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Too bored for sports? Adaptive and less-adaptive latent personality profiles for exercise behavior

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A R T I C L E I N F O

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A B S T R A C T

Physical exercise is an effective tool for improving public health, but the general population exercises too little. Drawing on recent theorizing on the combined role of boredom and self-control in guiding goal-directed behavior, we test the hypothesis that individual differences in boredom and self-control differentiate high from low exercisers. The role of boredom as a non-adaptive disposition is of particular interest, because research on boredom in sports is scarce. Here, we investigate the role of such individual differences in self-reported weekly exercise behavior (in minutes) in a sample of $N = 507$ participants ($n = 200$ female, $M_{age} = 36.43$ (± 9.54)). We used the robust variant of Mahalanobis distance to detect and remove $n = 51$ multivariate outliers and then performed latent profile analysis to assess if boredom (boredom proneness; exercise-related boredom) and self-control (trait self-control; if-then planning) combine into identifiable latent profiles. In line with theoretical considerations, the Bayesian Information Criterion favored a solution with two latent profiles. One profile was characterized by higher-than-average exercise-related boredom and boredom proneness and lower-than-average self-control and if-then planning values. This pattern was reversed for the second profile. A one-sided Bayesian two-sample *t*-test supported the hypothesis that the first profile is associated with less exercise behavior than the second profile, BF = 16.93. Our results foster the notion of self-control and if-then planning as adaptive dispositions. More importantly, they point to an important role of boredom in the exercise setting: exercise-related boredom and getting easily bored in general are associated with less exercise activity. This is in line with recent theorizing on boredoms' and self-controls' function in guiding goal-directed behavior.

Physical inactivity causes around 5 million deaths per year (Lee et al., 2013). To illustrate, in the United States around 8% of deaths have been linked to inadequate levels of physical activity (Carlson, Adams, Yang, & Fulton, 2018). In addition to its effect on global mortality, physical inactivity also represents a major economic burden for the healthcare system (Ding et al., 2017), producing global costs well beyond 50 billion dollars per year (Ding et al., 2016). In short, insufficient physical activity is a pandemic (Ding et al., 2017). This makes physical exercise one of the most cost-effective and most readily available tools for improving public health (Kohl et al., 2012). Indeed, an overwhelming body of research has provided evidence for the positive effects exercise has on physical (Netz, Wu, Becker, & Tenenbaum, 2005; Nocon et al., 2008) and mental health (Ahn & Fedewa, 2011; Netz et al., 2005; Rosenbaum, Tiedemann, Sherrington, Curtis, & Ward, 2014).

In an effort to combat this pandemic, health organizations have developed guidelines that specify the levels of physical activity individuals should meet (World Health Organization Global Recommendations on Physical Activity for Health, 2010). In regard to exercise, the World Health Organization (WHO) recommends at least 75 min of vigorous-intensity physical activity per week for adults (Physical activity, 2020). Underlining the importance of reducing inactivity and meeting these recommendations, a reduction of physical inactivity is amongst the WHO's targets that are specified in the "Global action plan for the prevention and control of noncommunicable diseases" (Global action plan for the prevention and control of noncommunicable diseases 2013-2020, 2013). In line with this, countries have developed strategies that are designed to help people meet these recommendations (Ding et al., 2017; Physical activity, 2020). In addition, researchers have

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developed diverse psychological interventions that help people to be more physically active (e.g., Vandelanotte et al., 2018). However, despite these considerable efforts and although the benefits of physical exercise are widely known, many people struggle to be physically active (Marcus et al., 2000). Indeed, global activity levels have remained largely unchanged over the last 15 years (Guthold, Stevens, Riley, & Bull, 2018).

On the surface, this is puzzling: If the benefits exercise conveys for physical and mental health are widely accepted and widely known, why don't (more) people exercise (more)? One simple (partial) answer might be that exercise is a self-control demanding (e.g., Strobach, Englert, Jekauc, & Pfeffer, 2020) volitional challenge (e.g., Bertrams & Englert, 2013; Martin Ginis & Bray, 2010) and potentially boring. Attesting to these assumed difficulties, of all people who intend to exercise, half of them fail to do so (meta-analysis by Rhodes & Bruijn, 2013). Here, we look at the role of individual differences in self-control (self-control; if-then planning) and boredom (boredom proneness, exercise-related boredom) for exercise behavior. While the role of self-control for exercise behavior is widely acknowledged (e.g., Finne, Englert, & Jekauc, 2019; Hagger, Wood, Stiff, & Chatzisarantis, 2010; Pfeffer & Strobach, 2018; Strobach et al., 2020; Wolff, Hirsch, Bieleke, & Shenhav, in press), the potential role of boredom has been largely overlooked so far. However, recent studies outside the exercise context have shown that self-control and boredom are closely linked on the state and on the trait level (Bieleke, Barton, & Wolff, 2020; Isacescu, Struk, & Danckert, 2017) and predict health behavior via different mechanisms (Bieleke, Martarelli, & Wolff, 2020; Danckert, Boylan, Seli, & Scholer, 2020; Wolff, Martarelli, Schüler, & Bieleke, 2020). Accordingly, very recent work has integrated functional conceptualizations of self-control and boredom, in order to provide a mechanistically sound theoretical framework that explicates boredom and self-control as key guiding signals for the orientation of goal-directed behavior (Wolff & Martarelli, 2020).

1. Exercise can be self-control demanding

Exercise produces the sensation of effort and can require foregoing alternatives that have higher hedonic short-term value. For example, instead of going for an exhausting run, one could also sit on the couch and eat some candy. From this perspective, exercise can be understood as a self-control demand. Self-control refers to the capacity to overcome competing responses in order to reach a goal (Shenhav, Botvinick, & Cohen, 2013). Thus, exercise relies on self-control to initiate goal-directed actions (e.g., to get up from the couch), to inhibit impulses (e.g., to run slower), and to continue with a chosen course of action (e.g., to complete the intended running distance) (Hoyle & Davisson, 2016). The sensation of effort is intrinsically linked to self-control (Kurzban, 2016) and part of its definition (de Ridder, Lensvelt-Mulders, Finkenauer, Stok, & Baumeister, 2012). Current theorizing on self-control proposes that the perception of effort that accompanies the application of self-control serves as a signal that quantifies self-control costs and biases behavior away from exerting further effort (Kurzban, Duckworth, Kable, & Myers, 2013; Shenhav et al., 2017; Wolff & Martarelli, 2020). While the nature of these costs - opportunity costs (Kurzban et al., 2013) and/or intrinsic costs of control (Kool & Botvinick, 2018) – is still an open research question, most current self-control theories seem to agree that self-control is only applied if its expected value outweighs the incurred costs (e.g., Kurzban et al., 2013; Shenhav et al., 2013; Wolff et al., in press; Wolff & Martarelli, 2020). This implies that choosing to eat some candy instead of going for a run must not necessarily be indicative of poor self-control, but rather reflect a reward-based choice where the costs of control outweigh its perceived benefits. From this perspective, high trait self-control might be beneficial because it makes tasks less costly, thereby biasing behavioral choices towards activities that prioritize long term rewards (e.g., fitness and health) over short term rewards (e.g., taste of candy).

Indeed, high self-control has been robustly linked to a plethora of positive short- and long-term life outcomes (for a meta-analysis, please see de Ridder et al., 2012). Likewise, the relevance of self-control in the context of regular exercise is widely acknowledged (e.g., Finne et al., 2019; Hagger et al., 2010; Pfeffer & Strobach, 2018; Strobach et al., 2020). To illustrate, high self-control has been linked to exercise adherence in general (Bertrams & Englert, 2013) as well as to higher persistence in one single exhausting bout of exercise (for meta-analyses, see Brown et al., 2020; Giboin & Wolff, 2019). Importantly, since physical exercise can be self-control demanding, it might even function as a self-control training in its own right. Indeed, a longitudinal study showed that participants who had taken up a regular exercise regime performed better at laboratory self-control tasks and reported to engage in more health behaviors that rely on self-control (Oaten & Cheng, 2006). This indicates that the frequent application of self-control makes the processing of self-control demands more efficient, thereby reducing its costs. In line with this, high trait self-control has been linked with a less steep increase in prefrontal cortex oxygenation during a strenuous physical effort task, indicating a more efficient processing of exercise-induced self-control demands (Wolff, Schüler, et al., 2019).

Since self-control is intrinsically linked with the costs of effort (Kurzban, 2016; Shenhav et al., 2017), researchers have looked for ways to make self-controlled behavior less costly (e.g., Ainslie, 2020; Duckworth, Gendler, & Gross, 2016). For example, to regulate one's behavior towards a valued goal (e.g., to become a marathon runner), it might be worthwhile to employ self-regulatory control strategies that make pursuing this valued goal less effortful. One such strategy that has been proposed to alleviate weak *willpower* is if-then planning (Bieleke, Keller, & Gollwitzer, in press; Gollwitzer, 2014; for a discussion of if-then planning in the exercise context, please see Wolff, Bieleke, & Schüler, 2019). If-then plans specify when, where, and how one wants to perform goal-directed behaviors to attain a goal, such as the goal to exercise regularly. These behaviors are linked to critical situations in an if-then format (e.g., "When I come home from work, then I go jogging in the park for half an hour"). Indeed, if-then planning has frequently been linked with more physical activity (Bélanger-Gravel, Godin, & Amireault, 2013) and better exercise adherence (Hagger & Luszczynska, 2014) and has been recommended as a tool for strengthening physical activity habits (Rebar et al., 2016). Its effects on persistence in one single exhausting bout of exercise have so far yielded mixed results (Bieleke, Kriech, & Wolff, 2019; Bieleke & Wolff, 2017; Thürmer, Wieber, & Gollwitzer, 2017) and appear to rely on participants' laytheories regarding the efficacy of applying control over aversive exercise-induced sensations (Hirsch, Bieleke, Schüler, & Wolff, 2020). However, attesting to its proposed effect on lowering self-control demands, participants who make if-then plans as a self-control strategy for enduring physical exertion display less activity in the PFC when compared with a control group (Wolff et al., 2018). This finding is particularly relevant to current theorizing of self-control, as it suggests that the cost of self-control can be lowered with if-then plans.

Importantly, individuals differ in their propensity to use if-then planning as a self-control strategy in everyday life (Bieleke & Keller, 2021). Thus, in addition to being an intervention that has frequently been employed in physical activity (for a meta-analysis, please see Bélanger-Gravel et al., 2013) and exercise research (for a review, please see Bieleke, Wolff, Englert, & Gollwitzer, 2020), if-then planning can also be understood as a relatively stable generalized behavioral tendency that individuals employ habitually (Bieleke & Keller, 2021). Thus, it is conceivable that, by lowering the costs of self-control, not only trait self-control, but also trait if-then planning is conducive to health behavior. Indeed, recent work on social distancing amidst the COVID-19 pandemic points towards an important role of trait if-then planning that goes beyond the effect of trait self-control in facilitating adherence to social distancing guidelines (Bieleke, Martarelli, & Wolff, 2020). However, in regard to physical exercise, the role of trait if-then planning has not yet been investigated.

2. Exercise might be boring

In addition to requiring the regulation of effort, exercise might be outright boring to some individuals and even professional athletes are frequently bored (Velasco & Jorda, 2020). Importantly, continuing with a course of action although one is bored should in itself represent a self-control demand (Wolff & Martarelli, 2020). While some might enjoy the solitude of a slow 5-km run, others might dread the monotony and count every step until they have finished their run, having to apply self-control to keep going despite being bored. Indeed, non-scientific publications on sports and exercise have long identified and discussed boredom as an important challenge that exercises have to cope with (10 Ways to Beat Boredom at the Gym - Fitness Center - Everyday Health; 8 Ways to Beat Exercise Boredom! 2010; Marathon Motivation - Expert Tips to Beat Mental Boredom, 2018). Given the abundance of such lay knowledge on the importance of boredom, it is striking that the role boredom proneness plays in regard to physical exercise has not yet been systematically investigated.

One reason for this lack of research might be the fact that until very recently boredom had not received much attention by researchers in general (Westgate & Wilson, 2018). Instead, boredom has frequently been pitted as an opposite of interest, has been likened to amotivation, or has been subsumed within the concept of sensation seeking (for a similar argument, see Pekrun, Goetz, Daniels, Stupinsky, & Perry, 2010). However, these treatments of boredom fall short in fully accounting for boredom, which has been defined as an “aversive state that occurs when we are not able to successfully engage attention (…) [and an] awareness of a high degree of mental effort expended in an attempt to engage with the task” (Eastwood, Frischen, Fenske, & Smilek, 2012, p. 481). Thus, in contrast to low interest, which is affectively neutral, or amotivation, which is characterized by a low drive to change one’s current situation, boredom is aversive and exerts a motivational force to change behavior (Danckert & Eastwood, 2020). Finally, while sensation seeking is linked to the craving of stimulating experiences, computational (Gomez-Ramirez & Costa, 2017) and empirical work (Geana, Wilson, Daw, & Cohen, 2016) on boredom shows that boredom drives changes in behavior without restricting this change to specific properties of said behavior (Bench & Lench, 2019). Taken together, while initially little functional relevance had been ascribed to boredom, this view is rapidly changing, and boredoms’ crucial role for driving exploration is now increasingly understood and acknowledged (Danckert & Eastwood, 2020; Westgate, 2020; Wolff & Martarelli, 2020).

The intuition that boredom can be a barrier to physical exercise aligns well with the emerging understanding of boredom’s functional relevance as a signal to orient one’s behavior elsewhere (Bench & Lench, 2019; Danckert, 2019; Westgate & Wilson, 2018; Wolff & Martarelli, 2020). Thus, although boredom is generally perceived as an aversive sensation that people try to avoid (Eastwood et al., 2012), boredom in itself is neither good nor bad per se, but it helps us to stop with a course of action that is not worth the effort (Danckert, 2019). However, if one gets bored while exercising, this is expected to act as a strong signal to do something else, making boredom a powerful motivator of behavior (Westgate & Wilson, 2018). Indeed, research outside the sports and exercise context has shown that boredom is a ubiquitous sensation (Harris, 2000) that has been linked to a plethora of maladaptive (Britton & Shipley, 2010) but also to adaptive behaviors (Elpidorou, 2018). Boredom occurs when one’s current activity is under-stimulating (or over-stimulating) and/or when it lacks meaning (Westgate & Wilson, 2018). It makes intuitive sense that exercise can create these very sensations. For example, running at a very low intensity in order to “burn calories” might be quite under-stimulating, and if one realizes that this effort has only burned 250 kcal one might even deem it meaningless. Similarly, strength training requires repetition of the exact same movement for numerous times and the gains from this training only accrue in small increments and over a longer period of time. Importantly, people differ in how easily they get bored (Struk, Andriy, Carriere, Cheyne, & Danckert, 2017) and by what they get bored (Chin, Markey, Bhargava, Kassam, & Loewenstein, 2017). Thus, it is conceivable that by making people more prone to seek out more rewarding behavioral alternatives, domain-general boredom proneness and exercise-related boredom act as barriers for engaging in regular physical exercise. Despite its intuitive appeal, we are not aware of any research that has tested this hypothesis.

3. The present study

Scientific evidence and lay knowledge point towards a key role for self-control and boredom in exercise behavior. Recent theorizing and empirical work has linked both concepts, indicating that the experiences that accompany boredom and the allocation of self-control subserve critical functions in orienting goal-directed behavior; namely to switch activity or to withdraw effort, respectively (Martarelli & Wolff, 2020; Wolff & Martarelli, 2020). Importantly, individual differences on the trait level are expected to affect the strength of these signals and recent work on adherence to social distancing guidelines amidst the COVID-19 pandemic has provided preliminary evidence for the proposed mechanisms (Bieleke, Martarelli, & Wolff, 2020; Danckert et al., 2020; Wolff et al., 2020): Boredom prone individuals perceived adherence to social distancing to be more difficult and as a consequence displayed lower adherence rates than less boredom prone individuals. In addition, individuals with high self-control were better at applying the effort needed to deal with the difficulties of adherence and displayed higher adherence rates than individuals with low self-control. Providing further evidence for the close link between both concepts, previous research has shown that trait self-control and boredom proneness are strongly and inversely related (Isacescu et al., 2017).

Based on these considerations, we first tested whether self-control variables (trait self-control and if-then planning) and boredom variables (boredom proneness and exercise-related boredom) combine into differentiable latent personality profiles. More specifically, we assumed that individuals display personality profiles that are potentially more adaptive (i.e., high in self-control; low in boredom) or less adaptive (i.e., low in self-control; high in boredom) in regard to goal-directed behavior. To test the presumed adaptiveness of the identified personality profiles, we then assessed whether the amount of self-reported weekly vigorous exercise behavior differed between the identified latent profiles. In a nutshell, we expected to find more adaptive and less adaptive personality profiles, and we expected people with more adaptive profiles to exercise more than those with less adaptive profiles.

4. Methods

Data collection was done online via Amazon Mechanical Turk with the assistance of TurkPrime (Litman, Robinson, & Abberbock, 2017). Respondents were invited to participate in a 10-min online questionnaire study and were compensated for their participation with 1.50 USD. Participants who entered the online study were informed about the purpose of the study, delivered informed consent, and confirmed that they participated voluntarily. The study was carried out in accordance with the 1975 Declaration of Helsinki.

4.1. Open-science practices

All materials, all data, and an annotated R script to re-run the analyses presented here can be found at https://osf.io/kuzgc/.

4.2. Participants and multivariate outlier detection

$N = 507$ respondents completed the questionnaire. Instead of excluding problematic data with traditional attention check measures, we employed a comprehensive multivariate outlier detection approach that takes into account all responses that would form part of the later analyses, thereby maximizing data quality for all relevant data. To do this, we used the robust variant of the Mahalanobis distance that has recently been introduced by Leys, Klein, Dominicy, and Ley (2018) because researchers have cautioned against the commonly used rule of using standard deviations around the sample mean as a method for outlier detection (Leys, Ley, Klein, Bernard, & Licata, 2013). The Mahalanobis distance quantifies how far observations deviate from the center of the multivariate matrix that is constituted by the data of interest. To get a robust estimate of this distance (which is not itself affected by outliers), Leys et al. (2018) propose to use the minimum covariance determinant (MCD) approach, where potential outliers are compared with the most central subsample (i.e., the subsample with the least variance) that has a size between $N/2$ and N. As per the recommendations by Leys et al. (2018), we computed this robust variant of the Mahanalobis distance with a most central subsample that consisted of 75% of the observation (denoted as MCD75) and whose estimate would therefore be unaffected even if our data consisted to 25% of contaminated data points. This approach classified $n = 51$ (about 10%) observations as outliers and the final sample therefore consisted of $N = 456$ respondents (59.9% male, 39.9% female, 0.2% missing/other) with a mean age of 36.5 years ($SD = 9.5$). The majority reported 12 years or more of education (77.4%) and was either working full-time (65.6%) or self-employed (12.7%). Most participants (66.9%) reported an annual income between \$20′000 and \$79′999, 21.9% reported to earn ≤ \$20′000, and 11.2% reported an income of ≥ \$80′000.

4.3. Measures

Exercise behavior was assessed with the vigorous activity subscale of the International Physical Activity Questionnaire short form (IPAQ-S; International Physical Activity Questionnaire, 2020). We focused on the vigorous activity subscale rather than the overall IPAQ-S score because a systematic review showed that only this subscale correlates sufficiently well with objective fitness measures (Lee, Macfarlane, Lam, & Stewart, 2011). The vigorous activity subscale of the IPAQ-S includes two items ("During the last 7 days, on how many days did you do vigorous physical activities like heavy lifting, digging, aerobics, or fast bicycling?" and "How much time did you usually spend doing vigorous physical activities on one of those days?"). For the first item, answers were given in numbers of days and for the second item in hours and minutes per day. From these values, we calculated the weekly minutes of self-reported exercise.

To assess whether or not participants perceive exercising as boring, we adapted the learning subscale of the Achievement Emotions Questionnaire (AEQ; Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011) to the exercise context (e.g., "Exercise bores me to death"; for similar approaches, please see Simonton, 2020). This *Bored of Sports Scale* (BOSS; see Appendix for the full scale) consists of 11 items that are aggregated to a mean score (α = 0.97). Items have to be answered on a 5-point Likert-type scale with answers ranging from "strongly disagree" to "strongly agree" with high values on the BOSS reflecting higher exercise-related boredom.

Boredom proneness was assessed with the Short Boredom Proneness Scale (SBPS; Struk et al., 2017), consisting of 8 items (e.g., "I don't feel motivated by most things that I do"; α = 0.92) that are aggregated to a mean score. This scale, too, requires the items to be answered on a 5-point Likert-type scale with answers ranging from "strongly disagree" to "strongly agree" and high values reflecting higher general proneness to be bored.

We measured self-control with the Capacity for Self-Control Scale (CFSCS; Hoyle & Davisson, 2016). The CFSCS consists of 20 items[1] that capture the three self-control main facets of self-control pertaining to inhibition (e.g., "I am able to resist temptations."), initiation (e.g., "I get started on new projects right away."), and continuation (e.g., "After I have started a challenging task, I find it easy to stick with it.") that are aggregated to a mean score, α = 0.93. All answers were measured on a 5-point Likert-type scale with answers ranging from "hardly ever" to "nearly always". High values on the CFSCS reflect higher ability for self-control.

If-then planning was assessed with the 8 items (e.g., "I plan how best to achieve my goals.") of the If-Then Planning Scale (ITPS; Bieleke & Keller, 2021). Answers ranged from "does not apply at all" to "does fully apply" on a 7-point Likert-type scale, with high values reflecting a higher propensity for engaging in if-then planning. The ITPS' internal consistency was α = 0.87 in our sample.

4.4. Data analysis

Multivariate outlier detection and Latent Profile Analyses (LPA) were conducted using the statistical software R (R Core Team, 2019) and JASP (JASP Team, 2020) was used to perform and visualize a Bayesian *t*-test to compare the extracted profiles. To assess whether different latent personality profiles could be extracted, we performed an LPA with the R package `tidyLPA` (Rosenberg, Beymer, Anderson, van Lissa, & Schmidt, 2018). LPA is a variant of the general mixture model that can be used when the variables of interest are continuous (Rosenberg et al., 2018). More specifically, it can be "used to identify a set of discrete, exhaustive, and nonoverlapping latent classes of individuals based on individual responses to a set of indicators" (Tein, Coxe, & Cham, 2013, p. 641). In addition to identifying varying numbers of latent profiles, the latent profiles can be identified with different constraints that are placed on the variance (varying or equal) and covariance (varying, zero, equal) of the profiles. Thus, an LPA can return multiple solutions that describe the data with varying numbers of classes, and for each solution, six different models in regard to the profiles' variance and covariance properties can be obtained. To assess with how many latent profiles, and with which variance and covariance properties, the data can be best described, a multitude of fit indices has been proposed (Foti, Bray, Thompson, & Allgood, 2012). The fit indices can then be used to guide the decision on class enumeration (Harring & Hodis, 2016). Importantly, it has been suggested that, rather than being the only decision criterion, these fit indices should complement theoretical considerations regarding the plausible class enumeration (Foti et al., 2012). Although knowing that Bayesian Information Criterion (BIC) has been considered as the best fit index for class enumeration (Nylund, Asparouhov, & Muthén, 2007; Tein et al., 2013), we will report the adjusted BIC and the Akaike Information Criterion (AIC) as additional fit indices. These criteria indicate how well each solution fits the data, with lower values indicating better fit. Additionally, we use the *p*-value of the bootstrap likelihood ratio test (BLRT), based on the likelihood ratio statistical test method. The BLRT compares each model (k_0) with the (k – 1) neighbor model to find out whether there is a significant improvement in the estimate. Furthermore, we use the entropy index as a classification of how certain the discrimination between the different profiles are, with higher values indicating greater certainty. These are the criteria to determine which solution fits the data best, and if these indices suggest different class enumerations, then we continue with the identified model that fits our theoretical framework in the most parsimonious way. Finally, for each individual, the probability of belonging to each identified class is then quantified, and individuals are classified into the class where their probability of belonging is highest (Harring & Hodis, 2016).

5. Results

Participants reported to exercise for 161 min per week (SD = 154.00). The bivariate associations between exercise, boredom proneness, exercise-related boredom, self-control, and if-then planning are shown in Table 1. As can be seen, exercise-related boredom ($r = -0.28$,

[1] Due to an error, item #19 ("I do nothing despite having plenty to do") was not included into the questionnaire.

Table 1
Mean, standard deviation, and correlations for vigorous activity and the four self-regulation and boredom scales.

	M	*SD*	1	2	3	4
1. Vigorous activity	160.9	154.0				
2. Exercise-related boredom (BOSS)	2.4	1.1	-.28*** [-.36, -.19]			
3. Boredom proneness (SBPS)	2.3	0.9	-.14** [-.23, -.05]	.59*** [.53, .65]		
4. Self-control (CSFCS)	3.6	0.8	.20*** [.11, .29]	-.58*** [-.64, -.52]	-.74*** [-.78, -.69]	
5. If-then planning (ITPS)	5.1	1.0	.19*** [.10, .27]	-.38*** [-.46, -.30]	-.35*** [-.42, -.27]	.57*** [.50, .63]

Note: M = mean, SD = standard deviation. Range BOSS: 1–5; Range SBPS: 1–5; Range CSFCS: 1–5; Range ITPS: 1–7. 95% confidence intervals in square brackets. $^{**}p < .01$. $^{***}p < .001$.

$p < .001$) and boredom proneness ($r = -0.14$, $p = .003$) are negatively associated with exercise behavior, whereas self-control ($r = 0.20$, $p < .001$) and if-then planning ($r = 0.19$, $p < .001$) are positively associated with exercise behavior. Furthermore, the boredom measures (boredom proneness and exercise-related boredom) are, as is to be expected, highly positively correlated with each other ($r = 0.59$, $p < .001$), as well as self-control and if-then planning ($r = 0.57$, $p < .001$).

The boredom measures and the self-control and if-then planning scales are negatively associated (ranging from $r = -0.35$ to -0.74 with $p < .001$).

5.1. Results of the latent profile analysis

A latent profile analysis was performed to group individuals into profiles based on their individual patterns of self-control, if-then planning, boredom proneness, and exercise-related boredom. Table 2 provides the fit statistics for possible profile structures. Using the Bayesian Information Criterion (BIC) as a fit criterion, a solution with two latent profiles of varying variance and covariance was favored (BIC = 4411.16; see Table 2), with a moderate certainty of classification (entropy = .66). This solution exhibited not only lower BIC but also lower SABIC and AIC values in comparison with models one to three. Additionally, the significant BLRT p-value indicates that there is an improvement of model estimation in comparison to Model 6 with only one latent class. Although the three-profile solution had slightly lower SABIC and AIC values in comparison with the two-profile solution, the two-profile solution is the most parsimonious and best solution considering our theoretical propositions. Therefore, we chose it as the frame of reference for further inspection and subsequent reporting.

Table 2
Model Fit of the latent profile analysis.

Model	No. of latent classes	BIC	SABIC	AIC	Bootstrap LRT *p*	entropy
1	1	5221.26	5195.87	5188.28	–	1
1	2	4680.92	4639.66	4627.33	.009	.853
1	3	4621.93	4564.80	4547.72	.009	.720
1	4	4539.54	4466.55	4444.72	.009	.815
2	1	5221.26	5195.87	5188.28	–	1
2	2	4659.07	4605.12	4588.99	.009	.840
2	3	4431.16	4348.64	4323.97	.009	.883
2	4	4429.25	4318.17	4284.96	.009	.848
3	1	4479.86	4435.43	4422.15	–	.1
3	2	4430.65	4370.35	4352.32	.009	.803
3	3	4460.00	4383.83	4361.06	.772	.649
3	4	4479.17	4387.14	4359.62	.139	.697
6	1	4479.86	4435.43	4422.15	–	1
6	**2**	**4411.16**	4319.12	4291.61	.009	.663
6	3	4424.24	4284.60	4242.85	.009	.767
6	4	–	-	-	–	–

Note. The optimal model, according to BIC, is highlighted in boldface. Other fit indices are reported for completeness. Model 1 = equal variances and covariances fixed to 0; Model 2 = varying variances and covariances fixed to 0; Model 3 = equal variances and covariances; Model 4 and 5 cannot be estimated with the tidyLPA package; Model 6 = varying variances and covariances. For Model 6, the 4-profile version could not be estimated. BIC = Bayesian Information Criterion; SABIC = sample size-adjusted BIC; AIC = Akaike Information Criterion; LRT = likelihood ratio test; If less than 0.05, a model with k_0 latent classes provides significantly better fit than a model with (k – 1) latent classes. Entropy value indicates the certainty of correct classification to a latent class. Range is from zero to one, where higher values indicate better classification.

As can be seen in Fig. 1, individuals with the highest allocation probability for being in the class that is visualized in blue font are characterized by higher than average exercise-related boredom (M = 0.40, $SD \pm 0.97$) and boredom proneness (M = 0.41, $SD \pm 0.94$) and lower than average self-control ($M = -0.37$, $SD \pm 0.92$) and if-then planning values ($M = -0.19$, $SD \pm 1.00$). In regard to goal-directed behavior, this is expected to be a less adaptive *normal* profile. This pattern is reversed for the profile that is visualized in red, which is expected to be a highly adaptive profile. Individuals in this class show higher than average if-then planning ($M = 0.37$, $SD \pm 0.88$) and self-control ($M = 0.75$, $SD \pm 0.69$) and lower than average boredom proneness ($M = -0.82$, $SD \pm 0.48$) and exercise-related boredom scores ($M = -0.79$, $SD \pm 0.42$). The two profiles differ in size, with $n = 152$ (33.3% of sample) individuals in the highly adaptive and $n = 304$ in the less adaptive normal profile (66.7% of sample). Participants in the highly adaptive profile were classified as such with an 81.2% probability, and participants in the normal profile were classified as such with a 93.8% probability, thereby indicating a high accuracy for class membership classification. Table 3 provides the non-standardized estimates for mean, variance, and covariance for the favored two-profile solution. As can be seen from the non-standardized estimates, the highly adaptive profile is characterized by very high values of self-control and if-then planning, and with very low values of boredom proneness and exercise-related boredom. In contrast, the less adaptive profile is characterized by less extreme values in both regards. Thus, it should not be considered as non-adaptive, as this would suggest very high values of boredom and very values of low self-control, respectively, that we did not observe (The visualization of the LPA with non-standardized values can be found at https://osf.io/2rfm3/.).

To test the hypothesis that a more adaptive personality profile is associated with more exercise behavior than a normal personality profile, we performed a one-sided Bayesian two-sample t-test, and we report the Bayes Factor (BF_{10}) to quantify evidence for this hypothesis (Fig. 2a). The BF_{10} obtained from this analysis is 16.93, indicating strong evidence in favor of the hypothesis that the highly adaptive profile is linked with more exercise ($M = 191.35$, $SD \pm 156.44$) than the less adaptive profile ($M = 145.69$, $SD \pm 150.73$). As an estimate for the effect size and the uncertainty regarding its size, we report the 95% credible interval around the posterior distribution of the standardized effect size δ obtained from this t-test. The credible interval shows that, under the assumption that the effect exists, its true size is between 0.101 and 0.48. Additionally, the obtained BF_{10} is relatively robust against different prior specifications (Fig. 2b). Finally, we assessed if participants with the highly adaptive profile had a higher rate of meeting the WHO criteria of 75 min of vigorous intense activity per week than those with the normal profile. Indeed, 75.0% in the highly adaptive group fulfilled this criterion, whereas in the less adaptive group, this was only the case for

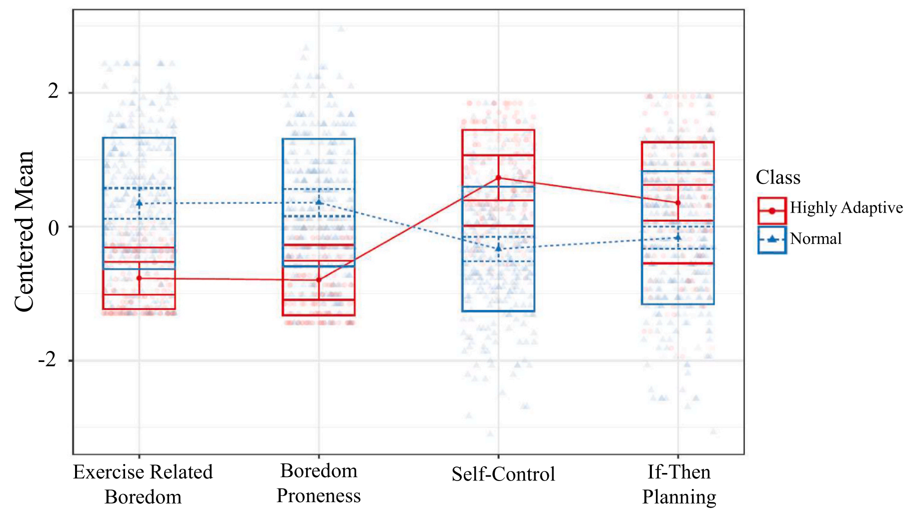

Fig. 1. *The selected profile solution according to BIC with varying variance and covariance (Model 6) and two latent profiles.*
Latent profiles based on the Bored of Sports Scale, the Short Boredom Proneness Scale, the Capacity for Self-Control Scale, and the If-Then Planning Scale. The means of all questionnaires were centered. The bars display 95% confidence intervals for the class centers. The boxes display the standard deviations within each class. Raw data points indicate through their density how certain they can be classified. One profile, the highly adaptive one, scores very high on self-control and planning and scores very low on the two boredom scales. The less adaptive or normal profile shows a less extreme pattern in both regards.

Table 3
(Not standardized) Estimates for mean, standard error (in brackets), variances (diagonal), and covariances for each of the profiles of the two-profile (Model 6) solution, respectively.

Class	Measure	*M*	1	2	3	4
highly adaptive	1. Exercise-related boredom (BOSS)	1.56*** (.13)	.24** (.08)			
	2. Boredom proneness (SBPS)	1.56*** (.13)	.20* (.08)	.22** (.08)		
	3. Self-control (CSFCS)	4.15*** (.13)	-.18** (.07)	-.16** (.06)	.30*** (.08)	
	4. If-then planning (ITPS)	5.42*** (1.5)	-.17 *n.s.* (.09)	-.13 *n.s.* (.09)	.22* (.11)	.82*** (.18)
less adaptive (normal)	1. Exercise-related boredom (BOSS)	2.76*** (.11)	1.11*** (.10)			
	2. Boredom proneness (SBPS)	2.59*** (.09)	.34*** (.09)	.71*** (.05)		
	3. Self-control (CSFCS)	3.33*** (.06)	-.31*** (.06)	−.39*** (.05)	.51*** (.05)	
	4. If-then planning (ITPS)	4.90*** (.09)	-.32** (.10)	-.22** (.08)	.40*** (.05)	.99*** (.08)

Note: M = mean. Range BOSS: 1–5; Range SBPS: 1–5; Range CSFCS: 1–5; Range ITPS: 1–7.
n.s. = non-significant **p* < .05. ***p* < .01. ****p* < .001.

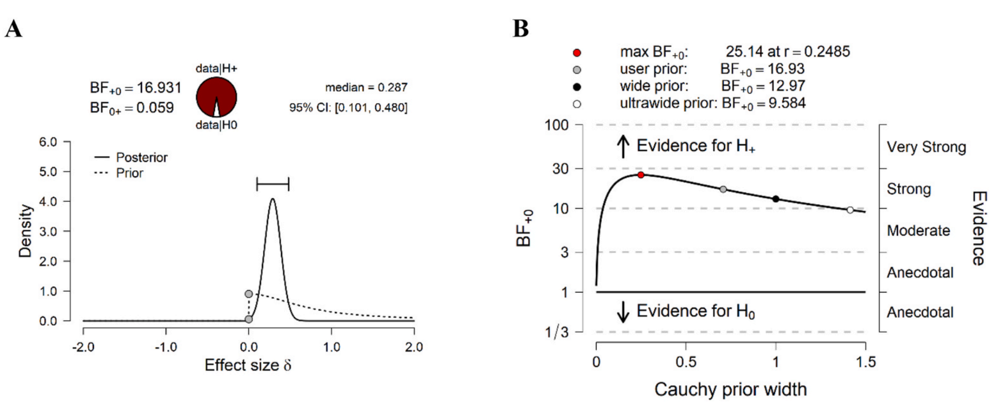

Fig. 2. *Effect size of the Bayes Factor (Panel A) and Bayes Factor Robustness as a function of prior width (Panel B).*

58.2%, χ^2 (1) = 11.64, p < .001.

6. Discussion

This is the first study to apply latent profile analysis to investigate the joint role of individual differences in boredom and self-control in the context of exercise behavior. We identified two latent personality profiles. The highly adaptive profile was characterized by low boredom proneness, low exercise-related boredom, high self-control, and high if-then planning. Conversely, the comparatively less adaptive normal profile was characterized by lower self-control and if-then planning and higher boredom proneness and exercise-related boredom. Validating the proposed adaptivity of the extracted profiles in regard to exercise behavior, the weekly exercise levels of people who displayed the highly adaptive profile were higher compared to those who displayed the less adaptive normal profile. Interestingly, our data indicate that, on average, participants were meeting the WHO criteria for vigorous activity. However, this has to be taken with a grain of salt because, while the vigorous activity scale of the IPAQ-S has been shown to correlate with objective measures, such self-report measures are prone to overestimation of the absolute exercise time (Prince et al., 2008). Importantly, to further substantiate our findings, compared to people in the highly adaptive profile, people in the normal profile also were substantially less likely to meet the WHO criteria according to their self-reports.

Our findings are in line with recent empirical and theoretical work outside the sports setting, which has highlighted the joint impact of boredom and self-control on goal-directed behavior (Wolff et al., 2020; Wolff & Martarelli, 2020). More specifically, it has been suggested that boredom indicates that one should do something else, thereby making it more difficult to continue with the task at hand. Self-control on the other hand can help people deal with such difficulties. Our results indicate that people who get easily bored are also less likely to be good at self-control and this seems to combine into a personality profile that is not well equipped to face the challenges exercise might impose. In other words, the person who gets bored during a 5-km run and feels the urge to do something else is very likely to be less well equipped to regulate this urge - which represents an added self-control demand - and keep on running.

Attesting to the relevance of all chosen variables, we found significant negative correlations between exercise behavior and both boredom measures (i.e., boredom proneness and exercise-related boredom) and positive correlations between exercise behavior and the self-control variables (i.e., self-control and if-then planning). Our findings add to existing knowledge on the importance of self-control in regard to exercise behavior (e.g., Hagger et al., 2010). Beyond self-control, this is the first study to show that a general disposition to engage in if-then planning as a self-control strategy (rather than if-then planning interventions) is linked with more exercise. Even more importantly, this is the first study to provide empirical evidence for the crucial role of boredom in the exercise context. More specifically, we show that not only exercise-related boredom but also domain-general boredom proneness covaries with lower exercise levels. Thus, not only does boredom seem to be regularly associated with exercise, the tendency to get easily bored might indeed be a dispositional barrier for regular exercise.

6.1. *Personality profiles can help in designing effective interventions*

The identified latent personality profiles indicate that relevant dispositions co-occur in a systematic fashion, and this might render some individuals particularly ill-equipped to become regular exercisers. This has direct implications for designing interventions to promote exercise behavior. First, given that individual differences in boredom proneness and self-control are related to individuals' exercise levels, one might use these variables to screen who should be targeted with an intervention in the first place. Second, an intervention that is tailored to a non-adaptive personality profile should directly address boredom and the self-control demands that can arise in the exercise setting. Theoretical work on boredom and self-control offers conceptual frameworks that can be used to reduce boredom and to lower the self-control demands of exercise. In regard to boredom, it is crucial to create (or help people create) exercise environments that are less boring, by matching demands to resources (thereby avoiding over- and under-stimulation) and by enriching the experience with meaning. Interestingly, recent years have seen the rise of platforms that seem to succeed in creating such environments. For example, virtual bike racing on indoor trainers, where exercisers can choose to compete with competitors of similar fitness levels or choose to simply join a virtual group ride with an emphasis on social interaction, has developed into a multi-million dollar industry that has attracted millions of paying exercisers (Lunden, 2018). In regard to self-control, it might be instructive to create exercise environments that place less situational self-control demands (Duckworth et al., 2016) on the exerciser, and to be particularly conscious of boredom being one such situational self-control demand (Wolff & Martarelli, 2020). Going back to the example of virtual indoor cycling, the situational self-control demands of doing a social ride in the living room might be lower than doing the same ride outside in the cold rain (similarly, they might be substantially increased if ones partner is sitting on the couch, eating candy, while one is sweating on the cycling ergometer). Finally, although people differ in the tendency to engage in if-then planning as a self-control strategy, making effective if-then plans can be easily taught in a way that is time- and cost-efficient. For example, mobile phone applications have been developed that help people make tailored if-then plans on their own (Home — WOOP My Life, 2020). Thus, individuals with a low propensity to engage in if-then planning might benefit particularly from such an intervention. Again, keeping the strong link between self-control and boredom in mind, it might be worthwhile for prospective exercisers to focus on boredom and self-control demands as specific challenges to their exercise goals and formulate if-then plans accordingly.

As a direct implication of the present findings, one should be conscious of such personality profiles when designing an intervention and address each of its constituent variables as part of the intervention because neglecting either one might introduce a predetermined breaking point into the interventions effectiveness. We believe this finding can provide a much needed impetus for theory-driven research that jointly investigates the role of self-control and boredom in the context of exercise behavior. For example, starting from this broad categorization into two latent profiles, future research might focus on less parsimonious solutions to identify distinct personality profiles of potential high-risk subgroups. In the same vein, it will be an intriguing question for future research to assess if different sporting environments moderate how personality profiles covary with exercise behavior. For example, do boredom prone individuals tend to choose exercise environments that are potentially less likely to induce boredom (e.g., a running group vs. running alone) and does the accessibility of such environments offset the barrier this personality trait might impose otherwise? Ideally, such future studies would also employ objective measures of exercise behavior to overcome the limitation of relying solely on self-report measures.

6.2. *Introducing a measure of exercise-related boredom*

In line with lay knowledge (10 Ways to Beat Boredom at the Gym - Fitness Center - Everyday Health; 8 Ways to Beat Exercise Boredom! 2010), this is the first study to provide empirical support for the proposed relevance of boredom in the exercise setting. However, attesting to the shortage of research on boredom in sports, dedicated self-report measures for the assessment of exercise related boredom are lacking. To address boredom in the exercise context, we adapted the learning-related boredom subscale of the AEQ, an instrument that is frequently used in the educational setting (Pekrun et al., 2011), to the exercise setting. Importantly, this Bored of Sports Scale (BOSS) exhibited excellent internal consistency and was linked with self-reported exercise behavior. Thus, these findings suggest that some individuals associate exercise with boredom and these people in turn exercise less. This finding can be interpreted as a first indicator of the criterion validity of the BOSS. In addition, providing evidence for convergent validity, we found a strong positive correlation between BOSS and the domain-general boredom proneness and, providing evidence for discriminant validity, we found substantial negative correlations between BOSS and the self-control variables trait self-control and if-then planning. Taken together, these findings provide preliminary evidence that the BOSS might be a reliable and valid instrument for assessing boredom in the exercise context.

7. Conclusion

The present findings support the theoretical proposition that boredom and self-control are closely linked in their effect on goal-directed behavior (Wolff & Martarelli, 2020). They do so by revealing two latent personality profiles with inverse levels of boredom and self-control, and by showing that these personality profiles are linked with exercise behavior. This indicates that a less adaptive personality profile (high boredom; low self-control) might put people at risk of being physically inactive. Importantly, as the constituent variables in the identified profiles represent (mostly) domain-general concepts, their presumed adaptiveness might extend well beyond the exercise context and lend further credence to the proposed joint role of boredom and self-control as drivers of goal-directed behavior. We believe assessing this possibility is a particularly promising route for further research. Beyond identifying these latent personality profiles, the present contribution is the first study to link planning propensity to exercise behavior, thereby showing that if-then planning as a personality trait covaries with exercise behavior. Given the frequency with which if-then plans are used in intervention studies, we believe this is a crucial finding, as it opens the door for utilizing an individual difference approach in maximizing intervention effects. Finally, we introduce a new measure for measuring exercise-related boredom. As our findings underline the relevance of boredom in the context of exercise, we believe this is particularly important, as it provides the research community with a time-efficient, psychometrically sound measure to assess boredom in the exercise context.

CRediT authorship contribution statement

Wanja Wolff: Conceptualization, Methodology, Formal analysis, Resources, Writing - original draft, Writing - review & editing, Supervision, Project administration, Investigation. **Maik Bieleke:** Conceptualization, Writing - review & editing. **Johanna Stähler:** Writing - review & editing, Formal analysis, Data curation, Visualization. **Julia Schüler:** Writing - review & editing, Conceptualization, Resources.

Declaration of competing interest

The authors declare no conflict of interest.

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Appendix

Bored for Sports Scale (BOSS): Instruction and Items.

In the next set of questions, we are interested in your thoughts and feelings when you think about exercising. To answer these questions, please envision yourself during a training session (e.g., working out in the gym). Read each statement and indicate how much you agree with it. (Answers are given on a five-point Likert-scale ranging from *strongly disagree* to *strongly agree*.)

1. The training session bores me to death.
2. Exercising bores me.
3. Exercising is dull and monotonous.
4. While doing this boring training session, I spend my time thinking of how time stands still.
5. The training session is so boring that I find myself daydreaming.
6. I find my mind wandering while I exercise.
7. Because I'm bored, I have no desire to exercise.
8. I would rather put off this boring training session till tomorrow.
9. Because I'm bored, I get tired while exercising.
10. The training session bores me so much that I feel depleted.
11. While exercising I seem to drift off because it's so boring.

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