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FROM SPORT PERFORMANCE TO DIGITAL HEALTH: UNDERSTANDING KEY PSYCHOLOGICAL VARIABLES FOR DEVELOPING A PHYSICAL ACTIVITY APP

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Introduction

Physical activity is defined as “any bodily movement produced by skeletal muscles that requires energy expenditure” (WHO, 2010). This definition encompasses a broad variety of different behaviours that range from fundamental human functions to more intense exercise activities. Indeed, there are many different forms and levels of intensity of physical activity. These include basic movement skills, leisure activities, such as walking, hiking and biking, sports and structured exercise.

Health benefits of physical activity are undeniable and supported by an enormous corpus of research that is continuously growing (Watburton & Bredin, 2016). The practice of regular physical exercise is a protective factor against multiple chronic medical conditions, known as non-communicable diseases (NCDs; i.e., coronary and respiratory diseases, type 2 diabetes, breast and colon cancer), and premature mortality (Pedersen & Saltin, 2015; Watburton, Nicol, & Bredin, 2006). It has been estimated that, in Europe, physical inactivity causes 5.5% of the burden of disease from coronary heart disease, 6.8% of type 2 diabetes, 9.3% of breast cancer, 9.8% of colon cancer, and it is responsible for 8.8% of all-cause of mortality. As a consequence, elimination of physical inactivity would increase the life expectancy of European population by 0.63 years (Lee, Shiroma, Lobelo et al., 2012) and it would reduce the economic burden for healthcare systems. Indeed, direct costs due to physical inactivity in 2013 were estimated around 53,8 billion of dollars worldwide and 11,7 billion of dollars in Europe (Ding, Lawson, Kolbe-Alexander et al., 2016). Such epidemiological evidences are even more alarming if recent trends regarding the European population aging are considered. Indeed, by 2060, mean life expectancy in the European Union is expected to increase by 8.5 years for men (to 84.5 years), and by 6.9 years for women (to 89.0 years). Because of physical inactivity has been shown to increase with age (Hallal, Andersen, Bull, et al., 2012), it is possible to foresee that the negative impact of physical inactivity on health and healthcare systems will be even more noticeable in the next decades. Concerning this, public expenditure on healthcare is expected to rise from 6.7% of

gross domestic product (GDP) in 2007, to 8.2% by 2060 in European countries (Rechel, Grundy, Robine, et al., 2013).

The effect of physical activity on disease and premature death prevention is mediated by several biological mechanisms including cardiovascular and musculoskeletal fitness, body composition and metabolism (Watburton, Nicol, & Bredin, 2006). Such mechanism, in turn, are activated by transient changes in response to single exercise sessions, such as reductions in triglyceride levels, increases in HDL cholesterol level, decreases in blood pressure, reductions in insulin resistance and improvements in glucose control (Thompson, Crouse, Goodpaster, et al., 2001). Furthermore, another important factor that mediates the effect of physical activity on some specific NCDs is represented by an improved psychological well-being mainly due to a reduction in anxiety, depression, stress, and negative affects (Dunn, Trivedi & O'Neal, 2001; Penedo, & Dahn, 2005). Such a positive effect of physical activity on individual well-being is also supported by evidence highlighting better health-related quality of life, and grater individual happiness among individuals that exercise regularly (Bize, Johnson, & Plotnikoff, 2007; Richards, Jiang, Kelly, et al., 2015). In order to pursue such health-related and well-being benefits, the World Health Organization guidelines state that healthy adults (age between 18-65) should accumulate 150 minutes or more of moderate intensity physical activity per week, or 75 minutes or more of vigorous intensity physical activity per week, or an equivalent combination of moderate- and vigorous-intensity physical activity, accumulating at least 600 MET-minutes[1] per week. However, in spite of epidemiological evidences and physical activity recommendations, large part of the population doesn't meet physical activity guidelines and many individuals live a sedentary life. In Europe, estimates showed that more than one third of adults are insufficiently active. Such data are even more alarming in Mediterranean areas and particularly in Italy, where 60% of the population are completely inactive (Eurobarometer, 2015). As a consequence,

[1] MET refers to metabolic equivalent. It is the ratio of a person's working metabolic rate relative to the resting metabolic rate. One MET is defined as the energy cost of sitting quietly, and is equivalent to a caloric consumption of 1 kcal per kg per hour.

there is an overwhelming need for finding new and effective strategies to support and sustain physical activity among sedentary people.

With this aim, in the last recent years, healthcare practitioners and institutions have the possibility to benefit from the use of new technological potentialities in order to promote physical activity behaviour change (Hallal et al., 2012; Pagoto & Bennet, 2013). Indeed, new mobile technologies enables i) to deliver large-scale behaviour change interventions thanks to the widespread of smartphones, ii) to improve behavioural and psychological assessment methods (i.e., wireless health sensors, experience sampling), and iii) to develop computational models based on behaviour change theories (e.g., Consolvo, McDonald, Toscos, et al., 2008; Hekler, Michie, Pavel, et al., 2016). This latter aspect is particularly relevant since it permits to investigate the causes of physical activity by including validating applications of theoretical models and using theory-derived constructs in identifying modifiable factors that may influence the behaviour (Sallis, Owen, & Fotheringham, 2000). This approach is essential for planning, developing and improving behaviour change interventions because effective programmes will target factors known to cause inactivity (Bauman et al., 2012). Among these factors, ranging from demographic, biological to social and cultural factors, psychological aspects (e.g., self-efficacy, intention to exercise, expect benefits) have been shown to be important correlates and determinants of physical activity behaviour (Trost, Owen, Bauman, Sallis, & Brown, 2002). In particular, self-efficacy beliefs have been consistently identified as the clearest correlate and determinant of physical activity in various populations (Trost et al., 2002; Bauman, Reis, Sallis, et al., 2012). In addition, dispositional and motivational variables, such as personality traits and physical activity participation motives, have been recognized as correlates of regular exercise (Teixeira, Carraça, Markland, Silva, & Ryan, 2012; Wilson & Dishman, 2015). In light of such evidences and new technological opportunities, healthcare practitioners shouldn’t disregard the relevance of using mobile technology and theory- and evidence-driven models in order to design and deliver behaviour change interventions targeting physical activity.

The present thesis addresses the issue of physical activity behaviour change from a twofold perspective.

Section 1 will explore dispositional and social-cognitive correlates of physical activity, targeting a specific field for exercising that is organised sport activities. The aim of this section is to confirm and extend previous evidences regarding whether and how social-cognitive and dispositional variables are associate with participation, success and performance in sport.

Section 2 will describe the design of a digital behaviour change intervention to support physical activity among sedentary adults. The aim of this section is to introduce the steps that characterised the development of a physical activity smartphone application, called *Muoviti!*, In particular, the following goals will be addressed i) development of a computational model of self-efficacy (Bandura, 1997) embedded into the application, ii) selection of specific behaviour change techniques to support physical activity behaviour change, and iii) how such behaviour change techniques deserve to be translated into design features in order to promote effective users' engagement with the application.

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Part 1

Dispositional traits and self-efficacy beliefs in sport participation and performance

Physical activity is an important aspect of several areas of human life and it influences physical as well as psychological wellbeing. From an early age, individuals are involved in various types of physical activities across different contexts, such as school, travelling, and leisure time. However, with the transition to adulthood, individuals decrease their propensity to practise physical activity with subsequent risks for their health (Bauman, Reis, Sallis et al., 2012; European Union, 2014). As a consequence, an understanding of why people are physically active or inactive is important for developing actions targeting correlates and determinants of physical activity.

From a psychological perspective, there are strong evidences that dispositional factors and social-cognitive variables are related to natural variations in physical activity. For instance, meta-analytical studies framed in the Big Five personality model identified positive associations between physical activity and high level of Extraversion, Emotional Stability, Conscientiousness and Openness (Rhodes & Smith, 2006; Wilson & Dishman, 2015). Similarly, self-efficacy beliefs, theorized in Bandura's social-cognitive theory (Bandura, 1977; 1997) have been proven to be a positive correlate of the adoption and maintenance of exercise in adults (Bauman et al., 2012; McAuley & Blissmer, 2000; Trost, Owen, Bauman, Sallis, & Brown, 2002). However, in such meta-analyses and reviews, physical activity was investigated in its broader sense, encompassing studies that adopted different research designs (i.e., cross-sectional, longitudinal) and various measures of exercise (e.g., attendance to exercise programme, self-report questionnaires). For these reasons, physical activity was considered as an omnibus construct, without accounting for the various behaviours it comprises and the different settings where it may occur.

The present section focuses on a specific context that has received less attention in the large array of research on physical activity, that is organised sport. Organised sport activities are a preferential field for exercising, improving athletic and technical skills, and achieving personal goals and ambitions (Bandura, 1997). Focusing on this specific setting permits to investigate whether

and how dispositional and social-cognitive factors are associated with long-term outcomes of physical activity, such as athletic success and performance. Moreover, understanding how personality differs across discrete athletic and non-athletic populations and how self-efficacy influences sport performances would enable practitioners to translate knowledge form sport setting to exercise promotion contexts.

So far, previous research on sport and personality suggested that athletes display greater levels of extraversion than non-athletes and some studies have observed that athletes demonstrated higher levels of emotional stability and are more open to new experiences (Allen, Greenlees, & Jones, 2013), However, such studies are characterized by some relevant methodological issues. For instance, inadequate sample sizes, unclear effect sizes, and the lack of statistical methodologies that consider the latent psychometric constructs and the measurement invariance undermine the validity of the conclusions that can be drawn from available research in sport setting. Furthermore, previous research addressing personality differences among sporting and non-sporting populations mainly confined any athlete in only one all-inclusive sporting population, without accounting for the heterogeneity that characterize athletes (e.g., various levels of athletic success). Taken together, the available findings showed that personality has an important role in sport participation and athletic success but further research, characterised by the adoption of a strong methodological approach, is needed to confirm previous findings and to better quantify effect sizes.

Among the psychological factors that play a crucial role in determining exercise and high-level sport performance, self-efficacy beliefs represent one of the most important predictor (Bandura, 1997, Trost et al., 2002). Previous meta-analysis (Moritz, Feltz, Fahrbach, & Mack, 2000) evidenced a positive relationship (r=.38) between self-efficacy and performance in sport setting and it was consequently argued that approximately 16% of the variance in athletic performance can be attributed just to self-efficacy beliefs (Feltz, Short, & Sullivan, 2008). This value is particularly relevant and meaningful when all the factors that can affect the individual sport performance are considered. Such associations have been widely investigated adopting different study designs and methods (e.g., experimental, non-experimental), analytical approach (e.g.,

descriptive studies, multiple regressions, path analyses), and including various populations (ranging from children to professional athletes) (Feltz et al., 2008). Despite this heterogeneity, collectively, previous findings converged upon the significant and overwhelming relationship between self-efficacy and performance in various sport settings. However, there are some specific sport contexts in which such relationship has received little attention. One of them is risky sports. This particular context has been traditionally investigated with the purpose of understanding what psychological factors determine the participation and risk taking in such activities (see Jack & Ronan, 1998; Llewellyn & Sanchez, 2008), disregarding their role in relation to the performance achieved. Filling this gap and extending previous findings to risky sport contexts, would allow to further confirm the key role of self-efficacy beliefs as determinant for sport and exercise performance and provide additional support for recognizing it as a preferential construct that deserves to be leveraged in order to promote physical activity. In this direction, a further major advantage of applying interventions on self-efficacy relies on the fact that it constitutes a modifiable construct. Indeed, through the use of specific sources and behaviour change techniques, self-efficacy beliefs may be learnt, promoted, and enhanced (Ashford, Edmunds, & French, 2010; Bandura, 1997; Williams & French, 2011).

In the present section two studies focusing on the dispositional and social-cognitive factors associated with sport participation, success, and performance are reported.

- Study 1 explored the association among Big Five personality traits and involvement and success in organized sports. The study aimed to overcome most of the limitations of previous research to derive clearer and more valid conclusions on the relationship between personality and sports participation. In particular, the present research recruited a large sample size, adopted innovative statistical methodologies (i.e., Exploratory Structure Equation Modeling) to test measurement invariance and mean differences across the groups considered, and provided detailed information about the effect size related to population-based differences.

- Study 2 investigated the psychological factors that may explain performance in risky sport. For such purposes, previous findings concerning the determinants of the participation and risk

taking in risky sport (i.e., sensation seeking) were integrated with the psychological literature regarding the association between self-efficacy beliefs and sport performance. The study focused on a never-before-investigated risky sport, that is competitive freediving, and specifically considered two different disciplines of freediving characterized by different levels of risk (i.e., dynamic freediving, constant weight freediving).

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Study 1

Associations between personality, sports participation and athletic success. A comparison of Big Five in sporting and non-sporting adults[2]

Abstract

The present study investigates whether the Big Five personality traits are different among diverse sports populations. A sample of 881 male athletes and non-athletes completed a self-report questionnaire measuring their personality traits. The Exploratory Structure Equation Modeling (ESEM) approach is adopted to test measurement invariance and mean differences among groups. The results indicate that athletes who had experienced the most success in their sport scored higher than non-athletes in each personality dimension of the Big Five, with the exception of openness, while less successful athletes scored higher than non-athletes only in extraversion and agreeableness. The more successful athletes showed higher agreeableness, conscientiousness, and emotional stability than the less successful athletes. Individual-sport athletes were found to be more energetic and open than team-sport athletes. The current findings help clarify the relationships between personality traits, sports participation and athletic success.

1. Introduction

The study of personality in sports psychology is primarily focused on investigating the associations between personality, participation, and athletic achievement (Aidman & Schofield, 2004; Allen, Greenlees, & Jones, 2013; Allen & Laborde, 2014).

Previous research is either framed in the theory of the Big Five personality traits (Goldberg, 1993; McCrae & Costa, 1996) or Eysenck personality theory (Eysenck, 1970). The Big Five theory presents a model in which personality is organized into five factors: extraversion, agreeableness,

[2] The present study is based on "Steca, P., Baretta, D., Greco, A., D'Addario, M., & Monzani, D. (2018). Associations between personality, sports participation and athletic success. A comparison of Big Five in sporting and non-sporting adults. *Personality and Individual Differences*, *121*, 176-183."

conscientiousness, emotional stability and openness[3]. Meanwhile, the Eysenck personality theory states that personality is made up of three main factors: extraversion, neuroticism – corresponding to extraversion and emotional stability in the Big Five theory (Zuckerman, Kuhlman, Joireman, Teta, & Kraft, 1993) – and psychoticism.

Although associations between personality traits and natural variations in physical activity have been consistently shown – for example, between participation in regular exercise and extraversion, conscientiousness, emotional stability, and openness (Rhodes & Smith, 2006; Wilson & Dishman, 2015) – the association between personality and participation in organized sports has received modest attention and remains less clear. Taken together, previous findings referring to the context of organized sports have suggested that athletes score higher on extraversion (Egloff & Gruhn, 1996; Paunonen, 2003), conscientiousness (Kajtna, Tušak, Barić, & Burnik, 2004; Malinauskas, Dumciene, Mamkus, & Venckunas, 2014), emotional stability (Egan & Stelmack, 2003; Kajtna et al., 2004; McKelvie, Lemieux, & Stout, 2003), and openness (Kajtna et al., 2004) than non-athletes. Moreover, further results have suggested that personality traits are also related to the participation in specific types of sports. More specifically, individual-sport athletes demonstrated higher conscientiousness, openness and emotional stability as well as lower levels of extraversion than team-sport athletes (Allen, Greenlees, & Jones, 2011; Eagleton, McKelvie, & De Man, 2007).

In sports psychology, investigation of the association between personality and athletic success is a very attractive issue that permits an understanding of whether and which personality traits coincide with greater levels of success. The association is rather complex, and a variety of motivational and dispositional variables that are correlated with sports performance and success has been investigated (e.g., Baretta, Greco, & Steca, 2017). Athletic success has mainly been operationalized in terms of the competition level at which athletes compete (Allen et al., 2013), and previous results on the Big Five have shown that high-level athletes (e.g., athletes competing at a

[3] Several names have been used in referring to the Big Five factors. Such names include (1) extraversion vs. introversion (or energy, or surgency); (2) agreeableness (or friendly compliance vs. hostility, or friendliness); (3) conscientiousness (or will); (4) neuroticism vs. emotional stability; and (5) openness to experience (or culture, or openness, or intellect).

national or international level) are more agreeable, conscientious, and emotionally stable (Allen et al., 2011; Kirkaldy, 1982) than low-level athletes (e.g., athletes competing at a county or regional level).

Although previous findings evidenced associations among personality and various sporting populations, some critical flaws limit the conclusions that can be drawn from the available research. A first concern regards the sample sizes adopted in previous studies. While research regarding personality and physical activity usually involves hundreds or even thousands of participants per study (Rhodes & Smith, 2006), research on personality and sports participation uses sample sizes that barely exceed 200 participants (Allen et al., 2011; Malinauskas et al., 2014; Paunonen, 2003) and, in the worst cases, can amount to a mere 40 subjects per sports population (Eagleton et al., 2007).

Second, samples involved in previous studies were extremely heterogeneous because various sports were included in each study (Allen et al., 2011; Eagleton et al., 2007). Sports differ from each other in several ways, and each sport has its own specificity and requirements. For instance, sports may differ in terms of pressure (i.e., some sports are performed on multiple trials while other ones are one-shot trials against time) and in terms of intensity and duration (i.e., some sports last few seconds or minutes, while other ones may last hours). This type of heterogeneity affects comparisons between different studies because the sports considered are not equivalent. Thus, it is possible to argue that various results may be due, at least partially, to distinctive features that characterize each sport. An extreme example illustrating the lack of consideration placed on sport specificity involves cases in which the types of sports considered in studies are not even mentioned (Allen et al., 2011; Kirkaldy, 1982). Another issue regards the operationalization of sports participation; indeed, within the sporting population there may be great variability regarding athletic success and performance that should be taken into account instead of grouping all sport participants in one *sporting* group. These omissions make comparisons among studies difficult and prevent researchers from reaching valid conclusions about the relationship between traits and sports practice. More specifically, this issue is reflected by a lack of effect size synthesis referring to the difference in personality traits (Allen et al., 2013). To manage these issues, it is necessary to

i) accumulate a more substantial body of literature reporting effect sizes and ii) precisely define the outcome variables (e.g., sport performance, success, training time) and find an agreement on how to operationalize them. In this direction, a further aspect that deserves consideration is the adoption of statistical methodologies that take into account the latent psychometric constructs and subsequent systematic tests of measurement invariance (Meredith, 1993). Specifically, a comparison between groups as is usually performed (i.e., *t* test, ANOVA) requires prerequisite assumptions of invariant measurement operations across the groups being compared (Vandenberg & Lance, 2000). If such invariance across sports populations is not achieved, it is not possible to draw scientific conclusions as to how the group differences may be associated with personality dimensions. To test invariance, in recent years, a few studies (Marsh, Ludtke, Muthén, Asparouhov, Morin et al., 2010; Marsh, Morin, Parker, & Kaur, 2014) have noted that the classic Confirmatory Factor Analysis (CFA) is inappropriate for testing structure and invariance across groups of Big Five measures. This suggestion is in line with the position argued by Big Five researchers for years (e.g., Church & Burke, 1994; McCrae, Zonderman, Costa, Bond, & Paunonen., 1996) and with previous unsuccessful attempts to test Big Five measure structures through CFA (e.g., Cooper, Smillie, & Corr, 2010; Vassend & Skrondal, 1997). To overcome these limits, recent research has started to apply Exploratory Structure Equation Modeling (ESEM; Asparouhov & Muthén, 2009) to Big Five data (Chiorri, Marsh, Ubbiali, & Donati, 2016; Marsh et al., 2010; Marsh, Nagengast, & Morin, 2013). The advantages of the ESEM approach rely on exploiting the advanced statistical methods typically associated with CFAs and SEMs (e.g., testing for measurement invariance across groups, incorporate latent factors into subsequent analysis) without relying on excessively restrictive CFA constraints (i.e., secondary loadings fixed to zero). For these reasons, the ESEM approach has been proposed to be particularly suitable for testing the dimensionality and measurement invariance for Big Five measures (Marsh et al., 2014).

1.1. The present study

The purpose of the present study was to explore the relationship among Big Five personality traits and involvement and success in organized sports, a context that has received little attention in the

large array of physical activity. The present study aims to overcome most of the limitations of previous research to derive clearer and more valid conclusions on the associations between personality and sports participation. In particular, as claimed by Allen et al. (2013), the present research provides detailed information about the effect size related to population-based differences. Moreover, in line with recent suggestions (Marsh et al., 2010), the ESEM approach has been adopted to test measurement invariance and mean differences across the groups considered.

Based on the most consistent results from available literature, the following hypotheses were developed:

- It was expected that non-athletes would have lower levels of extraversion, conscientiousness, and emotional stability than athletes.
- High-level athletes were expected to be more agreeable, conscientious, and emotionally stable than low-level athletes.
- It was expected that individual-sport athletes would report more conscientiousness, openness, and emotional stability than team-sport athletes.

2. Material and methods

2.1. Participants

Participants who took part in this study were Italian male athletes (*n*=755; mean age=22.62; *SD*=3.56) and non-athletes (*n*= 126; mean age=23.78; *SD*=2.84) aged between 18 and 30. The athletes (see table 1) competed in individual (track and field; *n*=135; mean age=22.07; *SD* =3.45) or team sports (soccer and basketball; *n*=620; mean age=22.74; *SD* =3.58). Athletes competing at regional levels were categorized as low-level athletes (LLA; *n*= 558; mean age=22.25; *SD* =3.42), while those competing at the national level were categorized as high-level athletes (HLA; *n*=197; mean age=23.68; *SD* =3.77)[4].

[4] Sports-specific criteria for being included in the high-level group:
Soccer – participation in leagues: Serie A, Serie B, Serie C. Basketball – participation in leagues: Serie A, Serie A2, Serie B. Track and Field – meeting the performance requirements for taking part at the Italian Athletics Championship.

Table 1. *Sample size information for each sports group and subgroup*

	Individual sport (*n*=135)	Team sport (*n*=620)	
	Track and field (*n*=135)	Soccer (*n*=230)	Basketball (*n*=390)
Low-level athletes (*n*=558)	73	179	306
High-level athletes (*n*=197)	62	51	84

2.2. Procedure

2.2.1. Sampling procedures

Athletes were contacted during sporting competitions. They were asked if they would be willing to participate in a study on sports and personality. Participants were also told that all of the questionnaires would be anonymous. Non-athlete sampling was based on the "snowball" method with a ratio of 1:1 (i.e., one participant was asked to find another participant). All participants were provided with an informed consent form and a questionnaire for self-reporting. Both athletes and non-athletes were asked to carefully read and sign the informed consent form, individually complete the measures, and then return them to the researcher responsible for questionnaire administration. The time required for filling the questionnaire was between 3 and 4 minutes. During the assessment, participants were told that they could ask the researcher regarding any issue, doubt, or incomprehension. Participants received no incentive for their participation.

2.2.2. Measures

Athletes were asked to answer socio-demographic (gender and age) and sports-related (type and category of sport) questions. Non-athletes were asked to report socio-demographic factors (gender and age). Their personality was assessed through a list of 25 adjectives used in a previous study (Barbaranelli, Caprara, Vecchione, & Fraley, 2007). These adjectives (see Appendix) included those most frequently used to describe human personality traits, as well as those most representative of each dimension of the Big Five in the Italian lexicon (Caprara & Perugini, 1994). Furthermore, they overlap considerably with markers used in other languages (Peabody & De Raad, 2002). The list includes five markers for each of the following dimensions: Energy, Agreeableness, Conscientiousness, Emotional stability, and Openness. Adjectives are rated for how characteristic they are of each target on a 1 (not at all) to 5 (at all) scale. This instrument was

chosen because of its brevity, which made it particularly useful when there was only a short time available for questionnaire administration.

2.2.3. Statistical analyses

Analyses were conducted with Mplus 7.3 (Muthen & Muthen, 1998-2012). Preliminary analyses consisted of ESEM on the total group of participants to verify the five-factor structure of the personality measure. A robust maximum likelihood estimator (MLR) and oblique GEOMIN rotation were used.

Measurement invariance over the level of sport success (i.e., non-athletes, LLA, HLA) and type of sport (i.e., individual- and team-sport) was tested adopting the ESEM framework through a 13-nested model taxonomy of invariance tests that integrated factor and measurement invariance traditions (for a more detailed discussion of the invariance models see Marsh et al., 2010; Meredith, 1993). These models vary from the least restrictive model of configural invariance to a model of complete invariance that posits strict invariance, together with the invariance of the latent means and of the factor variance-covariance matrix. In this study, the sequence of measurement invariance was tested comparing the following models from Marsh and colleagues' taxonomy (2010): model-1 (configural invariance), model-2 (weak measurement invariance), model-5 (strong measurement invariance), model-7 (strict measurement invariance), and model-9 (strict and invariance of the factor variance-covariance matrix). If model-9 invariance is reached, the variances are equal to 1 in all groups, so that the mean differences are expressed in *SD* units as a function of the *SD* of the whole sample[5]. Big Five mean differences are compared by constraining the means of one group at zero and freeing them in the other group(s).

In line with previous studies testing Big Five structure and measurement invariance through ESEM (Chiorri et al., 2015; Marsh et al., 2010; Marsh et al., 2013), the fit indices considered are the root-mean-square error of approximation (RMSEA), Tucker-Lewis index (TLI), and comparative fit index (CFI). For TLI and CFI, values greater than .90 and .95 are typically interpreted to reflect acceptable and excellent fit to the data, respectively. For the RMSEA, value of less than .05 and

[5] The standardized difference between means is a measure of the effect size and is equivalent to Cohen's *d.*

.08 are typically interpreted to reflect a close fit and reasonable fit to the data, respectively (Marsh, Hau, & Wen, 2004). The comparison of fit across the different nested models (i.e., model-1 vs model-2, model-2 vs model-5, model-5 vs model-7, model-7 vs model-9) was based on CFI and TLI comparison. A CFI and TLI diminution of .01 or less between a more parsimonious model and the preceding more complex model indicated that the invariance hypothesis should not be rejected (Chen, 2007; Cheung & Rensvold, 2002).

3. Results and Discussion

3.1. Results

3.1.1. Total group analyses to verify the five-factor structure of the personality measure

The fit of the total group ESEM was acceptable ($\chi 2$ =478, *df*=185, *p*<0.001; CFI=.95; TLI=.92, RMSEA=.04), supporting the five-factor structure underlying the list of 25 adjectives. The internal consistency of the five-factor solution was corroborated by the factor scores determinacy coefficients (see Muthén & Muthén, 1998), which provide a measure of internal factor consistency: coefficients of .70 or better indicate stable factors (Tabachnick & Fidell, 1989). In the present study, these coefficients were .91 for Energy, .86 for Agreeableness, .89 for Conscientiousness, .89 for Emotional Stability and .92 for Openness. Cronbach's alpha coefficients were lower, but still adequate, at .79 for Energy, .68 for Agreeableness, .73 for Conscientiousness, .73 for Emotional Stability and .81 for Openness (see Appendix for factor loadings and sub-groups reliability information).

3.1.2. Measurement invariance over the level of sport success and type of sport

Table 2 reports the results of measurement invariance analysis across the non-athletes, LLA and HLA groups (i.e., level of sport success) and across the team- and individual-sport groups (i.e., type of sport). As shown, the measurement through the different nested models (i.e., from model-1 to model-9) was achieved for both the level of sport success and type of sport. Comparisons of each of these pairs of the models (i.e., model-1 vs model-2, model-2 vs model-5, model-5 vs model-7, model-7 vs model-9) resulted in an equivalent CFI and TLI (i.e., ΔCFI and ΔTLI <.01). The

most invariant model (i.e., model 9) provided a satisfactory level of approximate fit to the data, with CFI and TLI >.90, and RMSEA <.05.

Table 2. *Summary of the goodness-of-fit statistics for the total group ESEM and measurement invariance over the level of sport success and type of sport*

	χ2	*df*	CFI	ΔCFI	TLI	ΔTLI	RMSEA
Total group ESEM	478	185	.951		.921		.042
Measurement invariance across level of sport success							
Model-1 (configural invariance)	1028	555	.923		.875		.054
Model-2 (weak measurement invariance)	1124	755	.923	.000	.909	.034	.046
Model-5 (strong measurement invariance)	1304	795	.917	-.003	.906	-.003	.047
Model-7 (strict measurement invariance)	1393	845	.911	-.006	.905	-.001	.047
Model-9 (strict measurement invariance, factor variance-covariance)	1453	875	.906	-.005	.903	-.002	.047
Measurement invariance across type of sport							
Model-1 (configural invariance)	723	370	.934		.893		.050
Model-2 (weak measurement invariance)	849	470	.929	-.005	.910	.017	.046
Model-5 (strong measurement invariance)	903	490	.923	-.006	.906	-.004	.047
Model-7 (strict measurement invariance)	961	515	.917	-.006	.903	-.003	.048
Model-9 (strict measurement invariance, factor variance-covariance)	984	530	.915	-.002	.904	.001	.048

Note: CFI=comparative fit index; TLI=Tucker-Lewis index; RMSEA=root-mean-square error of approximation

3.1.3. Mean differences

3.1.3.1. Differences in Big-Five among non-athletes, LLA, and HLA

Examining the model in which the means were constrained to 0 in one group (non-athletes) and freely estimated in the other groups (LLA and HLA), it was apparent that LLA displayed significantly higher scores on energy (d=1.07, p<.001) and agreeableness (d=.36, p<.01) than non-athletes, while HLA demonstrated higher levels of energy (d=1.17, p<.001), agreeableness (d=.58, p<.001), emotional stability (d=.31, p<.05), and conscientiousness (d=.32, p<.05) than non-athletes. When the means were constrained to 0 in the LLA group and freely estimated in the other groups, it was possible to examine the differences between LLA and HLA. The results suggested

that HLA scored higher in agreeableness (*d*=.22, *p*<.05), emotional stability (*d*=.29, *p*<.01), and conscientiousness (*d*=.44, *p*<.001) than LLA (see table 3).

Table 3. *Mean differences as a measure of the effect size with confidence intervals (CI) among non-athletes, low-level athletes and high-level athletes.*

	Non-athletes (N=126)		Low-level athletes (N=558)		High-level athletes (N=197)	
	Constrained Mean		Mean	95% CI	Mean	95% CI
Energy	0		1.07***	[.80, 1.33]	1.17***	[.89, 1.46]
Agreeableness	0		.36**	[.10, .62]	.58***	[.28, .87]
Conscientiousness	0		-.13	[-.40, .15]	.32*	[.01, .62]
Emotional stability	0		.03	[-.23, .28]	.31*	[.03, .59]
Openness	0		-.06	[-.27, .15]	.05	[-.19, .29]
	Non-athletes (N=126)		Low-level athletes (N=558)		High-level athletes (N=197)	
	Mean	95% CI	Constrained Mean		Mean	95% CI
Energy	-1.07***	[-1.33, -.80]	0		.11	[-.07, .28]
Agreeableness	-.36**	[-.62, -.10]	0		.22*	[.01, .42]
Conscientiousness	.13	[-.15, .40]	0		.44***	[.25, .64]
Emotional stability	-.03	[-.28, .23]	0		.29**	[.10, .48]
Openness	.06	[-.15, .27]	0		.11	[-.07, .29]

Note: Mean differences between non-athletes and low-level athletes and between non-athletes and high-level athletes are expressed as the number of *SD* units (equal to Cohen's *d*) and are analyzed by constraining the means of non-athletes at zero. Mean differences between low-level athletes and high-level athletes are expressed in number of *SD* units (equal to Cohen's *d*) and are analyzed by constraining the means of low-level athletes at zero.
*<.05 (two-tailed)
**<.01 (two-tailed)
***<.001 (two-tailed)

3.1.3.2. Differences in Big Five traits between individual- and team sport athletes

To analyze the mean differences between individual- and team-sport athletes, the means were constrained to 0 in team-sport group and freely estimated in the individual-sport group. The results suggested that individual-sport athletes are more energetic (*d*=.38, *p*<.01) and open-minded (*d*=.36, *p*<.01) than team-sport athletes (see table 4).

Table 4. *Mean differences as a measure of the effect size with confidence intervals (CI) between team- and individual-sport athletes.*

	Team-sport athletes (N=620)	Individual-sport athletes (N=135)	
	Constrained Mean	Mean	95% CI
Energy	0	.38**	[0.14, 0.61]
Agreeableness	0	-.08	[-0.32, 0.16]
Conscientiousness	0	.21	[-0.04, 0.46]
Emotional stability	0	.06	[-0.18, 0.30]
Openness	0	.36**	[0.14, 0.58]

Note: Mean differences between team- and individual-sport athletes are expressed as the number of *SD* units (equal to Cohen's *d*) and are analyzed by constraining the means of team-sport athletes at zero.
*<.05 (two-tailed)
**<.01 (two-tailed)
***<.001 (two-tailed)

3.2 Discussion

The present study sought to outline personality differences among various sports populations: non-athletes and athletes, lower success and higher success athletes, and team-sport and individual-sport athletes. The first notable finding was that high-level athletes scored higher than non-athletes in each personality dimension of the Big Five, with the exception of openness, while low-level athletes scored higher than non-athletes only in extraversion and agreeableness. A large to very large effect size indicated that energy is the most important factor differentiating athletes from non-athletes, but not low-level from high-level athletes, suggesting that the level of energy is associated with participation in organized sport activities rather than with sport success, confirming that sports and physical activity are elective contexts of expression and development of energy features. The small to medium effect size in agreeableness was probably because athletes, by taking part in organized sport activities, attend to a social context that typically facilitates relationships with other sport mates. Conversely, conscientiousness and emotional stability differed only between non-athletes and high-level athletes, pointing out that such factors are more associated with athletic success rather than sports participation. According to most of the previous literature, no differences emerged in terms of openness. Taken together, the first results partially confirmed the first hypothesis, and suggested that different findings in the literature (Egan & Stelmack, 2003; Egloff & Gruhn, 1996; Kajtna et al., 2004; Malinauskas et al., 2014; Mckelvie et al., 2003; Paunonen, 2003) may be because comparisons between athletic and non-athletic populations were usually made without controlling for success within the athletic population.

Concerning the association between personality and sports success, the present results confirmed those of the literature (Allen et al., 2011), indicating that more successful athletes are significantly more agreeable, more conscientious, and more emotionally stable than less successful athletes. Such differences may be related to specific characteristics that typically distinguish sports played at a higher level, such as a higher number of sport competitions, more time spent practicing and travelling, and more frequent stressful events (e.g., injuries). Facets of conscientiousness, such as perseverance and diligence, as well as the capacity to manage stress and emotions (emotional stability) and find relational support in case of need (agreeableness), are

particularly relevant to managing these high-level sport characteristics. Conversely, these characteristics might provide athletes with frequent occasions to stimulate and improve their trait-related capacities as well as manage emotional disruptive states, foster interpersonal relationships, and pursue tenaciously ambitious goals. Among these personality differences, the largest effect size was related to conscientiousness, suggesting that characteristics such as diligence and responsibility are skills that primarily characterize high-level athletes. This result also confirms the pivotal role of conscientiousness in relation to successful outcomes in various life domains, such as career success and health (Martin & Friedman, 2000).

Finally, regarding the personality differences between individual- and team-sport athletes, the results indicated that the former group scored higher in energy and openness. The observed difference in energy is not in line with the previous literature (Allen et al., 2011; Eagleton et al., 2007). A possible explanation for this divergence might be represented by the different sports considered in the studies. Indeed, the present research focused on three specific sports, while previous studies considered several sports (Allen et al., 2011). As far as openness is concerned, the current result confirmed the result of Allen et al. (2011), supporting the idea that team-sport athletes are less open-minded than individual-sport athletes. A possible explanation may rely on the fact that soccer and basketball are the most popular sports in Italy; thus, the choice to take part in such sports reveals conformity rather than openness to experiment with less common sports.

4. Conclusions

Personality differences were observed between male athletes and male non-athletes, between high- and low-level athletes, and between individual- and team-sport athletes. The current findings suggest that the Big Five personality traits can help distinguish various levels of athletic involvement and achievement.

The present study contributed to the accumulation of relevant findings that may be integrated with previous research on personality and sports. One relevant characteristic of the present study was the adoption of a sample size that was much larger than any other study in the previous literature. Second, to the best of our knowledge, the current study is the first in sports and

personality research to adopt advances in statistical methodologies to test for measurement invariance and mean differences among groups. More specifically, the ESEM approach was used to verify the dimensionality, measurement invariance and mean differences among groups. Multiple advantages are associated with such methodologies: first, ESEM provides a better fit of Big Five data in comparison with traditional CFA, and second, it provides the opportunity to test mean differences evaluating latent variables' measurement instead of manifest variables' measurement.

Some limitations of the study should also be noted. First, the individual-sport category included one type of sport, whereas the team-sport category included two types of sports. Additionally, because only three sports were considered, the team- and individual-sport variable may be affected by the sport specificity. These issues limit the generalization of the current results to other sport contexts or, at least, offers a caveat. The generalization of the results is also limited by the gender composition of our sample. As we only included male participants we cannot exclude that different findings could arise considering females, also due to gender differences in personality traits (Caprara, Caprara, & Steca, 2003). Moreover, the sampling of athletes during competitions may have led to a considerable amount of state-variance due to the specific context in which the personality assessment occurred. Competitions may play a not negligible role in fostering specific personality facets, especially those related to emotional stability. Finally, the study used a cross-sectional sampling, so it is not possible to infer cause and effect when interpreting these findings, thus restricting any conclusion to an association level.

Further longitudinal research with the adoption of advances in statistics framed into the structure equation modelling approach may help shed light on the association between sports involvement and personality. In this direction, future studies may consider consistently measuring other crucial behavioral outcomes, such as multiple sports performance indicators, amount of time spent on sports activities and past sports practice. Moreover, the adoption of a typological approach aimed at finding prototypical profiles may be useful in testing the replicability of well-known personality typologies (Steca, Alessandri, & Caprara, 2010) in the sporting population.

Supplemental materials

Additional supplemental materials are available at DOI 10.17605/OSF.IO/YMHNC

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Appendix

Table 1. Big Five observed scores, ESEM factor scores determinacy coefficients, and ESEM standardized factor loadings and factor correlations based on responses to the 25-adjecitves personality measure.

	E	A	C	ES	O
Observed scores					
Overall (M, SD)	(3.62, .66)	(3.96, .55)	(3.64, .64)	(3.34, .68)	(3.43, .69)
α	.79	.68	.73	.73	.81
Non-athletes (M, SD)	(3.29, .74)	(3.83, .58)	(3.53, .71)	(3.21, .73)	(3.33, .65)
α	.82	.71	.76	.76	.73
Lower-level athletes (M, SD)	(3.71, .61)	(3.94, .56)	(3.59, .61)	(3.43, .64)	(3.45, .70)
α	.77	.66	.70	.70	.82
Higher-level athletes (M, SD)	(3.82, .58)	(4.09, .57)	(3.84, .64)	(3.60, .67)	(3.54, .65)
α	.78	.74	.75	.75	.79
Individual-sport athletes (M, SD)	(3.91, .61)	(3.97, .56)	(3.74, .70)	(3.53, .74)	(3.68, .70)
α	.79	.73	.77	.77	.82
Team-sport athletes (M, SD)	(3.70, .59)	(3.98, .56)	(3.63, .61)	(3.47, .63)	(3.43, .68)
α	.77	.68	.70	.70	.81
ESEM factor scores determinacy coefficients					
Overall	.91	.86	.89	.89	.92
Non-athletes	.89	.87	.88	.89	.92
Lower-level athletes	.89	.87	.86	.89	.92
Higher-level athletes	.89	.87	.88	.89	.92
Individual-sport athletes	.89	.88	.88	.89	.93
Team-sport athletes	.89	.88	.88	.89	.93
ESEM solution					
Item					
8. Determined	**.70**	-.03	.19	-.05	-.06
20. Resolute	**.64**	.01	.21	.04	-.02
13. Energetic	**.59**	.15	.03	-.13	.04
16. Dominant	**.53**	-.08	.02	-.08	.16
15. Entreprising	**.49**	.00	.03	-.02	.29
21. Friendly	.08	**.72**	-.08	-.02	.01
18. Cordial	-.11	**.58**	**.30**	.04	-.01
10. Affectionate	.02	**.48**	.12	.00	.17
23. Loyal	-.02	**.38**	.19	-.02	.05
4. Unselfish	.06	**.36**	.17	.12	-.02
19. Conscious	-.03	.22	**.63**	.00	-.01
12. Scrupolous	.02	-.05	**.62**	-.11	.09
22. Diligent	.08	.16	**.60**	.00	-.05
7. Responsible	.10	.05	**.59**	.03	-.03
17. Precise	.06	-.05	**.59**	-.01	.06
9. Calm	-.04	-.05	.25	**.75**	.01
1. Relaxed	.21	-.03	-.03	**.70**	.01
3. Patient	-.11	.05	**.32**	**.58**	-.01
25. Serene	**.41**	.15	-.02	**.49**	-.02
5. Optimistic	**.58**	.02	-.06	**.32**	.04

11. Creative	-.01	.00	.04	.02	**.84**
2. Immaginative	-.08	.07	-.08	-.05	**.74**
6. Innovative	.23	-.08	.06	.05	**.63**
14. Original	.20	.04	-.08	-.02	**.62**
24. Modern	.29	.22	-.04	.06	.23
Correlation with A	.18				
Correlation with C	.25	.21			
Correlation with ES	-.14	.28	.05		
Correlation with O	.37	.20	-.05	-.03	

Note: ESEM = exploratory structural equation modeling; E = Energy; A = Agreeableness; C = Conscientiousness; ES = Emotional Stability; O = Openness. α = Cronbach's Alpha. Underlined coefficients in the ESEM solution are target loadings while factor loadings higher than .30 are in boldface.

Table 2. Mean (M), standard deviation (SD), and correlations among the 25 adjectives.

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1. Relaxed	3.13	.87	1																								
2. Immaginative	3.40	.95	.04	1																							
3. Patient	3.37	1.07	.34	-.09	1																						
4. Unselfish	3.89	.82	.16	.09	.29	1																					
5. Optimistic	3.62	.98	.29	.15	.16	.20	1																				
6. Innovative	3.27	.88	.08	.49	-.03	.07	.33	1																			
7. Responsible	3.95	.89	.07	-.07	.23	.21	.11	.09	1																		
8. Determined	4.07	.83	.03	.08	-.02	.14	.35	.30	.36	1																	
9. Calm	3.37	1.01	.50	-.08	.59	.18	.12	.03	.18	-.04	1																
10. Affectionate	3.69	.98	.11	.20	.15	.25	.17	.15	.18	.16	.14	1															
11. Creative	3.40	.93	.07	.63	-.03	.04	.20	.56	.02	.17	-.01	.25	1														
12. Scrupolous	3.40	.90	-.02	-.01	.10	.15	.06	.11	.31	.23	.03	.14	.07	1													
13. Energetic	3.83	.86	.01	.18	-.06	.16	.34	.30	.18	.51	-.11	.22	.23	.20	1												
14. Original	3.49	.92	.03	.47	-.07	.04	.22	.54	.00	.21	-.06	.18	.58	.04	.34	1											
15. Entreprising	3.53	.83	.03	.30	-.04	.09	.35	.42	.12	.42	-.06	.17	.38	.13	.41	.44	1										
16. Dominant	3.15	.98	.01	.18	-.17	.02	.28	.32	.06	.39	-.11	.13	.30	.14	.40	.31	.44	1									
17. Precise	3.46	1.00	.01	-.05	.17	.13	.07	.09	.36	.22	.14	.13	.06	.45	.19	.05	.13	.19	1								
18. Cordial	3.89	.82	.16	.03	.26	.29	.09	.03	.27	.08	.23	.37	.06	.20	.11	.03	.06	.00	.21	1							
19. Conscious	3.73	.82	.09	-.03	.25	.24	.09	.06	.45	.20	.20	.25	.01	.37	.13	-.02	.09	.10	.34	.43	1						
20. Resolute	3.80	.84	.09	.12	-.01	.12	.36	.27	.28	.58	.08	.14	.19	.23	.44	.23	.38	.42	.28	.13	.28	1					
21. Friendly	4.10	.81	.12	.15	.15	.29	.17	.10	.09	.12	.13	.39	.17	.00	.22	.19	.16	.05	.05	.43	.18	.19	1				

22. Diligent	3.63	.81	.08	-.08	.21	.22	.18	.08	.44	.27	.18	.19	.02	.44	.18	-.01	.17	.09	.36	.31	.49	.27	.21	1			
23. Loyal	4.23	.80	.08	.09	.13	.29	.09	.13	.24	.11	.11	.24	.09	.09	.11	.08	.07	.04	.14	.27	.26	.15	.30	.23	1		
24. Modern	3.70	.89	.14	.20	.01	.17	.22	.36	.07	.22	.02	.23	.29	.10	.25	.36	.30	.29	.11	.17	.08	.25	.26	.10	.18	1	
25. Serene	3.70	.91	.46	.05	.26	.21	.42	.16	.13	.20	.33	.23	.14	.09	.21	.17	.19	.16	.11	.24	.17	.26	.25	.16	.15	.30	1

Study 2

Understanding performance in risky sport: The role of self-efficacy beliefs and sensation seeking in competitive freediving[6]

Abstract

Sensation seeking and self-efficacy beliefs have been shown to be associated with participation and risk taking in risky sport. Little attention, however, has been given to their role in relation to performance. The purpose of the study was to investigate whether and how self-efficacy and sensation seeking predict sport performance in lower- and higher-risk freediving disciplines. A sample of 129 freedivers practising a lower-risk freediving discipline (N=86) and a higher-risk freediving discipline (N=43) completed a self-report questionnaire assessing socio-demographics, freediving experience and performance, sensation seeking, and freediving self-efficacy. The results provided evidence that the performance in the lower-risk discipline was predicted by freediving experience and freediving self-efficacy, while the performance in the higher-risk discipline was predicted by freediving self-efficacy and sensation seeking. The results suggested that sensation seeking and self-efficacy represent two different predictors of the performance in the higher-risk freediving discipline. Further research is needed to verify whether current findings may be extended to other risky, competitive sports.

1. Introduction

High-risk sports have become ever more popular since they started to gain public fame in the 1990s with the establishment of extreme sport competitions, commercial advertising, specific TV channels and video sharing websites (Breivik, 2010). Breivik (1995) defined a risky sport as any sport in which one must accept the possibility of severe injury or death as an inherent aspect of the activity. This definition relies on two basic components. First, any risky sport is a *sport*: it means

[6] The present study was based on "Baretta, D., Greco, A., & Steca, P. (2017). Understanding performance in risky sport: The role of self-efficacy beliefs and sensation seeking in competitive freediving. *Personality and Individual Differences*, *117*, 161-165."

that the participants must possess considerable skills and abilities (physical, technical, and psychological) to acceptably execute specific physical activities according to the rules. Second, risky sports are characterized by extreme features and significant elements of danger associated with practicing the sport. The participation and risk taking in risky sport have been found to be associated with sensation seeking (Jack & Ronan, 1998; Zuckerman, 1983) and self-efficacy beliefs (Llewellyn & Sanchez, 2008; Llewellyn, Sanchez, Asghar, & Jones, 2008; Slanger & Rudestam, 1997). Taken together, previous findings have suggested that participants in higher-risk sport generally had significantly higher levels of sensation seeking than participants in lower-risk sport, participants in non-risky sport or control groups. Additionally, it was shown that risky sport participants who have high self-efficacy tend to take more calculated risks, due to their confidence that they will successfully perform specific risky activities.

Although the determinants of the participation and risk taking in risky sport have been widely studied, rather little attention has been paid to the performance in risky sport. So far the investigation of the sport performance has addressed various types of sports but without specifically considering the risky ones. Concerning that, in sport psychology research, there is a general consensus about the importance of self-efficacy in predicting the sport performance. Previous research has consistently highlighted a positive correlation between self-efficacy and performance (Moritz, Feltz, Fahrbach, & Mack, 2000) and provided evidence that self-efficacy is a significant predictor of sport performance (Bandura, 1997; Feltz, Short, & Sullivan, 2008).

The present study integrated previous findings concerning the determinants of the participation and risk taking in risky sport with the psychological literature regarding sport performance in order to investigate the psychological factors that may explain performance in risky sport. The study focused on a never-before-investigated risky sport: competitive freediving. The term *freediving* designates a sport event in which athletes hold their breath while keeping their faces below the surface of the water. Specifically, the current study considered two disciplines of competitive freediving:

- *Dynamic freediving* (DYN) – athletes aim to cover the maximal horizontal distance by swimming in apnoea with or without fins. The event is usually conducted in a swimming

pool, and the risks related to dynamic freediving are surface blackout and shallow-water blackout[7].

- *Constant weight freediving* (CWT) – athletes must cover the vertical distance in apnoea down to the declared depth without any change in their weight during the whole performance with or without fins. The event usually occurs in open water (i.e., sea or lake), and the risks related to constant weight freediving are surface blackout, deepwater blackout, pulmonary and middle-ear barotrauma, pulmonary edema and, in the worst case, death.

In light of the different risks associated with these disciplines, the DYN was considered a lower-risk discipline while the CWT was considered a higher-risk discipline.

On the basis of previous findings, the following main hypotheses were developed:

1- Since self-efficacy has been shown to predict sport performance in various sporting populations, freediving self-efficacy was expected to predict the freediving performance in both the lower- (DYN) and the higher-risk (CWT) freediving discipline, regardless of the level of risk that characterises each discipline.

2- Since the CWT discipline is characterized by greater risks, it was expected that sensation seeking would influence performance in the higher-risk discipline (CWT) but not in the lower-risk discipline (DYN).

The effect of the socio-demographic (i.e., sex and age) and sport-related (i.e., years of freediving experience) variables having a significant relationship with the outcome variable was kept under control in the model.

2. Materials and methods

2.1. Participants

The participants (N=129; 86 men, 43 women; mean age=39.76, sd=9.28) were Italian freedivers who competed at the elite level in the DYN or CWT discipline. Athletes who took part

[7] Blackout (once incorrectly known as syncope) is a loss of consciousness caused by cerebral hypoxia towards the end of a breath-hold dive.

exclusively in elite DYN competitions (N=86; 54 men, 32 women) were included in the lower-risk group, while athletes who competed only in elite CWT contests (N=6; 3 men, 3 women) or who participated in both DYN and CWT competitions (N=37; 29 men, 8 women) were considered higher-risk athletes, since taking part in higher-risk competitions was the necessary and sufficient condition to be included in the higher-risk group. To sum up, the lower-risk group was made up of 86 athletes (mean age=39.36, sd=8.69; mean freediving experience=4.26, sd=3.10), while the higher-risk group was made up of 43 athletes (mean age=40.56, sd=10.43; mean freediving experience=5.58, sd=3.51).

2.2. Procedure

2.2.1. Sampling procedures

Freediving athletes were contacted during sporting competitions or via mail in the period between May 2014 and October 2016. Athletes who were contacted during competitions filled out a paper-and-pencil self-administered questionnaire, while those who were contacted via mail filled out an online version of the same questionnaire. The athletes were asked to read and accept the informed consent form, individually complete the measures, and then return the questionnaires to the researcher. The participants received no incentive for their participation.

2.2.2. Measures

Freediving performance was measured in the following ways, according to each specific discipline:

- DYN performance was measured in metres and referred to the maximum diving length reached by the athletes during an official competition (mean=141.76; sd=30.38; min=75; MAX=240).
- CWT performance was measured in metres and referred to the maximum diving depth reached by the athletes during an official competition (mean=53.33; sd=16.63; min=26; MAX=100).

Sensation seeking was measured using the Italian version (Primi, Narducci, Benedetti, Donati, & Chiesi, 2011) of the Brief Sensation Seeking Scale (BSSS; Hoyle, Stephenson, Palmgreen, Lorch, & Donohew, 2002).

Freediving self-efficacy was assessed with two ad hoc developed self-efficacy scales (one for each of the freediving disciplines) since an up-to-date, validated measure of self-efficacy specific to the domain of freediving was not available in the literature. To develop the self-efficacy scales, the major variables comprising the perception of technical efficacy in DYN and CWT freediving were identified inductively by semi-structured interviews with active recreational freedivers (N=5), freediving instructors and coaches (N=2) and academic specialists in the areas of social cognitive theory (N=2) and sport psychology (N=3). The *DYN self-efficacy scale* (DYNSES) consists of 9 items that refer to the specific technical skills required in DYN competitive freediving, while the *CWT self-efficacy scale* (CWTSES) consists of 8 items that refer to the specific technical skills required in CWT competitive freediving (see Appendix). Both the DYNSES and the CWTSES were aimed at measuring a unique dimension of domain-specific technical self-efficacy labelled *dynamic self-efficacy* and *constant weight self-efficacy*. According to Hu and Bentler's guidelines (Hu & Bentler, 1999), the confirmatory factor analysis (CFA) confirmed the single-factor structure for both the DYNSES ($\chi 2=41$, df=26, $p<.05$; CFI=.96; RMSEA=.08, pRMSEA>.05; SRMR=.05.) and the CWTSES ($\chi 2=20$, df=18, $p>.05$; CFI=.98; RMSEA=.05, pRMSEA>.05; SRMR=.07). Both the scales showed a good internal consistency: DYNSES $\alpha=.86$; CWTSES $\alpha=.84$.

2.2.3. Statistical analysis

Pearson correlation was carried out to explore associations among the demographic, psychological, and sport-related variables in DYN and CWT. Two multiple regression analyses, one for each discipline, were performed: CWT and DYN performance were entered as dependent variables while self-efficacy and sensation seeking were entered as predictors. Sex, age and freediving experience were included in the regression analyses in order to take into account their potential effect on freediving performance.

3. Results and discussion

3.1 Results

3.1.1. Correlations among demographic, sport-related and psychological variables

The first preliminary correlations included the whole freediving sample and indicated a negative association (r=-.32, p<.001) between age and sensation seeking, no correlation (r=-.14, p>.05) between sex and sensation seeking and a positive correlation between age and freediving experience (r=.20, p<.05). The discipline-specific correlations among the demographic, sport-related and psychological variables are shown in Table 1. The results showed different association patterns for each specific discipline. A negative relationship was found between sex and DYN performance, indicating that male freedivers perform better than their female counterparts. Freediving experience was positively associated with DYN performance but no association emerged between freediving experience and CWT performance. On the other hand, freediving experience was positively associated with CWT self-efficacy but not with DYN self-efficacy. DYN and CWT self-efficacy were positively related to DYN and CWT performance, respectively. Sensation seeking was correlated with DYN self-efficacy but not with CWT self-efficacy. Finally, sensation seeking was positively associated only with CWT performance.

Table 1. Correlations between age, freediving experience, freediving self-efficacy, sensation seeking and best individual performance referring to each specific discipline.

DYN (N=86)				CWT (N=43)			
	DYN self-efficacy	SS	DYN performance		CWT self-efficacy	SS	CWT performance
Age	-.13	-.36**	-.02	Age	.14	-.26	-.14
Sex	-.09	-.15	-.23*	Sex	-.14	-.10	-.03
Freediving experience	.13	-.04	.41***	Freediving experience	.33*	-.16	.23
DYN self-efficacy	1	.22*	.37***	CWT self-efficacy	1	-.06	.41**
SS	.22*	1	.15	SS	-.06	1	.34*

Note: SS = sensation seeking.
In *sex* coefficients, positive values corresponded to higher values for male freedivers.
*<.05 (two tailed)
**<.01 (two tailed)
***<.001 (two tailed)

3.1.2. Multiple regression analysis for the prediction of freediving performance

Freediving experience and DYN self-efficacy proved to be significant predictors of DYN performance. Differently, sensation seeking and the other controlling variables did not predict the performance in DYN. The overall model accounted for 27% of the variance of the DYN performance (adjusted R^2; F=7.18, p<.001) (see table 2).

CWT self-efficacy served as a significant predictor of CWT performance, as well as sensation seeking. None of the controlling variables proved to predict CWT performance. The overall model accounted for 26% of the variance of the CWT performance (adjusted R^2; F=3.94, p<.01) (see table 2).

Table 2. Multiple regression analysis for variables predicting sport performance in DYN and CWT freediving.

DYN (N=86)			CWT (N=43)		
	DYN performance			CWT performance	
Variable	B (95% CI)	β	Variable	B (95% CI)	β
DYN self-efficacy	16.20 (5.51, 26.89)	.29**	CWT self-efficacy	12.04 (3.22, 20.85)	.39**
Sensation seeking	3.20 (-6.17, 12.56)	.07	Sensation seeking	8.90 (1.84, 15.67)	.36*
Age	-.07 (-.85, .71)	-.02	Age	-.24 (-.70, .23)	-.15
Sex	-12.40 (-25.41, .61)	-.18	Sex	.96 (-9.55, 11.48)	.03
Freediving experience	4.04 (1.97, 6.11)	.37***	Freediving experience	.92 (-.49, 2.33)	.19
R^2	.31		R^2	.35	
Adjusted R^2	.27		Adjusted R^2	.26	

Note: unstandardized (B) and standardized (β) coefficients are reported. CI = confidence interval.
In *sex* coefficients, positive values corresponded to higher performances for male freedivers.
*<.05 (two tailed)
**<.01 (two tailed)
***<.001 (two tailed)

3.2. Discussion

The purpose of the present study was to investigate the association among self-efficacy, sensation seeking, and freediving performance in lower- and higher risk freediving disciplines.
In line with previous literature (Jack & Ronan, 1998), the preliminary correlation analysis suggested a negative association between age and sensation seeking in the whole sample. Furthermore, the correlation values between self-efficacy and sport performance are similar to the average one found in a previous meta-analytical study (Moritz et al., 2000).

In line with the hypotheses, multiple regression analyses indicated that freediving self-efficacy predicted the freediving performance in both the DYN and the CWT discipline. This first result supported the idea that domain-specific self-efficacy, regardless of the level of risk related to the sport, is a significant predictor of sport performance (Bandura, 1997; Feltz et al., 2008). Differently, sensation seeking emerged as a significant predictor only of CWT performance, suggesting that, in addition to being associated with the participation and risk taking in risky sport, it may constitute an appropriate predictor of performance in risky sport. On the basis of this finding it seems plausible to hypothesize that the performance variance explained by sensation seeking may be associated with the risk taking component that characterises the performance in the higher-risk discipline. The overall results confirmed the current hypotheses and underlined that sensation seeking and self-efficacy constitute two separate, not overlapping predictors of performance in risky sport. Finally, it is interesting to note that freediving experience predicted DYN performance, but it was not a predictor of CWT performance. This difference between the disciplines is probably due to the fact that there are not as many occasions to train for CWT (due to logistic and safety difficulties) as for DYN, hence CWT performance is less influenced by experience. These results suggested that sensation seeking, rather than experience, has an influence on the performance in the higher-risk discipline.

4. Conclusions

The main contribution of the present research was to investigate the association among self-efficacy, sensation seeking and freediving performance. While previous research mainly focused on explaining participation and risk taking in risky sport or performance in non-risky sport, the current research tried to integrate these different perspectives in order to address the question about what determines performance in risky sport. For this purpose, the study targeted a never-before-investigated risky sport – competitive freediving – that has become ever more popular in the last two decades with the organization of national and international official freediving competitions. Even though the current research focused on such a specific risky sport, it provided some interesting insights that deserve to be tested in other contexts.

Some limitations of the study should also be noted. First, the current study adopted a cross-sectional design, so it is suitable to adopt some caution in generalizing the present findings. This is particularly relevant in reference to the association between self-efficacy and performance. Self-efficacy influences performance as well as performance influences self-efficacy (Bandura, 1997), and in the study, the reported best freediving performance occurred before the self-efficacy assessment. The current research, however, involved elite freedivers with substantial experience, hence it seemed reasonable to hypothesize that their freediving self-efficacy, although estimated from a post-performance measure, would be consistent over time since it was the result of several years of training and competitions. Finally, the DYN and the CWT freediving groups are not equivalent in terms of sample size. Even though this discrepancy represents the percentage of DYN and CWT freedivers within the elite population, the smaller CWT sample size may have influenced the possibility to identify small to medium effect sizes.

In order to overcome these issues, future research should involve larger samples and focus on longitudinal studies with a repeated measure of both the behavioural and the psychological variables. Furthermore, as with most sports, the explanation of the performance in freediving obviously involves additional factors beyond those investigated by the present study. Thus, it would be interesting to investigate the factors (i.e., equalization skills, hypoxic tolerance, breathing abilities, relaxation) and the respective self-efficacy beliefs that may contribute to depicting a more comprehensive representation of the determinants of freediving performance. Finally, further research is needed to verify the generalizability of current findings to other risky, competitive sports characterised by larger groups of practitioners (e.g., motorcycle racing, alpine skiing or high diving).

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Appendix

Dynamic self-efficacy scale (DYNSES)

Instructions: The following questions are about a series of typical situations and actions that characterized your dynamic free diving performance. We ask you to carefully read each question and indicate **how well you feel you can** do each thing.

For each question, think about the "ideal freediver", that is, a freediver who is capable of doing each thing perfectly.

Use the following scale for your answers:

NOT AT ALL	NOT VERY WELL	MODERATELY WELL	VERY WELL	PERFECTLY
1	**2**	**3**	**4**	**5**

Remember that "NOT AT ALL" means that you cannot do that thing and that "PERFECTLY" means that you can do it as well as the ideal player.

HOW WELL CAN YOU:

Dyn1. Take in enough air on your last breath to optimally perform a dynamic apnea?	1	2	3	4	5
Dyn2. Do a push-off start from the side of the pool so as to go as far as possible.	1	2	3	4	5
Dyn3. Correctly use ballast to keep an efficient and appropriate balance throughout the dive regardless of the depth of the pool.	1	2	3	4	5
Dyn4. Control the breadth and rhythm of fin kicks or arm strokes / frog kicks throughout your dive?	1	2	3	4	5
Dyn5. Keep your strokes and kicks symmetrical despite fatigue?	1	2	3	4	5
Dyn6. When you get to the end of the pool, turn and get the breadth and rhythm of your strokes and kicks back without increasing the energy you spend in movement?	1	2	3	4	5
Dyn7. Efficiently alternate between engaging muscles for propulsive action and relaxing them during rest.	1	2	3	4	5
Dyn8. Synchronize propulsion movements with diaphragm contractions to keep your mind and body relaxed?	1	2	3	4	5
Dyn9. At the end of the dive, find a foothold and do the exit protocol even if you are fatigued?	1	2	3	4	5

Constant Weight self-efficacy scales (CWTSES)

Instructions: The following questions are about a series of typical situations and actions that characterized your constant weight free diving performance. We ask you to carefully read each question and indicate **how well you feel you can** do each thing.

For each question, think about the "ideal freediver", that is, a freediver who is capable of doing each thing perfectly.

Use the following scale for your answers:

NOT AT ALL	NOT VERY WELL	MODERATELY WELL	VERY WELL	PERFECTLY
1	**2**	**3**	**4**	**5**

Remember that "NOT AT ALL" means that you cannot do that thing and that "PERFECTLY" means that you can do it as well as the ideal player.

HOW WELL CAN YOU:

Cwt1. Fill your lungs with enough air on your last breath to achieve the longest dive you can?	1	2	3	4	5
Cwt2. Adapt to the marine weather conditions on the surface before your dive?	1	2	3	4	5
Cwt3. Take advantage of the push-off to plunge and maintain the right position in front of the rope?	1	2	3	4	5
Cwt4. Save energy when descending and ascending by keeping your force proportionate to your balance and the depth?	1	2	3	4	5
Cwt5. Stay close to the rope and maintain the same position when descending and ascending regardless of the strength or direction of the current?	1	2	3	4	5
Cwt6. Keep propulsion movements symmetrical despite changes in balance due to depth?	1	2	3	4	5
Cwt7. Maintain a state of physical relaxation at the greatest depths?	1	2	3	4	5
Cwt8. After your ascent, control how you float and manage the exit protocol even when you are fatigued?	1	2	3	4	5

PART 2

Linking new technologies to behaviour change theories and techniques: Design and development of *Muoviti!*, an innovative smartphone application to support physical activity among sedentary adults

Non-communicable diseases such as cardiovascular and respiratory diseases, cancer, diabetes and obesity are the main cause of mortality in western countries and cause unimaginable costs for public health (Boutayeb & Boutayeb, 2005). Although physical activity constitutes an important protection factor against such diseases, large part of the population doesn't respect the recommended physical activity guidelines and live a sedentary life (WHO, 2010). Hence, there's the need to find new, effective and large-scale solutions to promote behaviour change in the direction of a higher physical activity. Rapid technological progresses and the widespread adoption of smartphones have open the way to the development of *Digital Behaviour Change Interventions*[8] (DBCI; West & Michie, 2016), such as smartphone applications (apps), oriented to promote and sustain physical activity (Lathia, Pejovic, Rachuri, et al., 2013; Pagoto & Bennett, 2013). There are several technological advantages and potentialities that can be exploited in order to deliver more effective digital interventions.

Smartphones are unobtrusive, ubiquitous and sensor-rich computing devices. The availability of data from embedded sensors (e.g., accelerometer, Bluetooth, GPS) enables to i) infer physical states, such as running or walking, ii) pair smartphones with other wearable devices (e.g., heart rate monitor), and iii) track users' locations. Taken together, such sensors assure a more objective and accurate monitoring and assessment of physical activity, overcoming the problem of unreliable self-report measures (Bort-Roig et al., 2014; Case, Burwick, Volpp, & Patel, 2015). Thanks to smartphones' sensors and wearable devices, physical activity can be quantified

[8] Digital Behaviour Change Interventions (DBCI) have been defined as "a product or service that uses computer technology to promote behaviour change. It includes computer programs, websites, mobile applications (apps), wearable devices, body and environmental sensors and telecommunications." (West & Michie, 2016; p.2)

in terms of both motion-related (e.g. number of steps, speed, distance) and physiological (e.g. heart rate) parameters. Such parameters can be converted into an estimation of the physical activity energy expenditure, obtaining an overall index (i.e., Metabolic Equivalent of Task – MET) of how much physical activity has been performed (Strath et al., 2013). Additionally, with the ubiquity of smartphones and the recent technical advances, digital experience sampling methods have become increasingly easy to do (see Hofmann & Patel, 2015). This opportunity is particularly relevant because it enables to assess psychological determinants and outcomes of physical activity in real setting and, consequently, intervene as appropriate. Finally, the possibility to continuously collect objective data supports the adoption of advanced methodologies, based on innovations in statistics, machine learning, and big data analytics, in the evaluation of digital interventions (Van Poucke, Thomeer, Heath, & Vukicevic, 2016).

Aware of such technological potentialities, research institutions, healthcare providers and technology giants are increasingly developing smartphone apps to support physical activity. This growing interest towards digital technology is well exemplified by the proliferating number of scientific publications and physical activity apps available on the app stores. Scientific publications addressing physical activity apps passed from 28 in 2012, through 74 in 2014, up to 119 in 2016[9]. Similarly, *Health & Fitness* apps available in *Google Play* moved from 17756 in 2014 to 102548 in October 2017 (AppBrain: *Android Market Stats*). Despite such a huge proliferation of physical activity apps, there are some important issues that still affect their effectiveness and uptake.

Early evidence reviews have found that technology-based interventions can help people increase their physical activity (Davies, Spence, Vandelanotte, Caperchione, & Mummery, 2012), however evidence about more recent digital behaviour change interventions, such as smartphone apps and wearables, is still relatively scarce. Furthermore, even though a previous meta-analysis suggested that DBCI that made a more extensive use of behaviour change theories were associated with larger effect sizes (Webb, Joseph, Yardley, & Michie, 2010), reviews of physical activity apps commonly note their lack of adherence to theory (Cowan, Van Wagenen,

[9] Results from a search strategy on Scopus based on terms (‘physical activity’ AND ‘app’) in title, abstract, or key-words.

Brown, et al., 2013). This is a crucial point because behaviour change interventions would benefit from using behaviour change psychological theories (Rothman, 2004), and such benefits are even more relevant with recent technological opportunities of developing computational models based on behaviour change theories (Hekler, Michie, Pavel, et al., 2016). Indeed, although theories are determinant to effectively develop and personalize digital behaviour change interventions and to facilitate health promotion by providing support in the "real world" (Patrick, Griswold, Raab, & Intille, 2008; Riley, Rivera, Atienza, et al., 2011), computational models provide the additional possibility of i) testing complex predictions related to dynamics (i.e., directionality and magnitude of effects that characterize links among variables), and ii) using simulation techniques to a further study of behavioural phenomena (Hekler et al., 2016). For these reasons, in the last recent years, we assisted to the first innovative attempts of developing physical activity apps based on computational models grounded on social cognitive theory (e.g., Pirolli, 2016).

Another concern that characterises physical activity apps is the low uptake and engagement with them. Indeed, it has been shown that health apps suffer from low engagement (Consumer Health Information Corporation, 2017). One possible explanation as to why users disengage quickly from health apps is that they do not take into account users' needs, values and circumstances (Kelders, Pots, Oskam, Bohlmeijer, & Gemert-Pijnen, 2013). A useful way to develop apps that better meet users' needs is to involve potential users in the design process, addressing directly their preferences and motivations. Indeed, it has been argued that some psychological characteristics of the intended users (e.g., personality, motivations, expectancies), may influence their engagement and appreciation of various aspects (i.e., content, way of delivery) of the intervention (Perski, Blandford, West, & Michie, 2016). For instance, as far as physical activity apps regard, recent research has shown that personality traits are associated with preferences for specific Behaviour Change Techniques (BCTs) (Belmon, Middelweerd, te Velde, & Brug, 2015). However, preferences for particular BCTs are not just confined to personality traits but may be related to other personal aspects that characterize participants (e.g., exercise participation motives). Furthermore, in addition to preferences for specific BCTs, users' psychological characteristics may also influence design features, that is how BCTs are actually implemented in

apps. This last point is particularly relevant because BCTs can be designed and implemented into DBCIs in a variety of manners that can be perceived by the users in different ways according to their needs and motivations. For instance, setting a behavioural goal in terms of average pace or heart rate may fulfil experienced runners' motivations, but not beginners' ones. For all these reasons, a deep understanding of the personal factors underlying the target behaviour, physical activity in our case, acquires an even greater importance. In order to elicit and address users' needs and characteristics, ensuring that digital interventions are usable and engaging, recent guidelines in matter of digital interventions development suggested to preferentially adopt qualitative methods (e.g., focus group, think aloud studies, in-depth interviews) (Yardley, Morrison, Bradbury, & Muller, 2015). This approach – defined Person-Based Approach – is intended to integrate and enrich the theory- and evidence-driven approaches in the development of digital behaviour change interventions. This complementary approach is needed to understand the most effective way to apply behaviour change theories and techniques to the specific context of the intervention and to the individual who will use it.

The present section will describe the development of *Muoviti!*, a digital behaviour change intervention that supports physical activity among sedentary adults and is delivered by a smartphone app and wristband heart rate monitor system. *Muoviti!* aims at promoting physical activity among sedentary adults by focusing on a computational model of self-efficacy (Bandura, 1997). Moreover, in order to better fulfil the intended users' needs and motivations, the intervention contents and features have been defined through the adoption of quantitative and qualitative methodologies, with a particular focus on the latter ones. The present section will present three studies.

-Study 1 will introduce an innovative computational model, embedded in *Muoviti!,* that is conceptually framed in Bandura's self-efficacy theory. More specifically, the computational model combines input data collected through mobile technology (i.e., amount of physical activity collected through a heart rate monitor, self-efficacy beliefs assessed through Digital Ecological Momentary Assessment) in order to set physical activity goals that are dynamically adapted to each individual's achievement and change in self-efficacy over time.

-Study 2 will focus on understanding which physical activity participation motives characterise the intended users of *Muoviti!*, and whether and how they relate to i) preferences for specific BCTs, ii) behavioural information (i.e., amount of physical activity performed during a week), and iii) anthropometric data (i.e., Body Mass Index). The output of the present study constitutes a first contribution to guide the development of contents and feature that will characterise *Muoviti!*.

-Study 3 will present two qualitative studies that aim to guide the characterisation of design features to be implemented in *Muoviti!*. Specifically, the main goal is to understand what and why design features are hypothesised to foster aneffective engagement and maintain it over time. In order to address these goals, the current studies are characterized by the adoption of qualitative methodologies, as suggested by the Person Based Approach. In particular, study 3a adopts focus group methodology with element of co-design to better understand how potential users would like to 'design' a physical activity app that is able to address their needs and expectancies. Study 3b explores what apps' features are considered to be important for engagement at different stages of use. More specifically, the study examines what features influence the users' engagement during a first exposure to never-used physical activity apps and what features are judged to be determinant for supporting engagement and satisfactory experiences after a 2-week usage. For such purposes, the present study utilizes think aloud methodologies and in-depth interviews to investigate users' experiences.

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Study 1

Developing *Muoviti!,* a digital behaviour change intervention based on a computational model of self-efficacy theory to promote physical activity among sedentary adults

Abstract

Mobile technologies offer several opportunities for increasing PA, especially if supported by behaviour change theories and if combined with model-based reasoning systems and personalized human computer interaction. This paper presents a smartphone app and wearable device system called *Muoviti!* that targets PA promotion among sedentary adults. *Muoviti!* is based on a computational model grounded on self-efficacy theory and exploits Bayesian Networks in order to provide tailored PA goals and to predict changes in PA behaviour.

1. Introduction

Recent availability of effective and inexpensive sensors, generally embedded into commercial devices, such as wearables and smartphones, has open the way to the development of smartphone applications (apps) oriented to promote and sustain health behaviour change. Thanks to them, healthcare apps are becoming one of the most important and promising tools for delivering behaviour change interventions (Lathia, Pejovic, Rachuri, et al., 2013; Pagoto & Bennett, 2013). With regards to physical activity (PA) behaviour, mobile sensors can perform direct, intense and longitudinal measurements of some physical parameters (e.g. the heartbeat) and may produce detailed records of the individual behaviour (e.g., exercise) that are immediately available for analysis. Thanks to such opportunities for data collection, new technologies can rapidly manage and combine different input datasets, provide accurate predictions about the influence pattern among variables (e.g., behavioural, psychological), and deliver interventions that are adaptive to individual and context changes over time. For these reasons, mobile technology has been hypothesized to support the science of behaviour change and it constitutes a preferential *tool* both for modeling behaviour change theories and for testing them in real world settings (Nilsen, & Pavel, 2013; Patrick, Hekler, Estrin, et al., 2016). In spite of that, existing PA apps are characterized by a

lack of adherence to behaviour change theories and relatively little attention has been paid to the adoption of specific computational models grounded in behaviour change theories (Cowan, Van Wagenen, Brown, et al., 2013; Riley, Rivera, Atienza et al., 2011). More specifically, although health smartphone apps should be guided by current behaviour change models, Cowan and colleagues (2013) evidenced that *Health & Fitness* apps mostly did not include theoretical constructs.

Social Cognitive Theory (SCT; Bandura, 1977; 1997) provides a recognized theoretical model that is suitable to explain behaviour change over time and it has been successfully adopted to design effective digital health behaviour interventions (Webb et al., 2010). In recent years, we assisted to the first attempts of developing computational models based on SCT and its core constructs (e.g., outcome expectancies, self-efficacy beliefs) in order to promote PA (Martin et al., 2015; Pirolli, 2016). SCT is particularly suitable to be modeled because of its nature that is explicitly *dynamic* (i.e., it takes into account time-varying information such as individual achievements, self-efficacy beliefs and expectations) and, thus, permits to adapt the intervention to the individual over the course of the intervention itself (Riley et al., 2011). The advantages of developing a computational model based on a behaviour change theory, such as SCT, mainly rely on the capacity to predict directionality and magnitude of effects among variables (e.g., target behaviour and its psychological determinants), and to simulate and test how they change and influence each other across contexts and over time (Hekler et al., 2016). Taken together, new technologies (e.g., smartphone, wearable devices) and computational methodologies (e.g., modeling of behaviour change theories) provide extraordinary opportunities for designing dynamic, tailored, adaptable, and precise models of behaviour change (Nilsen, & Pavel, 2013).

This paper presents an innovative computational model, embedded in a mobile app and heart rate monitor system (called *Muoviti!*), that is conceptually framed in SCT with a particular emphasis on perceived self-efficacy (SE) construct. *Muoviti!* aimed at the promotion and support of PA among sedentary adults. More specifically, the computational model combines input data collected through mobile technology (i.e., amount of PA collected through a heart rate monitor, SE assessed

through Digital Ecological Momentary Assessment) in order to set PA goals that are dynamically adapted to each individual's achievement and change in SE over time.

This paper is organized as follows. Paragraph II presents a description of self-efficacy theory and the reciprocal influence pattern among SE, behaviour and goal setting. Paragraph III describes the *Muoviti!*system including the rationale for goal setting strategies. Paragraph IV presents how the model was constructed. Paragraph V discusses simulation results for hypothetical user profiles. Paragraph VI provides conclusions and outline future activities that are needed to define the content of *Muoviti!*.

2. The role of self-efficacy beliefs in increasing PA behaviour

Self-efficacy (SE) has been defined as the belief in one's capabilities to organize and execute the courses of action required to produce given attainments (Bandura, 1977). Self-efficacy affects several areas of human endeavor (Bandura, 1997) and these effects are particularly relevant with regards to health-related behaviours (Schwarzer & Luszczynska, 2005). More specifically, it has been consistently shown that self-efficacy is a key determinant for the adoption and maintenance of PA behaviour in healthy adults (Bauman, Reis, Sallis et al., 2012; Kaewthummanukul & Brown, 2006; Rovniak, Anderson, Winett et al., 2002; Sharma & Sargent, 2009). Furthermore, experimental evidences have demonstrated self-efficacy to be a mediator of the effects of interventions on objectively measured physical activity behaviour (Ashford, Edmunds, & French, 2010; Burke, Beilin, Cutt et al., 2008; Darker, French, Eves et al., 2010; Dutton, Tan, Provost et al., 2009). Self-efficacy beliefs develop as a consequence of four sources of information: enactive mastery experience, vicarious experience, verbal persuasion, and physiological or affective states management (Bandura, 1997). Among them, mastery experience is considered the most potent source of self-efficacy in different domains and populations (Bandura, 1997; Britner & Pajares, 2006; Loo & Choy, 2013; Warner, Schüz, Wolff, et al. 2014). It refers to the direct experience of performing a specific task and, hence represents an authentic indicator of the individual ability to accomplish similar tasks in the future. Indeed, when people engage in tasks and activities, they interpret the results of their actions and they use such interpretations to develop beliefs about their

capability and to subsequently act according with the created beliefs. Experiences interpreted as successful generally increase confidence while experiences interpreted as unsuccessful generally undermine it (Bandura, 1997). As a consequence, in light of the reciprocal influence between self-efficacy and behavior, the selection of any specific behavioral goal should be set with the aim to gradually support both the achievement of successful experiences and the increasing of self-efficacy. For this purpose, goals should be i) achievable in order to permit individuals to master successful experiences, and ii) challenging in order to adequately reinforce self-efficacy beliefs once the goal has been achieved (Bandura, 1997; Weinberg, 2002). Furthermore, it is worth considering that the effect of goal setting on PA behaviour is moderated by additional factors, such as providing support for action planning, and arrange for feedback about progresses in relation to the goals (Latham & Locke, 2002; Weinberg, 2002). Finally, goal timeframe and goal setting/modification deserve a proper consideration when defining a goal setting strategy. Indeed, targeting a combination of daily and weekly PA goals, and the opportunity to modify goals on a weekly basis have been shown to be effective strategies to set PA goals (McEwan, Harden, Zumbo, et al., 2016).

Based on the association among psychological (i.e., self-efficacy, goal setting) and behavioural (i.e., physical activity) variables, the computational model embedded in *Muoviti!* dynamically adjusts the proposed PA goals to the variations in self-efficacy and mastery experiences over time. Moreover, *Muoviti!* adopts effective strategies in setting and supporting PA goals (i.e., action planning, feedback, daily and weekly timeframe, weekly goal modification).

3. The *Muoviti!* system

3.1 Components and system dynamics

The experimental system that constitutes *Muoviti!* is made of three key components (see figure 1a):

- A heart rate (HR) wristband needed to measure the amount of PA performed. More specifically, two commercial, low-cost and reliable HR monitors (i.e., MioAlpha, PulseON) have been tested. Such devices nonetheless provide an estimate of the relevant physiological parameters

which is precise and reliable enough for our purposes (Stahl, An, Dinkel, et al., 2016; Valenti, & Westerterp, 2013).

- A smartphone app which i) handles the user interface (see figure 1b), ii) ecologically assesses SE through an *ad hoc* short questionnaire, iii) collects information from the heart rate monitor, and iv) transfers information to/from the back office.
- A back office with a server that stores the data relative to each person and executes the modeling algorithm, thus formulating suitable suggestions for the next training period.

Muoviti! operates as follows. At the beginning of each weekly training period, a suggested PA goal for the week is generated on the basis of two different input data: past weekly goal achievement and SE beliefs in mastering past week PA experiences. The computation of the PA goal for the new training period (i.e., output data) is expressed in terms of METs (Metabolic Equivalent of Task) that is a measure of the amount and quality of performed PA normalized to the physical characteristics and age of the subject. Finally, *Muoviti!* splits the weekly PA goal into daily short-term goals, translates them into concrete PA tasks (e.g. minutes of running, or fast walking), and presents them to the user.

3.2. Assessing the user: collecting input data

Input data are quantified and collected in the following way.

Physical activity

PA is quantified in terms of MET, that is the ratio of the metabolic rate (the rate of energy consumption) during a specific physical activity to a reference metabolic rate:

$$1MET = \frac{kcal}{kg} * h \quad (1)$$

MET is used as a mean of expressing the intensity and energy expenditure of activities in a way comparable among persons of different weight. Actual energy expenditure (e.g., in calories or joules) during an activity depends on the person's body mass; therefore, the energy cost of the same activity will be different for persons of different weight. When the subject begins performing a PA training session, she/he asks the app to start the collection of PA data through the Bluetooth

connection with the wristband. The app translate the HR collected by the wristband into the equivalent energy expenditure (METs), given by the following formula (Armstrong & Bull, 2006):

$$MET\ minutes = 4 * Time^{MPA} + 8 * Time^{MPA} \quad (2)$$

where $Time^{MPA}$ and $Time^{VPA}$ are the periods of time the subject is involved in moderate physical activity (MPA) and vigorous physical activity (VPA), and parameters 4 and 8 represent the corresponding MET expenditure per minute. A PA session is defined moderate if the registered HR values are in the range $[6 * \frac{MHR}{10}, 7 * \frac{MHR}{10}]$, while it defined vigorous if the registered HR values are in the range $[7 * \frac{MHR}{10}, 8 * \frac{MHR}{10}]$. MHR represent the maximum heart rate depending on the subject age and it is calculated by subtracting *age* to a standard value (i.e., 220 – *age)*.

Self-efficacy

SE beliefs are ecologically assessed at the end of each training session, through a set of questions to the person, each concerning a specific aspect of the physical activity. Currently, two questions are proposed to the user to evaluate his/her self-efficacy referring to the PA they have just performed:

- *How much do you feel able to do a similar training next week, despite its duration?*
- *How much do you feel able to do a similar training next week, despite its intensity?*

The SE score is given by the arithmetic mean of the provided answers:

$$SE_i = \frac{\sum_{i=1}^{n} answer_i}{n} \quad (3)$$

where *n* is the number of questions posed to the user and $answer_i$ is the value given by the user on a 4-point Likert scale, ranging from 1 (not able at all) to 4 (absolutely able). The advantages of assessing SE through digital Ecological Momentary Assessment (EMA) rely on the opportunity to minimize recall bias, maximize ecological validity, and better understand behaviour in real-world contexts (Shiffman, Stone, & Hufford, 2008).

3.3. Decision rules: combining input data to set tailored goals

Muoviti! aims to homogeneously merge physical and psychological variables into a unique conceptual framework, in order to build up tailored PA plans. For this purpose, at the end of the weekly period, the app interacts with the user by notifying the degree of accomplishment of the weekly goal, and sends the recorded data to the back office. *Muoviti!*'s back office aggregates PA accomplishments and SE scores from each single training session in order to infer a global evaluation of the users' PA accomplishments and SE beliefs over the week. The global evaluation of PA achievements and SE beliefs over the weekly period may assume the following facets and codes:

- Physical activity:
    - The weekly PA goal was achieved (PA-);
    - The weekly PA goal was not achieved (PA+);
- Self-efficacy:
    - The weekly PA self-efficacy was high – average SE equal or higher than 2.5 (SE+);
    - The weekly PA self-efficacy was low – average SE lower than 2.5 (SE-).

After this assessment is made, the PA goal for the next week is proposed. Table 1 shows how global evaluations of PA and SE are combined in order to set new goals.

Table 1. Decision rules and rationale for setting new weekly goals

Condition	**Goal for the new training period (NEW_PLAN)**	**Rationale for the goal setting strategy**
(PA+) & (SE+)	Increase PA goal	Setting a harder goal is challenging but achievable for the person, indeed it is in line with the physical capability and supported by strong SE beliefs
(PA+) & (SE-)	Maintain the same PA goal	Maintaining the same goal is a strategy to reinforce the self-efficacy beliefs through the achievement of the same goal, thus train the person for successive more difficult goals
(PA-) & (SE+)	Maintain the same PA goal	Maintaining the same goal is a strategy to avoid disappointing motivations and self-efficacy beliefs, thus

		provide the person with a further opportunity to achieve a goal corresponding to his/her SE beliefs
(PA-) & (SE-)	Decrease PA goal	Setting an easier goal is a strategy to allow the person to become familiar with the behaviour through an easier task and reinforce self-efficacy beliefs through more likely successful experiences

According to the user preferences, the PA goal for the next training period is successively split in daily short-term goals in order to support an effective action planning. The goal setting strategies at each period are taken with the aim of obtaining a successful result in a long-term perspective, that is determined according to the general guidelines for PA promotion, which state that a person should perform 600 METs per week of PA (WHO, 2010).

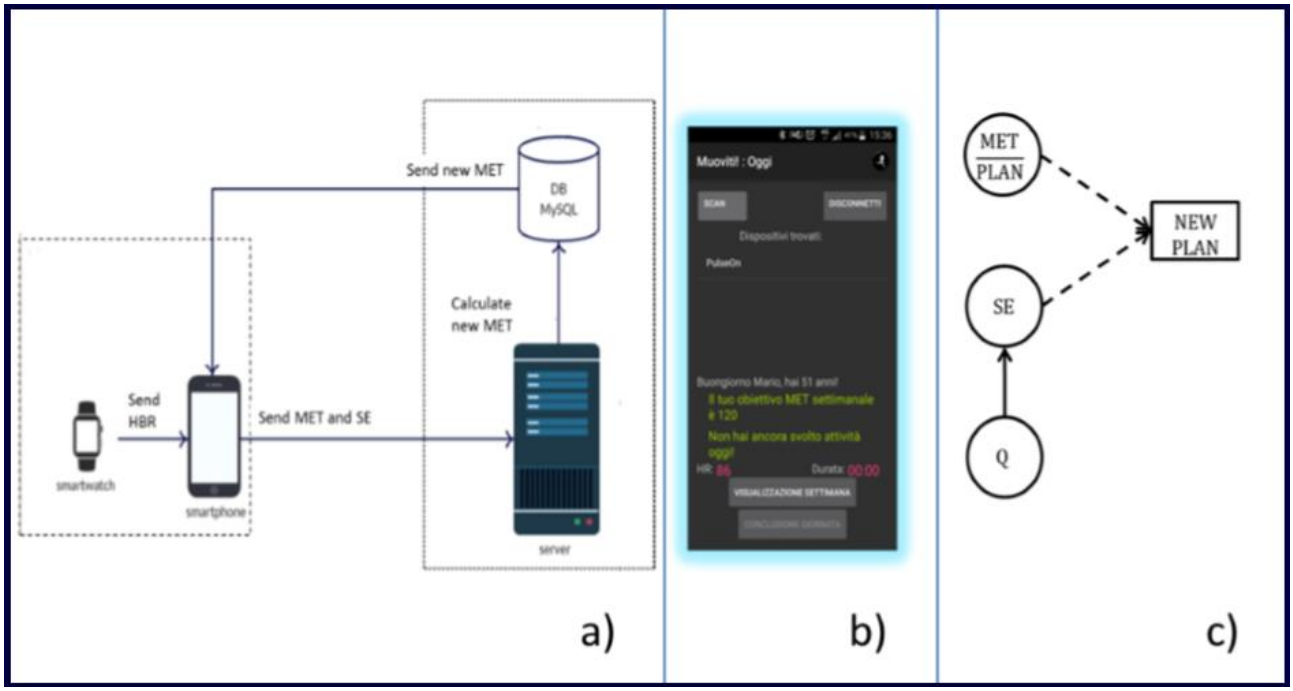

Figure 1. Part a) The general architecture of Muoviti!; Part b) The graphical user interface of *Muoviti!*; Part c) The model basic decision step.

4. The computational modeling

The developed computational model combines knowledge about the PA performed, measured through the data collected by the wearables, and an ecological momentary assessment of self-efficacy beliefs.The model was employed to define, and adapt dynamically, a PA plan consisting of suggestions about the PA goal to be carried out every week, with the aim of maximizing the

probability of bringing the person to an acceptable PA level at the end of the long-term training period. The mathematical model adopted is a Dynamic Decision Network (DDN), a sequence of simple Bayesian Networks (BN), each representing the person's situation at a specific training period (i.e., one week). The basic BN embodies variables which represent the physical activity performed, the estimated self-efficacy of the period and the possible external factors influencing the performed activity. The DDN model includes decision variables at each training stage, which represent the PA goal proposed for the week, and a utility function on the final level of PA achieved. The DDN model has been preferred to other approaches available in the literature, for instance based on neurocognitive simulation (Pirolli, 2016) or on the theory of dynamic systems (Martin et al., 2015), because it represents with accuracy the sequence of decision points (the weekly PA goals) that have been envisioned in our approach. Moreover, the mathematical model of *Muoviti!* clearly combines psychological determinants with objective measurements of PA, being able to build up a personalized plan taking into account possible different trajectories towards the final goal. An explanation of the model can be given by referring to Figure 1. The *newPlan* variable (on Part c) represents the decision to be taken at the beginning of each training period. It is influenced by the two basic variables describing the state of the subject: the SE and the level of success obtained in the preceding period, measured as the ratio of achieved METs with respect to the current PLAN. The achieved METs can be measured directly in our experimental system, and the SE can be evaluated from the result Q of a set of questions posed to the subject. The structure of the model can be explained by considering its main purpose that is planning decisions and goal setting. The sequence of decisions represented by the $PLAN_i$ variables must lead the subject to achieve the desired PA level before the end of the program: the decision to be taken in each period must be compatible with this long-term target. We call the sequence of decisions from the present time until the end of the program a *strategy*. The overall objective is modeled by defining a utility function computed on the expected value assumed by the MET variable in a stable, long term situation. The utility value distribution can be computed, for each strategy, on the basis of the present state assuming no external interference. In this way, an updated assessment of the possible strategies can be carried out at each decision step.

The model tuning consists in the derivation of the conditional probability tables (CPT) from the experimental collection of data, as described in section 5 below.

5. Simulation study

The current computational model represents a mathematical description of a behaviour change model based on SCT that need to be tuned according to real case studies. To this scope, we assume that the users of the system can be classified into different basic profiles and that such profiles are represented by the different values in the CPTs present in the model. For these purposes, we hypothesize five different profiles, namely *capable*, *inconstant*, *slow but gradual*, *static*, and *complicated*, representing potential clusters of users. Profiles are developed adopting user personas techniques from user-centered design (LeRouge, Ma, Sneha, & Tolle, 2013), in order to attempt to understand intended users' self-efficacy beliefs and PA achievements variations over time in potential real-life settings. It is important to notice that the users' profiles we developed are just assumptions of users' behaviours and cognitions, but they were necessary for tuning the computational model and simulating potential scenarios. Table 2 shows variations in PA achievements and self-efficacy beliefs over time according to the developed profiles, and subsequent goals for the following week.

Table 2. Potential users' profiles and their variations in PA achievements, self-efficacy beliefs, and goal setting

	Week							
	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**
Profile 1 - *Capable*								
Goal (METs)	120	240	360	360	480	600	600	720
Achievement	YES	YES	YES	YES	YES	YES	YES	YES
Self-Efficacy	HIGH	HIGH	LOW	HIGH	HIGH	LOW	HIGH	LOW
Profile 2 - *Complicated*								
Goal (METs)	120	240	240	240	120	240	240	240
Achievement	YES	NO	YES	NO	YES	YES	YES	YES
Self-Efficacy	HIGH	HIGH	LOW	LOW	YES	LOW	LOW	HIGH
Profile 3 - *Inconstant*								
Goal (METs)	120	240	360	480	360	480	360	240
Achievement	YES	YES	YES	NO	YES	NO	NO	YES
Self-Efficacy	HIGH	HIGH	HIGH	LOW	HIGH	LOW	LOW	HIGH

Profile 4 - *Slow but gradual*								
Goal (METs)	120	240	360	240	360	240	360	360
Achievement	YES	YES	NO	YES	NO	YES	YES	YES
Self-Efficacy	HIGH	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH
Profile 5 - *Static*								
Goal (METs)	120	240	240	240	240	360	360	360
Achievement	YES	NO	YES	NO	YES	NO	YES	YES
Self-Efficacy	HIGH	HIGH	LOW	HIGH	HIGH	HIGH	LOW	LOW

We have simulated 100 training sessions using the *Muoviti!* App: each session started from 120 MET (corresponding to 30 minutes of MPA) to do in the first week, increasing /decreasing the PA plan for the next week by 120 MET or leaving it the same as before. The physical activity was monitored on a time-period of 8 weeks, generating a set of 100 different records, clustered as shown in table 3. For example, the "capable" profile is able to reach the planned MET quantity every week, and his/her self-efficacy value is high for more than five weeks. The average MET value is 435 per week, corresponding to more than 90 minutes of physical activity, reaching the maximum value of 720 METs, corresponding to 180 minutes PA per week. Other profiles can be described in a similar way, looking at the values in the table. These profiles will be used as a starting point to derive CPTs for each person involved in the next steps of experimentation.

Table 3. User profiles emerging from the test and their features.

User Profile	**Average MET**	**Maximum MET**	**SE High**	**Timeline for achieving maximum MET**
Capable	435	720	5 or more	8 weeks
Complicated	210	240	4 or less	6 weeks or less
Inconstant	330	480	5 or less	5 weeks or less
Slow but gradual	285	360	5 or more	6 weeks or less
Static	270	360	5 or more	5 or less

6. Further studies and extensions

This paper presented and discussed an innovative approach to promote PA behavior change among sedentary adults. The approach is based on the development of a computational model grounded in self-efficacy theory and on the integration of mobile technologies and dynamic decision networks to monitor behavioural (e.g. physical activity) and psychological (e.g. self-efficacy) variables. Such variables are combined by the computational model and then used to

suggest personalized PA goals, adjusting them from one week to the next one, on the basis of opportune profiles.

Next steps, before testing *Muoviti!* and its computational model in real world settings, will be devoted to the definition of the Behaviour Change Techniques (BCTs; Michie, Richardson, Johnston, et al., 2013) and the corresponding design features and functionalities that will characterize the content of the app. This process will be guided by the aim of promoting an effective user engagement with *Muoviti!* and, consequently, supporting the effectiveness of the digital intervention. For these purposes, next stages will focus on a deep understanding of the target users, their motivations to practice PA, and their perspectives and views about how smartphone apps could support their PA behavior change.

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Study 2

Users' motivations and preferences for behaviour change techniques as guiding principles for informing the content development of a physical activity smartphone app.

Abstract

Physical activity (PA) smartphone apps represent one of the most spread Digital Behaviour Change Interventions (DBCI) to promote PA. One of the main issues associated with the development of PA apps regards which Behaviour Change Techniques (BCTs) deserve to be implemented in order to be effective and fulfil the users' perspectives and motivations. The aim of the present study is to inform the development of a smartphone app (called *Muoviti!*) to increase PA among sedentary adults, addressing the request for a deep understanding of the users' PA participation motives and their views regarding the BCTs that the app is intended to deliver. A sample of 192 adults completed an online survey assessing socio-demographic and anthropometric information, leisure time PA, participation motives, and preferences for specific BCTs. Results suggested that enjoyment, fitness, and appearance are the most important participation motives, which, at the same time, differentiated active participants from sedentary ones. For what concern BCTs preferences, potential users revealed a specific interest for the BCTs referring to a self-regulation dimension while secondary relevance was attributed to BCTs referring to social features. Further results suggested that self-regulation BCTs are associated with each of the participation motives, pointing out their potential value in fulfilling the users' motivations.

1. Introduction

Smartphone applications (Apps) have become ever more popular in the last few years and represent one of the most spread and accessible *Digital Behaviour Change Interventions* (DBCI – West & Michie, 2016) to promote physical activity (PA). Nevertheless, one of the main issues associated with the existing PA apps concerns the evaluation of their effectiveness in promoting PA. Indeed,

there are just few and not updated evidences for a small positive effect of internet-delivered programs on physical activity (Davies, Spence, Vandelanotte, Caperchione, & Mummery, 2012). Additionally, PA apps available in the app stores are rarely evidence-based or evaluated using high standard research methods, such as randomised controlled trials (Pagoto & Bennett, 2013). However, in the absence of high-quality evidence of effectiveness, it is possible to benefit from an informed review of the inclusion of Behaviour Change Techniques (BCTs – Abraham & Michie, 2008; Michie, Richardson, Johnston, Abraham et al., 2013) in PA apps. For this purpose, recent research adopted BCT taxonomies to review PA apps in terms of implemented BCTs (Conroy, Yang, & Maher, 2014; Direito et al., 2014; Middelweerd, Mollee, van der Wal, Brug, & te Velde, 2014). These studies observed that the most frequently implemented BCTs in PA apps (i.e., self-regulation techniques, plan social support or social change), substantially overlap with the most effective ones in promoting PA behaviour change. In particular, it has been shown that BCTs referring to the self-regulation theory (Carver & Scheier, 1981, 1982) (e.g., prompt intention formation, prompt specific goal setting, provide feedback on performance, prompt self-monitoring of behavior, and prompt review of behavioral goals) and planning social support or social change seem to be effective in promoting PA behaviour change interventions (Greaves, Sheppard, Abraham, et al., 2011; Michie, Abraham, Whittington, et al., 2009; Williams & French, 2011)[10]. Such correspondence between the most implemented and most effective BCTs posits the potential effectiveness of PA apps. Additionally, a recent systematic review (Perski, Blanford, West, & Michie, 2017) suggested that DBCIs that include part of the overmentioned BCTs, such as action plans, goal setting, feedback and self-monitoring have been found to be associated with higher level of engagement. This is particularly relevant since there is evidence for a positive association between engagement and intervention effectiveness (Alexander, McClure, Calvi, et al., 2010; Cobb, Graham, Bock, Papandonatos, & Abrams, 2005) and, more specifically, engagement with DBCIs is considered a precondition for intervention effectiveness (Yardley, Spring, Riper, et al., 2016). Engagement with DBCIs has been defined both in terms of extent of usage (e.g., amount, frequency) and subjective experience characterised by attention,

[10] Such reviews have been published before 2012, as a consequence the samples considered are mainly made of studies that didn't use PA apps as delivery tool or that, at least, made a scarce use of digital interventions.

interest and affect. In addition to the over mentioned BCTs, engagement has been hypothesized to be influenced by other variables such as the psychological and demographic characteristics specific to the target population (Perski, et al., 2017). For this purpose, various research approaches, such as the *user-centered design* (van-Gemert-Pijnen, Nijland, van Limburg et al., 2011) and the *person based approach* (Yardley, Morrison, Bradbury, & Muller, 2015), emphasize the importance of involving the target population in the DBCI development. While the former approach focuses more on the development of all the digital products around the target user characteristics (e.g., knowledge, skills, behaviour, motivations, context), the latter integrates theory-driven approaches by emphasizing users' views of the BCTs the intervention is intended to deliver and their implementation accordingly to their motivations and preferences. Although such approaches suggested to adopt qualitative methodologies, users' preferences for specific BCTs have been also explored through the adoption of questionnaires (Belmon, Middelweerd, te Velde, & Brug, 2015).

In designing a DBCI, it is fundamental to address users' motivations underlying the target behaviour since they have been consistently found to be positively associated with engagement (Bossen, Buskermolen, Veenhof, de Bakker, & Dekker, 2013; Henshaw, McCormack, & Ferguson, 2015; McCabe & Price, 2009). As far as concern the motivations associated with PA, a large corpus of evidence has shown the value of Self-Determination Theory (SDT; Deci & Ryan, 1985; 2002) in understanding and promoting exercise behaviour (Teixeira, Carraça, Markland, Silva, & Ryan, 2012). SDT argued that human behaviour is regulated by different types of motivations that vary between intrinsic and extrinsic motivation. *Intrinsic motivation* is defined as engaging in an activity because of its inherent pleasures and satisfactions, while *extrinsic motivation* refers to doing an activity in order to attain some outcomes separable from the activity itself (Ryan, Williams, Patrick, & Deci, 2009). More specifically, extrinsic motivation is a rather complex category of motivation, indeed it is characterized by various types of regulations (i.e., external regulation, introjected regulation, identified regulation, integrated regulation) which differ in the degree to which they represent autonomy (Ryan & Connell, 1989). Previous results suggested that a predominance of intrinsic motivation is especially important for log-term exercise participation, while some forms of well-internalized extrinsic motivation, such as identified and integrated regulation, are important

factors for the initial adoption of the behaviour but provide limited support to maintain it over time (Teixeira et al., 2012). Consistently, previous literature suggested that more intrinsically-oriented motives (e.g., skill development, enjoyment) relative to extrinsically-oriented motives (e.g., body-related motives) were positively associated with exercise behaviour. In matter of health fitness motives and body related motives, the available literature pointed out a mix of positive and null associations between exercise and health and fitness motives, while a mix of negative and null associations were found between exercise and body-related motives (Teixeira et al., 2012). It should be noted that participation motives are not mutually exclusive and they may co-exist in the same person (Vansteenkiste, Niemiec, & Soenens, 2010), thus each of them may constitute a valuable leverage for increasing PA. As a consequence, even if intrinsically-oriented motives are more related to exercise than extrinsically-oriented motives, exercise promotion interventions should acknowledge, explore and address all the participation motives that characterize the target population.

The present study tried to integrate indications from the Person-Based Approach and the engagement literature concerning the design of DBCIs, and the SDT literature regarding participation motives underlying PA and exercise behaviour. The output of the present study will contribute to inform and characterize the development of a smartphone app for the promotion of PA called *Muoviti!*. In particular, the study addressed the request for a deep understanding of the users' motivations and their view regarding the BCTs that *Muoviti!* is intended to deliver. The aim of the study is to:

- Characterize the target population in terms of the predominant motives underlying exercise behaviour.
- Investigate associations between participation motives, exercise behaviour and behavioural outcomes such as BMI. More specifically, the hypothesis that more intrinsically-oriented motives relative to extrinsically-oriented motives are associated with a higher involvement in exercise is tested.

- Extend previous findings regarding preferences for BCTs in a population of young adults (Belmon et al., 2015), assessing the preference ratings of BCTs among potential users of *Muoviti!*.
- Investigate associations among BCTs ratings, participation motives, levels of physical activity and BMI.

2. Materials and methods

2.1. Participants

The development of a DBCI should involve a wide range of people from the target user populations (Yardley et al., 2015), as a consequence the present study involved people that are representative of the target population of *Muoviti!*. Healthy adults were eligible to take part in the present study if they met the inclusion criteria: age between 30 and 50 years, no chronic pathologies that would benefit from PA (e.g., diabetes, hypertension, severe obesity), no physical impairments that limited the opportunity to do PA (e.g., back pain, knees injuries). As far as regards the PA level, although *Muoviti!* targets sedentary adults (i.e., weekly energy expenditure lower than 600 METs[11]), we didn't consider it as an inclusion criteria because a greater variability in the level of PA would have permit to compare results from sedentary people with results from more active people, thus to better characterize the target population. A total of 202 individuals agreed to participate, but only 192 (82 male) were included in the final sample (mean age=40.11, SD=5.88). Four participants were excluded because their *Body Mass Index* (BMI) corresponded to a severe obesity (BMI>35) or a severe underweight (BMI<16). Further six participants were excluded because they didn't complete the survey.

2.2. Procedures

2.2.1. Sampling procedures

[11] A MET (Metabolic Equivalent) is defined as the ratio of a person's working metabolic rate relative to the resting metabolic rate. One MET is defined as the energy cost of sitting quietly, and is equivalent to a caloric consumption of 1 kcal/kg/hour. 600 METs represent a standard cut-off for differentiating sedentary from active people.

Participants were recruited through social media (e.g., facebook). They were asked if they would be willing to participate in a study regarding the development of a PA smartphone app. Those who agreed were invited to complete an online survey. Snowballing techniques were also used by asking participants to forward the link of the online survey to other people like friends and family members. Participant were told that all of the questionnaires would be anonymous and all of them gave informed consent. Participants were also informed that they would have received no incentive for their participation.

2.2.2. Measures

Socio demographic and anthropometric data were collected on: 1) age; 2) gender; 3) education level; 4) marital status; 5) height and weight.

Leisure time PA was assessed through the *Global Physical Activity Questionnaire* (GPAQ; Armstrong & Bull, 2006). It collects information about the duration (i.e., minutes) and intensity (i.e., moderate and vigorous PA) of the physical activity performed on a typical week. When calculating a person's weekly overall expenditure 4 METs are assigned to the time spent in moderate activities, and 8 METs to the time spent in vigorous activities. Additionally, the questionnaire asked to report the type of PA practiced during leisure time.

Participation motives for exercise and physical activity were measured using the *Motivation for Physical Activities Measure-Revised* (MPAM-R; Ryan, Frederick, Lepes, Rubio, & Sheldon, 1997). The measure is made of 30 items loading on factors representing five general motives for exercise participation: *enjoyment* (7 items), *competence* (7 items), *appearance* (6 items), *fitness* (5 items), and *social* (5 items). The items were evaluated on a 5-point Likert scale from 1 (Definitely false for me) to 5 (Definitely true for me). The Italian version of the MPAM-R is not available, thus the English version has been translated into Italian for the present study. In the present study, Cronbach's alpha coefficients were good, at .86 for enjoyment, .86 for competence, .85 for appearance, .86 for fitness, and .80 for social.

Preferences for BCTs were assessed using the scale developed by Belmon and colleagues (Belmon, et al., 2015) on the basis of the potential effective BCTs in promoting PA (Greaves et al.,

2011; Michie et al., 2009; Williams & French, 2011). The measure is made of 16 BCTs and ratings of specific BCTs were measured on a 5-point Likert scale from 1 (Not relevant at all for me) to 5 (Definitely relevant for me). In order to investigate the dimensions underlying the 16 BCTs, an exploratory factor analysis with principal axis factoring extraction and promax rotation was performed. Differently from previous research (Belmon et al., 2015), parallel analysis suggested the extraction of two factors. The first dimension, called *Self-regulation*, is represented by the BCTs that basically correspond to the *Goals and Planning* and *Feedback and Monitoring* clusters in the BCT Taxonomy (v1) and can be linked to Carver and Scheier's Self-Regulation Theory (1981; 1982). The second dimension, called *Social features*, is represented by the BCTs referring to social features, both in terms of support and comparison. The Cronbach alphas of the *self-regulation* and *social features* dimension showed an excellent (.93) and good (.86) internal consistency respectively. For items and factor loadings information see Appendix.

2.2.3. Statistical analysis

Statistical analysis were performed with SPSS 23 (IBM corp, 2014). Analysis of Covariance (ANCOVA) was conducted to test for i) participation motives, and ii) BCTs ratings differences between participants that meet the PA guidelines (i.e., more than 600 METs per week) and participants that do not. Gender, age, and BMI were considered as covariates in order to control for their potential effect. Homoscedasticity was controlled for with Levene's test. If the error variances for the dependent variables were not equal across the groups ($p>.05$), the α level was set at .025 to prevent a Type I error (Keppel & Wickens, 2004).

In the sub-sample of those who do not meet the PA guidelines, bivariate and subsequent partial correlation analyses were carried out to explore the association between participation motives and ratings for BCTs addressing *self-regulation* and *social features* dimensions. In partial correlation analysis, gender and BMI were considered as covariates in order to control for their potential effect.

3. Results and discussion

3.1. Results

Results indicated that 143 (75%) participants did not meet the PA guidelines (i.e., weekly METs less than 600). Overall, the most frequently reported types of physical activities (more than 80%) are walking, running, swimming, cycling and gym, while a small number of participants reported to take part in team-sport activities (e.g., soccer, basketball). Descriptive statistics and correlation among participation motives are presented in table 1. For what BCTs dimensions concern, participants are characterized by a moderate interest in self-regulation BCTs (M=3.59, SD=.31) whilst they displayed indifference for the social features BCTS (M=2.07, SD=.94). Table 2 reports mean scores for BCTs preferences.

Table 1. Means, standard deviations and correlation matrix for participation motives

	M (SD)	Competence	Enjoyment	Fitness	Appearance
Competence	2.94 (.91)				
Enjoyment	3.48 (.88)	.62*			
Fitness	3.81 (.90)	.38*	.30*		
Appearance	3.15 (.94)	.31*	.10	.72*	
Social	2.60 (.91)	.39*	.44*	.04	.06

Note. *<.001 (two-tailed)

Table 2. Mean preferences for behavior change techniques (BCTs) in a physical activity app

BCT		Mean (SD)
Self-regulation features		
	Self-monitoring of behaviour	3.88 (1.22)
	Self-monitoring of the outcome(s) of behaviour	3.81 (1.16)
	Graded tasks	3.80 (1.22)
	Goal setting (outcome)	3.76 (1.16)
	Review outcome goal(s)	3.73 (1.14)
	Review behaviour goal(s)	3.65 (1.17)
	Goal setting (behaviour)	3.61 (1.25)
	Feedback on outcome(s) of behaviour	3.51 (1.22)
	Discrepancy between current behaviour and goal	3.48 (1.19)
	Feedback on behaviour	3.45 (1.23)
	Problem solving	3.38 (1.28)
	Action planning	3.06 (1.24)
Social features		
	Social comparison	2.17 (1.14)
	Social support (emotional)	2.16 (1.21)
	Social support (practical)	2.04 (1.11)
	Social support (unspecified)	1.93 (1.03)

3.1.1. Participation motives differences between active and inactive participants

A one-way ANCOVA was conducted to compare participation motives between participants that meet the PA guidelines and participants that do not, whilst controlling for sex, age and BMI. The error variance for interest was not equal across groups ($p>.05$), hence the α level was set at .025. There were significant differences in enjoyment [$F(1,186)=$, $p<.01$, $\eta^2=.04$], fitness [$F(1,186)=7.88$, $p<.01$, $\eta^2=.04$], and appearance [$F(1,186)=6.56$, $p<.05$, $\eta^2=.03$] (see table 3). None of the covariates was associated with participation motives.

When comparing BCTs dimension scores between active and inactive people, the one-way ANCOVA (controlling for sex, age and BMI) suggested no significant differences neither for self-regulation BCTs nor for social features BCTs. Also in this case, covariates were not associated with preferences for BCTs dimensions.

Table 3. Participation motives and BCTs dimension mean differences between active and inactive participants.

	METs<600 (N=143)	METs>600 (N=49)
Participation motive		
Competence	2.86 (.91)	3.16 (.90)
Enjoyment**	3.37 (.92)	3.76 (.98)
Fitness**	3.71 (.94)	4.08 (.72)
Appearance*	3.07 (.95)	3.42 (.87)
Social	2.62 (.90)	2.49 (.94)
BCTs dimension		
Self-regulation BCTs	3.60 (.91)	3.56 (.89)
Social features BCTs	2.03 (.94)	2.21 (.93)

Note. *<.05 (two-tailed)
**<.01 (two-tailed)

3.1.2. Bivariate and partial correlation analyses between participation motives and ratings for BCTs dimensions

Correlation analyses were performed within participants who do not meet the PA guidelines in order to investigate associations between participation motives and preferences for BCTs. Bivariate correlation analysis indicated positive associations between preferences for BCTs underlying the self-regulation dimension and each of the PA participation motives (see table 4). Conversely, social features BCTs related just to competence and social motives, and, additionally, there were significant associations between preferences for social features, and BMI and gender.

Subsequent partial correlation analysis indicated that when controlling gender and BMI on the relationship between participation motives and preferences for social features, no more correlations were found. Differently, correlations between self-regulation BCTs and participation motives remained significant.

Table 4. Bivariate and partial correlation between BCTs dimensions and participation motives, gender, age, and BMI.

	Bivariate correlation		Partial correlation controlling for gender and BMI	
	Self-regulation BCTs	Social features BCTs	Self-regulation BCTs	Social features BCTs
Competence/Challenge	.28**	.19*	.29**	16
Enjoyment	.20*	.06	.19**	.05
Fitness/Health	.24**	.13	.23**	.15
Appearance	.19*	.08	.18*	.11
Social	.21*	.19*	.22**	.14
Gender	.01	-.27**	-	-
Age	.07	.01	-	-
BMI	-.05	.22**	-	-

Note. Negative correlation coefficients in gender indicate higher score for women.
*<.05 (two-tailed)
**<.01 (two-tailed)

3.2. Discussion

The study examined *Muoviti!* potential users' exercise participation motives and ratings of BCTs applied in a PA app. Furthermore, participation motives and ratings of BCTs were compared between active and inactive participants. Since *Muoviti!* primarily targets a PA inactive population, correlation analyses were performed in order to evidence associations between participation motives and BCTs ratings in the subsample of participants that did not meet the PA recommended guidelines.

As far as regard exercise participation motives, results supported previous literature (Texeira et al., 2012) suggesting that intrinsically-oriented motives (e.g., enjoyment) and internalized motives (e.g., fitness/health) are associated with the practice of regular PA. Differently from previous research, competence did not constitute an important motive for practicing PA. This result may be the consequence of the sample sporting characteristics, indeed participants reported to be mostly involved in exercise activities (e.g., walking, gym, running, cycling) that do not need the development of specific athletic and technical skills. In the matter of body related motives, appearance constituted a further motive that differentiated inactive from active participants.

Specifically, participants that meet the PA guidelines attributed a greater importance to body-related motives than inactive participants. Social motives were higher within inactive participants, however this difference was not significant. Regardless the fact that participants were active or inactive, the most relevant participation motives is fitness/health, followed by enjoyment and, then, appearance. Interestingly, such participation motives are even those that differentiated between active and inactive participants, arguing their potential role in fostering exercise behavior. Since a combination of intrinsic and more controlled motives characterize the target population, it seems arguable that a behaviour change intervention should consider all of them and, in line with previous evidences (Texeria et al., 2012), addressing controlled motives as a trigger for behavior change and the intrinsic ones to sustain it over time.

BCTs ratings have been reduced to two dimensions, one representing self-regulation features and the other one described by social features. In this case there was no difference in BCTs dimensions between active and inactive participants. In line with previous research (Belmon et al., 2015; Middelweerd, van der Laan, van Stralen, et al., 2015), BCTs regarding self-regulation (e.g., feedback, monitoring, goal setting, goal reviewing) were positively rated. More specifically the most preferred BCTs were monitoring (both behaviour and outcome), graded task, and goal setting and goal reviewing (both behaviour and outcome). Conversely, participants didn't appreciate the opportunity to have social features in a PA app neither in terms of support nor in term of social comparison, confirming what found in previous research (Belmon et al., 2015). Finally, it should be noted that participants didn't rate existing and real PA app features but they were asked to rate the importance of having specific BCTs in a hypothetical PA app. As a consequence, it is arguable that their judgment was based on their previous experience, needs, and requirements.

In the subsample of those who didn't meet the weekly PA guidelines, bivariate correlation analysis suggested that all the participation motives are positively associated with the preferences for self-regulation BCTs, while just competence/challenge and social motives were associated with social features BCTs. Additionally, male gender and BMI were positively associated with preference for social features. Social features were less appreciated among women who probably consider exercise a more private dimension than men. Differently, participants' BMI was positively

associated with the interest for social features. This result underlined the participants' insight about potential effective BCT in promoting PA behavior change, indeed previous research (Olander, Fletcher, Williams, et al., 2013) evidenced the effectiveness of social support in promoting PA among obese individuals. The subsequent partial correlation analysis, after having controlled for gender and BMI, confirmed the association between all the participation motives and self-regulation BCTs, however the associations between social BCTs, and competence/challenge and social motives were no more significant. These results suggested that regardless the degree of autonomy that characterize the participation motives, all of them are related to the relevance attributed to self-regulation BCTs. This last point is particularly interesting from a behavior change perspective because it evidenced that specific BCTs may satisfy participation motives, providing useful information to characterize the target users' needs and requirements.

4. Conclusion

The present study constituted a preliminary step to define Muoviti! potential users' preferences for specific BCTs and their motives for taking part in exercise activities. As *Muoviti!* potential users preferred self-regulation BCTs such as monitoring, goal setting, and goal reviewing, it is important for the app developers to understand how to translate them into functionalities in order to support the most important users participation motives (i.e., enjoyment, health/fitness, appearance). More specifically, thanks to the adoption of qualitative methodology, future research is expected to address the questions why potential users consider some BCTs more relevant than others and how to translate BCTs in app features in order to fulfil the users' needs and requirements, and to support their participation motives.

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Appendix

Table 1. Standardized factor loadings and factor correlations based on responses to the preferences for BCTs

Selected BCTs	Item included in the scale	Self-regulation	Social features
Self-monitoring of the outcome(s) of behaviour	It is important to me that I can monitor my long-term results in a PA app	**.86**	-.10
Goal setting (behaviour)	It is important to me that I can set short term goals in a PA app	**.83**	-.05
Reviewing behaviour goal(s)	It is important to me that I have an overview of my exercise goals to improve my PA in the short-term and can review my progress in a PA app	**.82**	-.03
Goal setting (outcome)	It is important to me that I can set long-term goals in a PA app	**.79**	-.02
Reviewing outcome goal(s)	It is important to me that I have an overview of my long-term PA goal and can review my long-term goal progress in a PA app	**.78**	.08
Feedback on the outcome(s) of behaviour	It is important to me that I get feedback on my long-term results in a PA app	**.76**	.03
Self-monitoring of behaviour	It is important to me that I can monitor my exercise activities in a PA app	**.76**	-.15
Feedback on behaviour	It is important to me that I get feedback on my level of PA in a PA app	**.72**	.02
Graded tasks	It is important to me that I can start with easy tasks and gradually make the exercise tasks more difficult in a PA app	**.68**	.08
Discrepancies between current behaviours and goal(s)	It is important to me that I can see the difference between my current exercise behaviour and my goals in a PA app	**.62**	.09
Problem solving	It is important to me that I can solve a problem that holds me back from exercising in a PA app	**.55**	.15
Action planning	It is important to me that I can plan my exercise activities in a PA app	**.47**	.16
Social support (practical)	It is important to me that I can receive practical advice from friends, family, or colleagues in a PA app to exercise more	-.04	**.98**
Social support (unspecified)	It is important to me that I can receive advice or support from friends, family, or colleagues in a PA app to exercise more	-.04	**.94**
Social support (emotional)	It is important to me that I can be encouraged by friends, family, or colleagues in a PA app to exercise more	.06	**.80**
Social comparison	It is important to me that I can compare my exercise activities with that of others in a PA app	.13	**.39**
Correlation with social feature dimension		.29	-

Note: BCTs (Behavior change techniques) based on the BCTTv1 (Michie et al., 2013)
Factor loadings higher than .30 are in boldface.

Study 3

Exploring users' needs, expectancies and experience in relation to the adoption and uptake of physical activity apps

Abstract

Smartphone applications (apps) has the potential to improve physical activity (PA) behaviour change interventions, however engagement with such apps is typically low. This may partly be due to the fact that existing apps often don't take into account users' needs and perspectives. The aim of the present research is to investigate what and how design features need to be implemented in a novel PA app (called *Muoviti!*) in order to address users' PA participation motives and to foster and sustain their engagement with the digital intervention. Two studies were conducted in parallel with potential PA app users who were interested in increasing their PA using a smartphone app. In the first study, participant (N=13) were asked to take part in focus groups characterised by element of co-design in order to elicit their insight and creativity. The second one consisted of a 2-weeks study. During baseline, a specific commercial PA app was assigned to participants (N=20), who were asked to download and to explore it whilst thinking aloud. Semi-structured interview techniques were used to allow participants to elaborate on their statements. After having used the app for two weeks, participants (N=17) were contacted for follow-up interviews. Verbal reports from both the studies were audio recorded, transcribed verbatim and analysed using inductive thematic analysis. Results suggested that self-regulation features (i.e., behavioural monitoring, feedback, goal setting) and health-related features (i.e., those features that link PA to fitness and weight loss) are considered as fundamental components to build the entire app around. Participants expressed their like for human support features (i.e., personal trainer support, peers support), but they reported to be basically annoyed by social comparison and competitive features because they consider PA as a private domain. Furthermore, proactive and smart features that integrate behavioural, psychological and contextual information in order to provide adaptive and flexible interventions (i.e., tailored and context sensitive action plans and suggestions) were highly appreciated; nevertheless, such features are mainly missing in the users' experience with

commercial PA apps. Finally, participants reported that usability, fairness and simplicity of PA apps constituted a precondition that allow them to relate to the app contents. Based on current findings, this study highlighted what different features may be liked and used by PA app users and, thus, deserve to be considered in the design of *Muoviti!*.

1. Introduction

Behaviour change interventions to increase physical activity (PA) have been found to be effective (Greaves, Sheppard, Abraham, et al., 2011) and there is evidence supporting their cost-effectiveness (Cobiac, Vos, & Barendregt, 2009; Gordon, Graves, Hawkes, & Eakin, 2007); however most of them have been delivered in face-to-face settings that are, for intrinsic reasons, unsuitable to target large populations and to support behaviour change in the "real world".Mobile technology has the potential to empower intervention effectiveness (Pagoto & Bennet, 2013; Patrick, Griswold, Raab, & Intille, 2008) and it constitutes an economically viable tool to reach large populations (Müller, Alley, Schoeppe, & Vandelanotte, 2016). Inspite of that, so far, there are just few evidences for a modest effect of web- and mobile-based interventions on physical activity (Davies, Spence, Vandelanotte, Caperchione, & Mummery, 2012; Fanning, Mullen, & McAuley, 2012; Müller et al., 2016). The effect varies greatly in relation to multiple factors (i.e., differences in study designs, way of delivery, intervention components, outcome measures, lengths of studies), therefore it would be better to take some cautions in interpreting and generalizing early evidences (Müller et al., 2016; Webb, Joseph, Yardley, & Michie, 2010). *Engagement* with digital intervention is a precondition for their effectiveness (Yardley, Spring, Riper, et al., 2016), however, it has been evidenced that they suffer from low engagement both in context of controlled trials (Davies et al., 2012; Kelders, Kok, Ossebaard, & Van Gemert-Pijnen, 2012) and in relation to health apps usage in real life settings (Consumer Health Information Corporation, 2017). Indeed, although it may be assumed that users who are motivated to change their behaviour might constantly engage over time, evidence suggests that is not the case (Eysench, 2005). For instance, it has been shown that 26% of health apps are downloaded and used only once and the 74% are abandoned after the 10th use (Consumer Health Information Corporation, 2017). As a consequence, understanding why

engagement with digital interventions varies over time acquire vital importance for designing PA apps that promote engagement on the long-term period. Previous findings suggested that the most frequently reported reasons underlining the low engagement with health apps and the subsequent attrition rates are the lack of desired features and the abandoning of the health goal (Murnane, Huffaker, & Kossinets, 2015). Furthermore, recent reviews argued that engagement with health smartphone apps may be enhanced by interactive features such as self-monitoring, feedback, interactivity, social support features and professional support features (Bardus, van Beurden, Smith, & Abraham, 2016; Perski, Blandford, West, & Michie, 2016). Nevertheless, little attention has been paid to understand potential users' views and preferences on such features and how to translate them into app functionalities that are able to fulfil users' motivations and health goals. This last point is particularly relevant since users' psychological determinants of behaviour, such as motivations and expectancies, have been hypothesized to influence both the engagement with digital interventions and the effect of specific BCTs on engagement (Perski et al., 2016).

In order to answer the request for a deep understanding of the determinants of engagement with digital interventions and to ensure that interventions are usable and engaging over time, it is advisable to elicit and address the needs, perspective, and experiences of potential users (van Gemert-Pijnen, Nijland, van Limburg, et al., 2011; Yardley, Morrison, Bradbury, & Muller, 2015). For these purposes, it is suitable to adopt mixed-methods research design with a specific focus on qualitative methodologies (e.g., focus groups, interview with open-ended questions, think aloud studies) (Jasper, 2009; van Gemert-Pijnen, Peters, & Ossebaard, 2013; Yardley et al., 2015). Qualitative methodologies may benefit from various techniques and design methods originated from other disciplines linked to digital technology, such as web design and user experience research. One technique that is gaining the attention of mHealth researchers is co-design. The term 'co-design' indicates the creative collaboration between researchers and users in the design development process, where the valuable role of the end users relies on their position of 'expert of their experience' (Sanders & Stappers, 2008). *Co-designing* an end product (e.g., a digital intervention) in cooperation with potential users assure several advantages in terms of better idea generation, higher quality and more effective products, better fit between users and product, and

more efficiency in the project management (Steen, Manschot, & De Koning, 2011). Altough co-design is a creative technique to co-create new products and services, it is inadequate to investigate the users' experiences and interactions with digital technology in real world settings. For this reason, in order to elicit users' thoughts about factors that are expected to be important for engagement in real life, a valuable approach is the adoption of existing commercial apps as a stimuli for conducting in-depth interviews (e.g., Perski, Blandford, Ubhi, West, & Michie, 2017; Puszkiewicz, Roberts, Smith, Wardle, & Fisher, 2016). Indeed, through the exploration and use of existing apps, potential users are prompted to reflect about what features and functionalities guide their attitudes and judgements about the app and what component may be considered as a facilitator or a barrier to the uptake of the digital intervention.

The current research aimed to guide the characterisation of design features to be implemented in a PA called *Muoviti!*. Specifically, the search for design features was driven by the aim to develop a PA app that is able to foster effective engagement and maintain it over time. In order to address these goals, two studies were conducted.

- Study 3a investigated what and why features are judged to be important for engagement by sedentary people. The study adopted focus group methodology with element of co-design to better understand what and why features deserve to be considered in the design process in order to fulfil the end-users' motivations.
- Study 3b focused on understanding what apps' features are considered to be important for engagement at different stages of use. More specifically, the study examined what features influence the users' engagement during a first exposure to never-used PA apps and what features are judged to be determinant for supporting engagement and satisfactory experiences after a 2-week usage of PA apps. For such purposes, the present study utilized think aloud methodologies and in-depth interviews to investigate users' experiences.

2. Study 3a

2.1. Materials and methods

2.1.1. Study design

A focus group methodology with elements of co-design was adopted to address users' perspective and expectancies in relation to a PA mobile app. The added value of introducing co-design aspects relied on the co-creation of a digital product that is fit-for-purpose and designed with the users and around the users. Indeed, co-design activities enable the users to express their creativity by exploiting their role as experts of their own experiences (Sanders & Stappers, 2008).

2.1.2. Participants

Participants were recruited in order to represent the target population of *Muoviti!*. Eligibility criteria for taking part in the study were i) age between 30 and 50 years old, ii) no pre-existing health conditions that would impede to practice PA or that would, iii) no clinical conditions related to physical inactivity (e.g., obesity, diabetes), iv) PA behaviour not in line with the recommended PA guidelines (i.e., 150 minutes of moderate PA or 75 minutes of vigorous PA per week), v) willingness to increase their PA behaviour and interest in doing so through mobile technologies. Participants didn't receive any monetary compensation for their participation in the study.

2.1.3. Sampling

Participants were recruited through social media (e.g., Facebook), snowball sampling methods, and poster placed in the university campus. The aim of the focus group and the eligibility criteria were specified in the recruitment materials. Recruitment for focus group stopped when no relevant different insights of participants' experiences and novel themes came up from focus groups (i.e., when theoretical saturation was achieved).

2.1.4. Procedure

Participants who were interested to take part in the study were invited at the University of Milan-Bicocca. Before starting the focus group session, participants read the information sheet, which described the nature of the study and subsequently provided informed consent. As a first focus group activity, participants were asked to introduce themselves and talk about their previous personal experience with PA and with mobile apps. Successively, participants were given a folder with materials for co-design and were asked to carry out a task in which they had to design their own PA app according to their preferences for specific functionalities and features. Since user-centered design methods emphasize the iterative nature of the design process, after the first focus group the materials and the track for the next co-design sessions were slightly adapted in order to better elicit the users' views about what and why specific functionalities are expected to be important. The first session was based on the evaluation and design of potential PA app features (functionalities and features were written on post-it previously given to participants) according to different topics (i.e., feedback and monitoring, goal setting and planning, challenges and social features, problem solving) and a brief discussion was conducted after each topic was completed. In the latter session, participants were asked to cut out images features printed on a paper sheet and, then, to paste them on a printed smartphone frame according to their preferences; a general discussion was conducted once the whole activity was accomplished. In both the co-design session, participants were also provided with blank post-it in order to propose further functionalities that deserve to be considered for the implementation in a PA app. The reason underlying the changes to the co-design task relies on the aim to characterize the activity with more concrete stimuli and to stress the creative act of co-creating the fit-for-purpose end-product. Therefore, changes to co-design materials did not influence the scope of focus group sessions (i.e., elicit potential users' views and preferences for design features) but, rather, provided opportunity for a better expression of participants' views and perspectives.

2.1.5. Co-design materials

The development of materials that served as stimuli for the co-design activities were mainly based on results from a previous study (see chapter 4). In particular, in characterizing the materials,

design features were primarily defined in order to fulfil the most relevant PA participation motives and to represent the most preferred BCTs emerged in chapter 4. Additionally, further features that are expected to be associated with engagement (i.e., rewards, reminders, social support) (Perski et al., 2016) were also included as stimuli. Finally, new materials were directly developed by participants during co-design sessions in order to benefit from their experience and their creativity.

2.1.6. Data Analysis

Focus group sessions were audio-recorded and transcribed verbatim. A qualitative analysis of the transcripts was performed using inductive thematic analysis (Braun & Clarke, 2006). Thematic analysis is characterized by six phases: have been identified: i) familiarising with the data, ii) generating initial codes, iii) searching for themes, iv) reviewing themes, v) defining and naming themes, and vi) producing the report. Data and repeated patterns that were considered pertinent to the aim of the study (i.e., understanding of users' expectancies and motivations in relation to PA apps) were coded by the primary researcher. New inductive codes were labelled as they were identified during the coding process and the results of the coding were iteratively revised. The next stage involved searching for themes; the primary researcher reviewed the codes one by one, organizing the findings in order to combine the different codes that have been considered focused on the same aspect. The ordered data were reviewed, revised, and subsequently organised into themes. Disagreements resolution and agreement on the final themes was reached through discussion within the entire research group. After having defined and named themes, examples of transcripts were selected to corroborate themes on the basis of their representativeness and relevance. Data were analysed in their original language to preserve the participants' original meanings, although coding and themes were formulated in English only.

2.2. Results and discussion

2.2.1. Results

Two focus groups were conducted (N=13; 8 men, 5 women). The average age of participants was 41.9 years (SD = 7.1). All the participants reported to practice less than 120 minutes of light to

moderate PA per week; four participants reported to have previously used smartphone apps to support PA.

Five themes were developed in relation to the research question and were named: "features that enhance self-regulation", "features that are relevant for health", "human support", "private dimension of PA", and "smart and tailored". Two subthemes were developed in relation to the "features that are relevant for health" theme: "medical guidance" and "fitness and weight management". Additional two subthemes originated from the "human support" theme: "peers support" and "virtual personal trainer support".

2.2.1.1. Features that enhance self-regulation

Most of participants perceived monitoring, feedback and goal setting features as a fundamental component to build the entire app around. Participants believed that such features are particularly relevant in order to regulate their own behaviour according to their progress or fails towards the goal.

"Io ritengo un aspetto fondamentale, nel senso, sapere quanto ho corso, quanto tempo e la distanza e tutte le altre informazioni di dettaglio sono il punto di partenza per poi andare ad aggiungere gli altri elementi che dovrebbe avere l'app"

"il percorso è fondamentale [...] nel senso individuare quanto tempo ho impiegato rispetto a prima rispetto a fare quel dato percorso… quindi non solo il tracciato [...] ma anche capire come siamo migliorati nel tempo"

"[la app] deve essere un qualcosa che mi aiuta a raggiungere l'obiettivo, dovrebbe essere un calcolatore di quello che ho fatto e di quello che dovevo fare… una calcolatrice"

Furthermore, participants were prone to practice open air activities like running and walking, thus they were more interested in opportunities of having records and statistics about specific itineraries.

"mi piacerebbe che tenesse un attimo traccia del percorso che fai o comunque regolare tutta una serie di cose. Magari potrebbe stimolarmi a fare di più, migliorando se stessi

sullo stesso percorso, magari avere in memoria i percorsi precedenti, lo storico di un percorso"

"a me piacerebbe che l'app tenesse in memoria gli allenamenti fatti e che, naturalmente è un mio pensiero, io mi alleno molto all'aria aperta e quindi mi piace che magari mi tenga in memoria i percorsi che ho fatto"

2.2.1.2. Features that are relevant for health

Focus group participants evidenced the importance of using a PA app that focuses on health outcomes and the related physiological parameters. Indeed, most of them reported that their intention to practice PA is not guided by intrinsic motivation but because they are aware about the positive effects on health and wellbeing.

"io vedo l'attività sportiva più che come un piacere, più come una cosa che sento che devo fare per stare bene più che non è proprio un piacere, è una cosa che mi sforzo di fare per sentirmi meglio"

"c'è per chi magari la palestra è un piacere quindi la fa con piacere, io la faccio perchè sento che mi fa bene, più che una cosa che mi piace"

In particular, features relevant for health are ascribable to the desire for medical guidance and a focus on weight loss and fitness that are conceived as primary goals of doing PA.

Medical guidance

Participants expressed a positive opinion about the opportunity to be informed and supported by medical sources, such as medical doctors and devices. This aspect would contribute to make the app more credible, reliable and trustworthy. Moreover, thanks to the presence of a medical perspective, participants expected the app to be able to provide feedback about physiological parameters strictly related to health.

"bisognerebbe farlo sotto controllo, quindi o ti tieni sotto controllo e vedi il medico sportivo per elettrocardiogramma sotto sforzo… più che altro sennò potrebbe essere pericoloso secondo me, cioè pericoloso…"

“un’altra cosa interessante potrebbe essere la pressione arteriosa visto che comunque ho la pressione abbastanza alta, quindi mi interesserebbe vedere gli sbalzi e l’andamento nel corso dell’attività fisica: queste sono le cose che cercherei”

“*un’affinità medica delle nuove tecnologie del futuro secondo me potrebbe essere la vera differenza”*

Fitness and weight management

Focus group participants reported to be mostly interested in doing PA in order to have some physical benefit such as weight loss and cardiovascular fitness.

“perché obiettivamente vorrei perdere un po’ di chili, essere un po’più tonica, un po’ più dinamica”

“questo tipo di attività hanno il vantaggio che alzano tantissimo il metabolismo e quindi ti consentono magari di mangiare un po' di più e con più soddisfazione, mantenendo il peso”

“*però la vedo sempre rapportata all’obiettivo principale che deve essere quello: perdere peso sicuramente, la pressione, il cuore. Ecco quest’app la vedo come supporto, aiuto al benessere fisico.”*

2.2.1.3. Human support

Participants evidenced the motivational component underlying the interaction with human elements. In their perspective, human support constitutes a trigger for practicing PA because it helps to create higher level of commitment and to make exercise a more enjoyable activity. In particular, two different types of human support came up.

Peers support

Social support was seen as an important element to boost the individual motivation and to leverage on social commitment through the organization of group activities. Participants described peers support as a way to overcome laziness and as a prompt for being more active.

“hai l'appuntamento, quindi non ti tiri indietro”

"un gruppo di amici per invogliarci con anche attività diverse ogni giorno così, spronarci, magari sì, un giorno con quell'amica, un girono con l'altro, comunque non proprio da sola"

"molto pigra da sempre e fondamentalmente la pigrizia è anche un fatto che non mi piace fare le cose da sola, quindi se ho qualcuno con cui farla, ok, sennò da sola non…"

"mi spronerebbe di più, per motivarmi di più a condividere con loro, quindi a stimolarmi a essere più attiva, io parlo per me in ogni caso e ad esempio anche il discorso legato alla competizione secondo me, sempre parlando per me non sarebbe interessante"

It was particularly interesting how the concept of *sharing* was re-framed, considering it in terms of sharing exercise activities rather than sharing results of PA through social networks.

"una delle mie massime è "preferisco essere socievole che essere social" […] qualcuno con cui poter andare a correre, quindi un discorso più di condivisione. Non però legata al mettere sto facendo questo, quindi al far sapere a sconosciuti o dal mio punto di vista"

Virtual personal trainer support

Participants agreed on the fact that the app should work as it was a personal trainer. The motivations underlying such a preference relies on the added value in having a trainer that knows each user and consequently suggest what to do in order to achieve personal goals and facilitate the receipt of emotional support.

"io sì, strofinerei il telefonino e farei uscire un bel personal trainer perché a me piacerebbe"

"se io decido di raggiungere una certa forma fisica o un certo… dal peso da stabilizzare la frequenza cardiaca… che ne so, cose di questo tipo. Che mi segua un po' di più come fosse un piccolo personal trainer"

"avrei bisogno di un'applicazione che sia invece molto un personal trainer che mi monitori comunque abbastanza, [...] io ho bisogno di qualcuno che mi stia dietro"

“vorremmo un genitore che ci conosce, ci vuole bene, ci dice cosa dobbiamo fare”

2.2.1.4. Private dimension of PA

Most of participants reported that PA is a personal aspect of their life, as a consequence they were not interested at all in competing against or being compared to other users.
Furthermore, participants manifested some concerns about features that can reveal sensitive information (e.g., geolocalization) to strangers.

“assolutamente non vorrei fare confronti con gli altri, non penso che sia una cosa utile mentalmente e personalmente. Non mi piace!”

“cioè non mi piace competere, preferisco appunto condividere piuttosto che competere, quindi primeggiare piuttosto che essere seconda”

“preferirei farlo per fini personali e non per fini competitivi a tutti i costi, non la vedo una cosa positiva”

“queste cose io non le condivido con nessuno, per me sulla parte di... siccome per me è un dovere, non è questione di piacere non è una cosa che metto su… in questo penso la parte social dentro di qua l'azzererei”

“per quanto riguarda la geolocalizzazione, la trovo una cosa pericolosissima, perché obiettivamente io trovo pericoloso quella per trovare altre persone che usano la stessa app. Per la privacy ma anche per una pericolosità perché… io faccio nordic [walking] in aperta campagna”

2.2.1.5. Smart and tailored

Participants imagined a PA mobile app that is able to understand and consequently adapt to individual circumstances and motivations. For this purpose, the app should take into account a series of personal parameters (e.g., physiological and affective states, progress in exercise ability, goals, contextual factors) and smartly integrate them to provide tailored and effective strategies to achieve goals.

“quando cominci l'allenamento ti dice "ma oggi come stai?" "mh oggi non ho voglia" "Beh allora ti faccio fare questo giro qua" e va a recuperare in memoria magari quel giro di quella volta che anche lì non avevi tanta voglia”

“deve essere un po’ anche personalizzata, nel senso magari oggi a livello proprio fisico non mi sento bene e lei non mi deve ogni volta… no! Se quel giorno magari sono un po’ così devo fare qualcosa di più leggero. Altre volte, se capita, magari sono un po’ più sprintosa e allora mi viene dietro in questo”

“in base a come tu compili i dati iniziali quando scarichi l’app, che hai gli obiettivi che vuoi mettere, che metti, e lui che ti dia un livello di difficoltà o dei paletti da andare a raggiungere in base a tu come ti stai allenando in quel periodo”

“qua si tratta di dare dei suggerimenti conoscendo la persona, conoscendo le motivazioni”

“cioè [le app] sono troppo generiche al momento, rendono delle informazioni che sono standard e probabilmente non sempre vanno bene”.

2.2.2. Discussion

The present study highlighted and deepen what and why potential features of a PA app are considered to be important for engagement by potential users. The study adopted a focus group methodology with elements of co-design in order to elicit participants to reflect about app features and help researchers to characterize the design process. The study found that features that enhance users’ self-regulation and those that focus on the PA impact on health were judged to be relevant for engagement. Human element was considered as a trigger for exercise, on condition that it adopts a supportive and motivational style; for this purpose, both a personal coach embedded into the app and opportunities to develop a network of PA peers were judged as relevant features. Differently, participants were sensitive to the private dimension that characterize their approach to exercising and, thus, preferred to avoid features that elicit social comparison or that share personal information. Finally, participants believed that a smart and tailored interaction between user and app would foster a more

effective engagement by providing user- and context-based strategies for achieving personal goals.

Potential users' preferences for self-regulation features are consistent with previous findings (see chapter 4) and corroborated results from a recent review (Perski, et al., 2016) suggesting that *behaviour change techniques* (BCTs) such as goal setting, feedback and self-monitoring are associated with higher engagement. Specifically, such features permit participants to monitor their progress, evidencing any potential discrepancy between their PA behaviour and goal. Interestingly, self-regulation features (i.e., setting goals, monitoring behaviour, receiving feedback, and reviewing relevant goals in the light of feedback) have been shown to be effective in increasing PA (Michie, Abraham, Whittington, McAteer, & Gupta, 2009). A similar convergence of empirical evidences clearly validated the idea that self-regulation features deserve to be considered as the core component of PA apps. It should also be noted that although commercial PA apps often implement such features (e.g., Middelweerd, Mollee, van der Wal, Brug, & te Velde, 2014), little is known about the quality of their implementation.

Partially consistent with a previous research (see chapter 4), in the present study the intention of exercising more seemed to be mostly related to health and appearance concerns. More specifically, improving cardiovascular fitness and losing weight were repeatedly reported as primary motivations for being active. In order to address this request, PA apps should encompass a wider and more integrated perspective of PA, involving medical guidance to help users to achieve and manage their health-related goals (e.g., weight control, aerobic improvements). For these purposes, new emerging mobile technology, such as self-tracking devices, may provide more reliable and integrated information about PA behaviour and its outcomes (e.g., indicators of weight loss, index of fitness, heart rate).

Human element was perceived by potential PA app users as a trigger for being more active and for increasing their engagement with the app. Although in a previous study (see chapter 4) social support features didn't seemed to be as much relevant as self-regulation

features, it is here interesting to notice that human interactions with peers and virtual coach are judged to be a prompt for being more active and for overcoming laziness. Features connecting the user with a virtual coach or a group of people with similar goals were expected to be important for engagement due to the formation of a shared commitment and to the opportunity of being emotionally supported. Current findings are consistent with previous research (Bickmore, Gruber, & Picard, 2005) suggesting that working alliance and desire to continue working with a digital behaviour change intervention to promote PA are higher when supported by the presence human-relational skills (e.g., empathy, social dialogue) designed into a computer interface. Corroborating findings from a scoped review of web-based interventions, evidenced the potential of supportive virtual coaches as a valuable remedy to low adherence in digital interventions (Scholten, Kelders, & van Gemert-Pijnen, 2017).

Consistent with previous research targeting different behaviours (Dennison, Morrison, Conway, & Yardley, 2013; Perski et al., 2017), potential users of PA apps are reluctant to share information with social networks about the PA performed. Indeed, users perceived PA behaviour change as a personal path and there is not merit in showing it to other users. The dislike for competition and social comparison is coherent with a previous study (see chapter 4), indeed competence and competition were among the less relevant motives for practicing PA and social comparison came up as one of the less liked BCT. Furthermore, participants definitely reject the idea to think about PA from a competitive perspective, probably because any source of social comparison or competition with more successful users might discourage them and constitute an additional stressful element.

Finally, participants imagine a smart and tailored PA app that is able to 'understand' the users and consequently support them as and when required. For example, action planning strategies based on the user's time-table and suggestions tailored to the user's level of progress towards a specific goal were expected to be more engaging and effective. A similar need for a tailored approach was also found in previous research investigating users' preferences for design features related to smartphone apps for drinking reduction and

smoking cessation (Perski et al., 2017). Additionally, participants emphasized the interest into a flexible PA app that in real time adapts the intervention content to the specific context and to the variations in the users' motivational and emotional states. This suggestion is in line with recent emerging research that paid attention to the development of Just-in-Time Adaptive Interventions (JITAIs) (Hekler, Michie, Pavel, et al., 2016) and that focused on tailoring PA interventions on motivational aspects, such as self-efficacy beliefs (see chapter 3; Pirolli, 2016).

3. Study 3b

3.1. Materials and Methods

3.1.1. Study design

This study used a one-arm pre-post design with a 2-week follow-up using qualitative methodologies. Specifically, think aloud methodology and semi-structured interviews techniques were used. Think aloud is a method that required subjects to talk aloud while performing a task. The distinctive and most relevant value in adopting think aloud methodology relies on the fact that it generates data directly from the ongoing thought process during a specific experience (Jaspers, Steen, Van Den Bos & Geenen, 2004). In the present study, such a methodology was used during baseline in order to ask participants to verbalize their thoughts, impressions and feelings whilst engaging with a specific and never-used PA app provided by the researcher. Semi-structured interviews provided researchers with an additional tool to retrospectively investigate i) the exploration of the app during baseline, and ii) the app use during the 2-week follow-up.

3.1.2. Participants

Participants were recruited in order to represent the target population of *Muoviti!*. Eligibility criteria for taking part in the study were i) age between 30 and 50 years old, ii) no pre-existing health conditions that would impede to practice PA, iii) no clinical conditions related to physical inactivity (e.g., obesity, diabetes), iv) PA behaviour not in line with the recommended PA guidelines (i.e., 150

minutes of moderate PA or 75 minutes of vigorous PA per week), v) willingness to increase PA and interest in doing so through mobile technologies; vi) own an Android or iOS smartphone with internet access that is capable of running mobile apps.

3.1.3. Sampling

Participants were recruited through social media (e.g., Facebook), snowball sampling methods, and posters placed in the university campus. The aim of the research and the eligibility criteria were specified in the recruitment materials. Participants enrollment stopped when no relevant different insights of participants' experiences and novel themes came up from interviews (i.e., when theoretical saturation was achieved).

3.1.4. Measures

Self-report questionnaires were administered before conducting the focus groups. Participants were asked to report information about: 1) age; 2) gender; 3) pathologies or physical conditions that prevent participants to be physically active; 4) pathologies associated with sedentary behaviour; 5) physical activity during leisure time, measured using the Global Physical Activity Questionnaire (GPAQ; Armstrong, & Bull, 2006); 6) intention to increase PA; 7) interest in increasing PA with the aid of a mobile app; 8) whether participant have ever used an app to increase physical activity (if yes which app). The screening questionnaire was hosted by Qualtrics survey software.

3.1.5. Procedure

Prior to the study, participants filled out an on-line screening questionnaire (see paragraph 3.4.) in order to verify if they were eligible to take part in the study. Participants who respected the inclusion criteria were contacted by the researcher to schedule the baseline assessment. Before conducting the baseline activities, a PA app was randomly allocated to each participant, who were informed of the allocation during the think aloud task. Baseline activities were characterized by a pre-task interview, a think aloud task, and a semi-structured interview (see appendix 1). After

completing the baseline assessment, participants were asked to use the app for the following two weeks. They received no indications in terms of app use (e.g., how many times per week) in order to avoid to influence their engagement and experience with the app. Participants were just encouraged to use the app in the real world setting, trying to use it to increase their PA accordingly to their intentions. After one week, participants were contacted to verify whether they were actually using the app and if they were will willing to continue for one more week. Two weeks after baseline, participants completed an audio-recorded semi-structured telephone interview, using an interview schedule (see appendix 2) as a guide.

3.1.6. Mobile applications

The PA apps chosen for the study were *Runtastic Running & Fitness Tracker*, *Endomondo - Running & Walking*, & *Runkeeper - GPS Track Run Walk* (henceforth shortened as *Runtastic*, *Endomondo*, and *Runkeeper* respectively). The researchers have no association with the developers of such apps. The three PA apps which are commercially available to download by the general public were chosen on the basis of the following criteria:

- *Type of physical activity:* targeting aerobic PA;
- *Monitoring:* being able to monitor PA without the need for other external devices (e.g., HR monitor, external pedometer);
- *Popularity:* more than 10 mln downloads;
- *Ratings:* user ratings above 4,5 stars;
- *Category:* belonging to health and fitness app;
- *Stability:* launched at least 2 years prior to the study;
- *Availability:* availability on both iOS and Android devices;
- *Free:* freely downloadable from both iTunes and Google Play.

The selected PA apps served as stimuli to provide the users with real experiences and, thus, to elicit their views and perspectives after their use. The methodological choice to adopt three apps, rather than only one, aimed to provide participants with multiple stimuli and potentially raise more aspects to be discussed. However, a number of apps higher than three was hypothesized to be

associated with too variance, with a resulting risk of exposing participants to too different apps features. For this reason, as additional caution, before conducting the study, apps were characterized in terms of implemented BCTs in order to control for potential differences in their features. Table 1 provides a description of the BCTs incorporated in the selected apps and coded by adopting the Behaviour Change Technique Taxonomy (v1) (Michie et al., 2013).

Table 1. App characteristics

App (Developer)	**Behaviour Change Techniques (BCTs)**
Runtastic Running & Fitness Tracker	1.1. Goal setting (behaviour) 2.2. Feedback on behaviour 2.3. Self-monitoring of behaviour 2.4. Self-monitoring outcome(s) of behaviour 2.7. Feedback on outcome(s) of behaviour 3.3. Social support* 4.1. Instruction on how to perform the behaviour 5.1. Information about health consequences 5.4. Monitoring of emotional consequences 6.2. Social comparison* 9.1. Credible source 10.5. Social reward
Endomondo - Running & Walking	1.1. Goal setting (behaviour) 1.9. Commitment 2.2. Feedback on behaviour 2.3. Self-monitoring of behaviour 2.4. Self-monitoring outcome(s) of behaviour 2.7. Feedback on outcome(s) of behaviour 3.3. Social support* 6.2. Social comparison* 10.5. Social reward
Runkeeper - GPS Track Run Walk	1.1. Goal setting (behaviour) 1.3. Goal setting (outcome) 1.4. Action planning 2.2. Feedback on behaviour 2.3. Self-monitoring of behaviour 2.4. Self-monitoring outcome(s) of behaviour 2.7. Feedback on outcome(s) of behaviour 3.3. Social support* 5.4. Monitoring of emotional consequences 6.2. Social comparison* 10.5. Social reward

Note. these BCTs are not directly delivered by the app itself, however it allows the user to create groups and organize challenges with friends.*

3.1.7. Data analysis

A qualitative analysis of the focus group transcripts was performed using inductive thematic analysis (Braun & Clarke, 2006). Thematic analysis is characterized by six phases: have been

identified: i) familiarising with the data, ii) generating initial codes, iii) searching for themes, iv) reviewing themes, v) defining and naming themes, and vi) producing the report. Baseline and follow-up transcripts were considered two different data sets and were analysed separately in order to address the different research questions. Data and repeated patterns that were considered pertinent to the aims of the study (i.e., understanding what features shape users' engagement expectancies and evaluation during a first exposure to never-used PA apps and what features are judged to be determinant for supporting engagement and satisfactory experiences after a 2-week usage of PA apps) were coded by the primary researcher. New inductive codes were labelled as they were identified during the coding process and the results of the coding were iteratively discussed with other two researchers. The next stage involved searching for themes; the primary researcher reviewed the codes one by one, organizing the findings in order to combine the different codes that have been considered focused on the same aspect. The ordered data were reviewed and revised in discussion with the other two researchers and were subsequently organised into themes. Recruitment stopped when theoretical saturation was achieved (i.e., no new themes were identified). Disagreements resolution and agreement on the final themes was reached through discussion within the entire research group. After having defined and named themes, examples of transcripts were selected to corroborate themes on the basis of their representativeness and relevance. Data were analysed in their original language to preserve the participants' original meanings, although coding and themes were formulated in English only.

Quantitative data from the on-line screening questionnaire were analysed using descriptive statistics with SPSS 22 (IBM corp, 2014).

3.2. Results and discussion

3.2.1. Results

Twenty participants (55% male; mean age=39.8 years; *SD*=7.0) took part in the study. Among them, 35% had made an attempt to increase their PA in the past six months and another 35% of participants had already used a PA app as a support to increase their PA. Participants were contacted for follow-up interview after having used the app for two weeks in a real setting. Among

the 20 participants who completed baseline activities, 17 participants completed the follow-up interview as well, one participant was excluded because he never used the app during the two weeks, and two participants dropped-out.

Six themes were developed in relation to the first research question and were named: “features that enhance a fair and simple user experience”, “features that enhance self-regulation”, “fitness and weight related features”, “human support”, “private dimension of PA”, and “tailored goal and action planning”. One subtheme originated from the “features that enhance self-regulation” theme: “efficient and reliable monitoring and feedback of PA”. Additional two subthemes were developed in relation to the “human support” theme: “peers support” and “personal trainer support”. Four themes came up in relation to the second research question. Specifically, three of them completely overlapped with the ones related to the first research question, thus the same labels were maintained: “features that enhance a fair and simple user experience”, “features that enhance self-regulation”, “fitness and weight related features”. Furthermore, one additional theme was developed: “Proactive features to enhance users’ motivation”.

Results are organized in order to present firstly those themes that were developed in relation to both the first and second research question; successively, themes specific to each particular research question are introduced separately.

3.2.1.1. What features influence users’ engagement during a first exposure to never-used PA apps and after a 2-weeks use?

3.2.1.1.1. Features that enhance a fair and simple user experience

Baseline

Participants evidenced the importance of PA apps able to promote a simple, easy, and fair interaction with the users. In particular, as suggested by participants, the app should be simple and not cognitive demanding or time consuming.

“Dev’essere semplice, non con troppa roba che poi ti complica la vita” P11

"Deve essere semplice, intuitiva perché è molto ricca questa applicazione, secondo me ci si perde un pochino" P17

"Se ci vuole il manuale di istruzioni e una settimana per capirla, ho già mollato il colpo" P1

"Se io devo passare ore e ore a cercare informazioni, dopo un po'mollo la partita" P15

Participants reported to feel particularly in discomfort when they are asked to register data and information about themselves; rather, they would prefer an app that automatically register information.

"Se uno è come me che non sta attaccato al cellulare ogni secondo e che smanetta dappertutto, dopo un po' fa fatica insomma a mettersi lì e registrare tutto" P1

"Odio quando ti devi registrare per qualsiasi cosa!" P2

Participants manifested a strong dislike about obtrusive interactions, such as inappropriate reminders or advertisements.

"Non mi piace tanto il fatto che a volte vada a finire su internet ehm… non so, quanto meno dovrebbe forse avvisare, dire non so stai andando sul negozio… poi va beh uno lo impara probabilmente che premendo sulle pubblicità di abbigliamento va a finire su internet" P16

"Deve essere una notifica proattiva ed efficace, non deve rompermi ogni 5 secondi" P19

<u>*Follow-up*</u>

After a 2-week use, participants still reported simplicity and easy-to-use as essential prerequisites for supporting an engaging and in-depth use of the app. The quality of the interaction influenced the overall judgement about the app and affect the opportunity to fully exploit its functionalities.

"Mi è piaciuto perché appunto l'ho trovata di facile consultazione" P6

"È molto veloce da consultare, facile da far partire" P7

"La ricerca di alcune informazioni o capire come funziona non è così immediato e devi stare, perderci un po' di tempo, poi probabilmente io di tempo ne avevo poco però

ehm, appunto non è così semplice, non è così immediato; secondo me dovrebbe essere strutturato in un modo più facile ecco." P9

"Una volta sono riuscita ad usarla effettivamente, le altre volte però non riuscivo a capire come fare a farla partire." P13

As emerged during baseline, participants still reported their dislike of pushy advertisements and upgrade-dependent features.

"Ci sono delle pubblicità un po' fastidiose che appaiono sempre essendo la versione non a pagamento" P16

"Le cose più interessanti sono tutte a pagamento, per cui è un po' limitante da quel punto di vista." P11

3.2.1.1.2. Features that enhance self-regulation

<u>*Baseline*</u>

Participants perceived monitoring their own progress as a fundamental strategy for regulating their behaviour towards the goal. For this purpose, they expected to have features that display users progress, evidencing discrepancies between current behaviour and goals.

"Vedere appunto magari la percentuale di raggiungimento magari segnalata da una notifica che mi dice: sei sotto la media, sei sopra la media, stai raggiungendo il tuo impegno oppure no, può essere un modo per ricordarmi dell'impegno preso e vedere la percentuale di raggiungimento di questo impegno" P16

"Però nel contempo devi raggiungere dei miglioramenti che devono essere tangibili e registrarti in modo che tu hai la coscienza che stai facendo qualcosa e stai migliorando" P6

"Alla fine quello che ti motiva dopo che hai fatto una corsa, vai a vedere cos'hai prodotto quindi poi se uno lo fa quotidianamente o costantemente meglio ancora con l'idea che poi può vedere: settimana scorsa facevo tot chilometri in tot tempo, adesso l'ho migliorato, peggiorato, non vado da quindici giorni, ti controlli, ti riesci a monitorare un po'" P3

Follow-up

After having used the app for two weeks, participants confirmed that self-regulation features, such as monitoring and feedback, had a positive effect on their engagement with the app.

"Devo dire che è stimolante il fatto che registra tutte le camminate che fai, quante calorie bruci, ti dice che idratazione hai perso, la velocità media a cui sei andato, che poi sono cose che hanno tutte le app, però secondo me sono abbastanza coinvolgenti. Poi ogni volta ti viene da registrare e da attivarla." P1

"La cosa più interessante di un'app che usi per attività fisica deve essere che ti deve informare, quindi quante calorie hai bruciato esattamente quanti km hai fatto, poi deve usare il GPS per sapere che percorso hai fatto." P2

"Beh penso che sia una cosa che ti sproni di più. Cioè è lì scritto nero su bianco, quindi ti dà più stimolo per quanto mi riguarda." P4

"Capire quanto ho camminato durante i miei 4 giorni all'estero è stato comunque interessante, divertente." P9

In particular, participants appreciated the possibility to monitor their progress over time and, consequently, regulate their own behaviours.

"Mi fa innanzitutto vedere quanto ho dato ogni settimana, se ogni settimana vado ad incrementare il mio livello di attività fisica oppure se vado a peggiorare." P8

"Ti consente di avere una sorta di classifica delle performance, che ti dice se sei migliorato o peggiorato." P19

"Mi è piaciuta perché come ti dicevo questo diario prende nota di quello che fai ed è carino andare a vedere come cambi nel tempo." P11

In particular, participants seemed to be very sensitive to the quality of monitoring in order to collect reliable information about the PA performed and consequently regulate their own behaviour. This aspect constituted a further sub-theme.

Efficient and reliable monitoring and feedback of physical activity

Both during baseline and follow-up participants expressed the desire of having a mobile app that is efficient in monitoring PA and the related parameters (e.g., calories, heart rate). For this purpose, it was evidenced the importance of adopting an app that distinguishes specific types of PA and that provides pertinent and reliable monitoring and assessment of PA parameters, such as calories, distance, speed.

"La precisione, un'app deve essere precisa anche dal punto di vista del rilevatore gps, se devo utilizzare un'app deve darmi info precisi e non generiche, se no non serve a niente" P8 baseline

"Una buona precisione sull'attività fisica effettivamente svolta, ce ne sono alcune che contano anche i tragitti non effettivamente camminati, ehm… qualcosa di un po' più performante" P17 baseline

"In modo tale da veder che cosa ho fatto come allenamento, il tempo, la frequenza, poi se si può appunto collegare. Beh c'è da capire poi nel mio caso, nel tennis, è chiaro che mi dovrei mettere una fascia per vedere la frequenza cardiaca" P16 baseline

"Ci starebbe che un'app possa aggiungere quelli che sono gli allenamenti fatti di altre attività fisiche che non siano corsa o bicicletta." P8 follow-up

"Mi sembra che non ci sia la possibilità di rilevare le pulsazioni… in alcune app simili tu puoi misurarti la pressione per i fatti tuoi con un misura pressione e monitorare ogni giorno minima e massima" P1 follow-up

Specifically, in case the activity can be tracked by GPS (e.g., running, walking, hiking), participants reported their interest in having itineraries available.

"Ah questo è carino! Il fatto di fare dei percorsi come fanno gli altri magari ti dà l'idea di correre in alcune zone intorno a te… che non ci hai mai pensato, magari qui vicino. Questo secondo me non è male, è interessante" P7 baseline

"E' una curiosità, sono stata in giro tutto il giorno, abbiamo fatto percorsi, mi piacerebbe anche guardare sulla mappa… tracciasse il GPS... per questo guardavo se c'era il GPS... il percorso che abbiamo fatto, non so… curiosità di quello che abbiamo fatto" P18 baseline

"Mi è piaciuta l'affidabilità e il fatto che segnasse i percorsi" P19 follow-up

"Mi piacerebbe più avanti poter sfruttare il fatto dei percorsi... quelli che puoi salvare…" P20 follow-up

3.2.1.1.3. Fitness and weight related features

Baseline

Participants manifested their interest for a mobile app that links together PA- and nutrition-related features. Indeed, weight loss and fitness were repeatedly reported as the main goals for being physically active.

"Dipende dai risultati che vuoi ottenere e dal tipo di obiettivo che ti prefiggi, diciamo che nel mio caso è raggiungere un peso forma migliore" P6

"Potrebbe essere un obiettivo anche perdere tot chili, legato sia all'alimentazione che allo sport" P7

"Sarebbe bello tenere uno storico del peso per vedere come varia nel tempo" P19

For these purposes, features that permit users to set goals and monitor their calories intake and energy expenditure were highly appreciated.

"Potrebbe essere integrata da, anche con l'alimentazione ad esempio… quindi calorie bruciate, calorie acquistate" P16

"Il fatto che tu possa fare un piano di allenamento e allo stesso tempo controllare il battito cardiaco e l'alimentazione e vedere come le cose si bilanciano secondo me sì. Queste cose sono quelle che secondo me rendono un'app coinvolgente" P1

Follow-up

After having used the app for two weeks, participants reaffirmed their positive opinion about features related to weight loss and fitness, arguing that such features may definitely support engagement with PA apps. In particular, nutrition suggestions, feedback about calories intake and consumption, and weight loss were greatly appreciated.

"Se fosse completa e integrata con altri menu, come calorie, una dieta, dei consigli sull'alimentazione, aspetti che non ci sono in quest'app o che sono a pagamento, probabilmente coinvolgerebbe di più, altrimenti uno si stufa dopo un po'" P16

"Ci sono le calorie, che a noi donne piacciono tanto perché ci sembra di essere già più magre, e in base a quanto hai fatto e al tempo che hai utilizzato" P12

"Ho visto che potevo collegare anche quello degli alimenti, su cosa mangiare e tutto questo mi è molto piaciuto" P4

"Sicuramente la parte dell'alimentazione potrebbe essere interessante, quindi introdurre quelli che sono i tuoi dati e le tue abitudini alimentari e capire in che modo l'app ti può aiutare ad avere una dieta un pochino più bilanciata, un pochino più sana" P9

3.2.1.2. What features influence the users' engagement during a first exposure to never-used PA apps?

3.2.1.2.1. Human support

Participants expected the apps should provide opportunities for human support. In their perspective, human support is considered as a value in itself and it is mainly conceived as an empathic way to obtain emotional and practical support.

"Secondo me deve essere… non so come dire… mh un po' più umana" P15

"I tuoi amici posso fare… wow, il tifo per te" P3

"In alcune app commerciali c'è la possibilità di interagire in chat con persone che ti rispondono in tempo reale, in caso di dubbio o se devi fare una richiesta." P13

"Se invece parto motivata e mi arriva la notifica che dice "oh, sveglia, hai deciso di fare una cosa, portala avanti!", sarebbe uno stimolo" P11

Specifically, two types of support came up.

Peers support

Opportunities for doing physical activities with peers and interact with them are perceived as a way to boost motivation each other. Participants expected that sharing a same PA goal with peers would help to strengthen their commitment and doing PA together with friends would make the exercise more enjoyable.

"Di solito queste cose tengo a farle nel privato perché so di non essere costante, forse ecco il gruppo potrebbe aiutarti nella costanza però" P11

"Io credo che galvanizzi, è un po' come quando vai in palestra da solo o con un amico, il concetto è quello, ti dai man forte a vicenda" P17

"Magari ho il piacere di dire a un'amica di correre insieme, e finita la mezz'ora mentre recuperi fai quattro chiacchiere" P1

"Oppure con qualcun altro che corre perché così hai qualcuno con cui dire non so facciamo un piano insieme, allora sì!" P7

Virtual personal trainer support

Participants expressed their positive view about the possibility to have a personal trainer – or similar features – embedded into the app in order to obtain practical suggestions and emotional support. Like in real life, the personal trainer should constitute a guide for the users that want to increase their PA.

"*Il miglior modo per raggiungere un obiettivo è avere una persona che comunque ti assiste, a questo punto l'app dovrebbe sostituire un personal trainer" P2*

"Credo che l'app vada un po' a sostituire quello che è l'allenatore in palestra" P15

"Qualcosa che ti monitora man mano che fai questa cosa, come se avessi un allenatore accanto, per essere veramente valida dovrebbe essere così" P21

3.2.1.2.2. Private dimension of PA

The most part of participants considered PA as a private behaviour. As a consequence, they believed that sharing information with one's wider social network is inappropriate and, more

generally, they expressed the desire to avoid social comparison and to keep the focus on themselves

"Non mi piace condividere… perché mi sembra un po' di farmi vedere, no'? quindi non lo so, io quando faccio una cosa la faccio per me, non mi va di mettere in mezzo troppa gente" P11

"Se devo avere un obiettivo, non so… fare un allenamento o decidere di correre tot giorni, non è che mi entusiasmi così condividere la cosa ecco" P16

"Secondo me non deve avere troppe interfacce con i social perché dev'essere una cosa privata" P6

"Mi dà fastidio far sapere agli altri quello che sto facendo, sinceramente sono fatti miei e il confronto è con me stessa" P1

Some participants expressed their like also in relation to more competitive aspects, on condition that competition is conceived as a friendly way to support each other instead of competing against other users.

"La competizione la vedrei a livello ironico, non ho più l'età per mettermi in competizione con nessuno. Per il gruppo bisognerebbe trovare qualcuno con le tue stesse motivazioni" P11

"Bella la cosa della competizione: ognuno fa il suo percorso e poi ognuno fa il tifo" P3

Finally, few participants seemed to be prone to compete against other users and took it seriously. However, due to their current fitness conditions, they would prefer not to compete till the moment their physical condition will improve.

"Sono molto competitivo, quindi farò la mia competizione quando so di essere al top" P2

"Classifica, con gli amici… no non voglio andare subito in competizione, faccio schifo" P3

3.2.1.2.3. Tailored goals and action planning

Features that help users to implement intentions and achieve goals were judged to be relevant for engagement with PA apps. For such purposes, participants expected the app provides plans to achieve individual goals.

"Ecco questa è una cosa carina: creare un piano in base ai tuoi obiettivi." P1

"Ti danno il piano di allenamento e raggiungi i tuoi obiettivi, bellissimo questo." P4

"È come avere un personal trainer… se uno vuole fare un allenamento mirato per un obiettivo specifico" P17

"Mi basterebbe potergli dare il mio obiettivo, che ne so la maratona, voglio fare la maratona tra 6 mesi… quindi dirgli cosa voglio fare, in quanto tempo voglio farlo e basta e poi lui dovrebbe darmi un paio di possibilità per... come piani insomma…" P18

In developing action plans, PA app should be as a guide that step-by-step provide the users with suggestions and advises about how to exercise.

"Eh almeno ti [piani di allenamento] danno un'idea di cosa fare, perché io essendo proprio agli inizi non saprei neanche da che parte iniziare. Invece lì proprio... cioè... ti spiegano proprio tutto bene." P4

"Che ti guidi in qualche modo verso degli step, degli obiettivi da raggiungere piano piano, magari indicandoti anche che tipo di attività fare, dandoti consigli." P16

3.2.1.3. What features are judged to be determinant for supporting engagement and satisfactory experiences after a 2-week usage of PA apps?

3.2.1.3.1. Proactive features that enhance users' motivation

After a 2-weeks use of the app, participants expressed their skepticism about the capacity of the app to boost motivation and to provide novel features that spark their interest. From their perspective, the app was more a functional tool rather than a trigger for starting exercising.

"Devi avere tanto spirito e buona volontà per accedere all'app e andare a correre, è giusto che l'app non può fare più di tanto" P2

“Era un po’ la mia forza di volontà che mi faceva andare a correre, non tanto l’app onestamente” P15

“Però posso dirti lei, l’applicazione di per sé, no, non mi ha stimolato a cambiare la mia attività questo te lo posso dire” P18

“Non mi ha coinvolto particolarmente, forse proprio perché non aveva funzionalità in più all’altra che avevo già utilizzato, quindi il fatto di aver utilizzato quest’app non mi ha spinto a voler fare di più per avere più informazioni, più statistiche, più allenamento, cose così” P8

“Cioè non ha un valore aggiunto, non ha nulla di più” P18

Participants who had enjoyed their experience with the app expressed their positive judgment for proactive features, such as reminders and suggestions, that worked as a trigger both for doing PA and for supporting effective engagement with the app.

“Ti dà le indicazioni su quanta attività fare in settimana, come aumentarla eccetera eccetera, questo mi è piaciuto!” P1

“ci sono dei suggerimenti che ti aiutano a prendere piano piano confidenza con il movimento” P12

“Mi è piaciuto il fatto della sveglia, cioè che ti dica guarda che oggi è mercoledì e devi fare l’allenamento” App15

“L’altro aspetto positivo sono le notifiche che arrivano ogni tanto, che non disturbano ma stimolano a riprendere l’app, quindi c’è la giusta frequenza di notifiche” P16

In a similar way, participants who experienced a gap of proactive features expressed their desire for having a more interactive and prompting app.

“*Un coinvolgimento da 10 sarebbe una persona che mi butta giù dal letto e mi dice vieni a correre con me.” P2*

“*Avrei preferito che mi ricordasse di fare attività, tipo: "sei una pigra, guarda che devi andare a camminare" [...] quest’app non si fa sentire, non ti stimola” P11*

"Potrebbe in qualche modo spiegare, non essere solo un'app che registra le cose che fai, ma che ti educhi in qualche modo, quindi con anche parti da leggere, notifiche con alcune informazioni che possano poi dare uno stimolo ecco" P16

Finally, after having used the app for two weeks, some participants pointed out that social incentives and challenges might contribute to make the app more stimulating. Indeed, participants interested in social features, started to consider them as a further potential way to be motivated by external cues and to enjoy PA.

"Poi il fatto di collegarsi anche con gli amici, con la gente della zona… è una cosa che ho scoperto adesso!" P4

"L'ho utilizzata io questa settimana senza pensare di coinvolgere altri, poi magari utilizzandola in modo regolare può essere interessante, come ti dicevo più per condividere le cose fatte, per la sezione sfida che c'era che può essere interessante." P16

"Magari si può fare una gara con persone che non si conoscono per aumentare le proprie prestazioni" P8

3.2.2. Discussion

The study investigated what features of PA apps are considered to influence engagement during a first exposure to a never-used app and to sustain it after a 2-week use. Participants' perspectives were elicited through a direct experience of PA apps in real setting in order to obtain ecologically valid insights. This last point is particularly relevant because it permitted to address some aspects related to user's experience that didn't emerge in study 1. Indeed, in addition to preferences for specific content features, participants from study 2 consistently expressed their desire to have a mobile app that is simple to use, intuitive, and that doesn't annoy the user with pushy advertisements. Such a theme, that emerged both during baseline and follow-up interviews, confirmed research advises arguing that the involvement of users with technology during real-time usage is needed to assess the easy-of-use of a digital product and how it fits with the users' everyday life (van Gemert-Pijnen et al., 2013).

Features that enhance self-regulation and those that focus on fitness and weight loss were considered important for engagement both during a first exposure to PA app as well as after two weeks of use. Preferences for self-regulation features confirmed previous findings (see study 2; study 3a; Middelweerd, et al., 2015) suggesting that potential users of PA apps are prone to monitor their own behaviour, receive feedback and consequently adjust their behaviour in order to achieve PA goals. Thanks to monitoring systems and feedback from the app, users, as they said, are able to monitor their progress and place their motivation and satisfaction in their achievement or, otherwise, put greater efforts in regulating their behaviour in case there is a discrepancy with the goal. As evidenced during the interviews, it is important to support users with efficient and reliable tools for monitoring and assessing PA; furthermore, it is essential to give the opportunity to monitor different types of physical activity according to the users' preferences, providing information about the respective most relevant parameters and indices. For instance, people who prefer running or hiking reported to be satisfied by GPS information with feedback about itineraries and elevation gain; differently, people who played activities like football or tennis may benefit more from devices that are able to assess human movement (i.e., accelerometer) or energy expenditure (i.e., heart rate monitor). Participants considered features related to fitness and weight loss relevant for engagement with PA apps. Preferences for such features, interpreted on the basis of results from a previous study (see study 2), are probably due to their suitability in answering the prevalent users' PA participation motives. Differently from study 3a, participants seemed to be less focused on medical guidance but more strictly interested to benefit from suggestions about how to lose weight (both in terms of PA to do and nutrition advises) and to have the possibility to keep all the relevant parameters under control (i.e., weight loss, discrepancy between calories intake and consumption).

Consistent with study 3a, users' need for human support features emerged also during a first exposure to PA apps. In particular, participants believed that opportunities for sharing support with peers may help to develop a climate of social commitment that boosts motivation and makes exercising a more enjoyable activity. The motivational aspect associated with human support was also mirrored by the users' preferences for coaching features directly embedded into the app. Such

results further corroborated users' suggestions emerged in study 1, results from a focus group study about preferred PA app features (Middelweerd, et al., 2015), and previous findings arguing the positive effect of a 'relational skilled' digital technology on engagement (Bickmore, et al., 2005; Sholten et al., 2017).

Similarly to study 3a and in line with previous findings (Dennison et al., 2013; Perski et al., 2017), participants tended to consider the behaviour change process as a personal aspect of their life, confirming their reluctance to share PA information through social networks. Such point of view may be related to the particular age that characterized the sample. Indeed, conversely, previous research (Middelweerd, et al., 2015) evidenced positive attitudes of young adults (aged between 18 and 25 years) towards sharing personal PA achievements through social media. Users' judgements about competitive features were partially reconsidered in the current study. Indeed, some participants expressed a positive judgment about such features, on condition that competitions help to provide occasion for mutual social support. Other participants would compete against other users, but just once they will have gained a better fitness. It is interesting to notice that "private dimension of PA" came up as a theme during baseline interviews but not during follow-up. Such result was probably due to the fact that social features, such as opportunities for sharing PA through social networks or competing against other users, are optional and users are not forced to interact with them.

One further theme labelled "tailored goals and action planning", that emerged just during baseline interviews, relates to the guiding role of the app in supporting users to implement their intentions and to achieve their goals. More specifically, users expressed their desire to be provided with PA plans and suggestions that are tailored to their goals and progress. Such theme is similar to the one emerged in study 1 and labelled "smart and tailored", however, in this case, participants, didn't evidence any active role of the app in interpreting the user's needs and, consequently, in being flexible to adapt the intervention in real time. Participants' preferences for tailored planning features underlined the users' awareness about the crucial role of action planning to promote goal attainment (see Schwarzer, 2014).

A final theme labelled “proactive features that enhance users’ motivation” emerged during follow-up interviews. After having used PA apps for two weeks, some participants admitted that the real push for exercising relied on their motivation and willpower rather than on the prompts from the app. Both participants who liked the app and those who didn’t like it reported the desire to interact with a proactive app. Indeed, proactive features (e.g., suggestions, reminders) were highly appreciated by participants who enjoyed the experience with the app and were mentioned as a point of improvement by those participants who weren’t completely satisfied. Hence, it was possible to argue that a different dosage of proactive features may influence users’ engagement with the digital intervention. Furthermore, it seemed plausible to hypothesize that the influence of such features on engagement and behaviour change may be moderate by users’ self-regulation skills. Indeed, users with less self-regulation skills might rely more on proactive features than other users. In this sense, app proactivity is mainly required to integrate self-regulation features and to avoid that the whole behaviour change process depends on the users’ self-regulation skills.

4. General discussion and implication for the design of *Muoviti!*

By triangulating findings from study 3a and study 3b, it was possible to outline a comprehensive picture of the users’ preferences for PA app features (see table 2 for a summary). Design requirements and guideline principles for the development and implementations of *Muoviti!* will originate from this synthesis.

The findings that potential users are interested in self-regulatory features supported current design practice in PA apps, however some improvements can be introduced. First, users should be able to monitor and assess the PA they perform in an efficient way. As a consequence, devices like reliable HR monitors and PA trackers deserve to be considered as complementary tools in order to i) permit the users to self-monitor their PA without wearing smartphones, and ii) to provide the more relevant feedback (e.g., HR, GPS track, pace) for each specific type of PA performed. Furthermore, features that enable users to draw their attention to PA progresses and to any discrepancy between PA behaviour and goals may surely help to guide their self-regulation and efforts.

As potential users would practice PA in order to improve fitness and to lose weight, PA apps should i) deliver suggestions about what and how to exercise in order to achieve specific health-related goals, ii) provide nutritional advises and opportunities for monitoring the food intake, iii) monitor and provide feedback on health-related progress (e.g., weight loss, waistline reduction, blood pressure), and iv) permit users to estimate the daily and weekly difference between calories intake and consumption. For these purposes, it is important that healthcare and medical professionals collaborate with app developers in order to ensure the validity of health-related advises and support.

While interacting with PA apps, simplicity and usability influenced the users' perception of the app. Indeed, simple apps were seen as more easy-to-used and, thus, more immediate and useful. In particular, users expected that apps shouldn't be cognitive demanding nor time consuming. As a consequence, developers are asked to design PA apps that assures an immediate and efficient use and consultation, avoiding that a poor and inadequate user experience constitutes a barrier to engagement and behaviour change. To this end, design and implementation phases should be characterized by a constant and iterative evaluation of the app usability through cycles of low- and high-fidelity prototypes testing. Finally, in order to preserve a sense of professional credibility and fairness, advertisements for upgrades and companion commercial products (e.g., sportswear) should be removed from PA apps.

Potential users mainly didn't appreciate the opportunity of sharing PA achievements with other people and they considered PA as a private domain of their life. Although some of them argued that competition with peers might work as a trigger for exercising more, social comparison features didn't emerge as must-have features. As a consequence, in the first instance developers should give the priority to other more important and cost-effective features (e.g., self-regulation features).

The finding that users would like to have a smart app that is able to 'understand' the users implies that developers should tailor the content of PA apps in order to address personal goals, achievements, cognitions, and emotional states. For this purpose, a continuous ecological assessment of psychological determinants of PA can help to set goal and develop more effective

action plans. Such results provided support for the validity of recent research (see chapter 3; Hekler et al., 2016; Pirolli, 2016) that aimed at developing digital intervention that integrate behavioural, psychological, and contextual variables in order to deliver more tailored and potentially effective strategies to increase PA. To this end, flexible and adaptive action plans and suggestions tailored to the users' achievements might help to support their self-regulatory skills.

Finally, findings suggested that human support is perceived as a crucial element that i) permits to create a stronger commitment to PA goals, ii) provides emotional support, and iii) makes exercising a more enjoyable activity. In order to address such requirements, the design of PA apps may be improved by providing opportunities to connect users one another and to easily arrange for social PA events. As pointed out, there may be merit also in designing PA apps that interact with users in the same way as a personal trainer. Hence, developers may consider the opportunity to characterise PA apps by the presence of human-relational skills or components (e.g., virtual agent, empathy, social dialogue).

As evidenced during follow-up interviews in study 3b, proactive features (human support, tailored PA plans and suggestions, and context aware prompts) constitute one of the main gaps of commercial PA apps. This is a crucial point because, as emerged in the current studies, the development of a proactive app that is able to tailor the intervention content according to individual differences and different circumstances is hypothesized to be a key element for supporting effective and sustained engagement with digital interventions. To overcome this limit, a close collaboration between behavioural and computer scientists is required for developing machine-learning techniques that permit to understand, predict and meaningfully address users' needs.

Table 2. Summary of themes and subthemes identified in a) the focus groups, b) the baseline interviews, and c) the follow-up interviews

Theme	Description	Focus group (Study 1)	Baseline (Study 2)	Follow-up (Study 2)
Features that enhance self-regulation	Features that permit users to self-regulate their behaviour according to their progress towards goals (e.g., self-monitoring, feedback, goal setting).	√	√	√
Efficient and reliable monitoring and feedback of PA	Features that support an efficient monitoring of PA and the related parameters (e.g., calories, heart rate).		√	√
Features that are relevant for health	Features that permit to relate PA behaviour to healthy outcomes, such as fitness and weight loss. Health related features may be implemented in terms of feedback and suggestions.	√	√	√
Medical guidance	Opportunity to be informed and supported by medical sources, such as medical doctors and devices.	√		
Fitness and weight management	Features that permit to relate PA to fitness and weight loss goals, with a particular focus on monitoring and receiving feedback about calories intake and energy expenditure.	√	√	√
Human support	Features that stress the motivational component underlying the interaction with human elements in order to create a higher level of commitment.	√	√	
Peers support	Features that provide opportunity to benefit from peers' support in order to overcome laziness and as a prompt for being more active	√	√	
Virtual personal trainer support	Coaching features that suggest what to do in order to achieve personal goals and facilitate the receipt of emotional support.	√	√	
Private dimension of PA	Dislike in competing against or being compared to other users and concerns about features that make sensitive information (e.g., geolocalization) public.	√	√	
Smart and tailored	Features that permit the app to understand the user and consequently adapt the intervention to individual circumstances and motivations. For this purpose, the app should smartly integrate input data (e.g., physiological and affective states, contextual factors) to provide tailored and effective strategies to achieve goals.	√		
Fair and simple user experience	Features that enhance an easy, simple and fair interaction with the users, avoiding to be cognitive demanding or time consuming.		√	√
Tailored goal and action planning	Features that help users to implement intentions and achieve goals through the predisposition of tailored plans.		√	
Proactive features to enhance users' motivation	Features that prompt and stimulate the users by sparking their interest and motivation (e.g., reminder, suggestion, social activities).			√

5. Limitations and conclusions

Although the adoption of qualitative methodologies is a distinctive point of the studies and it is consistent with a user-centred approach to intervention design (e.g., Yardley et al., 2015), the magnitude of relationships between beliefs and attitudes, intentions and PA behaviour couldn't be assessed. Thus, quantitative observational research and interventional studies in larger samples should be conducted to test current findings, including objectively measure engagement (for an operationalization of engagement see Perski et al., 2016) and PA behaviour. Furthermore, as participants in the present studies had different digital literacy, it is possible to argue that less 'digitally educated' participants had more difficulties to interact with PA apps and, thus, less opportunities to engage with them.

The current study sought to explore users' needs, motivations, and experiences regarding PA apps through the adoption of various perspectives: while co-designing an imaginary PA apps, during a first exploration of a never-used app, and after a 2-weeks use. Study 1 adopted co-design methodology to prompt users' creativity in order to elicit any novel idea without confining users' insights to real experiences and stimuli. Conversely, study 2 exploited existing apps to understand what design features foster or hinder (sustained) engagement with PA apps in real settings. A triangulation of findings from current studies permitted to outline design features and requirements that deserve to be implemented in *Muoviti!*. To our knowledge, this was the first attempt to adopt and integrate various qualitative methodologies (i.e., co-design, think-aloud, in-depth interview) and experiences in real life to provide valuable information for future app-based interventions that target sedentary adults.

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Appendix 1. Baseline

Think aloud activity

Pre-task interview

1. Can you tell me about an app that you are using regularly?
2. Have you ever used a health or fitness app? Can you tell me about it?
3. What do you think a physical activity app should provide or do?
4. What is your relationship with physical activity and sport? What do you think about it?

Verbal instructions

"During this session, you will be given one smartphone-based task to complete. I would like to emphasise that this is not a test; I am interested in the task themselves, not your performance. I would like you to complete the task whilst "thinking aloud". This means that I would like you to complete the tasks, and while you do so, try to say everything that goes through your mind. I would like you to pretend that you are at home and try to forget that I am here.

Thinking aloud usually feels a bit strange at first, as it is an unusual task. Don't worry about it, most people find it a bit unnatural at first, but quickly get used to it! We will start off with a practice task to make sure that you feel comfortable. I would like you to change the ring tone on your smartphone whilst trying to say everything that goes through your mind."

Task

"Imagine that you have selected a physical activity (randomly assigned) app that you would like to try. Please download it, complete the baseline questions and explore the app whilst thinking aloud. Feel free to explore the app as you prefer but pretend that you are really checking that the app fits with you interests and expectations."

Post session interview

1. Ask about the participant's ability to download and install each app
2. I noticed that you mentioned that you thought that [...] was ... Can you tell me a bit more about that?
3. I noticed that you made a comment about [...]. Can you elaborate on that?

4. How do you understand the term “engagement” in the context of apps?
5. Do you think that this app was engaging? Why/why not?
6. Do you think that you would find the app/those particular features engaging longer term? Why/why not?
7. You mentioned that you thought that [...] was ... How do you think that feature would fit into your daily life?
8. How important is it for you to be able to relate to the app’s content?
9. How do you think engaging with the app would help you to increase your physical activity?
10. How do you think that [...] would help you to increase your physical activity?

Appendix 2. Follow-up (after 2-weeks usage)

Semi-structured interview (audio recorded phone call)

1. Ask participant to confirm which app they have tried
2. Ask participant to:
    - Start by giving overall opinion of the app
3. Depending on amount of detail provided in overview, ask participant to:
    - Expand on any points raised in overview
    - Comment on likes/dislikes
    - Comment on specific app functionalities (linked with BCTs)
    - Characterise the app in term of engagement. Get information about:
        - Enjoyment (like/dislike). Ask for a justification.
        - Interest (interesting/not interesting). Ask for a justification.
        - Attention (superficial/deep experience). Ask for a justification.
        - Frequency of use (how many times the app has been used)
        - Intensity of use (how much time last each session more or less)
4. Discuss how appropriate and relevant the app was for their personal intention to increase physical activity
5. Discuss if the specific type of proposed PA fits with their interests or not
6. Discuss types of physical activity which should be promoted, including intensity, frequency, type of activity and with relevance to current physical activity guidelines (i.e. 150 minutes MVPA and 2 sessions of strength/resistance based exercises per week) and how apps could promote these types of physical activity (if at all).
7. Discuss how (if at all) the apps could be improved. If so, what adaptations/functions should be addressed?

General discussion

Physical inactivity is a public health concern. Even though exercise benefits are globally renown, a considerable part of the European population is completely inactive, causing alarming health problems and a subsequent economic burden for healthcare systems. In order to get meaningful insights for developing interventions for the promotion of physical activity, the first part of this thesis focused on organised sport context in order to explore dispositional and social-cognitive factors associated with sport participation, success, and performance. In the second part of the thesis we moved the focus on the development of a smartphone application, called *Muoviti!*, aiming to promote physical activity among sedentary adults. Specifically, we introduced the advantages associated with digital mobile technology and described the development of the computational model of *Muoviti!* framed on Bandura's self-efficacy theory. Furthermore, we investigated what and why behaviour change techniques and design features deserve to be implemented in *Muoviti!* in order to support physical activity and users' engagement with the digital intervention.

In the present general discussion, first, findings of the studies will be summarized. Second, the strengths of the current contribution will be considered. Finally, the main implications of the findings and future directions will be addressed.

Summary of findings

Part 1

The first section of the thesis focused on a specific physical activity context, that is organised sport. The aim was to investigate whether and how personality traits and self-efficacy are associated with long-term outcomes of physical activity, such as athletic success and performance. Answering such questions would allow researchers to translate knowledge and insight form sport setting to exercise promotion contexts.

Study 1 evidenced that Big Five personality traits can help distinguish various levels of athletic involvement and achievement. Specifically, high-level athletes scored higher than non-athletes in

each personality dimension of the Big Five, with the exception of openness, while low-level athletes scored higher than non-athletes only in extraversion and agreeableness. Concerning the association between personality and sports success, the study indicated that more successful athletes are significantly more agreeable, more conscientious, and more emotionally stable than less successful athletes. Taken together current findings evidenced that personality traits associated with sport participation and those associate with athletic success are not the same, with the exception of agreeableness. Energy emerged as the most important factor differentiating athletes from non-athletes, but not low-level from high-level athletes, confirming that organized sports and physical activity are elective contexts of expression and development of energy features. Conversely, conscientiousness and emotional stability played a significant role in relation to the achievement of long-term outcomes of sport (i.e., athletic success) that require resilience and perseverance. Interpreted in a healthcare perspective, current findings indicate that energy is a facilitating factor for the engagement in physical activity and exercise programs, while conscientiousness and emotional stability are relevant for supporting the practice of physical activity on the long-term period and in spite of difficulties and barriers. Finally, findings suggested that agreeableness is associated both with sport participation and athletic success. Indeed, organized sport activities, as well as exercise programs, are preferential contexts for developing social interactions and relationship with sport mates or peers that can serve as a motive for practicing physical activity and for remaining engaged on the long-term period.

Study 2 investigated the association among self-efficacy, sensation seeking and performance in risky sport, targeting a never-before-investigated sport, that is competitive freediving. Findings indicated that freediving self-efficacy predicted the performance in both the low- and high-risk freediving disciplines. Such results supported the idea that domain-specific self-efficacy, regardless of the specific features that characterize each sport, is a significant predictor of sport performance. Furthermore, findings provided additional support for recognizing self-efficacy as a key construct that deserves to be leveraged in order to increase exercise performances and support the practice of physical activity.

Part 2

The second section described the first stages of development of an innovative smartphone application, Muoviti!, that exploits mobile technologies and cloud computing opportunities to promote physical activity among sedentary adults. Study 1 described the elaboration of the computational model, grounded in Bandura's self-efficacy theory, that characterises Muoviti!. The proposed computational model aims to integrate behavioural (i.e., amount of physical activity performed) and psychological (i.e., self-efficacy) information to suggest new personalized weekly goals. More specifically, at the beginning of each weekly training period, Muoviti! suggests a physical activity goal for the week on the basis of two different input data: past week goal achievement and self-efficacy beliefs in mastering past week physical activity experiences. The decision rules underlying the new weekly goal are developed in order to foster the simultaneous enhancement of both physical activity performances and self-efficacy beliefs. Finally, Muoviti! splits the goal for the next week into daily short-term goals and translates them into concrete tasks (e.g. minutes of running, or fast walking) in order to support effective action planning strategies.

If study 1 described the theoretical basis and the mathematical model underlying Muoviti!, studies 2 and 3 explored what behaviour change techniques should be implemented into the app and how to design them in order to fulfil users' needs, motivations and perspectives. Specifically, study 2 evidenced that potential users' of Muoviti! are mainly oriented to practice physical activity in order to enjoy and improve their fitness and aesthetic appearance. They reported preferences for behaviour change techniques that support self-regulation skills (i.e., feedback, monitoring, goal setting, goal reviewing) but a weak interest into behaviour change techniques referring to social aspects, such as support from others and social comparison. Finally, findings suggested that preferences for self-regulation behaviour change techniques rely on their potentiality to fulfil users' participation motives. In order to gain a better insight into users' motivations and perspectives, study 3 explored what and why features are expected to influence users' engagement with physical activity apps and sustain it over time. For such purposes, in line with the Person-based approach, the study was characterized by the adoption of qualitative methodologies, such as focus group, think aloud, and in-depth interview. Main findings from study 3a and 3b confirmed what found in

study 2, suggesting that potential users would prefer design features that support their self-regulation skills (i.e., progress monitoring, goal setting, feedback) and that focus on behavioural outcomes, such as a better cardiovascular fitness and weight loss. Moreover, they expressed a discomfort about sharing personal achievements with other people, in particular, through social networks. However, differently from study 2, participants manifested a preference for features that supply human support. In practical terms, this suggestion may be implemented by providing opportunities for connecting users one another and by designing apps that interact with users in the same way as a personal trainer. Furthermore, potential users suggested that a fair and easy user experience is a precondition for using and be engaged with the app. Finally, a crucial point regarded the proactive role of the app and how it interacts with the user in a relevant and personalized way. Indeed, both in study 3a and 3b emerged the users' interest into a physical activity app that is able to understand the user and, consequently, adapt the intervention to individual circumstances and behavioural and psychological states. Such preferences can be addressed by the implementation of personalized goal setting and action planning strategies, social activities, and feedback and suggestions that are adaptive to real-time variations in contexts and individual states.

Strengths

This thesis adds to the scientific literature about 1) the psychological correlates of participation and performance in organised sports and 2) the development of physical activity apps that are theory driven and design around users' needs. In doing so, the present thesis tried to integrate such a double perspective, transferring findings from organised sport context to a physical activity promotion setting.

Confirming and extending previous literature regarding the association between Big-five personality traits and sport participation and success is a strength of this thesis. Such associations were investigated thorough the adoption of a strong methodological approach that relied on the involvement of a considerable sample size, novel statistical approaches for testing population-based differences (i.e., Exploratory Structure Equation Modeling), and a more accurate

characterization of the athletic populations. Similarly, investigating the predictive role of self-efficacy beliefs in a novel sport setting is another positive aspect of the thesis. More specifically, we extended the existing evidences to risky sports, highlighting the suitability of self-efficacy to explain physical activity performances in disparate contexts and tasks.

Another strength of the thesis was the development of a computational model of Bandura's self-efficacy theory that constitutes the basis of an ongoing project that will lead to the development of Muoviti!. The advantages of developing a computational model of self-efficacy mainly rely on the capacity to predict the influence pattern among behavioural and psychological variables and to simulate and test how they change and influence each other across contexts and over time. In reason of that, the behaviour change intervention that Muoviti! is intended to deliver is tailored to the individual psychological states and progress in practicing physical activity.

One of the challenges presented when developing behaviour change interventions is that a deep understanding of the users' needs, motivations and perspectives is essential for supporting effective engagement. Indeed, physical activity apps tend not to be used repeatedly, and attrition is most severe during early stages of use. Having considered this aspect is a further strength of this thesis. Specifically, user needs for a physical activity app were identified by conducting three different studies that characterize the second part of the thesis. In study 2, potential users' participation motives and their preferences for behaviour change techniques were assessed through self-report questionnaires. In study 3, users' needs were addressed through the adoption of qualitative methodologies with the aim to answer what and why features are judged to be important for supporting a sustain engagement with physical activity apps. A distinctive characteristic of study 3 was the evaluation of users' needs from three different perspectives: during co-design activities, during a first exposure to a never-used app, and after a 2-weeks use. Having explored users' needs by adopting a mixed-methods approach is a further strength of this thesis. Indeed, the integration of both quantitative and qualitative methodologies allowed to explore users' motivations and preferences on a large scale and, subsequently, to gain an in-depth understanding about how such preferences may be implemented in a physical activity app.

Implications

Taken together, current findings provided clear and useful guidelines for researchers and designers involved in the development of physical activity apps, as well as practitioners in the sport and exercise field.

As potential users of PA apps tend to prefer self-regulation features, it is important that developers take care of providing opportunities for:

1) monitoring physical activity in a reliable way through the adoption of companion devices, such as HR monitors and activity trackers. Specifically, monitoring tools should be able to supply the most relevant behavioural information according to the specific exercise activity performed by each user.

2) monitoring the progress towards the behavioural goals in order to allow the users to regulate their efforts and to adopt effective coping strategies. For such purposes, graphical feedbacks may represent the most viable solution for illustrating any discrepancy between behaviour and goal in an easy and immediate way.

3) setting physical activity goals that are personalized for each user. Goals may be either directly set by the users or suggested by the app on the basis of individual states and progression (as introduced in study 1, part 2). However, understanding which goal setting strategy is the most effective in promoting behaviour change deserves further investigation in experimental trials (see future directions below).

One of the main reasons for practicing physical activity is represented by fitness- and health-related motives (e.g., improve cardiovascular fitness, weight loss). As a consequence, there may be a potential merit of developing PA apps that monitor and provide information about health-related parameters. More specifically, it seems arguable to find novel and meaningful ways to show the users how a specific amount of physical activity is reflected into a health and fitness improvement. Evidencing this link between physical activity and its outcomes may constitute a trigger for keeping the users engaged with the behaviour change intervention over time.

Social aspects associated with the practice of physical activity emerged as an intricate issue. Indeed, although users principally reported to dislike sharing their PA achievements through

social networks and to be involved in competitions, at the same time they positively evaluated the opportunities for receiving support from peers. Furthermore, users' judgements about social features were somehow heterogeneous, thus it seems to be preferable to consider such features as optional. Specifically, developers might develop physical activity apps considering social features as an optional module that users can add to or remove from the app on the basis of their preferences. In addition to facilitate support from peers, it is worth developing more supportive and emphatic interactions between the users and the app. An interaction of this kind is believed to create a stronger commitment to PA goals and to provide emotional support. In practical terms developers may consider the opportunity to characterize PA apps by the presence of human-relational skills or components (e.g., virtual agent, empathy, social dialogue).

The user interaction with the app is also facilitated by a fair and simple user experience that is not too demanding, distracting and time consuming. For this reason, it is important for healthcare professionals to collaborate with interaction design experts in order to develop physical activity apps that ensure high usability standards.

Finally, a close collaboration between behavioural and computer scientists would help to develop computational models of behaviour change theories that permit to understand, predict and meaningfully address users' needs in real-life settings. This is possible through an ongoing assessment of individual (i.e., behavioural, psychological) and contextual states, and the definition of decision rules that enable to deliver flexible and adaptive action plans and suggestions tailored to each user. This last point is of crucial importance because, although flexibility and adaptability are among the most relevant characteristics that users expected from PA apps, so far, commercial apps don't take into account such aspects.

Future directions

The present thesis described the essential phases that characterized the early development of *Muoviti!*. Further steps are necessary in order to finalize the beta version of *Muoviti!*, to test the computational model, and to evaluate its effectiveness in promoting behaviour change. It is important to recognise that evaluation of digital interventions involves much more than effect size

estimation. Indeed, it includes assessing how far the intervention is reaching the intended users, how far they are engaging with it in the way believed to maximise effectiveness. For these reasons, in the first instance, a feasibility study will be conducted with a small group of users in order to determine whether *Muoviti!* is appropriate for further testing. This study will allow to understand how the intended users react to the intervention and, consequently, will permit to identify what and how components and features of *Muoviti!* need modification. A specific focus of this study will concern whether the intervention options of the computational model (i.e., proposed goals for the next week) are suitable and effective in supporting the increase in physical activity. For such purposes, it is advisable to integrate qualitative methodologies (e.g., focus group, in-depth interviews) in order to gain a better insight about users' experiences with behavioural information collected through the app. If the intervention options and the decision rules of the computational model fail to describe and promote behaviour change, the theoretical model will need to be re-modelled and refined before testing its effectiveness on a large-scale experiment. Once the study provides support for the feasibility of the behaviour change intervention, *Muoviti!* and its computational model will be tested through a concurrent A-B testing. We intend to develop different versions of *Muoviti!* and give them to different groups of users. More specifically, three versions of the app will be developed: i) a full version with the refined computational model presented in study 1 in part 2, ii) a version in which the app set physical activity goals on the basis of previous physical activity achievements, but without accounting for self-efficacy beliefs, and iii) a version characterized by the absence of any goal setting strategy. The primary outcome of the experiment will be represented by the intervention effectiveness in increasing physical activity while the secondary outcome will be the engagement with the app. Findings form this future study will provide information whether theory-driven goal setting strategies tailored on self-efficacy beliefs are more effective and engaging than non-tailored and no strategies.

Such feasibility and experimental studies are expected to ensure a first evaluation of *Muoviti!* and to provide indications for further refinements and iterative cycles of development.