Understanding the Mechanics of Persuasive System Design: a Mixed-Method Theory-driven Analysis of the Mobile Fitness Coach Freeletics

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ABSTRACT

While we know that persuasive system design matters, we barely understand *when* persuasive strategies work and *why* they only work in some cases. We propose an approach to systematically understand and design for motivation by studying the fundamental building blocks of motivation, according to the theory of planned behavior (TPB): attitude, subjective norm, and perceived control. We quantitatively analyzed (N=643) the attitudes, beliefs, and values of mobile fitness coach users with TPB. Capacity (i.e., perceived ability to exercise) had the biggest effect on users motivation. Using individual differences theory, we identified three distinct user groups, namely followers, hedonists, and achievers. With insights from semi-structured interviews (N=5) we derive design implications finding that transformation videos that feature other users success stories as well as suggesting an appropriate workout can have positive effects on perceived capacity. Practitioners and researchers can use our theory-based mixed-method research design to better understand user behavior in persuasive applications.

Author Keywords

behavior change, fitness application, theory of planned behavior, persuasive technology, personal values.

ACM Classification Keywords

H.5.2. Information Interfaces and Presentation (e.g. HCI): User Interfaces—theory and methods, user-centered design.

INTRODUCTION

In HCI, research on health, fitness and behavior change technologies is picking up over the last decade [28]. At the conference CHI 2015[1], for example, an entire track was dedicated to health and fitness-related topics exclusively. Researchers see a high potential for technology to help individuals to better manage their own health and fitness and, thereby, help societies to gain control over increasing health care costs and societal problems such as obesity [22].

[1]http://chi2015.acm.org

CHI'16, May 07 - 12, 2016, San Jose, CA, USA

ACM 978-1-4503-3362-7/16/05...$15.0
DOI: 10.1145/2858036.2858290

Figure 1. Motivational mantra of Freeletics and a picture of athletic men and women, communicating an image of strong and tough people. (Credits: Freeletics)

One key challenge of health and fitness technologies is to maintain a high user motivation. This is usually approached by persuasive system design [21]. It was shown that persuasive system design indeed influences adherence to web-based intervention programmes [31]. Yet, so far there is no coherent theory that explains and predicts which persuasive elements work in which context and for whom [47]. Constructing and validating such a theory is difficult because the effectiveness of persuasive system features does not only depend on behavior and context but also on individual characteristics and preferences of the user [26, 30, 56]. In addition, as Klasnja et al. [33] pointed out, it remains unclear *how* behavior technology should be evaluated. Hence, researchers and designers have to rely on trial and error. In both research (e.g., [9, 16, 17]) and practice (e.g., [19, 23, 49]), we can observe the success of persuasive systems. However, we can rarely observe the attempts that failed to increase motivation, with the exception of some research projects (e.g., [24]).

In this work we use well-established psychological theories to better understand the persuasive system design of a successful fitness application. In contrast to prior work that usually centers around research applications with small numbers of users [27], we investigate a commercial app that is being actively used by more than 6 million people. Thus, we can comprehensively assess the persuasive design including community effects, which is usually difficult with small-scale apps.

Our approach is in line with the 'turn towards practice' approach present in the HCI community since 1990: taking on a 'practice perspective', researchers study problems and solutions 'in the wild' as this allows them to understand phenomena that work in a real-world setting as opposed to the lab [32] and develop a systematic understanding of persuasive design that applies to research and practice.

This paper investigates persuasive system design through the lens of two validated theories, namely the theory of planned behavior (TPB) [2] and individual differences theory (i.e., users' personal values) [50]. TPB explains the relations among beliefs, attitudes, subjective norms, perceived control, behavioral intentions, and behavior. It allows us to identify elements of the fitness application's persuasive system design that speak to or change users' beliefs and, thereby, have an effect on users' intentions and behavior (according to TPB). Individual differences theory allows us to understand the shared common values of the users, to identify user groups with different values and to investigate whether groups with different values are also motivated by different factors as identified through TPB.

Contributions

The contribution of this work is four-fold: (1) We present a quantitative analysis of motivational factors of mobile fitness coach users. (2) We show how to use well-established theories to understand behavior change technology users and to identify cluster of users who share similar beliefs and values. (3) We show that individual differences theory supports the design of more fine-grained persuasive strategies. (4) We constructively continue the discourse whether existing behavioral theories are still valuable to understand and guide the persuasive design of interactive systems.

Research Questions

RQ1 – Intentions and Behaviors: How do users' attitude, subjective norm and perceived control influence their intention to workout using a mobile fitness coach?

RQ2 – Individual Differences: Are groups of users (clustered according to personal values) motivated differently?

RQ3 – Design Implications: How do the 'active ingredients' of behavior change technology fit to mobile fitness coach users' intention structure?

RELATED WORK AND THEORETICAL BACKGROUND

Our research studies users' intentions and behavior (RQ1) and analyzes differences in their motivational structure based on users' personal values (RQ2) to derive design implications for mobile fitness coaches (RQ3). Specifically, RQ1 aims at better understanding users' initial motivations to pick up and use health and fitness technology. However, research on behavior change technology [26, 30, 56] has shown that people's motivations vary widely. Hence, we don't expect to find answers to RQ1 that hold true for all user types. To address this, RQ2 aims at identifying groups that share the same values and motivational beliefs. RQ3 aims at translating the findings of RQ1 and RQ2 to actionable design implications. We structure relevant related work and theoretical background according to these research questions.

Users Intentions and Behaviors (RQ1)

The goal of behavior change technologies is to reinforce, change, or shape attitudes and/or behaviors [21, 43]. However, to do so, one must first understand what constitutes behavior. In social sciences, *behavioral theories* provide a systematic way to understand behavior by illustrating the relationships between *constructs* [28]. *Constructs* are a theory's fundamental 'building blocks', such as 'self-efficacy' (i.e., belief in one's ability to succeed) or 'outcome expectations' (expectations about the consequences of one's actions) [7].

The use of strong behavioral theories is vital for developing effective behavior change interventions [52]. Extant behavioral theories vary in their level of generalizability, ranging from meta-models over conceptual models to empirical findings [28]. Hekler et al. [28] suggest to choose *conceptual frameworks* to inform the design of behavior change systems because they are more specific than meta-models, but also more generalizable than empirical findings. One conceptual model is TPB by Ajzen [2]. We chose this theory because of its clearly defined approach for applying it to a specific behavior, widely appreciated by researchers [38, 5, 6, 39].

The goal of TPB is to both predict and explain human behavior. At the core of TPB is the concept of *intention*. Intention captures motivational factors influencing behavior. In essence, it indicates "how hard an individual is willing to try" [4]. According to TPB, *intention* is influenced by three main factors: (1) *attitude*, i.e., the person's opinion of the behavior under study, ranging from favorable to unfavorable; (2) *subjective norm*, i.e., the perceived social pressure to perform or not to perform the behavior, and (3) *perceived control*, i.e., the perceived ease or difficulty of performing the behavior [4]. In general, the more favorable the *attitude* and *subjective norm*, and the greater the *perceived behavioral control*, the stronger an individual's *intention* to perform the behavior. However, the relative importance of *attitude*, *subjective norm*, and *perceived behavioral control* in the prediction of *intention* is expected to vary across behaviors and situations [4].

Behavior is a function of salient information or beliefs that influence, in turn, *attitude*, *subjective norm*, and *perceived behavioral control* with respect to *behavior*. More precisely, attitude is influenced by *behavioral beliefs*, subjective norm is influenced by *normative beliefs*, and perceived control is influenced by *control beliefs* [2]. These salient beliefs are specific to the respective behavior and have to be elicited from respondents of the target group. Eliciting and evaluating salient beliefs requires pilot work, but allows behavior to be explained on a behavior-specific level and gives the theory a generative power: Salient beliefs can be used to design effective programs of behavioral intervention [3].

Individual Differences (RQ2)

Individuals differ in their personality [20]. These differences affect users' behavior and thus play an important role in designing applications that should appeal to a broad user audience [40, 45]. In the past, individual differences research has helped to understand individuals' reaction to both games [8, 56] and behavior change technology, e.g., health and fitness interventions [26, 30, 56].

The classification of user archetypes by Bartle [8] emerged from the games literature. Games are remarkably successful in what behavior change technology aims to do: reinforcing or changing users' behaviors. Bartle's [8] player taxonomy distinguishes between *achievers, explorers, socializers*, and *killers*. This taxonomy was derived from expert workshops and builds on the assumption that the preference for one type of play (e.g., achievement) suppressed other types of play (e.g., socializing). Ye [57] empirically tested this assumption by conducting an online questionnaire (N = 3000) with online game players. He found that motivations do not suppress each other, meaning that a player can score high on both achievement and socializing simultaneously. Looking specifically at health games for youth, Xu et al. [56] created a player taxonomy that distinguishes between *achievers, active buddies, social experience seekers, team players*, and *freeloaders*. Again, these player types vary in their motivation, behavior during the game, and their influence on other players.

Xu et al. [56] derived their taxonomy from qualitative interviews and focus groups with over 200 students who participated in the health game *The American Horsepower Challenge* (AHPC) and their teachers. The AHPC was a multi-month school-based competition to encourage students to increase their daily activity level. Participating students gained points for their school, however, their individual score was never visible to other players. In contrast, the fitness coach in our study broadcasts an individual user's performance and does not provide the possibility to compete as a group against other groups. Hence, the descriptions of *achievers*, *active buddies*, and *social experience seekers* might apply in our case, but *team players* and *freeloaders* will not.

These taxonomies of gamers [8, 56] are categorizations of players' motivations and behaviors. It is assumed that players can transition between different types [57, 56], thus, player types are regarded as states. However, it is also possible that some preferences and behaviors related to technology use do not change and are bound to stable personal attributes, so called traits, commonly defined as stable, mental structures.

Some researchers investigated this hypothesis. More precisely, they examined whether people's usage behavior is connected to their personality [26, 30]. In this regard, existing HCI research is mainly based on personality traits, i.e., related to the Big Five personality constructs. Two studies by Halko and Kientz [26] and Karanam et al. [30], both found that individuals' personality correlates with their preferences and usage of behavior change technology [26, 30]. Halko and Kientz [26] conducted an online survey (N=240) using storyboards depicting eight different persuasive strategies, while Karanam et al. [30] instructed participants (N=35) to track three self-chosen daily habits for five days. Both studies relied on the Big Five construct to assess individual differences. Their findings are complementary: Halko and Kientz [26] found that *agreeableness*, *conscientiousness*, and *openness* were positively associated with competitive or authoritative technologies (such as mobile fitness coaches). Karanam et al. [30] found that people, who scored high on *openness*, preferred rewards, challenges, and quests.

Similar to personality traits, personal values help to understand differences in user behavior. While research defines personality traits as essentially innate, personal values (i.e., beliefs or transsituational goals) are generally defined as a set of beliefs or guiding principles for life, which are learned over time and influenced by the individual's environment [44, 50]. So far, however, few studies have included personal values in their analysis, with some notable exceptions [34, 35, 36]. In our work, we integrate theory on personal values with TPB to better understand the behavior and intentions of mobile fitness coach users. We consider the more fluid nature of personal values more appropriate to investigate the effect of technology on behavioral change of different user groups (differing in their personal values).

Schwartz's human value theory [50, 51] is currently seen as one of the best resources to understand individual differences in values [14]. Besides being theoretically well grounded, his proposal shows strong validity across numerous cross-cultural studies [18]. To study the effect of individual differences in the behavior of mobile fitness coach users, our reasoning includes two of the four higher order value types developed by Schwartz [50], which can be conceptually linked to the Big Five dimensions *agreeableness*, *conscientiousness* and *openness* and should therefore appeal to the prototypical user of competitive or authoritative technologies, such as mobile fitness coaches. Specifically, *openness to change* resonates with individuals favoring independent thinking, action, and change. *Self-enhancement* includes values attributed to individuals, who focus on the pursuit of their own relative success and dominance over others [50]. Both higher order value types are reflected by a set of distinct values, namely self-direction and stimulation for *openness to change* as well as achievement and power for *self-enhancement*. Hedonism is a value conceptually shared by both *openness to change* and *self-enhancement*. Based on theory, we expect that individuals adopting mobile fitness coaches will score high on these five values. Yet, clustering potential user groups on the basis of their distinct value levels can add to our understanding of the mechanics of behavior change technology. However, to inform the design of behavior change technology, these findings, first, need to be translated to design implications.

From Theory to Design (RQ3)

Applying theoretical findings to the design of technology is hard as there is no clear process to follow [28]. To help researchers and practitioners alike to take design decisions, HCI research often aims to provide concrete design recommendations. Prior work on behavior change technology proposed a rich set of design recommendations (e.g., [10, 16, 21, 33, 46, 53]). For example, Consolvo et al. [15] recommend to (1) give users credit for activities, (2) provide personal awareness of activity level, (3) support social influence, and (4) to consider the practical constraints of users' lifestyles, while Klasnja et al. [33] recommend that new behavior change interventions should leverage social communities. Xu et al. [56] conclude that health games should support play style transitions and customizable privacy settings. Similarly, we aim to provide design implications relevant for the designers of health and fitness applications.

CASE STUDY: FREELETICS

Our work is based on an in-depth investigation of Freeletics, a high-intensity app-based fitness coach that incorporates a range of persuasive system features. Users are typically not very athletic in the beginning but go through a tough training plan to achieve their ideal fitness level and desired physical appearance. For this purpose, different – sometimes drastic and controversial – measures aim at maintaining a high user motivation, most prominently a social community and motivational messages such as ”No excuses”, ”Quitting is not an option”, or ”When do you leave average behind?” (Figure 1). The effect of these measures is difficult to study in the lab.

Freeletics is targeted towards people, who do not yet exercise (regularly). Most users presumable wish to become fitter, more athletic, and/or to loose weight, but have problems to achieve this. By adhering to a 15 weeks workout program and optionally a 15 weeks nutrition guide, users are meant to become fit and athletic. With this behavioral change and body transformation also comes an attitude change: Freeletics attempts to let users experience how much they can achieve.

A user’s personal Freeletics coach, including personal bests (the shortest time a user ever needed to perform a given workout), points, current level, and upcoming workouts are accessible through both a mobile application and a web platform. Users need to perform a fitness test when they start the Freeletics coach for the first time. Thereafter, the coach adapts to the current fitness level of the user. In addition, the web platform offers information (e.g., on fitness, nutrition, and lifestyle) and transformation videos (videos that show the 15 weeks body transformation of an individual, who is usually not athletic in the beginning but in the end). The wider technological context of Freeletics also includes public Facebook groups that allow users to connect to other users, exchange advice, motivate each other, and arrange collective workouts. The graphical design and marketing strategy of Freeletics appeal to both emotions (see Figure 1) and logic (the ability to work out flexibly and effectively).

ETHICAL CONSIDERATIONS

We examine a commercial product that persuades people not only to exercise (a goal that we can generally support) but also to buy a product. People will buy the coach only when they are determined to exercise. Hence, persuasive system design features primarily attempt to convince people to exercise. Those are the design features that we are interested in. We want to dissociate from any commercial goals. However, as fitness applications in the real world almost always have a commercial goal as well, we believe that the whole context of use of such systems is worth studying, e.g., to identify negative effects of commercial persuasive apps.

RESEARCH PROCEDURE

Our research consisted of three main steps, as depicted in Figure 2. Based on TPB, we decompose the behavioral structure of mobile fitness coach users (steps I and II). A TPB pilot study (step I) is required to derive users’ salient beliefs about the intended behavior of training with a mobile fitness coach. In the TPB main study (step II) we use questionnaire data

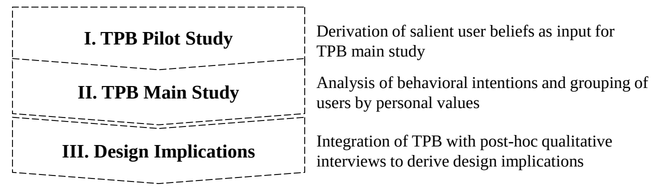

Figure 2. Three step research design integrating quantitative (Step 1 and 2) and qualitative findings (Step 3) to understand the behavior of mobile fitness coach users.

to quantify the relative influence of users’ attitude, subjective norm and perceived control on the intended behavior. In step III, we integrate the results of the TPB main study with results of post-hoc interviews to derive design implications for mobile fitness coaches and discuss the implications of individual differences in users’ personal values for choosing suitable persuasive strategies.

STEP 1: TPB PILOT STUDY

The design of our TPB questionnaire is based on a set of salient beliefs about the behavior under study that are shared within the target population [2]. Hence, it is necessary to first elicit such beliefs in a pilot questionnaire [3].

Subjects

Twelve unpaid subjects participated in the pilot online questionnaire (7 female, 19–57 years, mean=28 years). Study participants were recruited via Facebook in Freeletics groups and had a variety of backgrounds (e.g., graduates, automotive engineers, employees in corporate finance). All participants had several months of experience in working out with Freeletics.

Method

The pilot questionnaire consisted of open questions that identified accessible (i.e., readily available for recall among pilot study participants) behavioral, normative, and control beliefs [3]. Thus, our pilot questionnaire included the following groups of questions[2]:

Three questions to elicit salient behavioral outcomes: e.g., *”What do you believe are the advantages/ disadvantages of your working out with Freeletics at least 20 minutes three times a week in the next three months?”*

Five questions to elicit salient normative referents: e.g., *”Are there any individuals or groups who would approve/ disapprove of your working out with Freeletics at least 20 minutes three times a week in the next three months?”*

Three questions to elicit salient control factors: e.g., *”What factors or circumstances would enable you/ make it difficult for you to work out with Freeletics at least 20 minutes three times a week in the next three months?”*

The pilot questionnaire was analyzed using affinity diagrams and simple descriptive statistics. This procedure is in line with Ajzen’s original recommendations [3].

[2] full questionnaire available for download at http://data.ub.uni-muenchen.de/

Results

The following beliefs were mentioned at least twice in the pilot questionnaire and thus were included in the main questionnaire:

Salient behavioral outcomes. Anticipated advantages are *getting fitter*, *getting stronger*, and *getting healthier* through exercising regularly with Freeletics. Anticipated disadvantages are *having less time for other things*, and *being exhausted / having aching muscles*.

Salient normative referents. Individuals and groups, who might approve or disapprove exercising with Freeletics, are *friends*, *family members*, and *doctors*. Individuals, who are most likely to exercise with Freeletics, are *sportive people* and *friends*. Individuals, who are most unlikely to exercise with Freeletics, are *old* and *sick people*.

Salient control factors. Factors that make it easy for participants to exercise with Freeletics are *having enough time*, *working out in a group*, and *being in a healthy condition*. Factors that make it difficult for participants to exercise with Freeletics are a *lack of time*, *stress at work*, and *listlessness*.

STEP 2: TPB MAIN STUDY

Based on the results of the TPB pilot study, we constructed the TPB main study to assess the behavioral structure and personal values of mobile fitness coach users.

Recruiting and Sample

We used an online questionnaire distributed over sports-related social network channels and discussion groups (i.e., Freeletics groups on Facebook) to assess the behavioral structure and personal values of participants[3]. We used these channels to ensure that our participants had already experience with the Freeletics coach. As a token of appreciation, participants received a discount code for the Freeletics coach. Over a period of two weeks, 1,236 individuals followed our invitation to participate. At the end, 643 participants finished the questionnaire. On average it took participants about 31 minutes to complete the survey, which indicates that participants were willing to invest significant time to answer our questions.

Participants were on average 34 years old with the majority being male (61.40%), with at least four years of bachelor-level education (64.23%), and mostly no children (79.90%). The majority of participants (57.70%) live in metropolitan areas with 100,000 citizens or more. Participants' average annual income amounted to 35,513 EUR. We used these demographic variables as control variables in our study.

After a block of questions about *demographic data* such as age, gender, and athletic condition, our questionnaire consisted of (1) TPB questions and (2) questions about personal values.

The TPB part contained formative questions to measure salient beliefs and reflective questions to measure the latent variables attitude, subjective norm and perceived control.

[3]full dataset available for download at http://data.ub.uni-muenchen.de/

Each salient belief was assessed using two questions. The first question assessed belief strength, e.g., *"Training with the Freeletics App three times per week for the next three months will make me fit."* Answers were given on a 7-point Likert-scale (1=definitely bad to 7=definitely good). The second question assessed the outcome evaluation, e.g., *"Getting fit is ... for me"*. Answers were given on a 7-point Likert-scale (1=extremely unlikely to 7=extremely likely).

The TPB questionnaire also measured latent variables reflectively, namely the experiential and instrumental quality of the activity (both influencing the latent variable attitude), injunctive and descriptive norms (both influencing the latent variable subjective norm), capacity and autonomy (both influencing the latent variable perceived control) and intention. Therefore, three similar but not identical questions were formed to assess these latent variables (e.g., *"I am confident that I am able to exercise with the Freeletics App three times per week for the next three months."*) to assess the latent variable capacity (1=absolutely impossible to 7=absolutely possible).

We relied on the *Portrait Value Questionnaire* (PVQ) to assess Schwartz's set of values per participant [51]. In a theory-driven approach, we surveyed participants' value set related to sport using 22 questions in two versions of the PVQ adapted to male and female participants [14]. Participants were asked to rate how much the person in the description is like them (1=not like me at all to 6=very much like me).

Data and Method

To analyze the behavior structure and to derive the constructs suggested in the TPB, we used structural equation modeling (SEM) [25], in particular partial least square (PLS) implemented in SmartPLS [48]. We used PLS because (unlike LISREL) it can handle formative constructs. To identify groups differing in personal values we used two-step clustering [12].

Analysis and Results

Our analysis consists of two main parts. First, we calculated a general partial least squares (PLS) path model for all participants to decompose their behavioral structure. Second, we clustered participants on the basis of their personal value levels and calculated separate models for each cluster.

Using SmartPLS, we calculated a PLS path model to analyze the behavioral structure of participants. We report results in two steps. First, we investigate the relationship between items and corresponding latent variables in a measurement model. Second, we investigate the relationship between latent variables (as suggested by TPB) as part of a structural model.

Measurement Model

We assessed the TPB beliefs (attitudinal, normative, and control beliefs) as formative indicators. At the item level, we used the weights of each item to assess their relative contribution to each indicator. We used bootstrapping to conduct significance tests of the weights. Except for four, all items had a significant contribution to the latent variable ($p<.05$). The items 'Time' (behavioral belief), 'Doctor' (normative belief), and 'Competition' and 'Friend' (control beliefs) did not have a significant influence on their corresponding latent variables.

	ρ_c	AVE	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Behavioral beliefs			-											
2. Normative beliefs			.17	-										
3. Control beliefs			.45	.12	-									
4. Attitude (experiential)	.90	.82	.40	.16	.48	.787								
5. Attitude (instrumental)	.90	.76	.51	.13	.53	.56	.837							
6. Subjective norm (injunctive)	.79	.57	.38	.39	.45	.35	.41	.601						
7. Subjective norm (descriptive)	.86	.67	.25	.57	.24	.26	.17	.51	.742					
8. Perceived behavioral control (autonomy)	.79	.65	.35	.09	.48	.31	.48	.30	.07	.487				
9. Perceived behavioral control (capacity)	.90	.74	.43	.11	.70	.47	.60	.43	.24	.59	.827			
10. Intention	.97	.91	.45	.14	.61	.48	.59	.47	.31	.38	.73	.950		
11. Past behavior	–	–	.20	.16	.42	.29	.26	.50	.32	.21	.45	.50	-	
12. Control variables			.09	.07	.17	.15	.13	.14	.06	.04	.18	.23	.24	-

Table 1. Showing Composite Reliability (ρ_c), Average Variance Extracted (AVE), the correlation between all variables used in the PLS path model as well as their Cronbach's Alpha values (in diagonal, only for latent variables).

In our model, we assessed the TPB standard direct measures (attitude, subjective norm, perceived control, and intention) as reflective measures. At the item level, we investigated loadings and cross-loadings between items and reflective latent variables. All items had loadings above the required threshold level of .40 [11]. We used bootstrapping to examine the significance of the item loadings. Except for one item, all loadings were significant ($p<.05$). However, we did not delete the items from the models, since according to Chin [11], items with low and insignificant loadings still contribute to the predictiveness of the model as long as the items do not cross-load higher with other items. Further, investigations of the Heterotrait-Monotrait Ratio (HTMT) (as recommended by Hensler et al. [29]) showed no problems with discriminant validity. Following recommendations [55], we looked at the standardized root mean square residual (SRMR) to asses the overall fit of the model. In line with general recommendations, our model's SRMR of 0.07 is below the threshold of 0.10 and thus indicates a good model fit [29]. In Table 1 we report measures indicating the model's predictive capabilities. Following recommendations by Weiber and Mühlhaus [54], we first looked at the Cronbach's Alpha values of all reflective measures. Except for *subjective norm (injunctive)* and *PBC (autonomy)*, all Cronbach's Alpha values of TPB constructs were above acceptable levels of 0.7 [13]. Thus, *subjective norm (injunctive)* and *PBC (autonomy)* have to be interpreted carefully. The composite reliability (ρ_c) of all TPB constructs was above the required threshold level of 0.7 [11]. Except for *subjective norm (injunctive)*, the average variance extracted (AVE) of all TPB constructs ranges above the required value of 0.6 [11]. We report all correlations in Table 1.

The results of the measurement model led us to conclude that our model fulfills the criteria required for further analysis.

Structural Model

We used bootstrapping in SmartPLS to calculate path coefficients, significance levels and confidence intervals of all TPB variables. Our results are reported in Figure 3. Importantly, when using bootstrapping, all TPB constructs showed significant path coefficients ($p<.10$). Control variables were included in calculating the PLS path model, but did not have any significant effect. Thus, our findings are not influenced by participants' age, gender, or income.

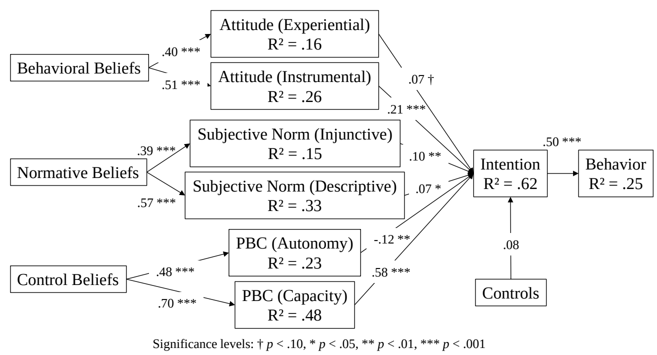

Figure 3. Showing the TPB model with path coefficients and respective significance levels as well as the R^2 for latent variables.

Behavior (in our model measured as past behavior) is predicted by *intention* (β=.50, $p<.001$). With our measurement of *intention* we can explain a reasonable large amount of variance of users' *behavior* (R^2=.25). According to TPB [2], *intention* is hypothesized to be predicted by *attitude*, *subjective norm* and *perceived behavioral control* (PBC). Together, these variables explained a large significant amount of variance in intention (R^2=.62). When investigating confidence intervals (for reasons of parsimoniousness not reported here), PBC (Capacity) (β=.58, $p<.001$) and *attitude (Instrumental)* (β=.21, $p<.001$) had the strongest influence on *intention*. Further, in accordance with TPB [2], all TPB belief constructs (behavioral beliefs, normative beliefs, control beliefs) had a significant positive effect on their TPB direct measure counterparts (attitude, subjective norm, perceived behavioral control) with path coefficients ranging from .39 to .70 ($p<.001$).

Unfortunately, the construct *PBC autonomy* was poorly measured (cf. the low Cronbach's Alpha in Table 1) and suffers from multicollinearity. Thus, even though *PBC autonomy* seems to have a significant effect on *intention*, this effect is likely to be confounded and deserves only limited interpretability. To ensure the robustness of results for the remaining constructs, we checked for model invariance calculating models with a subset of TPB constructs. All submodels explained a smaller amount of variance in *intention* compared to the full-model (Figure 3). When eliminating *PBC autonomy* (the factor suffering from multicollinearity), path coefficients, significance levels, and explained variance remained substantially unchanged, indicating robustness of results.

Cluster Analysis
In Table 2 we report means, standard deviations and correlations for all five personal values. All personal values exhibited acceptable Cronbach's Alpha values (i.e., self-direction .62, stimulation .72, hedonism .67, achievement .78, power .65) and were thus deemed appropriate for statistical analysis. We used two-step clustering using SPSS [12] to identify user groups on the basis of their personal values.

	M	SD	1.	2.	3.	4.	5.
1. Self-direction	4.64	0.83	.62				
2. Stimulation	3.91	1.08	.42**	.72			
3. Hedonism	4.32	0.94	.37**	.51**	.67		
4. Achievement	4.13	1.04	.33**	.25**	.24**	.78	
5. Power	3.37	1.04	.23**	.21**	.19**	.56**	.65

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 2. Showing mean, standard deviation, and correlation between all personal values. All personal values showed acceptable Cronbach's Alpha values (in diagonal) and were thus deemed appropriate to cluster participants into groups.

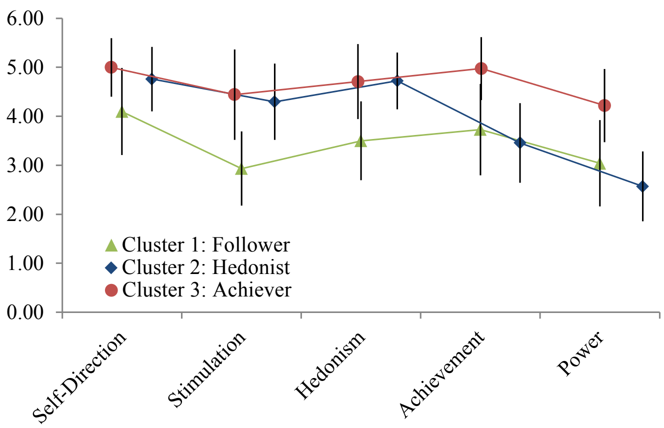

Figure 4. Showing the mean and 95%-confidence intervals of personal value characteristics of each cluster.

Our analysis identified three significantly distinct clusters ($p<.001$) (Figure 4). We calculated separate PLS path models for each cluster. In each model, *attitude*, *subjective norm* and *PBC* explained amounts of variance in *intention* at levels comparable among all three clusters and the general model (General: R^2=.62, cluster 1: R^2=.64, cluster 2: R^2=.58, cluster 3: R^2=.63). Respective path coefficients exhibited comparable levels across all three clusters and were in line with the general model, indicating a similar behavioral structure across models. However, the importance of the underlying salient beliefs differed between clusters. Hence, we present a short descriptive analysis of each cluster on the basis of the importance of salient beliefs (reported as standardized regression coefficients) for *attitude*, *subjective norm* and *PBC*.

Cluster 1: The Followers
Overall, participants in cluster 1 exhibited the lowest levels of personal values related to Schwartz' *openness to change* and *self-enhancement*. Their two strongest salient beliefs *"What my friends do is important to me"* (β=.61, $p<.001$) and *"I do Freeletics because my family wants me to"* (β=.40, $p<.001$) were significantly higher than in other clusters. Our data suggests that their motives to follow the recommendations of their friends and family are connected to their beliefs that *"Freeletics will make [them] fit* (β=.31, $p<.001$) *[and] healthy"* (β=.26, $p<.01$). Participants in cluster 1 also showed an increased importance (above all other clusters) of *"Having clear instructions"* to be able to do Freeletics (β=.20, $p<.01$). We thus coin participants of this cluster *the followers*.

Cluster 2: The Hedonists
Compared to cluster 1, participants in cluster 2 showed increased levels of self-direction, stimulation and hedonism, but similar levels of achievement and power. Thus, they embraced values connected to *openness to change* more than values connected to *self-enhancement*. When investigating their salient beliefs, they seemed to belief that *"Freeletics will make [them] fit"* (β=.26, $p<.05$) *[and] healthy"* (β=.18, $p<.05$). In addition they seemed to adhere more to their friends advice that *"[They] should do Freeletics"* (β=.25, $p<.01$) and have more *"Control over [their] time for Freeletics"* (β=.44, $p<.001$) (compared to participants of clusters 1 and 3). They seemed not to be concerned that *"Stress would prevent [them] from doing Freeletics"* (β=-.21, $p<.01$). At the same time, participants of cluster 2, seemed to have less *"Motivation to do Freeletics"* (β=.18, $p<.05$) compared to participants of clusters 1 and 3. In contrast to participants of clusters 1 and 3, participants in cluster 2 wanted to *"Avoid a competitive atmosphere when doing Freeletics"* (β=.13, p=.077). We thus coin participants of cluster 2 *the hedonists*.

Cluster 3: The Achievers
Last, participants of cluster 3 scored high on all values connected to *openness to change* and *self-enhancement*. Compared to participants in clusters 1 and 2, they had an increased belief that *"Freeletics will make [them] strong"* (β=.20, $p<.01$) and that *"Freeletics will make [them] exhausted"* (β=.16, $p<.01$). Interestingly, their belief that *"Freeletics will make [them] fit"* (β=.13, p=.09) as well as their belief that *"Freeletics will make [them] healthy"* (β=.15, p=.051) was less important to them than to participants of clusters 1 and 2. In addition, *"Stress will [not] prevent [them] from doing Freeletics"* (β=-.20, $p<.001$) and they believed to be able to *"Maintain high levels of motivation to do Freeletics"* (β=.31, $p<.001$). We thus coin participants of cluster 3 *the achievers*.

STEP 3: DESIGN IMPLICATIONS
To make our findings more useful for researchers and designers, we provide general and cluster-specific design implications. To validate that these design recommendations are in line with users' experiences, we conducted semi-structured interviews with five users. The goal of these qualitative interviews was to gain a better understanding of how existing Freeletics features are perceived by users and to provide a glance into users' perspectives through quotes.

Qualitative Study
Method
The interview script included both general questions (such as *"How did you first hear about Freeletics?"*, and *"Why did you start working out with Freeletics?"*) and questions related to specific system features (such as *"Do you pay attention to*

the feed that displays workout results of your friends? If yes, when and why do you look at it?"). Transcribed interviews were coded by two researchers (open coding technique).

Participants

We recruited 5 participants (1 female), with an average of 2 years of Freeletics usage (range: 1–2.5 years) and conducted qualitative interviews (avg. duration: 20 min).

Synthesis of Results

In this section we provide concrete design implications and relate them to users' perceptions of Freeletics' design elements. Furthermore, we compare the identified user groups with groups presented by Xu et al. [56] as they are in many regards similar and design implications are complementary.

Perceived Behavioral Control

In our study the most crucial motivational factor was *PBC (capacity)*. *PBC* refers to "people's perception of the ease or difficulty of performing the behavior of interest" [2]. Freeletics' training program is arguably hard and exhausting. However, some features aim at convincing users that they can, nevertheless, accomplish it. First, transformation videos demonstrate how other, (often) not very athletic users have managed to adhere to the program and to accomplish great results: *"Transformation videos show you what others have achieved in only 15 weeks, then you start to think maybe I can do this, too."*(P5). Second, the training is constituted in a way that requires minimal equipment and preparation: *"It's really easy and flexible, you need nothing except of shoes, clothes, and a mat. You can do it anytime and everywhere, and I usually just do it in my living room"*(P3). Third, the coach eliminates the cognitive effort to decide what exercises to perform: *"...it is convenient that I don't need to think about which workout I'm going to do today, the coach decides for me"*(P1).

While these features seem to perform well in convincing users that they can accomplish the program, they fall short in leading them back into training once they were unable to train for a period of time: *"When you have been sick or on holiday it is hard to get smoothly back into training. The coach doesn't seem appropriate anymore, the suggested workouts are just too hard after such a break."*(P5). Additionally, users might fear to lose their social status or achievements when they perform trainings much slower than last time. To convince users that they are able to get back into training, the fitness coach should provide the option to indicate setbacks (e.g., holiday; injury) such that the system can adapt to them. To help users to smoothly get into training again, the coach could, for example, suggest lower-intensity training sessions that are not posted publicly but promise to get the user back on track.

Support Flexibility

Similar to Xu et al.'s [56] findings, our results indicate that users of health and fitness applications can be grouped according to their values and behavioral beliefs. Hence, an important design implication is to accommodate the needs of different user groups. We suggest that this can be done either by explicit settings, an adaptive interface, or by ensuring that one interface allows for different usage styles. We present design implications for the identified groups in the following.

Followers

The most motivational factor for *followers* is that their friends exercise with Freeletics or would appreciate them to exercise. Hence, to foster followers' motivation, it is important that the application both allows users to (1) see when friends are training and (2) to appreciate their efforts.

(1) Freeletics users can see the efforts of their friends in a *Feed of Achievements*: *"Seeing in my feed that a lot of my friends worked out motivated me. Then I have an urge to workout, too"*(P2). Besides displaying the achievements of friends the feed also features active users, who might serve as role-models for *followers*. This, however, was perceived negatively by some users: *"It's only motivating to see people I know well and who are roughly as fast as I am. Seeing posts of the 'pros' in my feed doesn't motivate me"*(P5).

Xu et al. [56] recommended to allow the formation of small groups within a health game. This would allow groups of friends, who trust each other, to share their results in a save environment and to playfully compete without experiencing social anxiety or pressure. Such a feature would especially support the behavior of *active buddies*, a user group that Xu et al. [56] describe similar to followers. Freeletics does currently not allow users to build groups. However, users form private groups on other platforms such as Facebook and What's App:*"I'm not active in the huge anonymous Freeletics Facebook groups but I have a few Facebook groups with close friends. We workout together regularly and that is really helpful, because you have that trust and accountability. If I didn't join them for a few days they ask me, hey is everything alright, why didn't you come today?"*(P5)

Currently, the Freeletics coach generates a personal training plan for every user. Even though this personalization allows every user to progress in his/her own time, it takes away the possibility for a group of friends to perform the same exercises at the same time. To allow for *followers'* need of exercising together, the coach could allow a group of friends to synchronize their training plan (for a given time period). Such a feature would also allow friends to better compare their performances. Comparing performances in a teasing manner seems to be enjoyable for some users (*"If you meet someone, who is also doing it, it is fun to tease each other when you are faster at one workout than the other person."*(P1)). However, such behavior is not supported well through the system, as different users are rarely required to perform the same workout at the same time. P5 stated that comparing workout times is only fun when you are in a same stage as your friends: *"It only makes sense to compare your time with your own (previous) times. Everyone else is in a different stage in their own journeys. It would be different if everyone would have started the program at the same time"*(P3). A feature that allows users, who trust each other and exercise together, to build groups and to perform the same workouts on the same day would allow *followers* to compare their results, and to tease and motivate each other.

(2) Freeletics offers a "Clapclap"-feature (similar to the Facebook "Like-button") to show appraisal for other users' achievements and the option to comment on other users'

trainings. Users, indeed, make use of this feature to motivate their '*follower*' friends: *"When a friend of mine has achieved a really good result I give her a "Clap Clap". I think that might motivate her to do it more often."*(P4)

Hedonists

Hedonists score higher on *openness to change* than on *self-enhancement*. They are less convinced that they can maintain motivation, even though they are well in control of their time and don't feel like stress could prevent them from exercising. Hence, the biggest challenge for them seems to be not to lose interest in exercising per se. In this regard, *hedonists* are similar to *experience seekers* in Xu et al.'s [56] taxonomy. Xu et al. [56] recommend to provide the possibility to create personalized online representations to motivate young gamers. We further recommend to integrate playful group-based games and easter-eggs, as well as challenges and quests that stimulate curiosity, to keep *hedonists* entertained.

However, *hedonists* also dislike a competitive atmosphere. Hence, these challenges should be carefully designed so that they do not impose pressure and social anxiety: *"I want to relax and empty my head, I don't want to compete or to compare myself to others"*(P3). To minimize the chance of experiencing social pressure, we further agree with Xu et al.'s [56] that health and fitness applications should provide customizable privacy settings that e.g., allow users to share their achievements only with a trusted group.

Achievers

Achievers are convinced that Freeletics is exhausting and will make them strong. No matter how exhausting the training is, *achievers* are determined to continue the program and maintain motivation even when stressful times arise. According to their beliefs and intention, these users are least likely to give up and stop the program. In many regards, they are similar to achievers in Xu et al.'s [56] taxonomy. They focus on their personal goals and achievements: *"The 'personal best' (time) is very important, it is the only metric you have to judge your own performance."*(P2);*"After a while, you can't improve your 'personal best' each time you workout. Then it is really helpful to see your result on place 2 or 3 of your own leader-board."*(P4)

Rather than losing motivation, *achievers* may run into danger of prioritizing training over their health and well-being, potentially leading to over-training and injuries. This is also indicated by the low priority *achievers* assigned to becoming healthy and fit. An intense fitness program like Freeletics can be straining for the body and requires users to pay close attention to the way they perform exercises and to any changes or pain in their body. As there is no trainer present, who corrects incorrectly performed exercises, health and fitness applications must ensure to equip the user with all necessary information to perform the exercises correctly. Freeletics, for example, provides instruction videos that point out what users need to pay attention to. Additionally, a health and fitness coach that monitors the users' progress and training intensity could warn the user when she is in danger of over-training.

When focusing on achievements, being compared to other users, who may perform better, can be discouraging. In Xu et al.'s [56] study, *achievers* did not like to be compared, but wanted to prove themselves in front of others. Similarly, users in our interviews reported that *"In the beginning the feed was discouraging, because everyone in the community was faster than me. And I didn't want to do it for the community but for me."*(P5). We, therefore, agree with Xu et al.'s [56] conclusion that a health technology should offer announcing functions to leverage social affirmations, but also allow to control self-image. Freeletics automatically posts training results (time needed to finish a given set of exercises) publicly. While this feature allows *achievers* to leverage social affirmation it might also cause social anxiety or push them further then they might be comfortable to go. Again customizable privacy settings might reduce the social pressure users experience.

DISCUSSION

In HCI literature, the effect of behavior change technology is rarely robustly demonstrated [28, 42, 47]. Hekler et al. encourage three ways to evaluate behavior change technologies: mediation and moderation analysis, alternative experimental designs, and qualitative data. In this work, we relied mainly on mediation and moderation analysis, supplemented by qualitative data. This analysis helped us to understand which motivational factors influence which user groups most. This new understanding could now be used to choose appropriate strategies for mobile fitness coaches. Another benefit of the quantification of motivational factors is that it provides a straightforward method to evaluate the effectiveness of a new design by reapplying the quantitative analysis. An analysis of the same motivational factors after an intervention would allow to understand how chosen strategies worked (mediation) and for whom they worked (moderation). While we acknowledge that a quantitative survey and a path analysis requires a lot of resources, it might still be more feasible for HCI researchers than performing a randomized control trial [28].

With the mixed-method approach developed in this paper we follow calls in literature to integrate and rigorously test existing behavioral theories in the context of behavior change technologies [39, 47]. Linking the quantitative results of the TPB path model (see Figure 3) and aspects of individual differences with insights from post-hoc qualitative interviews we presented a set of design implications for three user groups, who differ in their values and motivational beliefs: *followers, hedonists*, and *achievers*.

Another purpose of our work was to evaluate whether TPB and individual differences theory can help to understand *what* constitutes motivation to use a mobile fitness coach, *how* this motivation can be fostered and to shed light on the influence of users' values. This is an alternative approach to work based on the Big Five personality traits. These studies reported for example that these persuasive strategies work better for some participants than for others: Karanam et al. [30] found that rewards were appreciated by people, who scored high on *openness*, and Halko and Kientz [26] found that competition is appreciated by *agreeable*, *conscientious*, and *open* users. We think that because of their more fluid nature (compared to traits) [50], values provide another interesting angle to understand *why* salient beliefs of users differ and *how* to use individual differences to better understand behavior change technology. Specifically, in our case study, integrating well-established behavioral theory (i.e., TPB) and individual differences insights (i.e., personal values) in behavior change theory helped to uncover why certain persuasive elements show variability across user groups.

LIMITATIONS AND FUTURE WORK

Although our research design was helpful in decomposing the behavioral structure of mobile fitness coach users and thereby follows a call in literature for more theory [28], we only tested our research design in one case study. Specifically, Freeletics users may be more self-motivated and self-directed individuals because they paid to use an app-based fitness coach. Hence, it remains unclear to what extent self-selection influences the generalizability of our results and if our approach is beneficial in understanding other behavior change technologies. However, we believe that our findings are applicable to other health and fitness apps as well and encourage both testing and extending our initial framework in future work.

Our research design only allowed us to derive design implications based on our findings of individual differences as moderators of users' intention. A/B testing of these recommendations might lead to a more thorough understanding of motivational factors for different groups.

Although theoretical grounded and well-established, TPB and individual differences theory have certain limitations with implications for our conceptual framework. They may disregard key factors that are out of the theoretical scope such as the organisational, cultural, or environmental context [28]. Another limitation of TPB is that it fails to account for psychological mechanisms that are not accessible to the respondents [1, 37, 41]. We appreciate these perspectives. The challenge to integrate such unconscious mechanisms of behavior change in a systematic approach is an opportunity for future work.

CONCLUSION

In this paper we applied well-established theory (TPB and individual differences theory) to understand motivational factors of mobile fitness coach users. We identified three clusters of users, which we coined *followers*, *hedonists*, and *achievers*. These groups are influenced by different beliefs with *followers* being motivated by friends who exercise and clear instructions, *hedonists* being more vulnerable to motivation drops, and *achievers* being motivated by the idea of becoming stronger. We conducted semi-structured interviews (N=5) to understand how the persuasive elements of the fitness coach influence users' motivation to exercise, finding that application features such as feed of achievements, possibilities to share appraisal, or recording users' personal bests can have positive effects on perceived capacity. Integrating these findings, we derive general and cluster-specific design recommendations. Based on these results and qualitative interviews, we found that persuasive elements such as suggesting a workout or recording users' personal bests can have a positive effect on perceived capacity while the possibility to share appraisal can have a positive effect on subjective norm. We encourage the use of our research process in future research aiming at dissecting the motivational structures of other classes of behavior change technologies. We hope that our findings related to mobile fitness coaches support both other researchers and practitioners in the field of behavior change technology.

ACKNOWLEDGEMENTS

We would like to thank Miriam Meyer, Alexandra Ronge, and the company Freeletics (especially Konradin Breyer) for supporting our research on mobile fitness coach users. Additionally, we would like to thank the statistics lab of the University of Munich for their valuable insights concerning structural equation models. Last but not least, we would like thank everyone involved in the review process for their insightful comments and help to improve this manuscript.

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