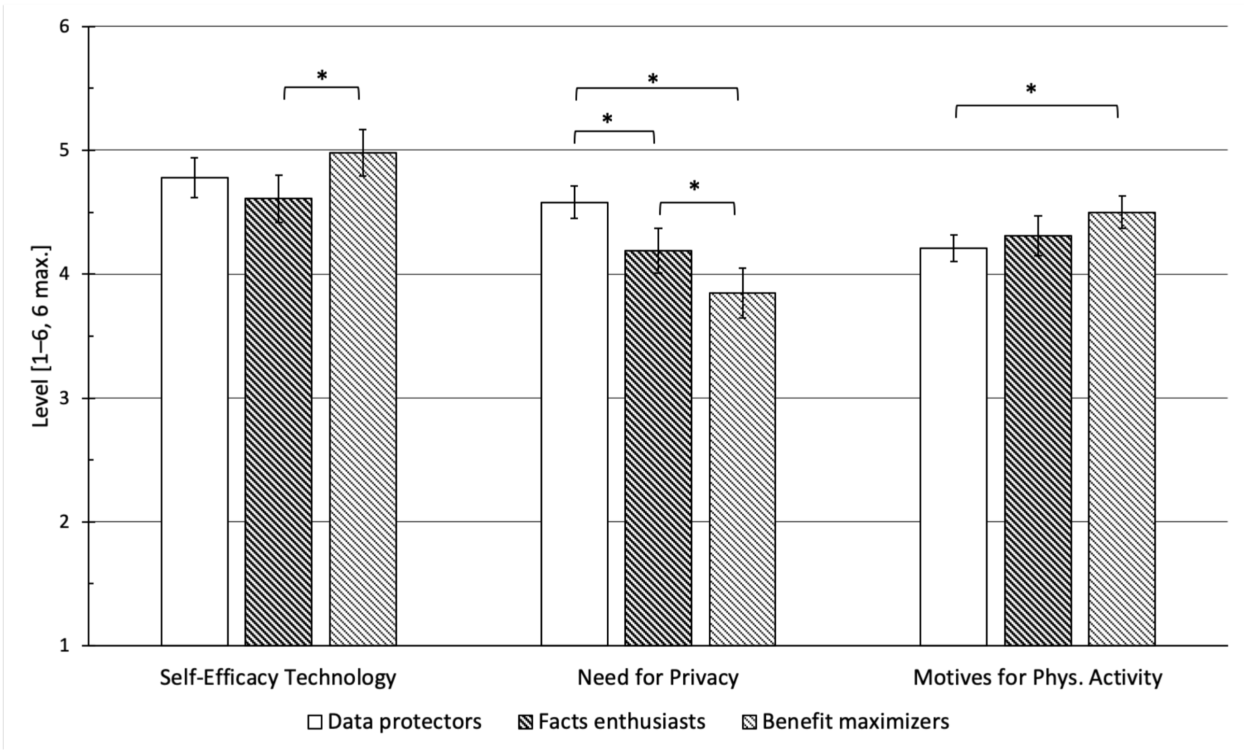

Figure 6: User characteristics by user segment / for data protectors, benefit maximizers, and facts enthusiasts. Error bars indicate the 95%-CI. . Square brackets denote significant differences between user segments.

of life-logging technologies (50%) followed by the facts enthusiasts (57%) and the *benefit maximizers* with the most users (62%). However, the slightly larger share of life-logging users among the group of *benefit maximizers* is not a systematic effect, as user segment membership and life-logging *usage* is not connected ($\chi^2(2) = 4.24$, $p = .120 > .05$, $\phi = .120$).

Data protectors use life-logging less than the other user segments ($M = 4.16$, 95%-CI [3.86, 4.46]) and their *intention to use* life-logging is lower ($M = 3.70$, 95%-CI [3.51, 3.90]). In contrast the *benefit maximizers* use life-logging most frequently ($M = 4.42$, 95%-CI [4.05, 4.79]) and their *intention to use* it is higher ($M = 4.59$ (95%-CI [4.33, 4.84])) in comparison to the other groups. The *facts enthusiasts* use life-logging more frequently than the *data protectors* and less frequently than the *benefit maximizers* ($M = 4.26$, 95%-CI [3.95, 4.58]). Their *intention to use* is between the others, too ($M = 4.06$, 95%-CI [3.80, 4.33]). We computed an ANOVA with the groups as independent variables and found that the *benefit maximizers* have a significantly higher *intention to use* life-Logging ($F(2, 397) = 13.42$, $p < .001$; $\eta^2 = .06$; Levene's test: $F(2, 397) = .90$, $p = .41$) than the *data protectors* ($M = 0.88$, 95%-CI [0.50, 1.27], $p < .001$) and the *facts enthusiasts* ($M = 0.52$, 95%-CI [0.09, 0.096], $p = .018 < .05$).

Dimension	Data Protectors	Benefit Maximizers	Facts Enthusiasts	p
Cluster Size	197 (48%)	95 (23%)	120 (29%)	
Gender	f=107, m=90	f=47, m=48	f=60, m=60	p=.653
Usage	50%	62%	57%	p=.121
Age	36.3 [34.6, 38.0]	32.9 [30.8, 35.1]	38.2 [35.9, 40.5]	$p^{B,C}$=.003<.05
Need for Privacy	4.58 [4.46, 4.71]	3.85 [3.65, 4.05]	4.19 [4.02, 4.37]	p^{D}<.001
Self-Efficacy Technology	4.78 [4.63, 4.94]	4.98 [4.80, 5.17]	4.61 [4.42, 4.80]	p^{C}=.031<.05
Motives for Phys. Activity	4.21 [4.10, 4.32]	4.50 [4.37, 4.63]	4.31 [4.14, 4.47]	p^{B}=.003<.05

Table 4: Characteristics of the three identified user segments (Significant differences between Data Protectors and Facts Enthusiasts (^{A}); between Data Protectors and Benefit Maximizers (^{B}); between Facts Enthusiasts and Benefit Maximizers (^{C}); between all groups (^{D}). Numbers in square brackets indicate the upper and lower limit of the 95%-CI.

5. Discussion

The present study investigated if (potential) users of life-logging rate privacy, motivational design, accuracy and utility differently or that it is of varying importance to them. The study also showed that different personality factors such as technical self-efficacy, need for privacy, and motives for physical activity influence users' preference for specifically designed devices.

In general, taking the analysis of the whole sample of typical users and non-users of life-logging technologies as basis, it was found that privacy design is considered as the most important criterion for the majority of participants, followed by the perceived utility of the wearable, and its measurement accuracy. The criterion perceived as least important was the motivational design of the respective life-logging device (app, wearable). The weighting of the levels within each of the attributes was in line with expectations: The participants had a clear preference for higher accuracy and systems that have a measurable utility, e.g., that facilitate the increase of physical activity. In terms of privacy design, users prefer that only they should have access to their data. However, there is no clear preference if the data may only remain on the device or if it can also be backed up in a cloud. Sharing own data in a fitness community was rather rejected, and still more disliked was the sharing of data to the whole circle of friends or to the public was unquestionably/clearly rejected.

In order to specifically tailor information and/or communication concepts for the usage of life-logging technologies for users, physiotherapists or even medical personnel it is helpful to understand why groups of persons decline or, conversely, are motivated to use life-logging technologies and under which circumstances.

A first step to segment users was the comparison of the users' group vs. the non-users of life-logging technologies. Beyond the finding that persons which already use life-logging devices have a lower threshold of privacy concerns and a higher need of accurate and detailed measurements, the differentiation between users and non users fell short in explaining different motivations and factors that contribute to perceptions of a high utility of life-logging devices.

A subsequent latent class analysis however revealed three distinct life-logging personalities or segments in regard to the perceived priorities: The *benefit maximizers* have their focus on the actual measurable benefits of the technology and, in our case, in increase in their daily step count. In contrast, the other evaluation criteria were evaluated as less important. For *data protectors* the privacy design is the dominating factor of a product and all other aspects, including its utility, are perceived as much less important. The *facts enthusiasts* evaluate the device's accuracy and its motivational design as slightly more important, but this group also had the lowest relative differences between the products' attributes.

The groups identified in our study relate well with the individual privacy-utility trade-off in the use of connected technology already identified in many other studies [70, 71, 72, 73]. Some users are not willing to reveal their data at all, not even to create a benefit. In mirror image, there are some users who attach more value to the utility and are willing to disclose their data because of it. In addition, there were also some people in our study for whom the said trade-off is not decisive, but who attach more importance to get more accurate data and an accurate device.

Within each of the identified segments the order of the attributes was comparable. It is no surprise that our participants prefer device configurations with high accuracy and neglect low accuracy configurations. Likewise, higher utility in form of increased step count is preferred over no utility.

In regard to the attributes *privacy design* and *motivational design* the coherent order across the three user segments is more puzzling: Most users preferred product configurations were the life-logging data is not shared to others; neither to the public, nor to friends, nor to peers in a fitness community. Likewise, the single preferred option in regard to the motivational design was a private history of ones progress, whereas other variants, such as private or public badges, or a public leader-board, were not preferred. This finding stands in a striking contrast to the design of many contemporary wearables or apps for life-logging. These often build on sophisticated persuasive design with gamification and reinforcement though competition and comparison with peers.

Our data suggests that privacy is important for most users, but that the different user segments attribute different weights to data protection and privacy policy. Accordingly, the importance of the other attributes fades into the background.

The motivational design of the wearable was evaluated as important only for the facts enthusiasts, whereas data protectors evaluated it as less and benefit maximizers even as least important. We were surprised that most people rejected the idea of getting motivated through elements of gamification and social support through communities, especially, as most contemporary wearables build on these. Here, it is unclear whether the soft push caused by these systems was not conceivable or assessable by the participants of our study or if a system without these concepts might fill a gap in the market.

The identified three different user segments are not only linked to different prioritizations regarding the design of the wearable, but also to the surveyed individual user factors.

The segment of the data protectors (as identified by the latent class analysis) also reported the highest *Need for Privacy*. This finding might not appear as particularly exciting, still it suggests a high validity of our conjoint-based methodology, as the clustering/segmentation from within the conjoint is in-line with the constructs measured outside the conjoint study. Surprisingly, this group also reported significantly lower *Motives for Physical Activities* than both other groups. However, we speculate that this finding is more likely an experimental artifact than an actual effect: The group of data protectors has a slightly higher share of women and on average women reported lower *Motives for Physical Activities* (see Table 2). Nevertheless, further studies should investigate if and why there is a systematic relationship between *Need for Privacy* and the *Motives for Physical Activities*.

Within the conjoint study, the benefit maximizers had the highest preference for the utility of the device. From the perspective of the user factors, they reported the highest *Motives for Physical Activities*, the highest *self-efficacy in interacting with technology*, as well as the lowest *Need for Privacy* This segments apparently not only traded utility (in form of increased step count) against privacy in the closely defined decision task of the conjoint, but also reported lower levels of *Need for Privacy* and higher *Motives for Physical Activity* beforehand. Consequently, this segment might be best addressed by highlighting that life-logging technologies can support the fulfillment of their desire towards physical activities and that they can facilitate the increase of daily step count and higher fitness levels.

The facts enthusiasts, who attributed the highest importance to the accuracy of the device and its motivational design in form of a private history, reported the lowest self-efficacy in interaction with technology (sig. lower than the benefit maximizers' *self-efficacy in interaction with technology*) and their *Need for Privacy* scores lay between the data protectors and the benefit maximizers. While this user type is neither focused on the security of their data nor in an increased utility in regard to higher physical activity, they seem to want to precisely keep track of their current and past activities. This user segment should be addressed by highlighting the accuracy of the measurements and by offering easy and enjoyable ways to systematically explore their past walks, runs, and exercises and to compare them with current ones.

Despite the strong and evident effect of the user segments on the prioritization of the attributes, the influence of the user factors assessed in this study on the identified segments is limited. Merely the factor *Need for Privacy* stands out and should be considered both in future research as well as in the development of wearable technologies.

As the current use of life-logging technologies is not linked to membership to one of the three user segments, this means that all three different priorities should be addressed as belonging to one group does not exclude interest in and benefit from life-logging. In turn, stakeholders should offer different options or packages, be it the available options of data disclosure or even marketing strategies, as to include all possible life-logging users. This could increase the amount of people who could give their life a more healthy and active spin.

6. Conclusion

This work shows that people have different demands in regard to the design of life-logging wearables and apps and that three different user segments can be defined based in these differences: The *data protectors*, the *facts enthusiasts*, and the *benefit maximizers*.

Each user segment individually weighs the tradeoffs between privacy, utility and facts and assigns different priorities to the investigated functions of the life-logging system. The data protectors assign highest priority to the privacy policy and data protection, fact enthusiast are especially interested in the measurable benefit of the system, and benefit maximizers focus on accuracy and the motivational design.

These user segments now make it possible on the one hand to develop tailor-made products and on the other hand to specifically address (potential) users. Data protectors will be particularly interested in products that are particularly secure in terms of data protection and where this security is particularly emphasized in marketing. On the other hand, benefit maximizers are most interested in the utility of the system. They can likely be persuaded to use life-logging systems by highlighting the projected increase in daily step count, increase physical activity, or better overall well-being. On the third hand, facts enthusiasts are most interested in the accuracy and the motivational design of the system. For them, the focus of the product design and marketing should be set on the accuracy of the system and how the users' measured behavior is presented, for example, by providing comparisons with ones historical behavior.

7. Limitations and Future Work

Of cause, this study is not without limitations.

Firstly, we used an online questionnaire with scenarios to study people's preferences in regard to life-logging wearables. Two methodological difficulties have to be taken into account here: On the one hand, the participants have to create a mental image of fictitious products to evaluate them. On the other hand, people's preferences might change, if they are able to experience a tangible life-logging wearable or if they can use them for a longer period of time. Regarding the latter, studies in the technology acceptance domain indicate that there is a degree of stability of the preferences across time (e.g., [48, 26]). Thus, relevant prerequisites and requirements for later use of a technology can be predicted in advance. Regarding the former, we ensured a valid design by selecting the attributes and levels of the study based on current research, discussions with domain experts, and preceding interviews and focus groups with users and non-users of life-logging technologies. In addition, the whole survey was pre-tested and iteratively improved, to ensure that the participants had a clear understanding of the presented scenario, as well as of the products' attributes and levels. This approach reduces the difficulty of the decision tasks and increases the quality of the results.

Secondly, the sample of our study is not focused on a specific target population that might have specific wants and needs. Consequently, the present findings model the perceptions and requirements of a broad sample of more or less healthy persons that are aiming at keeping up a healthy lifestyle by using life-logging technologies or simply because they are facts enthusiasts. However, life-logging could also be relevant for the medical context and people with health limitations. Here, future work will have to precisely narrow down the perspective and explore which usage and non-usage motives might apply for more vulnerable users and (chronically) ill patients towards the acceptance of life-logging technologies. As coping strategies, the attitudes towards frailness, and aging might also play a role, the analysis should again follow a multi-step empirical procedure which entails both, qualitative and quantitative procedure to capture the further perspectives.

In addition, the focus on the different importance regarding the life-logging systems' design provided new insights, such as the three user segments with their individual preferences but leaves other questions still open for future work. Firstly, the study shows that gamification aspects and community integration of life-logging-systems was not evaluated as important by our participants. Yet, most commercially available apps and wearables build on at least one of these concepts and many studies indicate the efficacy of persuasive systems. We postulate that no current technology acceptance model can reliably predict the effect of gamification or any persuasive system in advance. Consequently, future work should address this gap and develop approaches to adequately model the effect of gamification in advance.

Secondly, we purposefully neglected the price of the wearable as an attribute in this conjoint-based study. Obviously, studying the influence of price on the relative importances of the other attributes can reveal interesting insights. Such as, if and to what extend do people trade privacy for cheaper products or how much would they be willing to pay for more secure or more effective products? On the other hand, this allowed us to study the trade-offs and preferred product configurations in regard to privacy and motivation design, accuracy, and utility without requiring participants to consider price-value trade-offs (which might be shaped by socio-economic status).

More application oriented, future work needs to address the question whether products designed according to our suggestions reduce the observed decline in long-term usage [74] and lead to a measurable increase in the use and effectiveness of wearables fitness trackers.

Appendix A. Scales Used in the Study

	Self-Efficacy in Interacting with Technology: Items (n=412; $\alpha = .876$)
1	I can solve quite a few of the technical problems I am confronted with on my own.
2	I really enjoy cracking a technical problem.
3	Since I have coped well with previous technical problems, I am optimistic about future technical problems as well.
4	I feel so helpless with technical devices that I keep my hands off them.

Table A.5: Items of the scale Self-Efficacy in Interacting with Technology (SET).

	Motives for Physical Activity: Items (n=412; $\alpha = .889$)
1	Because I want to be physically fit.
2	Because it's fun.
3	Because I want to be with my friends.
4	Because I want to improve my appearance.
5	Because I want to obtain new skills.

Table A.6: Items for Motives for Physical Activity (MPAM).

	Need for Privacy: Items (n=412; $\alpha = .701$)
1	Compared to others, I am more sensitive when it comes to handling my data
2	Since I have nothing to hide, I have no problem with it if others know personal data of me
3	Compared to others, I find it more important to keep personal information to myself

Table A.7: Items to measure Need for Privacy (NfP).

	Intention to Use: Items (n=400; $\alpha = .850$)
1	Can you imagine using life-logging over a longer period of time?
2	Do you think that life-logging has/would change your lifestyle?

Table A.8: Items to measure the intention to use life-logging.

Appendix B. Acknowledgements

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