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Digital Coaching to Support University Students' Physical Activity

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Abstract In this paper, we aim to find out if digital coaching could support students to become physically more active. Studies show a worldwide trend of declining physical activity, and students are no exception. The search for means to keep the younger population physically active is not an easy task but technology will for sure play an important role in alleviating this trend. If a digital coach is one of the possible solutions it needs to offer support and feedback that are relevant to the students in their everyday activities. We carried out a survey with 138 undergraduate students to find out if features expected of a professional trainer who coaches athletes would be important also for a digital coach for it to be attractive and useful for students.

Keywords: • digital coach, everyday activities, training technology, physical activity

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1 Introduction

Physical activity is in decline all over the globe, and the young are no exception. Many technologies are available which claim to enable behaviour change and encourage to physical activity; e.g. activity trackers, smart watches and sports watches. In this paper we focus on training technology in its most advanced form – Digital Coaching – and raise discussion on the role this technology could play in students' lives.

Training technologies typically enable the user to track and monitor data e.g. on movement, sleep and heartrate. Digital coaching systems also include analysis and suggestions based on the data. A digital coaching system can help the user to set and achieve goals, give suggestions for structuring a training session, and offer possibilities to connect with others. A digital coaching system adapts according to the user's actions and progress.

Despite the prevalence of training technologies, there is a lack of tools to study them. In this paper we use physical/«real-life« coaching as our starting point. We adapt a validated tool to study physical coaching behaviors to the context of digital coaching. We also explore students' attitudes towards possible functions in a digital coaching tool, to see whether they meet the exercise support needs of the students.

The aim of the paper is thus twofold: (i) to apply a coaching behavior scale to a digital context, and (ii) to find out students' attitudes towards digital coaching.

The rest of the paper is organized as follows; in section 2 we will give an overview of students' physical activity and introduce coaching and digital coaching; in section 3 we introduce the Coaching Behavior Scale for Sport (CBS-S) and work out how it will serve our purposes, in section 4 we introduce the survey we carried out with 138 students, and carry out an analysis of the students' responses. Section 5 is a discussion of our results and we present some conclusions.

2 Literature Review

2.1 Students' physical activity

Being physically activitive is beneficial for all age groups. Physical activity is associated with increasing helth benefits whereas physical inactivity has been observed as one of the leading risk factors in many diseases as well as mortality (Goje et al. 2014). Thus regular physical activity is essential for maintaining as well as increasing health benefits. Recent findings show alarming physical inactivity trends among young people.

Fagarasa et al. (2015) carried out a study with 334 students to assess the level of physical activity of university students. The students first went through a (voluntary) anthropometrics test to decide their body mass index (BMI) after which they filled in the short form of the International Physical Activity Questionnaire (IPAQ) to report on their physical activities during a fortnight. The students reported on their vigorous, moderate and/or walking activities and their activities scored MET-minutes per week according to the IPAQ formula. The authors conclude that the findings show reasonable basis for health and active lifestyle among students.

Clemente et al. (2016) recruited 126 Portuguese university students (73 female) to find out if they meet the public health recommendations for physical activity. The students wore an ActiGraph wGT3X-BT accelerometer for 7 days to record the number of steps taken, time spent sedentary and time spent in light, moderate and vigorous physical activity. Clement et al

(2016) found that gender and day of the week had significant effects on physical activity. Male students reached the recommended 10 000 steps/day during the workweek but female students did not reach the target. Weekends increased sedentary time for both groups. The study was too short to show anything about health effects.

In a study by Haase et al. (2004) the link between physical activity and chronic disease and obesity is explicit. Haase et al. (2004) collected data on leisure-time physical activity, health beliefs, and health knowledge from a cross-sectional study of 19289 university students from 23 countries. They found that leisure-time physical activity is below recommended levels for a substantial proportion of the students, and connected this to cultural factors and the stage of national economic development in the countries involved in the study. They also noted that inactivity during leisure time had an average between 23% (North Western Europe) and 44% (developing countries) but found that the likelihood of leisure-time physical activity correlated positively with the strength of beliefs in the health benefits of physical activity. Nevertheless, knowledge about activity and health was low, only 40-60% knew that physical activity is relevant to the risk of heart disease.

Hallal et al. (2012) report on data collected on physical activity levels from 122 countries for adults [15+ years] and adolescents [13-15 years]. They found that 31.1% of adults are physically inactive but with variations between regions: 17.0% (Southeast Asia) to 43% (Americas, Eastern Mediterranean). They found that inactivity increases with age, is higher for women than for men and increases in high-income countries. The 13-15 year olds who do less than 60 min per day of physical activity of moderate to vigorous intensity is 80.3%, which they found alarming; boys are more active than girls. They proposed that programs should be worked out to seriously increase the levels of physical activities for adolescents (and to monitor that they are actually implemented). This will be a long-term strategy to reduce the probability for increase in non-communicable diseases.

In Finland, most of the young men (about 75%) serve in the Finnish Defense Forces (FDF) for 6-11 months. In 1975, the FDF started testing the physical activity levels of all recruits and has continued the tests since then without interruptions or changes. This has created a unique database. This test called Cooper's test builds on a 12 min run with an ideal result of 3000 m or more. In the first years, the average results were close to the ideal, with an average of 2750 m in 1979. After that, the results gradually decrease during 20 years and reached on average 2600 m; then in 1999-2002, the results jumped down to 2450 m and then stabilized around 2400 m; they were on average 2418 m in 2015. The proportion of recruits reaching the ideal 3000 m was 25.1 % in 1979 but only 6.1% in 2015; the proportion of weak results (2200 m or less) was 6.1% in 1979 and increased to 25,9% in 2015. The trend is clear and alarming; the physical endurance of Finnish males declines. A newly released Finnish physical activity monitoring study for children and adolescents (Liitu-2018) shows that only 38% of children and youth in Finland aged 9 to 15 fulfill the minimum recommendations for physical activities i.e. 60 minutes moderate-to-vigorous intensity physical activities per day. The older the children the less physical activities were reported, for example of those aged 15 only 19% fulfilled the recommendations. These results are of major concern for the society and indicate increasing possibilities for serious illness at later age. According to Janssen and LeBlanc (2010) "there is undisputed evidence that living a physically active lifestyle can be beneficial to the physical, social, and mental health. Thus, effective improvements are necessary and students represent a good target group for innovations and experiments.

2.2 Coaching and Digital Coaching

We will assume that it is possible to develop a digital coach but in order to do so we need to understand the main differences between an athletics coach and a digital coach. A personal trainer (PT) offers the kinds of services we expect from a professional coach (Passmore 2014). The PT, as a rule, is a certified professional working on a one-to-one basis with a client. The coach works out individualized exercise programs for the athlete, monitors and measures his/her progress, provides feedback, and gives advice on physical fitness, health and nutrition. The probably most important role for a PT is to motivate the athlete in achieving jointly agreed goals (Doğan 2017), in other words the PT has a unique opportunity to make significant changes in the everyday life of a client (Côté 1999).

Coaching typically is a series of activities that is the domain of personal trainers (as they developed the programs) but which now changes to support offered by digital coaches. Digital coaches are part of monitoring software for smart watches, activity bracelets, movement sensors, etc.

Coaching intends to change people's behavior, in our case to work out effective physical activities that could form wellness interventions in their daily routines. The interventions should be personalized, ubiquitous, seamless and (mostly) in real time (Fukuoka et al. 2010, Kranz et al. 2012, Kulyk et al. 2014, op den Akker et al. 2015, Schmidt et al. 2015, Warraich 2016) in order to be effective. However the reliability of the sensors and the network required for "real-time" and adequate coaching instructions are according to Klaassen et al. (2016) major challenges.

Literature shows the design and use of digital coaches that build on smart technologies that make use of data collected with activity sensors (Klaassen et al. 2016). The sensors represent a decisive development step as they offer inexpensive, accurate, reliable and objective assessments of physical activity that become numerical feedback on step counts, sleep hours and use of energy.

This data has become the first level of motivational feedback for users of smartphones, activity bracelets, smart watches, pulse monitors, activity trackers, etc. Data gets processed with smartphone apps, with algorithms on websites or through cloud services. There are efforts to develop advanced methods for processing activity sensor data using machine learning, computational intelligence, OWL 2 ontology, etc. in the belief that the feedback presented to users will be more instructive and offer deeper insight (Villalonga et al. 2017).

Klaassen et al. (2013) and Kulyk et al. (2014) implement most of these principles in the *Kristina* coaching system that will motivate and support users to change their lifestyle. The system supports self-monitoring of current behavior towards personal goals and offers tips on how to reach the goals, which now is a typical action plan for digital coaching. The *Kristina* is a multi-device coaching system that combines the advantages of single device feedback systems in one integrated service platform. It offers the user multiple contact points and can collect context information, which offers more effective feedback and guidance. An additional benefit is that a multi-device coaching system offers inter-usability across devices, platforms and contexts, which reduces possibilities to be frustrated or fed-up with the system.

Kranz et al. (2012) developed *GymSkill*, a smartphone system for comprehensive physical exercising support, which is a typical coaching tool. The system uses sensor data logging and activity recognition to make skill assessments using the smartphone's built-in sensors. The feedback produced is individualized, personalized and automatic. The *GymSkill* tracks training quality and success and gives continuous feedback to the user to motivate regular exercising. Schmidt et al. (2017) show that the use of activity tracking systems promotes improved self-awareness as the user follows his/her own fitness data and – in some coaching systems – compares performance with other users. The digital coach should identify use strengths and weaknesses, it should generate a physical activity plan and motivate and support like a personal trainer. Coaching contributes to learning, personal development and performance (Passmore 2014), which when offered as digital coaching is available where ever and whenever needed.

Klaassen et al. (2013, 2016) and Kulyk et al. (2014) demonstrate with *Smarcos* that a digital coach could work through a range of interconnected devices and inter-usable user interfaces. They found, when working with groups of users, that there are clear preferences for different types of messages on different devices. This shows that we should consider using multiple versions of a digital coach for different user contexts. Kulyk et al. (2014) found that a virtual conversational agent could have a positive effect on the perceived relationship between a patient and an eHealth system. The tailoring of software and the building of personalized service will motivate people as they can get personal information and feedback that follows their own physical activities, not comparisons with some standard averages of data collected from some other, unknown context. Zhou et al. (2018) tried out a more advanced coaching tool to test if assigning adaptively personalized goals would be more effective than assigned goals as goals change over time as individual behavior changes, which now is an important improvement. They use an automated iOS application called *CalFit*, which helps set personalized, adaptive step goals that are worked out with a behavioral analytics algorithm. The algorithm applies machine learning to individual goal and performance data to develop a predictive quantitative model for the progress of each *CalFit* user. The estimated model gives challenging (but realistic) step goal ways to maximize future physical activity.

Klaassen et al. (2013, 2016) and Kulyk et al. (2014) develop platforms that monitor physical activity with data collected with wearable sensors and produce personalized feedback. They found that tailoring and context awareness, when used as a basis for feedback and interaction, are key features for effective coaching. They tested different presentations forms – text, graphics and an anthropomorphic talking character – and found (to their surprise) that the talking character did not have any positive effect, but that personal motivation is of key importance for the effectiveness of the system. Op den Akker et al. (2015) found that tailoring – the process of adjusting system behavior to individuals in a specific context – is a prime design requirement. They noted that for physical activity monitoring systems standard requirements on usability, acceptance and compliance apply that typically are found for information systems that should be used continuously for long periods.

The healthcare sector shows a growing interest in using digital coaching technology to build good interfaces between patients, medical doctors and nurses. Carrino et al. (2014) developed a health companion for healthier lifestyles. The companion has an advanced interface, which assists and entertains the user but also gives adequate knowledge on alimentary education and physical activity. The companion offers assistance for life and works with a knowledge model of the user and his/her behavior. Kari et al. (2016, 2017) move beyond physical activity and show that nutrition and sleep can be monitored with similar self-tracking technology as physical activity. This offers the possibility for more holistic wellness solutions as physical exercise needs supporting diet and sufficient sleep in order to be effective. They also found in their experiments that the perceived wellbeing is rather minor and that the actual health effects are more long-term than first expected; there were no immediate health effects of self-tracking technology.

In summary, there are a few features that emerge as important for digital coaching design: digital coaches should be tailored to the context and the needs of the users, the coaching should be adaptive to the changing activity levels of the users, digital coaches should retrieve knowledge from the users and physical activity should get support from coaching on effective dietary choices and sufficient sleep and rest time.

3 Methods

In our study we started with the Coaching Behavior Scale for Sport (CBS-S) developed by Côté and colleagues, which we adapted to the context of digital coaching. As pointed out by Jain et al. (2018) CBS-S has been used in many empirical studies (for example in Koh et al. 2014) and recommended as a useful instrument for measuring effective coaching. The CBS-S is grounded in coaches' and athletes' experiences and it has originally been developed for assessing coaching behaviors from athletes' perspective and was co-created with coaches and athletes (Côté et al. 1999, Baker et al.2006). According to Côté et al. (1999) the scale presents a grounded instrument that may better examine coaching behaviors than other available scales. CBS-S is developed based on the Coaching Model framework (Côté et al. 1995). With the scale we are able to describe and treat digital coaching in terms of several measurable components.

The original CBS-S includes variables on seven dimensions: physical training and planning, technical skills, mental preparation, goal setting, competition strategies, personal rapport and negative personal rapport. We adapted the variables and dimensions to fit the digital coaching setting, in some cases only swapping the word 'coach' to 'digital coach' (e.g. *The coach provides me with immediate feedback*). Some items were excluded, most notably all items on the negative personal rapport dimension, as this dimension is not relevant in the digital context, as well as the items on the competition strategies dimension, as this dimension is only relevant when studying competitive athletes. We added items describing possibilities to connect with other users, e.g. *"allows you to compare your performance to others"*. Social support has been found to be a predictor for engaging in physical activities (Trost et al. 2002). In a previous study we found that social dimension is indeed perceived to be an enabler for participating in physical activities (Sell et al. 2017). We also added items on the handling and security of data in the system as data handling and capture have been found to be important factors in previous studies on wearable use (Fritz et al. 2014, Harrison et al. 2015, Walden and Sell 2017). We also added items inspired by the review of existing coaching systems for example on the adaptiveness of the digital coach. We cannot assume that the original seven dimensions are present in the first version of the Digital CBS-S, as variables have been adapted, added and removed, and the context is new; we perform factor analysis to examine dimensions in the adapted scale.

The empirical data was collected through a self-administered questionnaire in 2018. The questionnaire was available on-line for all first-year business students at the Åbo Akademi University in Turku, Finland and to participants in some courses at the School of Business and Economics at Linnaeus University in Kalmar, Sweden. We did not have access to contact information for the whole student populations and used convenience sampling. The number of completed, valid responses was 138.

4 Analysis and Results

We will start with an overview of the data we collected. The mean age of the sample is 28 and the sample lies between 19 years and 56 years, the median value being 24. Of our respondents, 53% were female and 46% were male. The highest degree that most of the students had finished by the time of the study was matriculation exam (61%), second highest was an undergraduate degree (22%). Most of them used their smartphones in support of daily exercise (34%) or weekly exercise (34%); much fewer used a smart watch (daily 4%, weekly 1%), sports watch (daily 3%, weekly 2%) or activity bracelet (daily 5%, weekly 3%); still fewer were using heart rate monitors, smart rings, smart scales, etc. Of the respondents 53% report using supporting apps on their smartphones to monitor their exercise and progress; the most typical apps are Runkeeper, Apple Health and Samsung Health. Mindfulness apps (for a relaxed and healthier state of mind) and Polar Flow were also mentioned by some students.

The students were asked how much time they spend during a normal week on “moderate physical activity” and on “vigorous physical activity”. The concepts moderate and vigorous physical activity are according to WHO (2019) about “…the rate at which the activity is being performed or the magnitude of the effort required to perform an activity or exercise”. It can be thought of "*How hard a person works to do the activity*". It is suggested that 75 minutes of vigorous activity matches the health benefits of 150 minutes moderate activity (National Health Service, 2019)

We gave the students examples of moderate and vigorous physical activities, the former being walking, cycling and fishing and the latter being running, hill climbing, ballgames and fitness swimming. The descriptive results for moderate, vigorous and muscular and/or balance training are presented in Table 1 and Figure 1.

Time in minutes per week	Moderate physical activity n=137	Vigorous physical activity n=137	Muscular and/or balance training n=136
0 min / not at all	2 / 1%	13 / 9%	15 / 11%
< 30 min	4 / 3%	18 / 13%	26 / 19%
30-60 min	19 / 14%	27 / 20%	25 / 18%
60-90 min	24 / 18%	21 / 15%	18 / 13%
90-120 min	22 / 16%	12 / 9%	12 / 9%
120-150 min	18 / 13%	11 / 8%	7 / 5%
> 150 min	48 / 35%	35 / 26%	33 / 24%

Table 1: Moderate, Vigorous and Muscular and/or Balance Training in Minutes per Week

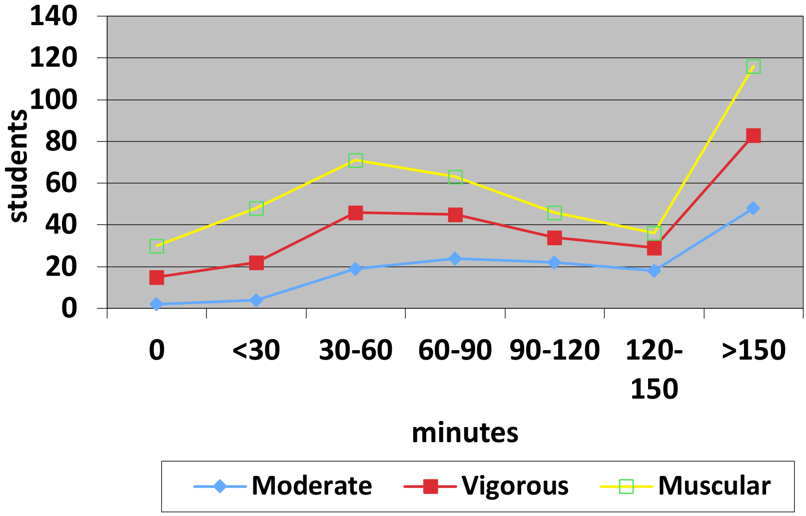

Figure 1: Time spent per week on different training activities

Students spend more time per week on vigorous physical activities than on moderate training and even more time on muscular and/or balance training than on vigorous training. From Figure 1 we can see that the three curves show similar patterns, those students who do more than 150 minutes training per week form the biggest group in all three training categories. Most of the students are active in all three categories, moderate, vigorous and muscular and/or balance training.

In order to better understand the students' exercise behaviors, we asked them to describe in free text the types of physical activities they are regularly involved in. The students show quite some variety in what they mentioned as their activities (number of respondents 124). We run a word cloud analysis on the activities mentioned by the students.

Figure 2: Physical activities that the students are regularly involved in

As can be seen (Fig. 2) gym training was the most frequently mentioned activity by the students (51 students). This is in line with Doğan (2017) who points out that training at the gym has become one of the most popular activities. Running (35 students), walking (25 students) and biking (15) were next among the popular activities. Also football, yoga, soccer, floorball and swimming were mentioned by several students. Most of the respondents volunteered in several activities, among them also more unusual activities such as kiteboarding and rope skipping.

In the first stage of the analysis, we conducted exploratory factor analysis with Direct Oblimin rotation, on the set of items describing the respondents' attitudes towards digital coaching. We found the best results with a five-factor solution, explaining about 75% of the total variance. Variable loadings above 0.7 were seen to contribute to the factors. Cronbach's Alpha is above 0.8 on all five factors (see Table 2). Each factor exhibited eigenvalues exceeding 1.0 and accounted for significant variance beyond that of the other factors. See Table 3 for details.

The factors are described as (1) *Exercise program*, (2) *Goal orientation*, (3) *Data handling*, (4) *Social functionality* and (5) *Mental support*. The dimensions of *Social functionality* and *Data handling* are distinct for the modified version of the CBS-S, not present in the original version of the scale. The other three dimensions have counterparts in the original CBS-S.

The items were measured on a five-point scale. Mean values, standard deviations and alpha values for the five dimensions are shown in Table 2. The *Data handling* dimension shows the highest mean value, above 4 on a 5-point Likert scale ranging from Not important (1) to Very important (5).

Dimension	M	SD	Alpha
1. Exercise program	3.48	.93	.87
2. Goal orientation	3.83	1.06	.87
3. Data handling	4.26	.89	.90
4. Social functionality	2.51	.96	.90
5. Mental support	3.74	1.10	.90

Table 2: Mean values, standard deviations and reliabilities

Item ("The digital coach....")	Goal orientation	Social functionality	Exercise program	Data handling	Mental support
Designs a detailed exercise program for you			.881		
Gives you advice for proper warm-up before exercise			.785		
Designs an exercise program that is suitably physically challenging for you			.838		
Designs an exercise program for a time period specified by you (e.g. two weeks, one month, three months)			.774		
Gives you advice on how to structure your training sessions			.783		
Gives you hints how to improve your training performance	.809				
Asks for input from you in order to tailor your program	.836				
Helps you set specific goals	.787				
Helps you identify training strategies to achieve your goals	.838				
Monitors your progress towards goals	.775				
You have control over how, where and which data is shared				.941	
You trust the system to keep your data safe				.893	
Allows you to observe other users' training behavior (e.g. you can see how similar users are training and reaching their goals)		.834			
Allows you to compare your performance to other users' performance		.879			
Allows you to communicate with other users		.853			
Allows you to compete with other users		.889			
Gives you access to success stories of people who have reached their goals		.804			
Allows you to team up with other users to together reach your goals		.767			
Helps you stay positive about yourself					.916
Helps you stay focused on your goals					.860
Helps you stay confident about yourself					.898
Eigenvalue	7.65	3.90	1.64	1.46	1.14
% of total variance	36.2%	18.6%	7.8%	6.9%	5.4%

Table 3: Factor loadings

In order to investigate our student sample through the lens of physical activity we utilized K-means cluster analysis with Ward's method to group our respondents. As input we utilized two variables where the respondents rated their weekly participation in (a) vigorous training and (b) muscular and/or balance training. Three distinct clusters emerged, see Table 4. The first cluster (41 respondents) is characterized by very frequent involvement in both types of training. The third cluster (44 respondents) is at the opposite end of the spectrum, characterized by low involvement in both types of training. The second cluster (45 respondents) falls in between these. Cluster membership is rather evenly divided in the sample. Cluster 1 has more male respondents (27, 66%, n=41), whereas cluster 2 and 3 include more female respondents (27 females, 63%, n=43 and 25 females, 48%, n=43).

	Cluster 1 (n=41)	Cluster 2 (n=45)	Cluster 3 (n=44)
How much time do you spend during a normal week on vigorous physical activity, e.g. running, ball games, hill climbing, fitness swimming?	6.00	4.80	2.11
How much time do you spend a normal week on muscular and/or balance training?	6.68	3.33	2.45

Table 4: Final cluster centers and cluster membership (n=130)

We analyzed the clusters for differences in their response to the attitude statements on digital coaching. Significant differences arose, especially between the most and least active clusters. Overall, the more active students rate functions more highly. See Table 5 for significant differences found through two-way ANOVA and post hoc tests (Bonferroni, or Games-Howell when equal variances could not be assumed).

Attitude statement (How important do you think the following features are in a digital coach for physical training?:)	*df*	*SS*	*MS*	*F*	*p*	**Cluster 1**	**Cluster 3**
Designs an exercise program that is suitably physically challenging for you	2, 125	10.38, 139.5	5.19, 1.12	4.65	0.011	M=4.06, SD=1.02	M=3.4, SD=1.18
Gives you advice on how to structure your training sessions	2, 125	12.98, 149.02	6.49, 1.19	5.44	0.005	M=3.93, SD=0.98	M=3.19, SD=1.18
Gives you feedback on your technique	2, 127	13.15, 151.65	6.57, 1.19	5.5	0.005	M=4.2, SD=0.98	M=3.4, SD=1.15
The digital coach is easily accessible to you	2, 127	10.1, 139.9	5.09, 1.1	4.58	0.012	M=4.24, SD=0.99	M=3.6, SD=1.2
The digital coach helps you set specific goals	2, 126	10.55, 131.93	5.27, 1.05	5.04	0.008	M=4.12, SD=0.87	M=3.49, SD=1.1
The digital coach helps you identify training strategies to achieve your goals	2, 125	13.86, 110.6	6.93, 0.89	7.83	0.001	M=4.22, SD=0.73	M=3.44, SD=1.16
The digital coach guides you to reach your goals through concrete training tasks	2, 125	10.19, 147.74	5.1, 1.18	4.3	0.015	M=3.63, SD=1.19	M=3.14, SD=1.1
The digital coach allows you to compare your performance to other users' performance	2, 125	11.07, 182.3	5.53, 1.46	3.79	0.025	M=2.8, SD=1.32	M=2.07, SD=1.22
The digital coach allows you to compete with other users	2, 123	11.05, 183.67	5.53, 1.49	3.7	0.028	M=2.8, SD=1.27	M=2.07, SD=1.14
The digital coach gives you access to success stories of people who have reached their goals	2, 123	12.53, 196.9	6.26, 1.6	3.9	0.022	M=2.85, SD=1.35	M=2.07, SD=1.18

Table 5: ANOVA summary table

5 Discussion and Conclusions

We have applied and adapted a scale for coaching behaviors to the digital context. We have found the adapted scale to have a factor structure, which seems to capture dimensions that are relevant in the digital coaching context. The addition of items on social functionality and data handling resulted in two novel factors necessary in the digital context. Further studies should seek to confirm the suitability of the scale for the digital coaching context, and identify possible other dimensions not identified in this study. The data handling dimension reflects the current interest towards 'quantified self', as well as the importance of data security and privacy.

When examining the respondents' attitudes towards digital coaching, it was interesting, but perhaps not surprising to see that those respondents who are more physically active also show more interest in many of the suggested features of digital coaching. It is possible that they are overall more interested in developing their physical performance, but this we cannot confirm based on the current study. Interestingly, there are no significant differences between the frequency that the most and least active respondents use technologies to support their training (e.g. smart phones and smart watches). In other words, the difference in attitudes is not explained by their differing current use of training technologies.

The modified CBS-S for digital coaching seems to capture a range of features relevant in digital coaching. In subsequent development of the scale, it is of interest to test additional features based on emerging research. Firstly, features using gamification would be a possible value-adding addition, which was verified in studies carried out by Kari et al. (2016, 2017). Secondly, as the sedentary students were the least interested in any of the functionalities offered, it would make sense to further investigate functionalities designed to raise exercise motivation and promote behavior change. The active students appreciated the offered functionalities the most – which makes sense, as they are already following an active lifestyle and the digital coach would simply support or enhance that lifestyle. The sedentary students are in a different position; they would require support to introduce new behaviors and routines – a behavior change support system. The features we describe in the "digital CBS-S" might be too far removed from their current everyday routines. In order to achieve a behavior change from a sedentary lifestyle to an at least comfortable – or even better – active lifestyle, they would need either an adaptive digital coach designed to introduce incremental changes, or a tailor-made program with an actual personal trainer. Finally, as previous research has shown that hedonic value is important in practically every information system, the digital coach is likely no exception. The role of hedonic value in a digital coaching solution should be considered in a future version of the scale.

The social functionalities of a digital coach garnered less interest from the students than other features. This is an important finding, considering that previous studies have identified the social dimension to be important in the context of physical activity, e.g. Trost et al. (2002) found social support to be a predictor for physical activities. The social functions thus warrant further research attention to capture social functionalities, which would fulfill the need of social support in a way that is acceptable to the users of the digital coaching system. In previous research we could find that social functionality was value-adding and appreciated by a group of adults, who participated in a fitness bracelet trial (Sell et al 2017) and our assumption was that the students would also find these features desirable. It is possible that we did not identify the *right* types of social functionality for this target group and future research should investigate other implementations of social functionality to see which social functions fulfill their need of social support. It is also conceivable that in actual use, students might find the value of social connectivity, but at this point fears of privacy overrode any interest in it. The students also showed a marked concern for how their data is handled and the privacy and integrity of their data. This is somewhat surprising, given the overall prevalence of social media use and the consequential data sharing. It is possible that exercise data is perceived to be rather sensitive. This warrants future attention.

Entering higher education is an important transition phase in life, comparable to retirement later in life. Previous routines and structures are left behind, and new ones are created. Our results offer indications on how technology can be harnessed to aid students in their physical activities.

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