The Influence of User Diversity on Motives and Barriers when Using Health Apps - A Conjoint Investigation of the Intention-Behavior Gap

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Abstract. Currently, there is a major health problem in our society, which partially is the result of an insufficient level of physical activity. Despite existing intentions, people sometimes fail to turn them into action and engage in physical activity. This intention-behavior gap provides a framework for the topic under study. Fitness apps offer a way to assist and support people in implementing physical activity in their daily routine. Therefore, this paper investigates the influence of user diversity on motives and barriers to fitness app use. For this purpose, a choice-based conjoint study was conducted in which 186 subjects were asked to repeatedly choose their favorite between three fictitious constellations of fitness apps. The apps were configured based on selected attributes. Differences in decision-making between men and women, exercisers and non-exercisers, as well as influences of certain personality dimensions and motivational types have been found. The results provide important clues that may help to customize fitness apps to specific user groups and for further research.

Keywords: fitness apps · health apps · privacy · group recommendation · user modelling · human-computer interaction

1 Introduction

Well-balanced nutrition and physical activity (PA) are essential for a healthy lifestyle. Even though this is general knowledge, people tend to neglect these aspects [19]. Especially insufficient levels of physical activity and resulting consequences represent a huge risk in our society today. According to the World Health Organization (WHO), the PA levels of many adults and adolescents do not meet the organization's recommendations for a healthy lifestyle [19]. Since

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the beginning of the COVID-19 pandemic, the topic has become even more important due to the increase in working in the home office and the decrease of opportunities to participate in sports clubs and activities in groups.

Even though many people have intentions to exercise, they sometimes fail to turn them into action [8]. This dissonance between intention and action is also called the intention-behavior-gap. It provides a framework for the topic under study and will be integrated in the theoretical part of this study. To support people in exercising, there is a broad offer of health-apps today. Especially in the given situation of the pandemic, apps like this provide an opportunity to exercise without the risk of infecting.

This study examines, which aspects should be integrated with a fitness-app for supporting fitness-activities and motivation. The study especially focuses on the aspects of user diversity. For this purpose, a choice-based conjoint study was conducted in which 186 subjects were asked to repeatedly choose their favorite out of three fictitious constellations of fitness apps. Specifically, our study examines how gender, age, and sports activity affect decision-making. In addition, the influence of personality dimensions and types of motivation towards exercising will be investigated. Our findings point out how fitness-app use can influence the intention behavior-gap in the context of PA and provide important clues for tailoring fitness apps to specific user groups.

2 Related Work

2.1 Relevance of physical activity and health apps

Although physical activity is essential for a healthy lifestyle, some people tend to neglect exercising. According to WHO, the PA level of 1 out of 4 adults and 3 out of 4 adolescents did not meet the organization's recommendations for a healthy lifestyle in the year 2018 [19]. This physical inactivity is the fourth most common risk factor of worldwide mortality at 5.5% [18] and "[...] is estimated to cause around 21-25% of breast and colon cancer burden, 27% of diabetes and about 30% of ischaemic heart disease burden" [18].

During the COVID-19 pandemic, the amount of PA decreased even more in some cases. In a review, Stockwell et al. bring together 66 studies to find out to what extent PA and sedentary behavior have changed during lockdown. Most studies demonstrate an overall decrease in PA and an increase in sedentary behavior [16]. It is noteworthy that most of the studies measured the level of PA by subjective assessments [16], but since many activities were severely restricted during the pandemic, it can be assumed that PA actually decreased.

These findings are alarming since PA seems to be even more important in a pandemic. Chastin et al. reviewed 55 studies and found that habitual PA can influence the immune system in a positive way [2]. "[...] higher levels of habitual physical activity are associated with a 31% lower prospective risk of infectious disease and 37% lower risk of infectious disease-related mortality" [2]. In addition, individuals who exercised an average of three times for 60 minutes over a period of about 20 weeks prior to vaccination show significantly higher levels of antibodies, compared to others who did not exercise [2].

Therefore, it is more important than ever to increase people's motivation for PA. Digital health apps can be one part of the solution. The number of such apps has risen rapidly in the past few years. While at the beginning of 2015 there were around 37,000 health and fitness apps in Apple's App Store, the number had already risen to over 82,000 by the third quarter of 2020 [15]. Among these are different types of health apps, e.g. for diagnosis, meditation, or medication intake. The number of health app users has also increased in recent years. While there were 9.7 million users in Germany in 2017, there are already 13.9 million in 2020. According to the forecast, the number of users could increase to 18.3 million by 2024 [14]. Again, not only apps to support sports activities, but also nutrition apps were taken into account. Both statistics show an increasing interest in digital health offerings. Due to the large number of these tools, the question arises of how an app should be designed to support users in achieving their goals and promoting their health. This task is essential because people often cannot bring themselves to engage in physical activity despite having the intention to do so.

Rhodes and De Bruijn were able to prove this discrepancy between the intention and the implementation regarding PA. They found this by reviewing 10 studies that examined the intention and implementation of PA in a total of 3899 individuals of different genders. The time between measurements of intention and measurements of PA ranged from 2 weeks to 6 months [8]. Rhodes and De Bruijn obtained the following results: 21% of the subjects did not intend PA and thus did not carry it out, whereas 2% of the subjects were active despite the lack of intention. Subjects who did not implement PA despite intention represent 36% of the sample, intenders who followed their plans 42%. Thus, only 54% of the intenders were able to implement their intended behavior [8].

2.2 Understanding the process of health behavior change

To get a better understanding of the aspects of changing health behaviors, the *Health Action Process Approach* (HAPA) by Ralf Schwarzer is a helpful tool. Schwarzer addresses the intention-behavior gap by identifying two phases in the process. "The model suggests a distinction between (a) pre-intentional motivation processes that lead to a behavioral intention, and (b) post-intentional volition processes that lead to the actual health behavior" [12]. In the motivation phase, risk perception, outcome expectancies, and action self-efficacy influence the formation of an intention. When this intention is formed, coping self-efficacy and recovery self-efficacy influence action initiation and maintenance in the volition phase. Here, action plans and coping plans also have an impact. Schwarzer defines action plans as When-Where-How plans, that can help individuals to implement an intended behavior. Coping plans, on the other hand, are used when the first-choice plan cannot be carried out for some reason. They represent alternatives for different situations that may emerge and should be designed beforehand [13]. This understanding of the different factors involved in health behavior change can be helpful in designing an app to optimally support this process.

2.3 Previous findings on the impact of gender and age on health app use

There is already some evidence of the effect of demographic features on fitness app use. In two studies, Klenk et al. [6] investigate the motives of German users of the app Runtastic, which is a mobile app for tracking sports activities. The aim of the studies was to identify differences between, e.g., men and women. Regarding gender, findings showed that for women, having fun and achieving their goals plays a greater role, while men are more inclined to share their results with others and use social functions [6]. Accordingly, differences based on gender regarding the desired app functions are also to be expected in the study conducted here. In terms of age, Cho et al. found that younger people use health apps more frequently than older people [3]. Klenk et al. found that the willingness to share results in the app Runtastic is rising with increasing age. However, other studies obtained opposite results on this issue [6]. Although the studies examined fitness app use from another angle than we will, it can be assumed that a difference between age groups is also evident here.

2.4 Scales used in the questionnaire

To examine various aspects of user diversity, a short version of the Big Five Inventory and the Sports Motivation Scale were integrated in the questionnaire. Both scales are briefly explained below.

Short version of the Big Five Inventory. To capture personality traits of the individual subjects, the German short version of the Big Five Inventory (BFI-K) [7] was integrated into the questionnaire. It was chosen because it reliably represents personality traits while taking only about two minutes to complete. The scale allows to examine possible correlations between certain personality traits and motives in the use of fitness apps during the evaluation. The five personality traits measured by the BFI-K are extroversion, agreeableness, conscientiousness, neuroticism and openness to experience, which are examined by 21 items in total. An example item for conscientiousness is "I make plans and execute them". There is already evidence on how personality affects physical activity. In a meta-analysis, Wilson and Dishman examine correlations between the named personality dimensions and PA. For this purpose, they consult 64 studies with a total of 88,400 participants [17]. They find that people with higher levels of extroversion, conscientiousness, or openness are more likely to engage in PA than people who show fewer of these personality traits. They find the opposite results for neuroticism: People with a higher level of neuroticism are less likely to engage in PA. No significant correlation could be found between agreeableness and PA [17].

Sports motivation scale. For this study, the German version of the Sports motivation scale (SMS28) by Burtscher et al. [1] was integrated into the questionnaire. The SMS28 is used to examine seven types of motivation, distinguishing between extrinsic motivation, intrinsic motivation and amotivation. *Intrinsic motivation (IM)* includes IM toward knowledge, IM toward accomplishments and IM toward stimulation. Extrinsic motivation (EM) includes external regulation, introjected regulation and identified regulation. Each type of motivation type contains four items, which refer to the question "Why do you practice your sport?". An example item for IM toward knowledge is "Because of the good feeling of knowing more about the sport I practice". The items for amotivation were not used in the questionnaire, because they are not relevant for examining the research questions.

2.5 Underlying research questions

In this study, our general question will be:

What are the motives and barriers while using fitness apps?

Concerning previous findings, our question will be divided in different parts. Since there were already age- and gender-related differences regarding PA and fitness app use found, we ask:

1. *How do age and gender influence the motives and barriers?*

Based on Schwarzer's HAPA, the question also arises whether the use of fitness apps is influenced by whether a person has already been able to realize the intention to be physically active. Therefore, the following questions are investigated:

2. *Is there a difference between physically active and inactive individuals?*
3. *How does the source of motivation in physically active individuals influence the use of fitness apps?*

Since Wilson and Dishman were able to find correlations between certain personality traits and physical activity, this aspect is also examined here. The following question arises:

4. *How do personality traits affect motives and barriers?*

Following is a description of the methodology used to investigate the mentioned research questions, before the findings are reported and discussed.

3 Method

To find out what motives and barriers occur in the use of fitness apps, a quantitative study was conducted in the form of an online questionnaire. It was created using the Sawtooth Lighthouse software. The main part of the questionnaire was a choice-based conjoint study, in which the subjects were asked to repeatedly choose their individual favorite out of three fictitious app configurations.

3.1 Sample

The study was conducted in Germany, mostly North Rhine-Westphalia, so the results are based on a German perspective. The questionnaire was sent privately to people in the area around Aachen, and was shared in location-based Facebook groups. To ensure that the sample was not limited to a small area, people from small towns in the greater area of Aachen as well as from large cities such as Cologne and Berlin were contacted in this way. A total of 405 records were collected, of which 195 were complete. Of the participants with incomplete data sets, most dropped out on the first page ($N = 70$) or on one of the first four CBC tasks ($N = 87$). In addition, nine more data sets had to be excluded due to insufficient processing time. After data cleansing, 186 records remained that were qualified for analysis. The sample consists of 74% female participants and 26% male participants. One person identifies as non-binary. The age ranges from 16 to 78 years, with a mean age of 42.2 years ($SD = 14.3$). While 62% of the respondents stated that they exercise, 38% negated that.

3.2 The questionnaire

In the first part of the questionnaire, participants were briefly introduced into the topic of the study. After a few questions regarding demographic data, the German short version of the Big Five Inventory was integrated to assess personality traits of the respondents. This scale consists of 21 statements, each of which subjects were asked to rate on a six-point Likert scale (from 1 = strongly disagree up to 6 = strongly agree). Since the questionnaire was already very time-consuming due to the conjoint study, the short version was chosen to avoid increasing the length even more while still preserving a reliable reflection of the full Big Five Inventory [7]. Extroversion, agreeableness, conscientiousness and neuroticism each contain four items. Openness to experience contains five items, because it shows less intern consistency compared to the other traits [7]. Further, respondents were asked about their exercising habits and current fitness app usage. Physically active participants then evaluated their motivation towards sports by rating statements of the German version of the sports motivation scale. The underlying question was "Why do you practice your sport?" and the statements should be rated on a five-point Likert scale (from 1 = does not apply at all, up to 5 = applies exactly). The items on amotivation were not included, as the reasons why a respondent is not motivated are irrelevant for the investigation. Subsequently, the decision scenarios of the choice-based conjoint study followed, which will be explained further in the following chapter.

The full German questionnaire and additional material is available at the Open Science Framework at `https://osf.io/xq43m/`.

3.3 Description of the choice-based conjoint study and decision scenarios

Main part of the study was the choice-based conjoint study (CBC). In this type of study, participants are repeatedly confronted with several concepts out of which they are asked to choose their individual favorite. Compared to a ranking, this allows to identify relative importances of the attributes and relative part worth utilities. In addition, the decision tasks are more realistic than a ranking and reflect real purchase decisions, which is why the subjects should typically find it easy to empathize with the situations [9].

The apps were configured based on the attributes *data*, *optimization* and *search for training partners*.

Table 1. Attributes and levels of the CBC.

Attribute	**Levels**				
Data	Activity data	Calendar data		Health data	
Optimization	Achievement progress	Motivation		Planning	
Search for training partners	Alone	in pairs		in a group	
		with friends	with App-Matching	with friends	with App-Matching

Data. We distinguish between three types of data that the fitness app can use. The first is *activity data*, which can be used to record steps, kilometers or the duration of activity. This enables users to view historical training data and evaluate the progress already made. If an app accesses *calendar data*, it can recognize when the user has free time slots and create corresponding training suggestions. For example, the app can recommend more intense training when there is little available time and longer activities when there is a lot of free time. When *health data* is used, weight, resting pulse or relevant pre-existing conditions, such as high blood pressure, are used to individualize the app and to support the search for suitable training partners. An app can access multiple data simultaneously. Activity data is required in each configuration.

Optimization. This attribute is also categorized into three aspects. This factor is used to optimize the training suggestions of the app in order to support the user most effectively. The aspect *training progress* optimizes the training suggestions for the most effective activities possible on basis of the available data. This helps the user to increase their performance and achieve training goals. With the *motivation* feature, an app suggests activities that increase motivation to exercise. For example, small challenges or visualizations can be integrated, which can motivate and encourage the user to reach their goals. In case of the aspect *planning*, the app ensures that the suggestions fit the user's schedule. For example, light workouts can be integrated on heavily scheduled days. A condition for this function is access to calendar data. The CBC was designed to support only one of these functions at a time.

Search for training partners. This attribute is divided into five levels. A distinction is made between whether an app supports training *alone*, *in pairs* or *in a group*. When training with others, there is a further distinction between training with known or unknown users. In case of training *with friends*, the app supports connecting with known users. These can be friends or other users with whom training has been done before. *App matching* supports training with unknown users. For this purpose, the app takes into account all data available, to find the optimal training partners or groups for the user. Criteria such as age, gender and search radius can be specified in advance. As with optimization, the CBC was also designed to support only one of these functions at a time (e.g., in a group of friends).

The participants were asked to repeatedly choose their individual favorite out of three fictitious app configurations (see Fig. 1).

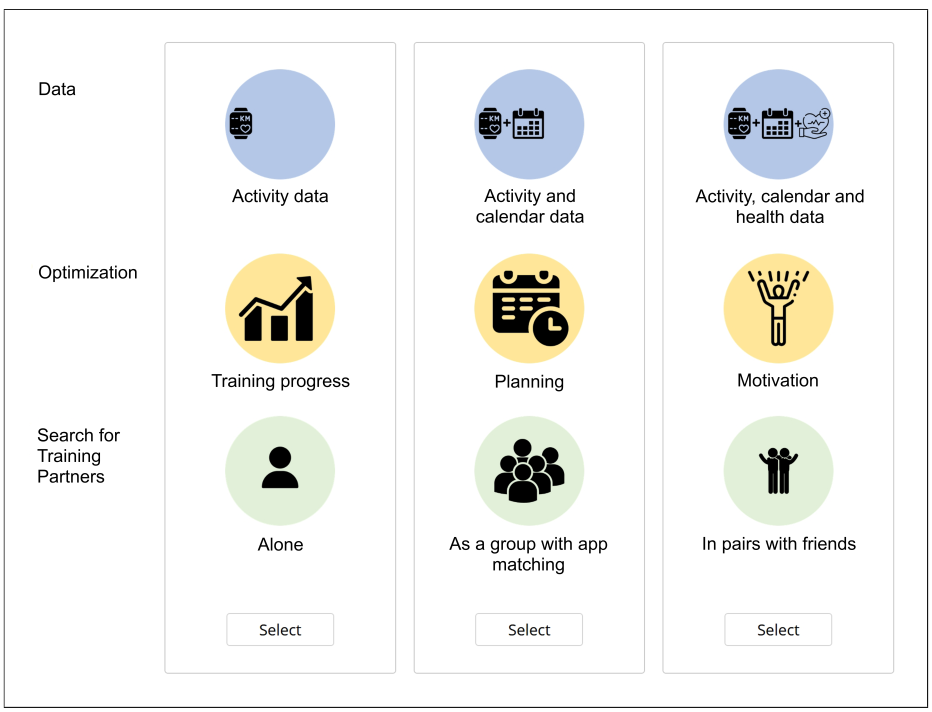

Fig. 1. Example of a CBC decision task

To examine the collected data in terms of the research questions, analyses were carried out with the programs Sawtooth Lighthouse and Jamovi after data cleansing. This included a latent class analysis (LC) and a hierarchical Bayes analysis (HB). The HB analysis is suitable because it can calculate estimates of the part-worth utilities even if the respondents make few decisions [10]. LC analysis is useful for additionally calculating which different types of decision-makers are represented in the sample. The findings are particularly valuable if the identified groups can be distinguished from each other on the basis of additional characteristics [11].

4 Results

4.1 Hierarchical Bayes Analysis

The Hierarchical Bayes analysis (HB) was conducted first because it provides an overview of decision-making for the overall sample. The results show that for the entire sample, training partner search has by far the largest effect on decision making. The attributes data and optimization show an equally large effect (see Fig. 2).

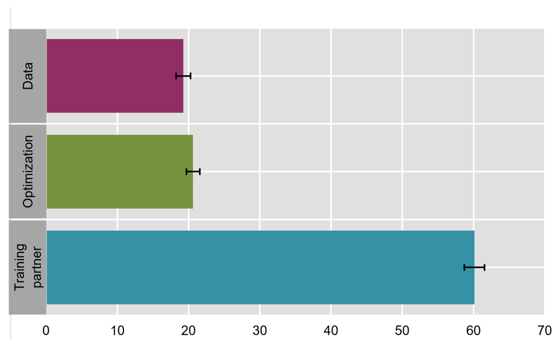

Fig. 2. Relative importance of attributes in decision making of the total sample. The sum of the importance scores is 100%. Error indicators represent the standard error.

The part worth utilities show a clear preference for training alone or in pairs with friends. In contrast, training in a group is clearly less preferred, especially with the app matching function. In optimization, there is a tendency to training progress. Subjects benefit significantly less from optimization in the sense of planning. In terms of data, the subjects benefit most from the combination of all data and least from an app that only uses the activity data (see Fig. 3).

4.2 Latent Class Analysis

Latent class analysis (LC) was used to identify different types of decision-makers. It turns out that at least two and at most five groups can be distinguished from

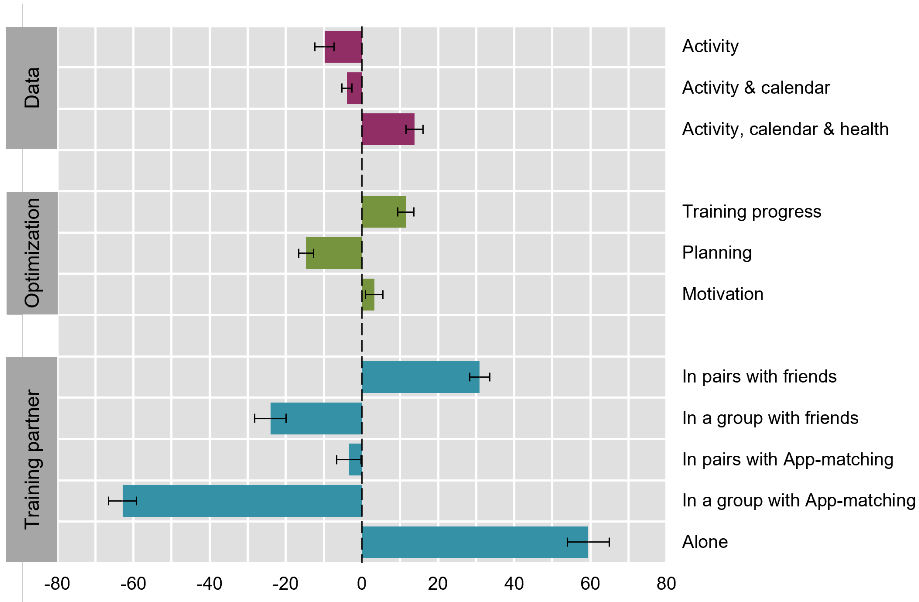

Fig. 3. Part-worth utilities of attribute levels in decision making of the total sample. The part-worth utilities are summed to zero for each attribute. Error indicators represent the standard error.

each other. First, we will briefly explain how the number of groups was selected before they are defined in more detail. Various information criteria can be used to determine the number of groups. “An information criterion can be defined (roughly) as the distance between the model at hand and the real model.” [4]. Consistent Akaike Information Criterion (CAIC), Percent Certainty (Pct Cert), and Relative Chi-Square are used here. CAIC is one of the most common information criteria when deciding on the number of segments. Smaller values are preferred [10]. Percent Certainty “indicates how much better the solution is compared to an ’ideal’ solution than the null solution”. Relative Chi-Square is based on Chi-Square, which indicates whether a solution fits significantly better than the null solution.

Now, based on the largest curvature in the individual graphs, it could be decided which number of segments is most suitable (see Fig. 4). Here, however, no clear decision can be made. Percent Certainty speaks for 3 groups, Relative Chi-Square for 2. CAIC, on the other hand, cannot be clearly interpreted. Therefore, group sizes and differences in group decision making are additionally considered. When distinguishing three groups, the group sizes equal about one third of the sample and they can be clearly distinguished from each other based on the relative importance of the attributes. Four groups are no longer as clearly distinguishable from one another in terms of content. Therefore, three groups are differentiated in the following.

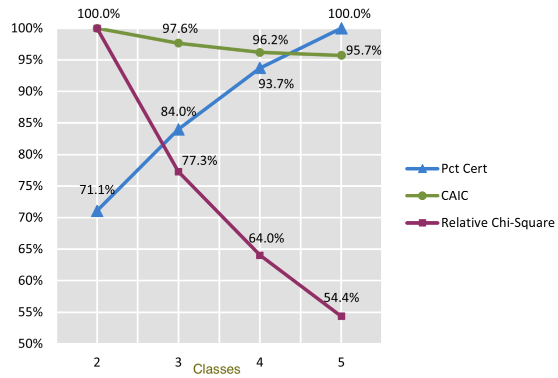

Fig. 4. Values of the selected information criteria for 2 to 5 groups. The criteria were normalized with the respective maximum value and are shown as a percentage of this value.

4.3 Decision-making of the groups

At the level of attribute importance, the training partner search is most important for decision-making for all three groups. Group 2 stands out in particular, as the other attributes have almost no influence on the decision-making process. Groups 1 and 3 make more balanced decisions in this respect (see Tab. 2). These different ratios show up clearly in the network diagrams in figure 5. For subjects in the first group, data usage is the second most relevant factor for decision-making; for group 3, optimization takes this place.

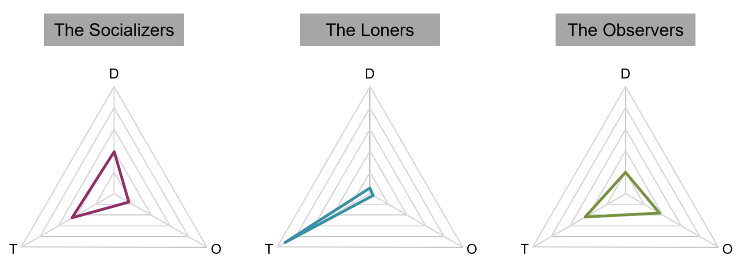

Fig. 5. Web charts for relative attribute importance in the LC groups. D = Data, O = Optimization, T = Training partner search.

To determine which specific characteristics influence the groups' decision-making, the relative part worth utilities must be considered (see Fig. 6). Based on these, the groups' decisions are now defined in more detail.

The Socializers. The decision-making of the first group is most influenced by the search for a training partner. They prefer training with friends, both in pairs

Table 2. Relative importance of attributes in LC-groups.

	Group 1 ($N = 62$)	Group 2 ($N = 67$)	Group 3 ($N = 57$)
Data	39.06	5.33	19.97
Optimization	15.76	3.39	36.51
Training partner	45.18	91.28	43.52

and in a group. In contrast, the use of an app matching function is clearly less preferred. In terms of data usage, they benefit most from the combination of activity, calendar and health data. At the optimization level, only minor differences in relevance are evident. Here, the subjects benefit most from an app that focuses on increasing motivation.

The Loners. For subjects in the second group, the search for a training partner is by far the most relevant for decision-making. It is most important for them to perform their workout alone. They benefit least from an app that supports training in groups, both in pairs and via app matching. At the data level, they are most likely to benefit from the combination of all data. With regard to optimization, they benefit most from the training progress function. For both attributes, however, the differences in relevance are very small.

The Observers. For subjects in this group, the highest value is optimization in terms of training progress. As the Loners, they also prefer training alone. In second place, they benefit most from training in pairs via app matching and with friends. On the data level, they benefit most from the usage of only data activity.

4.4 Gender, age and sport-activity in the groups

Next, we will examine whether the groups differ in terms of gender and age and whether there is a significant difference in the number of active or inactive participants between the groups. In terms of gender, the socializers and observers hardly differ from each other: socializers comprises 31% men, observers around 35%. For loners, on the other hand, the proportion of men is only about 13%. The number of sport-active individuals increases from socializers to observers. Whereas for socializers about half of the subjects do sports, observers has about 70% active in sports (see Fig. 7).

There is a significant difference in age between the socializers ($M = 40.4$, $SD = 13.6$) and the loners ($M = 44.4$, $SD = 14.5$). Observers ($M = 41.6$, $SD = 14.6$) lie with the average age between the other groups and shows no significant difference to them. Over the entire age range from 16 to 78 years, the distribution of age is similarly balanced in all three groups.

Fig. 6. Part-worth utilities of attribute levels in the three groups. The part-worth utilities are summed to zero for each attribute.

4.5 Further influence of gender, age and sport-activity

To further examine whether gender, age and sport-activity influence the decision-making of the sample, they are also examined independently of the groups found in the LC-analysis. For this purpose, correlations and independent T-tests were calculated with the individual values of the HB-analysis. For age, there is a negative correlation with optimization (r (184) = -.19, $p < .05$) and a positive correlation with training partner search (r (184) = .16, $p < .05$). No correlations were found between individual part-worth utilities and age.

Gender and sport-activity were examined with independent T-tests. To examine the influence of gender, the binary person was filtered out, since this statement was only made once. Significant correlations with gender exist for optimization (t (183) = -3.81, $p < .001$) and training partner search (t (183) = 3.66, $p < .001$). Optimization influences men's decision making ($M = 26.5$, $SD = 14.5$) more than women's ($M = 26.5$, $SD = 14.5$). In contrast, training partner search is more relevant to women's decision making ($M = 63.2$, $SD = 18.6$) than to men's ($M = 51.8$, $SD = 18.8$). In addition, there is a significant correlation between sport-activity and optimization, (t (183) = 2.05, $p < .05$). This influences the sport-active respondents ($M = 22.1$, $SD = 13.5$) in their decision more than those who do not participate in sports ($M = 18.2$, $SD = 10.8$).

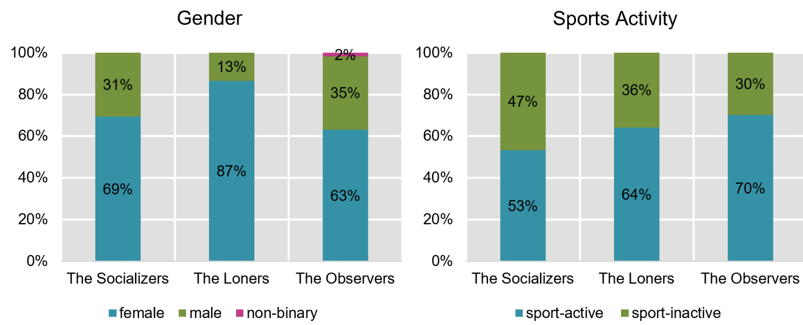

Fig. 7. Distribution of gender and sport-active subjects in the LC groups.

We also examined how the frequency of practicing sports per week affects decision-making. In this regard, no correlations could be found with the relative importance of the attributes. However, at the level of the part-worth utilities, there is a positive correlation with training progress (r (114) = .24, $p < .05$) and a negative correlation with motivation (r (114) = -.28, $p < .01$). No significant correlations were found with other levels of attributes.

4.6 Influence of personality and motivation sources on decision-making

To further investigate the influence of user diversity, dimensions of BFI-K and SMS28 were also examined with regard to the relative importance of the attributes. For this purpose, correlations were calculated in each case. Some of the variables of BFI-K first had to be recoded in order to subsequently combine them into scales. Prior to this, Cronbach's α was calculated in each case in order to test the reliability of the variables. Next, correlations with Pearson's r were calculated between the personality dimensions and the relative importance of the attributes. The results show no correlation between a personality trait and the importance of an attribute for the sample (see Tab. 3).

The same procedure was applied to the dimensions of SMS28 in order to also investigate how the motivational source of sport-active participants affects the decision-making. Here, linear correlations were found between identification and optimization (r (114) = .27, $p < .01$), and between identification and training partner search (r (114) = -.28, $p < .01$). No correlations were found for other types of motivation (see Tab. 4).

In addition, the dimensions of BFI-K and SMS28 were examined for correlations with the relative part-worth utilities. The most significant result for the personality dimensions is a correlation between agreeableness and training alone. Individuals with a higher level of agreeableness are less likely to choose this training option (r (184) = -.22, $p < .01$). They prefer training with a friend (r (184) = .17, $p < .05$).

Table 3. Correlations between BFI-K dimensions and CBC attributes. E = Extroversion, A = Agreeableness, C = Conscientiousness, N = Neuroticism, O = Openness to experience. The value of the degrees of freedom applies to all dimensions.

		E	A	C	N	O
Cronbach's α		.85	.59	.66	.79	.70
	df	184	-	-	-	-
Data	*r*	.06	.09	.08	.08	.07
	p	.40	.20	.27	.31	.38
Optimization	*r*	.01	-.04	.06	-.03	.01
	p	.87	.56	.44	.66	.94
Training partner	*r*	-.05	-.04	-.10	-.03	-.05
	p	.48	.60	.19	.66	.50

Further, there are significant correlations between some of the SMS28 dimensions and the part-worth utilities of training partner search. For both intrinsic motivation toward knowledge and accomplishment, it appears that subjects with higher levels of each type of motivation are more likely to choose training with a group of friends (r (114) = .20 / .21, $p < .05$) and less likely to choose training in pairs using an app matching function (r (114) = -.20 / -.21, $p < .05$). There are also significant correlations with identification. There is a negative correlation to training in pairs using app matching (r (114) = -.20, $p < .05$) and a positive correlation to training in a group using app matching (r (114) = .19, $p < .05$). Strong significant correlations also exist positively to training in a group of friends (r (114) = .34, $p < .001$), and negatively to training alone (r (114) = -.31, $p < .001$). Further correlations can be found in Table 5.

5 Discussion

In the following, the results are discussed on the basis of the previously identified research questions.

1. *How do age and gender influence the motives and barriers?*

The LC groups cannot be clearly distinguished from one another with regard to gender and age. Although there is a significant age difference between the socializers (M = 40.4) and the loners (M = 44.4), this result does not indicate a clear difference in terms of the life stages of the participants. It is therefore questionable to what extent the groups actually differ from each other on the basis of age. Independently of the LC groups, however, a gender-dependent difference could be found concerning the importance of the attributes. Here it appears that women's decisions are more influenced by training partner search, while men

Table 4. Correlations between SMS28 dimensions and CBC attributes. $^{**}p < .01$; K = IM to knowledge, A = IM to accomplishment, S = IM to stimulation, Id = Identification, In = Introjection, E = External regulation. The value of the degrees of freedom applies to all dimensions.

		K	A	S	Id	In	E
Cronbach's α		.82	.87	.82	.77	.71	.78
	df	114	-	-	-	-	-
Data	*r*	.02	-.10	.05	.14	-.09	.04
	p	.80	.28	.62	.15	.33	.66
Optimization	*r*	.08	.16	.11	.27	.08	.16
	p	.40	.08	.25	.003**	.39	.09
Training partner	*r*	-.07	-.03	-.11	-.28	.01	-.14
	p	.45	.72	.26	.002**	.89	.15

make their decisions more dependent on optimization. Overall, these results do not necessarily correspond to the expectations derived from other studies [3,6] regarding these attributes. In particular, the expectation that significant differences in age would be evident cannot be confirmed here.

2. *Is there a difference between physically active and inactive individuals?*

It was found that sports activity affects how important optimization is for decision making. In addition, among the participants who are active in sports, the question of how often they do sports is also significant. The more often subjects exercise per week, the more likely they are to choose optimization in terms of training progress and the less likely they are to choose motivation. These results could be explained by the assumption that people who exercise several times a week already have a high level of motivation and thus no longer need a corresponding motivational function. Since the motivation hurdle has already been overcome, the person is then more interested in observing the own performance.

3. *How does the source of motivation in physically active individuals influence the use of fitness apps?*

Some significant correlations were found in investigations with the dimensions of the SMS28. Here, the results at the level of training partner search stand out in particular. Subjects with a high degree of intrinsic motivation for knowledge and performance more often choose training in a group with friends and less often training in pairs via an app matching function. This could be explained by the assumption that people with a higher expectation of performance have already built up an environment with other athletes and thus do not need a

Table 5. Correlations between BFI-K/SMS28 and part-worth utilities. $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$; Table shows significant correlations only. A = Agreeableness, O = Openness to experience, K = IM toward knowledge, A = IM toward accomplishment, Id = Identification, E = External regulation.

		BFI-K		SMS28			
		A	O	K	A	Id	E
	df	184	-	114	-	-	-
Activity data	*r*	-	-	-	-	-	.20
	p	-	-	-	-	-	.03*
Motivation	*r*	-	-.16	-	-	-	-
	p	-	.04*	-	-	-	-
Planning	*r*	-	-	-	-	-	-.20
	p	-	-	-	-	-	.03*
in pairs - friends	*r*	-	-	-	-	-	-
	p	-	-	-	-	-	-
in a group - friends	*r*	.17	-	.20	.21	.34	-
	p	.02*	-	.03*	.03*	<.001***	-
in pairs - App Matching	*r*	-	-	-.20	-.21	-.20	-
	p	-	-	.03*	.03*	.03*	-
in a group - App Matching	*r*	-	-	-	-	.19	-
	p	-	-	-	-	.04*	-
Alone	*r*	-.22	-	-	-	-.31	-
	p	.003**	-	-	-	<.001***	-

function to search for other possible partners. Most correlations were found for the motivation type identification. Here a strong positive correlation to training in a group of friends and a strong negative correlation to training alone is found. There are also opposite results with regard to app matching: here the group is chosen more frequently, while training in pairs is chosen less frequently. This can be attributed to the fact that the items of the SMS28 examine, at the level of identification, the extent to which sport is an opportunity for the respondent to maintain contact with other people.

4. *How do personality traits affect motives and barriers?*

It can be noted that people with a higher level of agreeableness would rather train in a group with friends and are less likely to train alone. This result was expected, as people with a high level of agreeableness get along well with other people and, accordingly, probably prefer training alone less. However, this does not explain why there are no other correlations, for example, to exercising with another friend. In addition, individuals with a higher degree of openness to new experiences were less likely to choose to optimize app use in terms of motivation. One possible explanation would be that these individuals have a lower motivational barrier due to their openness. Overall, with respect to the results of Wilson and Dishman [17], even clearer correlations were expected, but nevertheless the assumption that personality influences the use of fitness apps can be supported.

5.1 Referring to the *Health Action Process Approach*

In order to optimize the adaptation of fitness apps to users, it is not only important to recognize different user groups, but also to understand how the process from an intention to an action proceeds. Here, the HAPA model [12,13] can provide assistance, as it shows the different components it takes to change a health behavior. With this understanding, an app could be designed to intervene in the different phases and support the user accordingly. A person who does not exercise regularly might need features at the beginning of the process that reinforce their intentions, while later features that encourage the maintenance of the implemented behavior would help. Someone who already does a lot of exercise, on the other hand, may only need the last. In addition, functions that support the creation of action and coping plans could be integrated to increase the likelihood of implementing physical activity. Since, as Rhodes & De Bruijn showed, many people have at least the intention of doing sports [8], a suitable fitness app could intervene at this point and support the conversion of intention into action.

5.2 Limitations of the study

In general, a choice-based conjoint study is very useful for investigating the research questions addressed here. In contrast to a ranking, this type of study makes it possible to determine the relative importance of attributes and attribute levels for the overall sample, subgroups or individual subjects. However, this study does not examine rejected attributes. Since subjects are forced to choose an attribute in each decision situation, it is possible that attributes are selected that would actually be rejected. On the other hand, a feature can have a strong negative value, while not being rejected. In order to be able to make statements about the rejection of attributes and attribute characteristics, combining the CBC with an additional study would be appropriate. In addition, it should be noted here that the search for participants can be difficult due to the size of the study. A large part of the subjects dropped out during one of the first decision tasks. This could be related to the complexity of the tasks and the high effort required to complete them. Although the tasks reflect real-life purchase decisions, the subjects have to process a lot of information each time before they can make a decision [9]. Therefore, in order to obtain a larger sample, a different concept for participant acquisition might need to be established. Also, in some aspects our sample was not balanced. Regarding gender our sample contained a lot more female than male respondents. A more balanced sample could show more significant differences in decision-making between men and women. Since the majority of the subjects in this study were acquired via Facebook groups, it can be assumed that they have a certain willingness to share data regardless of age, as well as a similar level of app knowledge. A sample with a wider spread in this regard could therefore demonstrate further differences.

6 Conclusion

The aim of this study was to find out which functions of fitness apps could motivate or discourage potential users. Differences in the decisions between men and women, sport-active and sport-inactive respondents, as well as influences of certain personality dimensions and motivation types could be found. The results offer a clue for adapting fitness apps to different user groups. It is a big task to change health behavior in our society. However, it is necessary to increase the level of physical activity in order to maintain a healthy lifestyle. Digital offerings such as fitness can be a powerful tool to support people in their health behavior and promote the level of physical activity as recommended by the WHO. Considering the large number of these offerings on the market and the differences in peoples needs, fitness apps have to address users individually to ensure long-term results.

Furthermore, our results can contribute to human-centered design of software applications, that are based on artificial intelligence (AI). In the area of physical activity, AI can be useful for responding even more individually to potential users of fitness apps and taking even greater account of the user's current state. For example, training suggestions could always be adapted to the current training progress, while additional information like the current weather could be considered. To develop products that focus on the individual user's needs, abilities, and preferences, creating personas can be a helpful tool, as Holzinger et al. showed recently [5]. Our study provides information that could be used to create personas for AI in the field of PA, like fitness app preferences, personality traits or motivation sources. To address the different types of users even more individually, further research would be required on how the different types of decision-makers can be distinguished from one another. It could be helpful, to select a broader sample, in which the gender distribution is more balanced. People with less technology or app experience could have other needs regarding fitness apps and therefore should also be in focus in further research.

Since this study only theoretically addresses the intention-behavior gap, further research is also needed to determine how a fitness app can actually influence the implementation of an intention into an action. Therefore, intentions for physical activity could first be recorded in order to subsequently test which functions of fitness apps support the implementation of the intentions and which inhibit them. Here, the use of different prototypes of fitness apps would be appropriate in order to compare the effects of different functions with each other.

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