Running head: SPORT MOTIVATION PROFILES

Predictors and outcomes of core and peripheral sport motivation profiles: A person-centered study

István Tóth-Király[1,2], Camille Amoura[3], Beáta Bőthe[4,2], Gábor Orosz[5,2], Adrien Rigó[2]

[1] Substantive-Methodological Synergy Research Laboratory, Department of Psychology, Concordia University, Canada
[2] Institute of Psychology, ELTE Eötvös Loránd University, Hungary
[3] Université d'Artois, Atelier Sherpas, France
[4] Département de Psychologie, Université de Montréal, Canada
[5] Department of Psychology, Stanford University, CA, USA

Corresponding author:
István Tóth-Király
Substantive-Methodological Synergy Research Laboratory
Department of Psychology, Concordia University
7141 Sherbrooke W, Montreal, QC, Canada, H4B 1R6
E-mail.: tothkiralyistvan@gmail.com; istvan.toth-kiraly@concordia.ca

Funding: The first author was supported in the preparation of the manuscript by a Horizon Postdoctoral Fellowship from Concordia University and by funding from the Social Sciences and Humanities Research Council of Canada (435-2018-0368). The third author was supported by a postdoctoral fellowship from the SCOUP Team – Sexuality and Couples – Fonds de recherche du Québec, Société et Culture. The fourth author was supported by the Hungarian Research Fund (NKFIH FK 124225). The previous version of this paper was written while the first author was doing his PhD studies at Eötvös Loránd University.

Conflict of interest: The authors declare no conflict of interest.

This document is a pre-publication version of the following manuscript:

Tóth-Király, I., Amoura, C., Bőthe, B., Orosz, G, & Rigó, A. (In Press, Accepted: 21 December 2019). Predictors and outcomes of core and peripheral sport motivation profiles: A person-centered study. *Journal of Sports Sciences*. doi: 10.1080/02640414.2020.1736765

Predictors and outcomes of core and peripheral sport motivation profiles: A person-centered approach

Abstract

While previous studies highlighted the importance of the different motivations for doing sports as proposed by self-determination theory, less emphasis has been put on the simultaneous presence of multiple motivations within the same individual. Therefore, the present study aimed to investigate the complex interaction of sport motivations and to identify core (common) and peripheral (uncommon) profiles of people engaged in sports based on a combination of motivations. To achieve this goal, latent profile analysis, a person-centered approach, was performed on responses from 506 participants engaged in sports. For better understanding the extracted profiles, basic psychological need fulfillment was included as profile predictor, while subjective vitality and various engagement-related indicators as outcomes. Four core and peripheral profiles were identified: Moderately Motivated, Highly Motivated, Amotivated, and Poorly Motivated. Contrary to theory, introjected regulation clustered more closely with self-determined motivations. Profile membership was significantly predicted by global need fulfillment, autonomy satisfaction as well as, to a smaller extent, autonomy, relatedness, and competence frustration. The four profiles differed along vitality and some, but not all, engagement-related outcomes.

Keywords: basic psychological needs; latent profile analysis (LPA); motivational profiles; self-determination theory (SDT); sport motivations; vitality;

Participation in sports has usually been considered as an adaptive activity as it has consistently been associated with increased positive (e.g., fitness or self-esteem) and decreased negative (e.g., social anxiety or depression) outcomes (Eime, Young, Harvey, Charity, & Payne, 2013; Vallerand, 2007). However, not all participants experience outcomes wholly and in the same way (i.e., not all individuals experience the same level of self-esteem or the same level of burnout after sports participation). Given that people may engage in sport for various reasons, examining these reasons (i.e., motivational sources) of sports participation has received significant scientific attention. Different motivations may explain important outcomes differently, and most studies so far highlighted their importance through variable-centered approaches (see Ryan & Deci, 2017, for an overview) that are designed to test how one variable is related to another variable. Still, the contribution of this approach might be limited because it focuses on motivations individually instead of their potential joint impact. The current study aims to remedy this weakness by taking a person-centered approach that might be more suitable for investigating the synergistic effects of different motivations. As relatively little attention has been paid to how these motivations interact within individuals by making up core (i.e., common) and peripheral (i.e., uncommon) motivational profiles, the goal of the present study was to examine the complex interplay of sport motivations through latent profile analysis, a person-centered approach. We also investigated how subjective vitality and indicators of the quantity of sports engagement are related to these profiles. Moreover, as it has been neglected so far, we also examined how the profiles are predicted by theoretically-relevant key variables, namely basic psychological need fulfillment during sport.

Self-Determination Theory's View of Motivations

Self-Determination Theory (SDT; Ryan & Deci, 2017) provides a well-established and comprehensive framework for understanding differences in sport engagement quality and well-being during or in relation to engagement. SDT postulates that people have an inner, innate tendency towards greater integration, and optimal engagement and wellbeing-related outcomes are theorized to manifest when this innate tendency is facilitated. One manifestation of this tendency is motivations (i.e., behavioral regulations), which are conceptualized as being multidimensional by nature. Within the framework of SDT, several regulations have been proposed which can be placed on a continuum based on the level of internalization (Ryan & Connell, 1989), namely intrinsic, extrinsic, and amotivation.

At one end of this continuum (ranging from the most to the least self-determined) is *intrinsic motivation* (IM), which involves the highest level of internalization and self-determination. IM is characterized by intrinsic regulation, where the sport is pursued as a result of pleasure and enjoyment associated with the behavior itself. Extrinsic motivation (EM) occurs when behavior is enacted for instrumental, rather than inherent reasons and based on the SDT, EM can be divided into four types of regulations. *Integrated regulation* is the most self-determined form and occurs when the behavior is in line with personal goals, objectives, and the sport becomes congruent with the values and the self. A less self-determined form of EM, compared to integrated regulation, is *identified regulation*, which is evidenced when one does sports due to the positive outcomes (e.g., improved health) associated with it. Moving further along the continuum is *introjected regulation*, which stems from the goal to avoid the subjective experiences of guilt, shame, or to enhance self-esteem through the sport. As the least self-determined form, *external regulation* occurs when either rewards or punishments orient the act of doing sports. Finally, *amotivation* (AM) refers to non-regulation and a lack of intention to act; thus, amotivated individuals do not know why they pursue their sport. In SDT literature (Ryan & Deci, 2017), intrinsic, integrated, and identified regulations are commonly referred to as autonomous or self-determined motivations, while introjected and external regulation are often referred to as controlled or non-self-determined motivations. Referring to the above-mentioned innate tendency, self-determined regulations are more indicative of a facilitated innate tendency, whereas non-self-determined regulations are more indicative of an obstructed innate tendency.

Over the years, several studies based on variable-centered approaches have examined the various predictors and outcomes of these behavioral regulations with the more self-determined forms being associated with adaptive and positive outcomes such as task involvement, positive affect, improved physical activity, or intention to partake in physical activity, while less self-determined regulations are linked to aggression, burnout, boredom, or even doping use (Cresswell & Eklund,

2005; Ntoumanis, 2001; Ntoumanis, Ng, Barkoukis, & Backhouse, 2014; Ryan & Deci, 2000; Sebire, Jago, Fox, Edwards, & Thompson, 2013; Standage, Duda, & Ntoumanis, 2003).

The variable-centered approach examines average levels of relations between variables and operates under the assumption that all individuals are drawn from a single population (i.e., population homogeneity), implying that the observed results can be generalized to all participants. For instance, using a motivational example, a variable-centered finding might show that intrinsic motivation is associated with higher wellbeing for all participants in the population. Since a variable-centered approach focuses on the *variable* as a unit of interest, it is not able to take into account that one may endorse several different motivations for doing sports. Conversely, a person-centered approach—as a complementary and uniquely informative alternative—relaxes this assumption and aims to identify distinct, homogenous subgroups of participants and categorizes them into these quantitatively and qualitatively distinct profiles based on their shared similarities. This way, a person-centered approach views the *individual* as a unit (instead of viewing the variable as a unit; Lubke & Muthén, 2005) in a more holistic fashion by focusing on a combination (instead of an isolated number) of characteristics. Returning to the previous example, a person-centered finding might show that intrinsic motivation is associated with higher wellbeing if it is not coupled with, for instance, external regulation. These points are also particularly important, given SDT's assertion that motivations are likely to occur in combinations (Vallerand, 1997). While it is true that interactions between variables could be tested (e.g., Marsh, Hau, Wen, Nagengast, & Morin, 2013), interaction effects involving more than three variables is almost impossible to interpret; on the other hand, no such limitations exist in person-centered approaches which can be estimated from any number of variables (Morin, 2016; Morin & Wang, 2016). Another advantage of a person-centered approach is that it becomes possible to identify a target group of participants with suboptimal motivations who might be specifically targeted with a well-tailored intervention, potentially making the interventions more effective (Morin & Marsh, 2015). Overall, a person-centered approach allows one to consider people as whole entities instead of focusing on a narrow set of individual characteristics, thus examining motivations on a within-person (instead of a between-person) level (Lindwall et al., 2017). For these reasons, to address this shortcoming stemming from complex motivational interactions, a person-centered approach was chosen that could identify motivational profiles.

Prior Findings on Sport Motivational Profiles

There have been some prior studies that served as a basis for the present investigation (see Table 1 for an overview). Generally speaking, respondents are grouped into smaller subgroups based on their shared similar characteristics (e.g., scoring high on a particular subscale). In prior studies, three to six profiles were extracted with the most common, *core profiles* being (1) an autonomous or self-determined profile characterized by high scores on the autonomous factors and low scores on the controlled factors, (2) an average or moderate profile characterized by average score on autonomous/controlled factors and low or average score on amotivation, (3) a controlled or non-self-determined profile characterized by low scores on the autonomous factors and high scores on the controlled factors and an autonomous-controlled profiles characterized by high scores on both the autonomous and controlled factors (e.g., Boiché, Sarrazin, Grouzet, Pelletier, & Chanal, 2008; Gillet, Vallerand, & Rosnet, 2009; Guérin & Fortier, 2012; Ntoumanis, 2002). Apart from these common profiles, several uncommon, *peripheral profiles* have also been extracted in several studies such as a moderately autonomous profile (e.g., Gustafsson, Carlin, Podlog, Stenling, & Lindwall, 2018) or a self-determined profile with equally high introjected regulation (Lindwall et al., 2017). In addition, these studies examined sport motivation profiles with different methodologies (e.g., cluster analysis or latent profile analysis).

However, there have been several criticisms of cluster analysis as it lacks clear guidelines for profile selection, it rests on rigid assumptions that are rarely met (e.g., precise assignment of individuals to a profile rather than considering participants' likelihood of membership in all profiles on the basis of their prototypical similarity), and it is also sensitive to clustering algorithms, distributions, and measurement scales (Meyer & Morin, 2016; Morin & Wang, 2016). In contrast, the present study focused on latent profile analysis (LPA), which is a flexible approach to profile construction and classification (Muthén, 2002). LPA uses a formal set of objective criteria that guides the process of classification and also allows the estimation of alternative profiles. Moreover, instead of being fixed, latent profiles are prototypical configurations that allow for substantial levels of within-profile

variation (i.e., all participants have a probability of membership of belonging to all profiles instead of being “forced” into a single profile). For this reason, we used LPA in the present study. Notwithstanding its improvements over cluster analysis, LPA still needs to be complemented with investigations of construct validity to examine the interpretation of the extracted profiles to ascertain that they are indeed meaningful and to make sure that no spurious profiles emerge (Morin, Morizot, Boudrias, & Madore, 2011). Among other things, this can easily be achieved by the direct incorporation of theoretically-relevant outcomes. Besides, while some studies (e.g., Boiché et al., 2008; Gustafsson et al., 2018) included profile outcomes, no person-centered study investigated how profile membership is related to key predictors.

Predictors and Outcomes of Sport Motivational Profiles

A central element of SDT is that the innate human tendency for growth and integration are a function of the fulfillment of three basic psychological needs (Ryan & Deci, 2017), namely autonomy (i.e., acting volitionally, in line with own values), competence (i.e., experiences of mastery and effectiveness), and relatedness (i.e., sense of belongingness and reciprocity). When these three psychological needs are met, individuals are more likely to have the capacity to internalize and integrate current behavioral regulations (Ryan, 1995); in other words, when needs are satisfied within an activity, people start to take ownership for their actions, thus facilitating the internalization process that is the basis for motivational, behavioral regulations. Put differently, when individuals' needs are fulfilled, they function in a healthy and effective way, which enables a higher level of internalization, resulting in more self-determined motivations. While the directionality between needs and motivations have always been assumed, a recent investigation explicitly tested this process model in the context of work and concluded that need satisfaction was indeed related to work motivations over time, but not the other way around (Olafsen, Deci, & Halvari, 2018). This finding is complemented by previous cross-sectional results from sport and health contexts where more self-determined motivations (i.e., intrinsic, integrated, identified) were positively related to need satisfaction, whereas controlled motivations and amotivation were either unrelated or negatively related to it (e.g., Ng et al., 2012; Pelletier, Rocchi, Guertin, Hébert, & Sarrazin, 2017; Weman-Josefsson, Lindwall, & Ivarsson, 2015). For these reasons, need fulfillment was included as a theoretically-relevant profile predictor.

Previous studies also highlighted several important distinctions from the perspective of outcomes. The inclusion of profile outcomes is important because individuals with more autonomous motivations (as opposed to controlled motivations) are theorized to perform more effectively in sport as well as enjoying it more because these motivations stem from a sense of volition and personal causation (Ryan & Deci, 2000). For instance, Gillet, Vallerand, et al. (2009) concluded that athletes from the least self-determined profile (moderately autonomous and low controlled) had the lowest overall performance throughout the subsequent season. In contrast, the results of Gillet, Berjot, and Paty (2009) suggested that having *both* autonomous and controlled motivations is detrimental to performance. Another investigation of Gillet, Berjot, Vallerand, Amoura, and Rosnet (2012) showed that the highly motivated profile (characterized by high intrinsic, identified and introjected regulation as well as moderate-to-low external regulation and amotivation) was associated with higher levels of performance, but also with higher levels of emotional and physical exhaustion. Gustafsson et al. (2018) examined burnout as a profile outcome and found that the less self-determined profile (amotivated and moderately controlled) was related to higher burnout symptoms. In the present study, subjective vitality was used as an outcome of the different motivational profiles. Vitality refers to the subjectively experienced positive feelings of aliveness and energy and is said to reflect organismic wellbeing and is available to the self (Ryan & Deci, 2017). Indirect evidence coming from cross-sectional sport-related results suggest that more self-determined motivations are positively, whereas controlled motivations and amotivation negatively associated with wellbeing outcomes of vitality (Pelletier, Rocchi, Vallerand, Deci, & Ryan, 2013; Yu et al., 2015).

Finally, the present study also considered a number of engagement-related indicators (i.e., the length, the frequency, and the duration of doing sports), which might be able to provide complementary information to the psychological factors about the quantity (or amount of) of engagement. Given that the focus of the present study was on doing sports in general (instead of a particular type of sport), we opted to use these three indicators as these were more general and could be answered with different sports backgrounds. These indicators were also thought to be better at capturing the self-reported engagement with and the self-reported behavioral aspects of doing sports.

Some previous studies have also considered similar engagement-related quantity indicators and reported more autonomous motivations to be associated with physical activity intentions (Standage et al., 2003), increased physical activity (Sebire et al., 2013), exercising behavior (Lindwall et al., 2017), and better performance at the end of the season (Gillet et al., 2012). We expected similar findings in that more self-determined profiles would be associated with higher sports engagement.

The Present Investigation

The primary purpose of this study was to examine how the different behavioral regulations proposed by the SDT combine within different subgroups of individuals within the context of sport. To achieve this goal, LPA was performed on responses provided by a sample of participants engaged in sports. Based on previous studies listed in Table 1, we expected (Hypothesis 1) two-to-three core profiles and (Hypothesis 2) at least some peripheral profiles to emerge. To support the interpretation and practical relevance of the latent profiles, the secondary purpose was to demonstrate that these profiles relate to key predictors and outcomes. We considered basic psychological needs as predictors, subjective vitality, and various engagement-related variables as outcomes. It was expected that (Hypothesis 3) need fulfillment would predict membership to the more self-determined profiles and that (Hypothesis 4) membership to the more self-determined profiles would be associated with higher levels of vitality and higher levels of self-reported engagement.

We sought to build upon and extend previous research in five ways. First, we included all types of regulations that are proposed by the SDT for a more comprehensive coverage instead of focusing on a subset of motivations that are typically done in variable-centered studies. Second, we used the most advanced person-centered method in the form of latent profile analysis instead of cluster analysis. Third, although it is often neglected in the literature except for some cases (e.g., Gustafsson et al., 2018), we also ascertained the measurement properties of all constructs in the form of preliminary measurement models, which could, in turn, minimize potential biases. Fourth, to better document the construct validity of the profiles, we included subjective vitality and various engagement-related indicators as profile outcomes. Fifth, also neglected in the literature are investigations on the potential predictors of profiles; we addressed this absence by including basic psychological need fulfillment as a profile predictor.

Method

Procedure and Participants

The study was conducted following the guidelines of the Declaration of Helsinki and with the explicit approval of the University Research Ethics Committee. Participants were recruited through different online forums, groups, and websites specialized in sports. First, they were informed about the aims of the study and ensured their anonymity. If they were willing to participate, they had to check a box to provide explicit consent; otherwise, they were excluded. They were then directed to a set of online questionnaires (presented in Hungarian) where they were also filtered out if they did not actively pursue any form of sports at the time of the data gathering.

In the end, 506 Hungarian respondents participated (78.1% female) who were aged between 18 and 66 (M = 26.3, SD = 8.5) and who were engaged in sports. They reportedly lived in either the capital city (54.2%), county capitals (7.9%), cities (26.9%), or country towns (11.1%). The vast majority of them were on amateur level (89.3%), pursued their sport for 1-6 months (20.9%), 7-11 months (9.1%), 1-2 years (17.8%), 3-4 years (16.8%), or 5 years or more (35.4%). Respondents were engaged in a variety of sports, including running, pole-sports (pole fitness, pole dancing), aerobic, rowing, football, gym exercises, basketball, yoga, and volleyball.

Measures

Translation procedure. All instruments previously not validated in Hungarian were translated and back-translated based on the protocol outlined by Beaton, Bombardier, Guillemin, and Ferraz (2000).

Sports motivation (profile indicator). The Sport Motivation Scale II (SMS II; Pelletier et al., 2013) was used to assess the different factors (and reasons) for practicing sports: intrinsic motivation (e.g., “Because it gives me pleasure to learn more about my sport”, α = .80), integrated regulation (e.g., “Because practicing sports reflects the essence of who I am”, α = .83), identified regulation (e.g., “Because I found it is a good way to develop aspects of myself that I value”, α = .80), introjected regulation (e.g., “Because I feel better about myself when I do”, α = .60), external regulation (e.g., “Because I think others would disapprove of me if I did not”, α = .66), amotivation (e.g., “I used to

have good reasons for doing sports, but now I am asking myself if I should continue", α = .71). Respondents were able to answer on a seven-point scale (1 = Does not correspond at all; 7 = Corresponds completely). This instrument demonstrated good psychometric properties in terms of factor structure and reliability (Pelletier et al., 2013, 2017).

Basic psychological needs (profile predictor). The Hungarian version (Tóth-Király, Morin, Bőthe, Orosz, & Rigó, 2018) of the Basic Psychological Need Satisfaction and Frustration Scale (BPNSFS; Chen et al., 2015) was used to measure need fulfillment. It is a 24-item measure with six factors (four items each) including autonomy satisfaction (e.g., "I feel a sense of choice and freedom in the things I undertake"; α = .76) and frustration (e.g., "I feel forced to do many things I wouldn't choose to do", α = .71), competence satisfaction (e.g., "I feel confident that I can do things well", α = .83) and frustration (e.g., "I have serious doubts about whether I can do things well", α = .87), and relatedness satisfaction (e.g., "I feel that the people I care about also care about me", α = .84) and frustration (e.g., "I feel excluded from the group I want to belong to", α = .79). Items were rated on a five-point scale (1 = Not true at all for me; 5 = Very true for me). The instruction was slightly modified so that it referred to the experiences of need satisfaction and frustration during sports by emphasizing in the instruction that the subsequent questions refer to experiences during sports and by starting each item with the stem "While doing sports…". Previous studies (e.g., Rodrigues et al., 2019) tended to support the questionnaire's reliability and factorial structure.

Subjective vitality (profile outcome). The Subjective Vitality Scale (Ryan & Frederick, 1997) measures vitality with seven items (e.g., "I feel energized"; α = .91) which are rated on a seven-point scale (1 = Not true at all; 7 = Very true). The instruction was slightly modified so that it reflected vitality during sports. Past sports research (e.g., Reinboth, Duda, & Ntoumanis, 2004) supported the factorial validity and internal consistency of this measure.

Quantity of engagement with sports (profile outcome). Participants were asked to respond to three indicators of the quantity of sport engagement (single-item measures for brevity[1]) that referred to: (1) the *length* of doing sports (i.e., for how long they were doing their sports) using a five-point scale (1 = 1-6 months; 2 = 7-11 months; 3 = 1-2 years; 4 = 3-4 years; 5 = more than 5 years); (2) the *frequency* of doing sports (i.e., the number of occasions they were doing their sport on an average week); and (3) the *duration* of doing sports (i.e., the amount of time spent they were spending doing their sport on an average occasion, expressed in minutes). For duration, a threshold of 240 minutes (4 hours) was used as an upper limit to minimize bias[2]. Higher values were recoded as missing. Participants reportedly were doing their sports for more than 5 years with an average four occasions per week, and, on an average occasion, they spent 85.93 minutes (SD = 58.85) with their sport. The three items were not summed and were treated separately during analyses.

Statistical Analyses

Preliminary analyses. The psychometric properties of the measures were tested with preliminary measurement models using the robust weighted least square mean- and variance-adjusted (WLSMV) estimator in Mplus 8 (Muthén & Muthén, 1998-2017) given that this estimator is more suitable for the ordinal nature of Likert scales and when response categories follow asymmetric thresholds (Finney & DiStefano, 2013; Morin, Myers, & Lee, 2018) such as in the present case. For the SMS II, we contrasted two alternative six-factor models, one based on confirmatory factor analysis (CFA) and the other on exploratory structural equation modeling (ESEM). In CFA, factors are defined by their corresponding scale items, but cross-loadings to other, non-target factors are forced to zero, while is ESEM, the same cross-loadings are estimated, but are targeted to be as close to zero as

[1] Results of prior studies suggested that single-item self-reported measures have adequate levels of reliability and validity and thus might be considered accurate as indicators of physical activity and sport engagement (e.g., Milton, Clemes, & Bull, 2013; van Poppel, Chinapaw, Mokkink, van Mechelen, & Terwee, 2010; Wanner et al., 2014).

[2] We based this decision on the available survey results of the Hungarian Central Statistical Office (2011) according to which an average Hungarian person (aged between 15 and 74) on an average day spends almost 12 hours (712 minutes in the report) with satisfying his or her physiological needs (i.e., eating, hygiene, sleeping). Almost 8 hours (461 minutes in the report) are spent on activities related to societal functioning (e.g., working), while the remaining approximately 4 hours (268 minutes in the report) are spent on free or leisure time activities. For this reason, we assumed that these 4 hours should be used as an upper threshold for the highest amount of free time one individual can have in our sample in order to minimize bias.

possible (see Browne, 2001 or Tóth-Király, Bőthe, Rigó, & Orosz, 2017). Recent investigations in motivations (Guay, Morin, Litalien, Valois, & Vallerand, 2015; Tóth-Király, Orosz, et al., 2017) highlight the importance of contrasting competing CFA and ESEM models as the latter often results in more precise parameter estimates. Need fulfillment was modeled as a bifactor-ESEM model (based on Tóth-Király, Morin, et al., 2018) representing a global factor of need fulfillment and six specific factors (satisfaction and frustration × autonomy, competence, and relatedness), whereas vitality was estimated in a standard CFA model. More information is available in Appendix 1 of the online supplementary document and in Table S1 to S7. The final preliminary models were then used to save factor scores (with a mean of 0 and a standard deviation of 1) that were used in the main analyses. While factor scores do not control for measurement error the same way as fully latent variables do, they still provide a partial control by giving more weight to items with lower errors (Morin & Marsh, 2015) and thus considered better in profile estimation relative to manifest scores.

Latent profile analyses (LPA). Models with one to eight profiles were estimated with the robust maximum likelihood (MLR) estimator available in Mplus 8. In order to avoid potential issues stemming from converging on suboptimal local maximum, 5000 random sets of start values were estimated with 1000 iterations, and the 200 best solutions were retained for final optimization (Hipp & Bauer, 2006). The means and the variances of the motivational factors were freely estimated in all profiles (Diallo, Morin, & Lu, 2016). To identify the most adequate solution with the optimal number of profiles, the meaningfulness, the theoretical adequacy, and the statistical adequacy of the solutions were considered (Morin, 2016). For statistical adequacy, a variety of indicators were examined: the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Constant AIC (CAIC), the Sample-Size-Adjusted BIC (SSABIC), the adjusted Lo-Mendell-Rubin (aLMR) likelihood ratio test, and the Bootstrap Likelihood Ratio Test (BLRT). A lower value on AIC, BIC, CAIC, and SSABIC suggests a better fitting solution. The aLMR and the BLRT tests compare the estimated model (e.g., four classes) with a model having one less class (e.g., three classes) and a non-significant p-value ($p > .050$) indicates that the model with one less class should be accepted. Finally, entropy highlights the precision of the classification with values ranging from 0 (lower accuracy) to 1 (higher accuracy). The information criteria (i.e., AIC, BIC, CAIC, and SSABIC) often keep improving with the addition of more profiles, a graphical examination of "elbow plots" could facilitate the decision making where the point after which the slope flattens suggest that the optimal number of profiles have been reached.

Following the suggestions of Diallo et al. (2016), more emphasis should be put on BIC and CAIC in the case of high accuracy (i.e., > .800), while SSABIC and BLRT are preferred in the case of low accuracy (i.e., < .500). At the same time, increasing statistical evidence suggests that AIC, aLMR, and BLRT should not be used during profile selection (e.g., Diallo et al., 2016; Henson, Reise, & Kim, 2007; Peugh & Fan, 2013). For this reason, these indicators are reported for the sake of transparency but are not used for profile selection. Instead, more emphasis was put on the interpretation of elbow plots.

Profile predictors and outcomes. Once the final solution was identified, multinominal logistic regression was conducted to test the associations between the predictors (global need fulfillment and its specific dimensions) and the likelihood of membership into the different profiles using the Mplus' auxiliary "R3STEP" function for predictors. The regression coefficients indicate the likelihood of belonging to the target profile compared to the referent one. For simplicity, these coefficients were converted to odds ratios (OR) which indicates how much the likelihood of group membership into the target group changes relative to the referent group (e.g., an OR of 2 suggests that respondent is two times more likely to be member of the target profile compared to the referent profile). The final profiles were compared on the outcomes using Mplus' auxiliary "BCH" function that is suitable for continuous outcomes (Morin, 2016).

Results

Fit indices for the different profile solutions are presented in Table 2. Generally, all entropy values were high for all profile solutions (> .800). With the inclusion of additional profiles, the information criteria of AIC, BIC, CAIC, and SSABIC continuously decreased; thus, elbow plots (see Figure S1 in the online supplements) were examined with a particular focus on BIC and CAIC (Diallo et al., 2016). This plot indicated that the flat part was reached around the 3-4-5-profile solutions. Carefully contrasting these alternative configurations revealed that the addition of a fourth profile did

result in a qualitatively distinct and relatively large profile, whereas moving from 4 to 5 only lead to arbitrary division of an existing profile into two similar ones. Consequently, the four-profile solution was retained which is graphically presented in Figure 1 with classification probabilities reported in Table S9 and the exact numerical values are presented in Table S10[3]. Profile 1 (28.3% of the respondents, n = 143) was identified as a *Moderately Motivated* profile as it was characterized by average levels on intrinsic, integrated, identified, and introjected regulations, but lower than average scores on external regulation and amotivation. Profile 2 (22.3% of the respondents, n = 113) was a *Highly Motivated* profile, as evidenced by the very high levels of intrinsic, integrated, identified, and introjected motivations with average levels of external regulation and lower levels of amotivation. Profile 3 (20.1% of the respondents, n = 102) was an *Amotivated* profile and was characterized by very low levels of intrinsic, integrated, identified and introjected motivations, average levels of external regulation, and higher levels of amotivation. Finally, Profile 4 (29.3% of the respondents, n = 148) was characterized by average scores on intrinsic, integrated, identified, and introjected regulations, but higher than average scores of external regulation and amotivation thus was labeled as a *Poorly Motivated profile*.

The predictors of general need fulfillment, and the specific factors were added to the final 4-profile solution. The multinominal logistic regression results support the meaningfulness of the extracted profiles with well-defined associations between the predictors and profile membership (see Table 3). General need fulfillment differentiated well between the profiles and was associated with lower likelihood of membership in the profiles characterized non-self-determined motivations compared to self-determined motivations (e.g., not experiencing need fulfillment decreased the likelihood of belonging to the Moderately Motivated profile [Profile 1] relative to the Amotivated one [Profile 3; OR = 0.155]). Autonomy satisfaction differentiated the profiles in a similar, theoretically-reasonable direction. Other specific factors also differentiated some profiles: relatedness frustration predicted higher likelihood membership to the Poorly Motivated compared to the Moderately Motivated and Amotivated ones, while autonomy-competence-relatedness frustration predicted higher likelihood of membership to the Highly Motivated profile relative to the Moderately Motivated one[4].

The outcomes of vitality and the quantity of sport engagement were added to the final 4-profile solution. The within-profile means, standard errors, and pairwise comparisons across the different profiles are reported in Table 4. All these comparisons are statistically significant, which further supports the construct validity of the retained profile solution. Subjective vitality significantly differed across all profiles, being highest in the Highly Motivated profile and lowest in the Amotivated profile. Members of the Highly Motivated profile were reportedly engaged in sport the most along the indicators of length, frequency, and duration of doing sports, followed by the Poorly Motivated, the Moderately Motivated, and the Amotivated profiles, although not all profiles differed from one another.

Discussion

The present study aimed to expand on previous variable-centered and cluster analytic approaches (e.g., Gillet et al., 2012; Ntoumanis, 2002) by identifying prototypical profiles of participants engaged in sports based on the simultaneous consideration of the different behavioral regulations proposed by the SDT (Ryan & Deci, 2017). Also, theoretically reasonable predictors and outcomes were incorporated into the final profile solution as it was important not just to investigate the potential consequences of the different behavioral regulations (Gustaffson et al., 2018), but also the relevant variables that orient these regulations. Thus, the application of the person-centered approach of latent profile analysis was particularly well-suited for this study, providing a way to assess the interplay of the different behavioral regulations.

The results revealed four distinct profiles representing different core (which manifest across different life contexts) and peripheral (which might only manifest in specific life contexts) configurations of behavioral regulations, thus supporting Hypothesis 1 and 2. More specifically,

---

[3] In interpreting the profiles, having a mean of zero signifies that profile indicator is on an average level, scores substantially higher than zero are considered above average, while scores substantially lower than zero are considered below average

[4] As the competence satisfaction specific factor might not be interpreted as well-defined, we also ran a model in which this particular specific factor was excluded as profile predictors. The results remained unchanged.

Profile 1 represented a *Moderately Motivated* profile average levels on intrinsic, integrated, identified, and introjected regulations, but lower than average scores on external regulation and amotivation. Possibly, these participants do not have any dominant reasons as to why they engage in sports as apparent by the fact that none of the profile indicators had higher than average scores. At the same time, having lower than average external regulation and amotivation suggests that these less optimal forms of motivation are not dominant. This configuration might be classified as a core profile as it has been reported in several previous studies (e.g., Boiché et al., 2008; Gillet et al., 2012) and in other contexts as well (e.g., Howard et al., 2016).

Profile 2 was a *Highly Motivated* profile and was characterized by high levels of intrinsic, integrated, identified, and introjected motivations with lower levels of external regulation and amotivation. Participants in this profile do not only engage in sports due to personal enjoyment or due to the positive effects of sports, but also because of internal pressures such as avoidance of guilt and shame or the pursuit of pride and self-esteem. Introjected regulation clustering more closely with the self-determined behavioral regulations as opposed to the controlled ones have already been reported in studies inside (Lindwall et al., 2017) and outside the field of physical activity (e.g., Howard, Gagné, Morin, & Van den Broeck, 2016; Litalien et al., 2018), suggesting that this finding might not be a unique phenomenon. Moreover, through meta-analytic approaches, Howard, Gagné, and Bureau (2017) identified introjected regulation as being equidistant from the adjacent regulations, implying that it might be a "greyer" regulation instead of being completely black or white. These findings underscore the importance of preliminary examination instead of the implicit clustering of factors.

Profile 3 included *Amotivated* participants (i.e., high level of amotivation, and very low levels of intrinsic, integrated, identified and introjected regulations with external regulation being around average) who reportedly did not know why they pursued sports. Using the work of Legault et al. (2006), amotivated participants might not see a value in doing sports or might question their beliefs about their abilities or the efforts that they make. Future studies are needed to examine the unique aspects of amotivation in more detail. Overall, this profile was similar to prior studies (Gustafsson et al., 2018; Gillet et al., 2012), suggesting that it might be interpreted as a core profile.

Finally, Profile 4 was a *Poorly Motivated* profile and included participants who did sports for predominantly controlled reasons (e.g., other people would disapprove non-engagement) or do not know why they engage in sports at all. This core profile solution is similar to the amotivated and controlled profile identified by Gustaffson et al. (2018) as well as Lindwall et al. (2017). These two studies are particularly relevant given that LPA was used in those studies as well, but more profiles were extracted, though there are some similarities in terms of the overall shape of the profiles (Morin & Marsh, 2015). These discrepancies between the studies might stem from methodological differences, given that sport motivations were modeled with ESEM which in turn resulted in a more precise representation that further supports the value of this approach not just inside (e.g., Howard, Gagné, Morin, & Forest, 2018; Tóth-Király, Vallerand, Bőthe, Rigó, & Orosz, 2019), but outside the scope of the SDT (e.g., Arens & Morin, 2016; Tóth-Király, Bőthe, & Orosz, 2017) as well. The minor differences might also be attributed to the different characteristics of the samples: for instance, participants with different characteristics than the ones recruited in this study might endorse different motivations of motivations (e.g., it is reasonable to assume that external regulation might be more predominant among professional athletes who earn money through sports compared to amateur athletes). The specifications of the models could also influence the results; for example, freely estimating profile indicator means and variances versus freely estimating only profile indicator means could theoretically lead to the identification of different profiles. Overall, our findings support the notion of Vallerand (1997) in that intentional acts such as sports involve different combinations of behavioral regulations with the results suggesting that participants engaged in sport indeed draw motivation from multiple sources, reinforcing the use of rigorous person-centered approaches. At the same time, we have to note that interaction tests in variable-centered approaches are not inherently wrong or biased and could lead to meaningful conclusions; still, we believe that variable- and person-centered approaches should instead be viewed as complementary rather than opposing and that using a combination of both could provide more detailed information of the constructs of interest (Bergman & Trost, 2006).

Predictors of Sport Motivation Profiles

Little research has been carried out to identify the variables that orient individuals toward different sport motivation profiles, a limitation that we sought to address by including the global need fulfillment and its specific factors as predictors. Our results revealed that the relative likelihood of profile membership differed as a function of general need fulfillment during sports; that is, individuals experiencing higher global need fulfillment belonged to the more self-determined profiles relative to the non-self-determined ones, supporting Hypothesis 3. Previous variable-centered analyses showed that psychological need satisfaction is positively related to more autonomous behavioral regulations (Sebire et al., 2013). Therefore, the global fulfillment of the three psychological needs during sports appear to be highly critical in the promotion of more autonomous motivations. As for the specific factors, autonomy satisfaction also predicted profile membership over and above the general factor and in a similar manner. When participants act voluntarily and feel free to act independently during physical activity, they engage in sports more autonomously (e.g., intrinsic motivation, integrated or identified regulation).

Other need fulfillment specific factors also significantly predicted profile membership, although to a lesser extent. Somewhat unexpectedly, autonomy-competence-relatedness frustration specific factors differentiated the *Moderately Motivated* and the *Highly Motivated* profiles in that frustration was associated with higher membership likelihood to the second profile. That is, when participants more strongly feel like a failure or when they feel alone and deprived of choice during sports; they are more likely to be highly motivated to engage in sports. From this perspective, engaging in sports might be perceived as a way of countering or compensating for the need frustrated experiences (Vansteenkiste & Ryan, 2013) which has been reported in prior studies as well outside the field of sports (Tóth-Király, Bőthe, Márki, Rigó, & Orosz, 2019). Need frustrated experiences may be associated with lower self-esteem, which could be compensated with sports, which mostly depends on one's efforts. When people feel like a failure and think that they are not competent enough in sports, they might experience self-doubt. However, based on our results, this sense of frustration could be countered by doing more sports so that self-worth may at least be partially restored by achieving a new personal best in running, for instance. As autonomous motivations are characterized by volition and choice, it is reasonable to assume that doing sports is a conscious and explicitly chosen way of compensation for need frustration. This proposition aligns well with the proposed need restoration role of competence which suggests that in a setback situation characterized by need frustration, people might put more effort into and have more autonomous motivations in their subsequent activity (Gardner, Pickett, & Brewer, 2000; Radel et al., 2013). Moreover, the cross-sectional findings are also in line with the experimental results of Fang et al. (2018), who also found support for the restoration process of competence frustration.

In a similar vein, experiencing loneliness during sports was related to membership to the *Poorly Motivated* profile compared to the *Moderately Motivated* and *Amotivated* ones. This finding is reasonable considering that the *Poorly Motivated* profile was characterized by external regulation (i.e., doing sports to gain social rewards or avoid social punishments) and relatedness frustrated participants might engage in sports to gain social rewards such as meaningful relationships with others. Relatedness has already been shown to have a unique predictive effect over and above the general need fulfillment factor (e.g., Sánchez-Oliva et al., 2017; Tóth-Király, Bőthe, Orosz, & Rigó, 2019) which is further supported in the present study. Still, future studies should investigate these findings to corroborate their replicability further.

Outcomes of Sport Motivation Profiles

Finally, the results presented above showed well-differentiated associations between outcomes of subjective vitality. Being a member of the *Highly Motivated* profile was related to increased levels of vitality, followed by the *Moderately Motivated*, the *Poorly Motivated*, and the *Amotivated* profiles. Ryan and Deci (2017) interpret vitality as an index of organismic wellness that is available to the self in the form of energy that can be used to conduct volitional activities. Vitality is said to be enhanced, on the one hand, by the satisfaction of basic psychological needs and, on the other hand, by performing activities for self-determined reasons. Consequently, doing sports for self-determined reasons (e.g., enjoying it, finding it an integral part of one's life or being able to develop certain aspects of the self through sports) could maintain or even enhance vitality. Conversely, non-self-determined behavioral regulations characterized by external rewards, punishment, or uncertainty stemming from amotivation could reduce vitality. These results also corroborate the cross-sectional

findings of Pelletier et al. (2013, 2017), who found that more self-determined motivations were associated with increased levels of vitality. It is also important to note that vitality was the highest in the Highly Motivated profile even though introjected regulation (which was also high in this profile) is typically unrelated to or negatively related to vitality (Assor, Vansteenkiste, & Kaplan, 2009; Pelletier et al., 2017). The presence of high self-determined motivations may be able to buffer the deleterious effects of introjected regulation, which has already been demonstrated to be the case for academic motivations (Gillet, Morin, & Reeve, 2017).

Other, sport-related variables (i.e., the quantity of sport engagement) were also compared as a function of profile membership. Most, but not all, variables differed across the profiles, partially supporting Hypothesis 4. The *Highly Motivated* profile was related to the most time spent with sports, members of this engaged in their sports for the longest time, and they also did so more frequently, thus making this profile desirable as members appear to be alive and energetic. Granero-Gallegos et al. (2012), as well as Lindwall et al. (2017), came to similar conclusions concerning weekly practice time. The more nuanced results pertain to the *Poorly Motivated* profile, whose members reportedly practiced their sports more than members of the *Moderately Motivated* and *Amotivated* profiles, yet their subjective vitality was lower. One potential reason for this finding might be that *Poorly Motivated* participants are driven by extrinsic social rewards and punishment, which, in turn, would suggest that doing sports is not fully endorsed by them and that they feel obligated to do sports. By contrast, members of the *Moderately Motivated* profile exercise less in terms of time and frequency, but they appear alive and energetic during sports engagement. Finally, the *Amotivated* profile might be the least desirable, which is in line with prior studies emphasizing the detrimental effects of amotivation (e.g., Howard et al., 2016; Lonsdale, Hodge, & Rose, 2009). All these results suggest that being more self-determined and volitionally motivated for sports is associated with an increased quantity of behavioral engagement.

Limitations, Future Directions, and Practical Implications

Some limitations of the present research need to be acknowledged. We relied on a single sample of Hungarian participants, which makes it hard to assess the generalizability of our findings to other groups. Replications should be made, including participants from other cultures or participants from other age groups. The sample was also not balanced in terms of gender, with females being overrepresented and was not representative of professional athletes, a limitation that should also be addressed in subsequent studies. As self-reported data was used, responses could be influenced by different biases (e.g., social desirability), particularly about the self-reported time one spends on doing sports. Although the utilized threshold was based on prior empirical evidence, future studies should circumvent this limitation by either obtaining objective information about sport (e.g., performance, measuring actual time spent on doing sports via, for instance, smartwatches or fitness trackers) or by collecting responses from relevant others (e.g., coaches, team-mates) as well. The use of single-item measures is also a limitation that should be addressed by using multi-item scales to more fully grasp the actual engagement of the participants. The quality of engagement should also be assessed in future studies (see Hodge, Lonsdale, & Jackson, 2009, for an example). We also relied on a cross-sectional design, which precludes any form of directional or causal interpretation. Although the treatment of predictors and outcomes was guided by theoretical considerations, similar to variable-centered studies (e.g., Olafsen et al., 2018), future longitudinal person-centered studies are needed to establish directionality between the variables and to examine the within-person and within-sample stability of the profiles. While vitality and engagement-related correlates are important indicators, more variables could be included that are of additional relevance, such as competition or burnout. Given recent advancements in person-centered studies and basic psychological needs (Gillet et al., 2019; Tóth-Király, Bőthe, Orosz, & Rigó, 2018), it might be interesting to test how need fulfillment profiles are related to sport motivation profiles.

There is accumulating evidence on the field of SDT suggesting that autonomy-supportive interpersonal behavior (i.e., autonomy-supportive coaching) is cardinal in the development of self-determined motivations, need fulfillment and a range of outcomes such as decreased burnout and increased flow, wellbeing, engagement, goal motives or physical self-worth (e.g., Gaudreau et al., 2016; Healy, Ntoumanis, van Zanten, & Paine, 2014; Isoard-Gautheur, Guillet-Descas, & Lemyre, 2010; Smith, Ntoumanis, & Duda, 2010; Thøgersen-Ntoumani & Ntoumanis, 2006). These associations between the need-supportive behavior and self-determined motivations do not only hold

within the context of sports, but outside of it as well (e.g., Wang, Morin, Ryan, & Liu, 2016). Social agents should aim to provide autonomy-support, involvement, and structure at the same time (Mageau & Vallerand, 2003; Yu, Chen, Levesque-Bristol, & Vansteenkiste, 2018) for their people engaged in sports. *Autonomy-supportive atmosphere* (i.e., the foundation of the need for autonomy) might be constructed by providing people engaged in sports with alternative choices and rationale behind the activities that they conduct and, at the same time, by relying on a non-evaluative and informational way of communication instead of the use of controlling language (i.e., "must"; Reeve & Jang, 2006). *Structure* (i.e., the foundation of the need for competition) is people's perceived associations between how they behave and what the result is going to be. An optimal structure might be achieved by setting optimal yet challenging tasks, explicit rules, and directions, encouraging them to try to improve, and also by setting clear guidelines and goals. This way, people engaged in sports are more likely to know the consequences of their behavior. Finally, *involvement* (i.e., the foundation of the need for relatedness) is present when social agents are concerned with the people engaged in sports and that they understand their perspective. Additionally, in the case of team sports, peers also contribute to the experiences of relatedness as well. In sum, in accordance with Reeve and Halusic (2009), basic psychological needs as antecedents of motivations could easily be used to elicit more self-determined motivations and profiles, which, in turn, may lead to positive outcomes. Thus, incorporating elements of need-supportive interventions and practices into the training program could have substantive implications.

References

Arens, A.K., & Morin, A.J.S. (2016). Examination of the structure and grade-related differentiation of multidimensional self-concept instruments for children using ESEM. *The Journal of Experimental Education, 84,* 330-355.

Assor, A., Vansteenkiste, M., & Kaplan, A. (2009). Identified versus introjected approach and introjected avoidance motivations in school and in sports: The limited benefits of self-worth strivings. *Journal of Educational Psychology, 101,* 482-497.

Beaton, D.E., Bombardier, C., Guillemin, F., & Ferraz, M.B. (2000). Guidelines for the process of cross-cultural adaptation of self-report measures. *Spine, 25,* 3186-3191.

Bergman, L. R., & Trost, K. (2006). The person-oriented versus the variable-oriented approach: Are they complementary, opposites, or exploring different worlds?. *Merrill-Palmer Quarterly (1982-),* 601-632.

Boiché, J., Sarrazin, P.G., Grouzet, F.M., Pelletier, L.G., & Chanal, J.P. (2008). Students' motivational profiles and achievement outcomes in physical education: A self-determination perspective. *Journal of Educational Psychology, 100,* 688-701.

Browne, M. (2001) An overview of analytic rotation in exploratory factor analysis. *Multivariate Behavioral Research, 36,* 111-150.

Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E.L., Van der Kaap-Deeder, J., ... & Ryan, R.M. (2015). Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and Emotion, 39,* 216-236.

Cresswell, S., & Eklund, R. (2005). Motivation and burn out among top amateur rugby players. *Medicine and Science in Sports and Exercise, 37,* 469-477.

Diallo, T.M.O., Morin, A.J.S., & Lu, H. (2016). Impact of misspecifications of the latent variance-covariance and residual matrices on the class enumeration accuracy of growth mixture models. *Structural Equation Modeling, 23,* 507-531.

Eime, R.M., Young, J.A., Harvey, J.T., Charity, M.J., & Payne, W.R. (2013). A systematic review of the psychological and social benefits of participation in sport for children and adolescents: informing development of a conceptual model of health through sport. *International Journal of Behavioral Nutrition and Physical Activity, 10,* 1-21.

Fang, H., He, B., Fu, H., Zhang, H., Mo, Z., & Meng, L. (2018). A surprising source of self-motivation: Prior competence frustration strengthens one's motivation to win in another competence-supportive activity. *Frontiers in Human Neuroscience, 12:*314.

Finney, S.J., & DiStefano, C. (2013). Non-normal and categorical data in structural equation modeling. In G. R. Hancock & R. O. Mueller (Eds.), *Structural equation modeling: A second course* (2nd ed., pp. 439–492). Greenwich, CT: Information Age.

Gardner, W.L., Pickett, C.L., & Brewer, M.B. (2000). Social exclusion and selective memory: How the need to belong influences memory for social events. *Personality and Social Psychology Bulletin*, *26*, 486-496.

Gaudreau, P., Morinville, A., Gareau, A., Verner-Filion, J., Green-Demers, I., & Franche, V. (2016). Autonomy support from parents and coaches: Synergistic or compensatory effects on sport-related outcomes of adolescent-athletes?. *Psychology of Sport and Exercise*, *25*, 89-99.

Gillet, N., Berjot, S., & Paty, B. (2009). Profil motivationnel et performance sportive [Motivational profile and sport performance]. *Psychologie Française*, *54*, 173-190.

Gillet, N., Berjot, S., Vallerand, R.J., Amoura, S., & Rosnet, E. (2012). Examining the motivation-performance relationship in competitive sport: a cluster-analytic approach. *International Journal of Sport Psychology*, *43*, 79-102.

Gillet, N., Morin, A.J.S., Cougot, B., & Gagné, M. (2017). Workaholism profiles: Associations with determinants, correlates, and outcomes. *Journal of Occupational and Organizational Psychology*, *90*, 559-586.

Gillet, N., Morin, A.J.S, Huyghebaert-Zouaghi, T., Alibran, E., Barrault, S., & Vanhove-Meriaux, C. (2019). Students' Need Satisfaction Profiles: Similarity and Change over the Course of a University Semester. *Applied Psychology*. Early view doi: 10.1111/apps.12227

Gillet, N., Morin, A.J.S., & Reeve, J. (2017). Stability, change, and implications of students' motivation profiles: A latent transition analysis. *Contemporary Educational Psychology*, *51*, 222-239.

Gillet, N., Vallerand, R.J., & Rosnet, E. (2009). Motivational clusters and performance in a real-life setting. *Motivation and Emotion*, *33*, 49-62.

Granero-Gallegos, A., Baena-Extremera, A., Pérez-Quero, F.J., Ortiz-Camacho, M.M., & Bracho-Amador, C. (2012). Analysis of motivational profiles of satisfaction and importance of physical education in high school adolescents. *Journal of Sports Science & Medicine*, *11*, 614-623.

Guay, F., Morin, A.J.S., Litalien, D., Valois, P., & Vallerand, R.J. (2015). Application of exploratory structural equation modeling to evaluate the academic motivation scale. *Journal of Experimental Education*, *83*, 51-82.

Guerin, E., & Fortier, M. (2012). Motivational profiles for physical activity: cluster analysis and links with enjoyment. *Revue phénEPS/PHEnex Journal*, *4*, 1-21.

Gustafsson, H., Carlin, M., Podlog, L., Stenling, A., & Lindwall, M. (2018). Motivational profiles and burnout in elite athletes: A person-centered approach. *Psychology of Sport and Exercise*, *35*, 118-125.

Healy, L.C., Ntoumanis, N., van Zanten, J.J.V., & Paine, N. (2014). Goal striving and well-being in sport: The role of contextual and personal motivation. *Journal of Sport and Exercise Psychology*, *36*, 446-459.

Henson, J.M., Reise, S.P., & Kim, K.H. (2007). Detecting mixtures from structural model differences using latent variable mixture modeling: A comparison of relative model fit statistics. *Structural Equation Modeling*, *14*, 202-226.

Hipp, J.R., & Bauer, D.J. (2006). Local solutions in the estimation of growth mixture models. *Psychological Methods*, *11*, 36-53.

Hodge, K., Lonsdale, C., & Jackson, S.A. (2009). Athlete engagement in elite sport: An exploratory investigation of antecedents and consequences. *The Sport Psychologist*, *23*, 186-202.

Howard, J.L., Gagné, M., & Bureau, J.S. (2017). Testing a continuum structure of self-determined motivation: A meta-analysis. *Psychological Bulletin*, *143*, 1346-1377.

Howard, J.L., Gagné, M., Morin, A.J.S., & Forest, J. (2018). Using bifactor exploratory structural equation modeling to test for a continuum structure of motivation. *Journal of Management*, *44*, 2638-2664.

Howard, J., Gagné, M., Morin, A.J.S., & Van den Broeck, A. (2016). Motivation profiles at work: A self-determination theory approach. *Journal of Vocational Behavior*, *95*, 74-89.

Hungarian Central Statistical Office. (2011). A 15–74 éves népesség napi ido˝felhasználása, 2010 [Time-use of the population aged between 15 and 74 in 2010]. *Statisztikai Tükör*, *5*, 1–4. Retrieved on September 11, 2019 from http://www.ksh.hu/docs/hun/xftp/stattukor/idomerleg10.pdf

Isoard-Gautheur, S., Guillet-Descas, E., & Lemyre, P.N. (2012). A prospective study of the influence of perceived coaching style on burnout propensity in high level young athletes: Using a self-determination theory perspective. *The Sport Psychologist*, *26*, 282-298.

Lindwall, M., Ivarsson, A., Weman-Josefsson, K., Jonsson, L., Ntoumanis, N., Patrick, H., ... & Teixeira, P. (2017). Stirring the motivational soup: within-person latent profiles of motivation in exercise. *International Journal of Behavioral Nutrition and Physical Activity*, *14*, 1-12.

Lonsdale, C., Hodge, K., & Rose, E. (2009). Athlete burnout in elite sport: A self-determination perspective. *Journal of Sports Sciences*, *27*, 785-795.

Lubke, G. H., & Muthén, B. (2005). Investigating population heterogeneity with factor mixture models. *Psychological Methods*, *10*, 21-39.

Mageau, G.A., & Vallerand, R.J. (2003). The coach-athlete relationship: A motivational model. *Journal of Sports Science*, *21*, 883-904.

Marsh, H.W., Hau, K.-T., Wen, Z., Nagengast, B., & Morin, A.J.S. (2013). Moderation. In T.D. Little (Ed.), *Oxford library of psychology. The Oxford handbook of quantitative methods: Statistical analysis* (pp. 361-386). New York, NY, US: Oxford University Press.

Marsh, H.W., Lüdtke, O., Trautwein, U., & Morin, A.J.S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person-and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling*, *16*, 191-225.

Meyer, J.P., & Morin, A.J.S. (2016). A person-centered approach to commitment research: Theory, research, and methodology. *Journal of Organizational Behavior*, *37*, 584-612.

Milton, K., Clemes, S., & Bull, F. (2013). Can a single question provide an accurate measure of physical activity?. *British Journal of Sports Medicine*, *47*, 44-48.

Morin, A.J.S. (2016). Person-centered research strategies in commitment research. In J.P. Meyer (Ed.), *The Handbook of Employee Commitment* (p. 490-508). Cheltenham, UK: Edward Elgar.

Morin, A.J.S., Maiano, C., Nagengast, B., Marsh, H.W., Morizot, J., & Janosz, M. (2011). General growth mixture analysis of adolescents' developmental trajectories of anxiety: The impact of untested invariance assumptions on substantive interpretations. *Structural Equation Modeling*, *18*, 613-648.

Morin, A.J.S., & Marsh, H.W. (2015). Disentangling shape from levels effects in person-centered analyses: An illustration based on University teacher multidimensional profiles of effectiveness. *Structural Equation Modeling*, *22*, 39-59.

Morin, A.J.S., Morizot, J., Boudrias, J.S., & Madore, I. (2011). A multifoci person-centered perspective on workplace affective commitment: A latent profile/factor mixture analysis. *Organizational Research Methods*, *14*, 58-90.

Morin, A.J.S., Myers, N.D., & Lee, S. (2018). Modern factor analytic techniques: Bifactor models, exploratory structural equation modeling (ESEM) and bifactor-ESEM. In G. Tenenbaum & R.C. Eklund (Eds.), *Handbook of sport psychology (4th ed.*). Hoboken, NJ: Wiley.

Morin, A.J.S., & Wang, J.C.K. (2016). A gentle introduction to mixture modeling using physical fitness data. In N. Ntoumanis, & N. Myers (Eds.), *An Introduction to Intermediate and Advanced Statistical Analyses for Sport and Exercise Scientists* (pp. 183-210). London, UK: Wiley.

Muthén, B.O. (2002). Beyond SEM: General latent variable modeling. *Behaviormetrika*, *29*, 81–117.

Muthén, L.K., & Muthén, B.O. (1998-2017). *Mplus User's Guide. 8th Edition*. Los Angeles, CA: Muthén & Muthén.

Ng, J.Y., Ntoumanis, N., Thøgersen-Ntoumani, C., Deci, E.L., Ryan, R.M., Duda, J.L., & Williams, G.C. (2012). Self-determination theory applied to health contexts: A meta-analysis. *Perspectives on Psychological Science*, *7*, 325-340.

Ntoumanis, N. (2001). A self-determination approach to the understanding of motivation in physical education. *British Journal of Educational Psychology*, *71*, 225-242.

Ntoumanis, N. (2002). Motivational clusters in a sample of British physical education classes. *Psychology of Sport and Exercise*, *3*, 177-194.

Ntoumanis, N., Ng, J.Y., Barkoukis, V., & Backhouse, S. (2014). Personal and psychosocial predictors of doping use in physical activity settings: a meta-analysis. *Sports Medicine*, *44*, 1603-1624.

Olafsen, A.H., Deci, E.L., & Halvari, H. (2018). Basic psychological needs and work motivation: A longitudinal test of directionality. *Motivation and Emotion*, *42*, 178-189.

Pelletier, L.G., Rocchi, M., Guertin, C., Hébert, C., & Sarrazin, P. (2017). French adaptation and validation of the Sport Motivation Scale-II (Echelle de Motivation dans les Sports-II). *International Journal of Sport and Exercise Psychology*, 1-18.

Pelletier, L.G., Rocchi, M.A., Vallerand, R.J., Deci, E.L., & Ryan, R.M. (2013). Validation of the revised sport motivation scale (SMS-II). *Psychology of Sport and Exercise, 14*, 329-341.

Peugh, J., & Fan, X. (2013). Modeling unobserved heterogeneity using latent profile analysis: A Monte Carlo simulation. *Structural Equation Modeling, 20*, 616–639.

Radel, R., Pelletier, L., & Sarrazin, P. (2013). Restoration processes after need thwarting: When autonomy depends on competence. *Motivation and Emotion, 37*, 234-244.

Reeve, J., & Halusic, M. (2009). How K-12 teachers can put self-determination theory principles into practice. *School Field, 7*, 145-154.

Reeve, J., & Jang, H. (2006). What teachers say and do to support students' autonomy during a learning activity. *Journal of Educational Psychology, 98*, 209-218.

Reinboth, M., Duda, J.L., & Ntoumanis, N. (2004). Dimensions of coaching behavior, need satisfaction, and the psychological and physical welfare of young athletes. *Motivation and Emotion, 28*, 297-313.

Rodrigues, F., Hair Jr, J.F., Neiva, H.P., Teixeira, D.S., Cid, L., & Monteiro, D. (2019). The Basic Psychological Need Satisfaction and Frustration Scale in Exercise (BPNSFS-E): Validity, Reliability, and Gender Invariance in Portuguese Exercisers. *Perceptual and Motor Skills, 126*, 949-972.

Ryan, R.M. (1995). Psychological needs and the facilitations of integrative processes. *Journal of Personality, 63*, 397-427.

Ryan, R.M., & Connell, J. (1989). Perceived locus of causality and internalization: Examining reasons for acting in two domains. *Journal of Personality and Social Psychology, 57*, 749-761.

Ryan, R.M., & Deci, E.L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*, 68-78.

Ryan, R.M., & Deci, E.L. (2017). *Self-determination theory. Basic psychological needs in motivation, development, and wellness*. New York, NY: Guildford Press.

Ryan, R.M., & Frederick, C. (1997). On energy, personality, and health: Subjective vitality as a dynamic reflection of well-being. *Journal of Personality, 65*, 529-565.

Sebire, S.J., Jago, R., Fox, K.R., Edwards, M.J., & Thompson, J.L. (2013). Testing a self-determination theory model of children's physical activity motivation: a cross-sectional study. *International Journal of Behavioral Nutrition and Physical Activity, 10*, 1-9.

Smith, A., Ntoumanis, N., & Duda, J. (2010). An investigation of coach behaviors, goal motives, and implementation intentions as predictors of well-being in sport. *Journal of Applied Sport Psychology, 22*, 17-33.

Standage, M., Duda, J.L., & Ntoumanis, N. (2003). A model of contextual motivation in physical education: Using constructs from self-determination and achievement goal theories to predict physical activity intentions. *Journal of Educational Psychology, 95*, 97-110.

Thøgersen-Ntoumani, C., & Ntoumanis, N. (2006). The role of self-determined motivation in the understanding of exercise-related behaviours, cognitions and physical self-evaluations. *Journal of Sports Sciences, 24*, 393-404.

Tóth-Király, I., Bőthe, B., Márki, A.N., Rigó, A., & Orosz, G. (2019). Two sides of the same coin: The differentiating role of need satisfaction and frustration in passion for screen-based activities. *European Journal of Social Psychology, 49*, 1190-1205.

Tóth-Király, I., Bőthe, B., & Orosz, G. (2017). Exploratory structural equation modeling analysis of the Self-Compassion Scale. *Mindfulness, 8*, 881-892.

Tóth-Király, I., Bőthe, B., Orosz, G., & Rigó, A. (2019). A New Look on the Representation and Criterion Validity of Need Fulfillment: Application of the Bifactor Exploratory Structural Equation Modeling Framework. *Journal of Happiness Studies, 20*, 1609-1626.

Tóth-Király, I., Bőthe, B., Orosz, G., & Rigó, A. (2018). On the importance of balanced need fulfillment: A person-centered perspective. *Journal of Happiness Studies*. Early view doi: 10.1007/s10902-018-0066-0

Tóth-Király, I., Bőthe, B., Rigó, A., & Orosz, G. (2017). An Illustration of the Exploratory Structural Equation Modeling (ESEM) Framework on the Passion Scale. *Frontiers in Psychology*, *8*:1968.

Tóth-Király, I., Morin, A.J.S., Bőthe, B., Orosz, G., & Rigó, A. (2018). Investigating the multidimensionality of need fulfillment: a bifactor exploratory structural equation modeling representation. *Structural Equation Modeling*, *25*, 267-286.

Tóth-Király, I., Orosz, G., Dombi, E., Jagodics, B., Farkas, D., & Amoura, C. (2017). Cross-cultural comparative examination of the Academic Motivation Scale using exploratory structural equation modeling. *Personality and Individual Differences*, *106*, 130-135.

Tóth-Király, I., Vallerand, R.J., Bőthe, B., Rigó, A., & Orosz, G. (2019). Examining sexual motivation profiles and their correlates using latent profile analysis. *Personality and Individual Differences*, *146*, 76-86.

Vallerand, R.J. (1997). Toward a hierarchical model of intrinsic and extrinsic motivation. *Advances in Experimental Social Psychology*, *29*, 271-360.

Vallerand, R.J. (2007). Intrinsic and Extrinsic Motivation in Sport and Physical Activity: A Review and a Look at the Future. In G. Tenenbaum and R. C. Eklund (Eds.), *Handbook of Sport Psychology Third Edition* (pp. 59-83). Hoboken, NJ: John Wiley & Sons.

van Poppel, M.N., Chinapaw, M.J., Mokkink, L.B., Van Mechelen, W., & Terwee, C.B. (2010). Physical activity questionnaires for adults. *Sports Medicine*, *40*, 565-600.

Wang, J.C., Morin, A.J.S., Ryan, R.M., & Liu, W.C. (2016). Students' motivational profiles in the physical education context. *Journal of Sport and Exercise Psychology*, *38*, 612-630.

Wanner, M., Probst-Hensch, N., Kriemler, S., Meier, F., Bauman, A., & Martin, B.W. (2014). What physical activity surveillance needs: validity of a single-item questionnaire. *British Journal of Sports Medicine*, *48*, 1570-1576.

Weman-Josefsson, K., Lindwall, M., & Ivarsson, A. (2015). Need satisfaction, motivational regulations and exercise: moderation and mediation effects. *International Journal of Behavioral Nutrition and Physical Activity*, *12*, 1-11.

Yu, S., Chen, B., Levesque-Bristol, C., & Vansteenkiste, M. (2018). Chinese education examined via the lens of self-determination. *Educational Psychology Review*, 30, 177-214.

Yu, C.A., Rouse, P.C., Van Zanten, J.V.J., Metsios, G.S., Ntoumanis, N., Kitas, G.D., & Duda, J.L. (2015). Motivation-related predictors of physical activity engagement and vitality in rheumatoid arthritis patients. *Health Psychology Open*, *2*, 1-9.

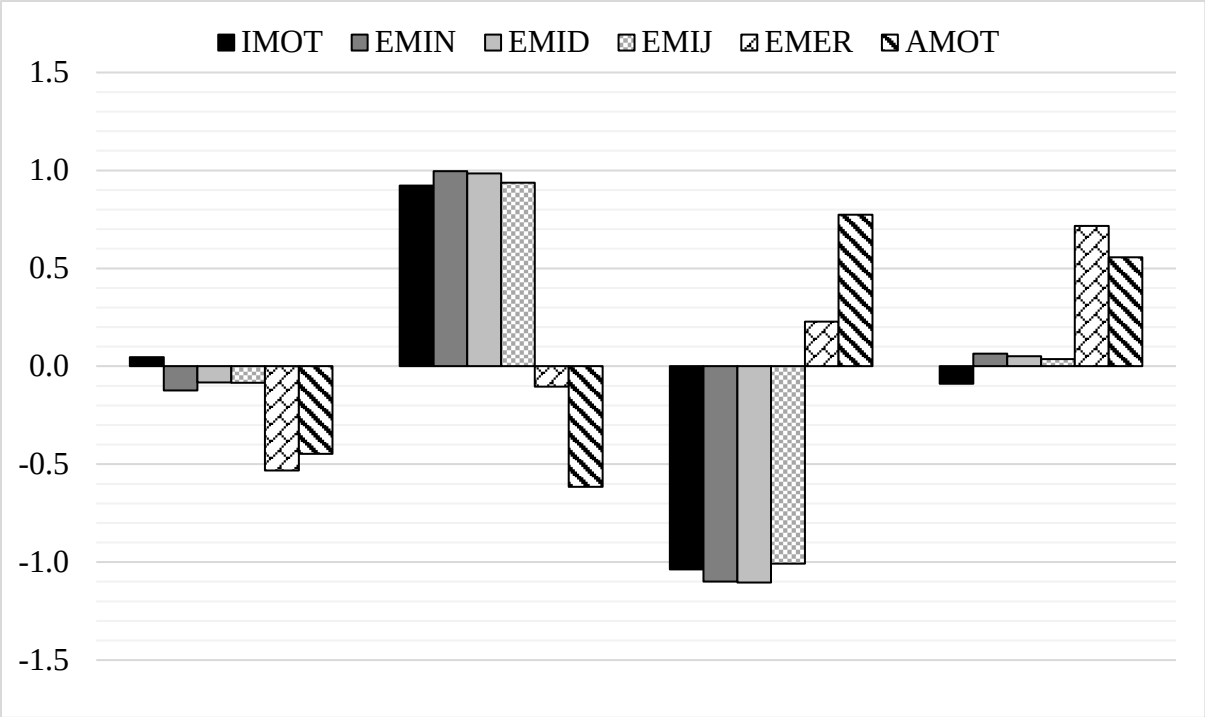

Figure 1
Characteristics of the latent profiles based on sport motivations

Note. Indicators are estimated from factor scores saved from preliminary measurement models with a mean of 0 and a standard deviation of 1 where zero signifies that a profile indicator is on an average level, scores substantially higher than zero are considered above average, while scores substantially lower than zero are considered below average.; IMOT: intrinsic motivation; EMIN: extrinsic motivation integrated regulation; EMID: extrinsic motivation identified regulation; EMIJ: extrinsic motivation introjected regulation; EMER: extrinsic motivation external regulation; AMOT: amotivation. Profile 1: Moderately Motivated; Profile 2: Highly Motivated; Profile 3: Amotivated; Profile 4: Poorly Motivated.

Table 1

Previous person-centered studies on motivational profiles†

Study	Participants	Profile factors	Method	#	Name of profiles
Boiché et al (2008)	N = 210 M_{age} = 13.26	Intrinsic motivation toward stimulation, intrinsic motivation toward knowledge or accomplishment, identified regulation, introjected regulation, external regulation, amotivation	CA	3	(1) self-determined with low amotivation (2) moderate with average amotivation (3) non-self-determined with high amotivation
Gillet et al. (2009)	N = 170 M_{age} = 13.42	Intrinsic motivation, identified regulation, introjected regulation, external regulation, amotivation	CA	4	(1) High autonomous – high controlled with low amotivation (2) Moderate autonomous – low controlled with low amotivation (3) High autonomous – moderate controlled with low amotivation (4) Moderate autonomous – high controlled with low amotivation
	N = 250 M_{age} = 15			3	(1) Moderate autonomous – low controlled with low amotivation (2) Moderate autonomous – moderate controlled with low amotivation (3) High autonomous – high controlled with low amotivation
Gillet et al. (2012)	N = 153 M_{age} = 14 N = 150 M_{age} = 41.29	Intrinsic motivation, identified regulation, introjected regulation, external regulation, amotivation	CA	3	(1) Low motivation with low amotivation (2) Moderate motivation with low amotivation (3) High motivation with low amotivation
Guérin & Fortier (2012)	N = 120 M_{age} = 47.3	Intrinsic motivation, identified regulation, introjected regulation, external regulation	CA	3	(1) self-determined (2) motivated (3) low motivated
Gustafsson et al. (2018)	N = 391 M_{age} = 20.6	Intrinsic motivation, identified regulation, introjected regulation, external regulation, amotivation	LPA	5	(1) amotivation (2) low motivation with low amotivation (3) moderately autonomous with low amotivation (4) amotivated and moderately controlled (5) highly motivated with low amotivation
Lindwall et al. (2017)	N = 1084 M_{age} = 45	Intrinsic motivation, identified regulation, introjected regulation,	LPA	6	(1) low motivation (2) self-determined with high introjected regulation and low amotivation (3) self-determined with low introjected regulation and low amotivation

		external regulation, amotivation			(4) self-determined with low amotivation (5) introjected & identified with low amotivation (6) controlled & amotivated
	N = 511 M_{age} = 22			6	(1) low motivation with low amotivation (2) self-determined with high introjected regulation and low amotivation (3) self-determined with low introjected regulation and low amotivation (4) self-determined with low amotivation (5) extrinsic motivation with average amotivation (6) amotivated
Matsumoto & Takenake (2004)	N = 486 M_{age} = 45.2	Intrinsic motivation, identified regulation, introjected regulation, external regulation, amotivation	CA	4	(1) self-determined with average amotivation (2) moderately motivated with average amotivation (3) non self-determined with high amotivation (4) amotivated
Ntoumanis (2002)	N = 428 M_{age} = 14.84	Intrinsic motivation, identified regulation, introjected regulation, external regulation, amotivation, effort enjoyment, boredom, cooperation, unequal recognition	CA	3	(1) self-determined with low amotivation (2) moderately motivated with average amotivation (3) controlling motivation with high amotivation

Note. † Literature search was performed on May 20, 2018.; N: sample size; M_{age}: average age of the participants; CA: cluster analysis; LPA: latent profile analysis; PE: physical education; #: number of profiles identified in the study.

Table 2

Fit statistics for the latent profiles and class enumeration

Model	LL	# of fp	Scaling	AIC	CAIC	BIC	SSABIC	Entropy	aLMR	BLRT
1 Profile	-3808.890	12	0.925	7641.780	7704.498	7692.498	7654.409	—	—	—
2 Profiles	-3384.286	25	1.105	6818.572	6949.235	6924.235	6844.882	0.811	< .001	< .001
3 Profiles	-3213.007	38	1.611	6502.015	6700.623	6662.623	6542.007	0.833	.421	< .001
4 Profiles	-3122.390	51	1.318	6346.779	6613.333	6562.333	6400.453	0.812	.085	< .001
5 Profiles	-3046.562	64	1.113	6221.125	6555.623	6491.623	6288.480	0.839	.016	< .001
6 Profiles	-2985.537	77	1.139	6125.074	6527.517	6450.517	6206.111	0.842	.389	< .001
7 Profiles	-2924.970	90	1.142	6029.941	6500.329	6410.329	6124.659	0.844	.124	< .001
8 Profiles	-2899.411	103	1.109	6004.823	6543.156	6440.156	6113.223	0.860	.033	< .001

Note. LL: loglikelihood; # of fp: number of free parameters; AIC: Akaike Information Criterion; CAIC: constant AIC; BIC: Bayesian Information Criterion; SSABIC: Sample-Size Adjusted BIC; aLMR: p-value associated with the adjusted Lo-Mendell-Rubin likelihood ratio test; p-value associated with the bootstrap likelihood ratio test.

Table 3

Results from the multinominal logistic regressions for the effects of the predictors on profile membership

Predictors	Moderately Motivated vs. Highly Motivated		Moderately Motivated vs. Amotivated		Moderately Motivated vs. Poorly Motivated	
	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR
Need fulfillment	0.604 (0.211)**	1.829	-1.862 (0.308)**	0.155	-0.905 (0.236)**	0.405
Autonomy satisfaction	1.071 (0.248)**	2.918	-0.893 (0.314)**	0.409	0.407 (0.238)	1.502
Relatedness satisfaction	0.179 (0.204)	1.196	0.336 (0.234)	1.399	0.004 (0.225)	1.004
Competence satisfaction	0.078 (0.267)	1.081	-0.259 (0.233)	0.772	-0.063 (0.221)	0.939
Autonomy frustration	0.444 (0.219)*	1.559	-0.050 (0.236)	0.951	0.337 (0.195)	1.401
Relatedness frustration	0.640 (0.245)**	1.896	0.085 (0.283)	1.089	1.078 (0.234)**	2.939
Competence frustration	0.605 (0.252)*	1.831	-0.073 (0.274)	0.930	0.148 (0.254)	1.160
Predictors	Highly Motivated vs. Amotivated		Highly Motivated vs. Poorly Motivated		Amotivated vs. Poorly Motivated	
	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR
Need fulfillment	-2.466 (0.322)**	0.085	-1.508 (0.231)**	0.221	0.957 (0.252)**	2.604
Autonomy satisfaction	-1.964 (0.349)**	0.140	-0.665 (0.227)**	0.514	1.299 (0.317)**	3.666
Relatedness satisfaction	0.156 (0.267)	1.169	-0.175 (0.211)	0.839	-0.331 (0.279)	0.718
Competence satisfaction	-0.336 (0.293)	0.715	-0.140 (0.275)	0.869	0.196 (0.232)	1.217
Autonomy frustration	-0.495 (0.260)	0.610	-0.107 (0.211)	0.899	0.388 (0.218)	1.474
Relatedness frustration	-0.555 (0.313)	0.574	0.438 (0.228)	1.550	0.993 (0.297)**	2.699
Competence frustration	-0.677 (0.313)*	0.508	-0.457 (0.257)	0.633	0.220 (0.296)	1.246

Note. SE: standard error associated with the coefficient; OR = odds ratio.; *$p < .05$; **$p < .01$; ***$p < .001$.

Table 4

Outcome means and pairwise comparisons between the four profiles of sports motivations

Outcome	Moderately Motivated	Highly Motivated	Amotivated	Poorly Motivated	Differences between profiles
	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)	
Vitality	0.248 (0.067)	0.461 (0.073)	-0.731 (0.069)	-0.096 (0.055)	2 > 1 > 4 > 3
Length of doing sports	-0.172 (0.096)	0.391 (0.075)	-0.386 (0.119)	0.127 (0.097)	2 > 4 > 1 = 3
Frequency of doing sports	-0.117 (0.068)	0.585 (0.133)	-0.493 (0.075)	-0.003 (0.091)	2 > 4 = 1 > 3
Duration of doing sports	75.854 (2.578)	91.538 (3.145)	67.645 (2.999)	83.941 (3.230)	4 = 1 > 3; 2 > 1; 2 = 4

Note. SE: standard error associated with the mean.; Outcomes (except for duration of doing sports) were estimated from factor scores with a mean of zero and a standard deviation of one where zero signifies that an outcome is on an average level, scores substantially higher than zero are considered above average, while scores substantially lower than zero are considered below average.

Online Supplements for:

Predictors and outcomes of core and peripheral sport motivation profiles: A latent profile analysis study

These online supplements are to be posted on the journal website and hot-linked to the manuscript. If the journal does not offer this possibility, these materials can alternatively be posted on one of our personal websites (we will adjust the in-text reference upon acceptance).

We would also be happy to have some of these materials brought back into the main manuscript, or included as published appendices if you deem it useful. We developed these materials to provide additional technical information and to keep the main manuscript from becoming needlessly long.

Appendix 1: Results related to the preliminary measurement models estimated in the present study

Model Estimation

In the present study, before conducting the latent profile analysis (LPA), preliminary measurement models were estimated on the scales measuring sport motivations, need fulfillment, and subjective vitality. This initial step was necessary (1) to verify the psychometric properties of the instruments and (2) to create factor scores on the basis of these measurement model to serve as indicators in LPA. Given that fully latent variables cannot easily be included in mixture models as they would substantially increase model complexity and computation time, previous studies have shown that factor scores are better, relative to scale scores, at preserving the underlying nature of measurement models and at providing partial control for measurement errors by giving more weight to the items with lower measurement errors (Kam, Morin, Meyer, & Topolnytsky, 2016; Morin, Meyer, Creusier, & Biétry, 2016).

During the estimation of preliminary measurement models, we relied on the work of Morin and colleagues (Morin, Arens, & Marsh, 2016a; Morin, Arens, Tran, & Caci, 2016a; Morin et al., 2017) by investigating the potential sources of construct-relevant psychometric multidimensionality for the constructs of interest. In the case of multidimensional constructs, it is often the case that more than one source of construct-relevant psychometric multidimensionality is present in the data. The first source refers to the association between items and their relation to conceptually-related, yet non-target constructs. This source can be accounted for by including freely estimated cross-loadings in the measurement models in the form of exploratory structural equation modeling (ESEM; Marsh, Morin, Parker, & Kaur, 2014) when it is theoretically reasonable. Additionally, simulation studies (Morin et al., 2016a, 2016b) and reviews (Asparouhov, Muthén, & Morin, 2015) also underscore the importance of freely estimated cross-loadings that, when set to zero, result in bias parameter estimates (i.e., factor correlations) and could potentially modify the meaning of the construct at hand. Prior empirical motivational studies on real data also supported the importance of comparing competing CFA and ESEM models (Guay, Morin, Litalien, Valois, & Vallerand, 2015; Litalien, Guay, & Morin, 2015; Tóth-Király, Orosz, et al., 2017). For this reason, alternative CFA and ESEM models were contrasted for the SMS II.

The second source reflects on the simultaneous assessment of global and specific constructs that are expected to be co-existent. This source can be accounted for by including a global theoretically-relevant factor in the measurement model in the form of a bifactor model (Reise, 2012). In this model, the global (G-) factor is thought to be coexistent with the specific (S-) factors. Therefore, an important advantage of bifactor models is that they allow the total item covariance matrix to be partitioned into global components (corresponding to the shared variance among all items) and specific components (corresponding to the covariance in a subset of items not explained by the G-factor). This modeling approach is of major relevance for need fulfillment as it has been used in relation to need satisfaction (Sánchez-Oliva et al., 2017), need frustration (Myers, Martin, Ntoumanis, Celimli, & Bartholomew, 2014) and need fulfillment (Tóth-Király, Morin, Bőthe, Orosz, & Rigó, 2018) as well. In addition, studies have also supported the use of bifactor modeling by showing that the G- and some (but not all) S-factors contribute to a wide range of outcomes (Sánchez-Oliva et al., 2017; Tóth-Király, Bőthe, Orosz, & Rigó, 2018). Based on these findings, building on first-order models, we contrasted bifactor CFA and ESEM models as suggested by Morin and colleagues (Morin et al., 2016a, 2016b, 2017). Given that subjective vitality is unidimensional, this construct was modelled following the standard CFA specification.

In model assessment, commonly used goodness-of-fit indices were relied on: the comparative fit index (CFI), the Tucker-Lewis Index (TLI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). In the case of CFA and TLI, values higher than .90 and .95 are respectively to indicate adequate and excellent fit to the data; for RMSEA, values smaller than .08 or .06 for the RMSEA support acceptable and excellent model fit, respectively; and for SRMR, values below .05 are considered good and values below .10 are considered acceptable (Hu & Bentler, 1999; Marsh, Hau, & Grayson, 2005). At the same time, parameter estimates (i.e., factor loadings and correlations) associated with each model were also compared. Finally, model-based omega composite reliability (ω; McDonald, 1970) was calculated from the final measurement models to examine the reliability of the factors. Compared to Cronbach's

alpha, omega has the advantage of providing a more realistic estimate of reliability by taking the standardized factor loadings and the corresponding error variances into account.

Results

As a first step, the adequacy of the measurement models was tested. Goodness-of-fit indices are reported in Table S1, while parameter estimates are presented in Table S2. For the SMS II, the fit of the CFA solution was borderline satisfactory and although the factors were well-defined by the corresponding factors loadings (|λ| = .432 to .941, *M* = .759), the associations between them (|r| = .018 to .909; *M* = .561) call into question the validity of this representation. Conversely, the ESEM solution did not only result in improved model fit (ΔCFI = +.060; ΔTLI = +.071; ΔRMSEA = -.063; ΔSRMR = -.052), but also similarly well-defined target factors (|λ| = .249 to .886, *M* = .611), reduced factor correlations (|r| = .010 to .621; *M* = .364), and small cross-loadings (|λ| = .001 to .427, *M* = .108) that do not undermine the definition of the factors. Latent correlations between the factors are reported in Table S3.

As for the predictor variable of need fulfillment, the comparison of the first-order CFA and ESEM solutions revealed that the ESEM solution had superior fit relative to the CFA one (CFI: .989 vs. .954; TLI: .980 vs. .947; RMSEA: .043 vs. .070; SRMR: .018 vs. .047). The examination of parameter estimates (Table S4) showed that factors were well-defined by their respective factor loadings (ESEM: |λ| = .009 to .917, *M* = .598; CFA: |λ| = .353 to .887, *M* = .783). Several cross-loadings were statistically significant, though these remained relatively small in magnitude (|λ| = .001 to .616, *M* = .116). One competence satisfaction item appeared to load more strongly on the opposing competence frustration factor, but it was deemed negligible as the definition of the factors was not undermined. Finally, inter-factor correlations were also reduced in the ESEM solution compared to the CFA one (ESEM: |r| = .184 to .523, *M* = .363; CFA: |r| = .289 to .879, *M* = .604; see Table S5). Based on the available information, the ESEM model was retained.

In the next step, the ESEM model was complemented with a general factor representing need fulfillment apart from the six specific factors. The fit of this model was also adequate (CFI = .993; TLI = .985; RMSEA = .038; SRMR = .016). Parameter estimates are reported in Table S6. In addition to the good fit, the general need fulfillment factor, which is of major theoretical relevance, was well-defined by the scale items (|λ| = .251 to .774, *M* = .614). While relatedness satisfaction (|λ| = .507 to .822, *M* = .637) retained a relatively high degree of specificity over and above the global factor, autonomy satisfaction (|λ| = .207 to .596, *M* = .406), autonomy frustration (|λ| = .224 to .601, *M* = .439), relatedness frustration (|λ| = .341 to .623, *M* = .486) and competence frustration (|λ| = .337 to .598, *M* = .443) retained a moderate amount of specificity, whereas competence satisfaction (|λ| = .025 to .438, *M* = .188) retained a relatively small amount of specificity once the global factor was taken into account. Finally, the magnitude of cross-loadings also decreased compared to the six-factor ESEM model (|λ| = .001 to .236, *M* = .090).

The Subjective Vitality Scale also had acceptable fit to the data (save for RMSEA) with correlated uniquenesses specified between two pairs of items. The first between items 6 and 7 was included a priori given the similar wording of these two items, while another one was included between items 1 and 2 during the preliminary analysis following the suggestions of modification indices. The inspection of standardized parameter estimates revealed a well-defined vitality factor (|λ| = .687 to .935, *M* = .800). Model-based reliabilities for all models—which can be seen in Table S8—indicate generally acceptable levels of reliability. In the case of the bifactor model, it also needs to be noted that S-factors are generally weaker in bifactor models where a global factor is modelled. Finally, these reliability indices highlight that it is important to rely on models with latent variables given that these are naturally corrected for measurement error and it would be more concerning if the present study relied on scale scores instead of completely reliable factor scores. Subsequently, these factor scores were saved and served as a basis for the correlation analyses (Table S8) and the LPA.

References used in the supplementary document

Asparouhov, T., Muthén, B., & Morin, A.J.S. (2015). Bayesian Structural equation modeling with cross-loadings and residual covariances: Comments on Stromeyer et al. *Journal of Management*, *41*, 1561-1577.

Guay, F., Morin, A.J.S., Litalien, D., Valois, P., & Vallerand, R.J. (2015). Application of exploratory structural equation modeling to evaluate the academic motivation scale. *Journal of Experimental Education, 83*, 51-82.

Hu, L., & Bentler, P.M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*, 1-55.

Litalien, D., Guay, F., & Morin, A.J.S. (2015). Motivation for PhD studies: Scale development and validation. *Learning and Individual Differences, 41*, 1-13.

Kam, C., Morin, A.J.S., Meyer, J.P., & Topolnytsky, L. (2016). Are commitment profiles stable and predictable? A latent transition analysis. *Journal of Management, 42*, 1462-1490.

Marsh, H., Morin, A.J.S., Parker, P., & Kaur, G. (2014). Exploratory structural equation modeling: An integration of the best features of exploratory and confirmatory factor analysis. *Annual Review of Clinical Psychology, 10*, 85-110.

Marsh, H.W., Hau, K.-T., & Grayson, D. (2005). Goodness of fit evaluation in structural equation modeling. In A. Maydeu-Olivares & J. McArdle (Eds.), *Contemporary psychometrics. A Festschrift for Roderick P. McDonald*. Mahwah, NJ: Erlbaum.

McDonald, R.P. (1970). Theoretical foundations of principal factor analysis, canonical factor analysis, and alpha factor analysis. *British Journal of Mathematical & Statistical Psychology*, *23*, 1-21.

Morin, A.J.S., Arens, A., & Marsh, H. (2016a). A bifactor exploratory structural equation modeling framework for the identification of distinct sources of construct-relevant psychometric multidimensionality. *Structural Equation Modeling*, *23*, 116-139.

Morin, A.J.S., Arens, K., Tran, A., & Caci, H. (2016b). Exploring sources of construct-relevant multidimensionality in psychiatric measurement: A tutorial and illustration using the Composite Scale of Morningness. *International Journal of Methods in Psychiatric Research*, *25*, 277-288.

Morin, A.J.S., Boudrias, J.-S., Marsh, H.W., McInerney, D.M., Dagenais-Desmarais, V., Madore, I., & Litalien, D. (2017). Complementary variable- and person-centered approaches to the dimensionality of psychometric constructs: Application to psychological wellbeing at work. *Journal of Business and Psychology, 32*, 395-419.

Morin, A.J.S., Meyer, J.P., Creusier, J., & Biétry, F. (2016). Multiple-group analysis of similarity in latent profile solutions. *Organizational Research Methods, 19*, 231-254.

Myers, N.D., Martin, J.J., Ntoumanis, N., Celimli, S., & Bartholomew, K.J. (2014). Exploratory bifactor analysis in sport, exercise, and performance psychology: A substantive-methodological synergy. *Sport, Exercice, & Performance Psychology*, *3*, 258-272.

Reise, S.P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research, 47*, 667-696.

Sánchez-Oliva, D., Morin, A.J.S., Teixeira, P.J., Carraça, E.V., Palmeira, A.L., & Silva, M.N. (2017). A bifactor-exploratory structural equation modeling representation of the structure of basic psychological needs at work scale. *Journal of Vocational Behavior, 98*, 173-187.

Tóth-Király, I., Bőthe, B., Orosz, G., & Rigó, A. (2018). A New Look on the Representation and Criterion Validity of Need Fulfillment: Application of the Bifactor Exploratory Structural Equation Modeling Framework. *Journal of Happiness Studies*. Early view doi: 10.1007/s10902-018-0015-y

Tóth-Király, I., Morin, A.J.S., Bőthe, B., Orosz, G., & Rigó, A. (2018). Investigating the multidimensionality of need fulfillment: A bifactor exploratory structural equation modeling representation. *Structural Equation Modeling, 25*, 267-286.

Tóth-Király, I., Orosz, G., Dombi, E., Jagodics, B., Farkas, D., & Amoura, C. (2017). Cross-cultural comparative examination of the Academic Motivation Scale using exploratory structural equation modeling. *Personality and Individual Differences, 106*, 130-135.

Table S1

Goodness-of-Fit Statistics for the Estimated Models

Model	χ^2	df	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR
Sport motivations							
Six-factor CFA	745.820*	120	.935	.917	.102	.095-.109	.066
Six-factor ESEM	107.025*	60	.995	.988	.039	.027-.051	.014
Need fulfillment							
Six-factor CFA	825.507*	237	.954	.947	.070	.065-.075	.047
Six-factor ESEM	287.257*	147	.989	.980	.043	.036-.051	.018
Bifactor CFA	1206.804*	228	.924	.908	.092	.087-.097	.067
Bifactor ESEM	222.530*	129	.993	.985	.038	.029-.046	.016
Subjective vitality							
One-factor CFA	94.502*	12	.991	.985	.117	.095-.139	.016

Note. CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; χ^2: Robust chi-square test of exact fit; df: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval of the RMSEA; *$p < 0.01$.

Table S2

Parameter estimates for the six-factor CFA and ESEM solutions of the Sport Motivation Scale

	CFA		ESEM						
	Factor (λ)	δ	IMOT (λ)	EMIN (λ)	EMID (λ)	EMIJ (λ)	EMER (λ)	AMOT (λ)	δ
Intrinsic motivation (IMOT)									
Item 1	**.749****	.439	**.638****	-.159**	.134**	.161**	.049	-.126*	.379
Item 7	**.812****	.341	**.643****	.009	.277**	-.067	.073	-.078	.306
Item 13	**.829****	.313	**.653****	.367**	-.007	-.015	-.061	.084	.266
Integrated regulation (EMIN)									
Item 4	**.821****	.326	.032	**.399****	.357**	.183**	-.106*	.024	.342
Item 10	**.827****	.317	.090*	**.651****	.125*	.006	.087*	-.199**	.242
Item 16	**.816****	.334	.121*	**.570****	-.118*	.333**	-.048	-.117**	.253
Identified regulation (EMID)									
Item 6	**.828****	.315	-.001	.024	**.817****	.114*	-.054	-.043	.159
Item 12	**.769****	.408	.427**	-.002	**.249****	.148*	-.083	-.102	.404
Item 18	**.818****	.330	.238**	.222**	**.452****	.063	.016	.008	.336
Introjected regulation (EMIJ)									
Item 2	**.829****	.313	.185**	.089	.071	**.577****	-.252**	.017	.329
Item 8	**.506****	.744	-.148*	.247**	.196**	**.415****	.298**	.069	.483
Item 14	**.592****	.649	-.076	.121*	.046	**.530****	.108	-.144**	.548
External regulation (EMER)									
Item 5	**.815****	.336	.040	.066	.001	-.070	**.672****	.229**	.353
Item 11	**.941****	.114	-.076	-.174**	-.051	.134*	**.886****	.010	.123
Item 17	**.432****	.813	.164*	.144*	-.013	-.059	**.660****	-.041	.573
Amotivation (AMOT)									
Item 3	**.728****	.471	-.109*	.056	.034	-.077	-.043	**.707****	.451
Item 9	**.921****	.151	.010	-.128**	.021	-.081	.045	**.775****	.230
Item 15	**.633****	.599	.103	-.085	-.084	.182**	.148*	**.696****	.449

Note. CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; λ: Factor loading; δ: Item uniqueness; Target factor loadings are in bold.; *$p < .05$; **$p < .01$.

Table S3

Latent Factor Correlations from the Six-Factor CFA and ESEM Solutions for the Sport Motivation Scale

	Intrinsic	Integrated	Identified	Introjected	External	Amotivation
Intrinsic motivation	—	.496**	.621**	.467**	-.191**	-.374**
Integrated regulation	.808**	—	.555**	.547**	.010	-.337**
Identified regulation	.909**	.877**	—	.528**	-.061	-.291**
Introjected regulation	.729**	.909**	.839**	—	.048	-.426**
External regulation	-.213**	-.159**	-.208**	-.018**	—	.501**
Amotivation	-.477**	-.586**	-.511**	-.548**	.624**	—

Note. CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; Values above the diagonal are from the ESEM model; Values below the diagonal are from the CFA model.; * $p < .05$; ** $p < .01$.

Table S4

Parameter estimates the six-factor CFA and ESEM solutions of the BPNSFS

	CFA		ESEM						
	Factor (λ)	δ	AS (λ)	RS (λ)	CS (λ)	AF (λ)	RF (λ)	CF (λ)	δ
Autonomy satisfaction (A-S)									
Item 1	**.601**	.639	**.531****	.159**	-.129*	-.181**	.033	-.013	.558
Item 7	**.836**	.301	**.824****	.021	.073	-.012	-.133**	.080*	.221
Item 13	**.791**	.374	**.719****	.077	.208**	-.026	-.116*	.200**	.299
Item 19	**.787**	.380	**.310****	-.027	.401**	-.283**	-.057	.043	.405
Relatedness satisfaction (R-S)									
Item 3	**.760**	.423	.094*	**.630****	-.066	-.182**	-.027	.037	.465
Item 9	**.832**	.307	.065	**.907****	.051	.093*	.001	.139**	.176
Item 15	**.887**	.214	-.082*	**.917****	.112**	.040	-.033	.046	.178
Item 21	**.858**	.264	.011	**.652****	.016	.013	-.260**	.006	.339
Competence satisfaction (C-S)									
Item 5	**.802**	.357	.413**	.123**	**.009**	.025	.083	-.616**	.201
Item 11	**.795**	.368	.284**	.109**	**.380****	.042	.080	-.403**	.331
Item 17	**.782**	.389	.227**	.128**	**.542****	-.080	-.026	-.075	.353
Item 23	**.812**	.341	.153**	.141**	**.480****	-.058	.093	-.359**	.309
Autonomy frustration (A-Fr)									
Item 2	**.353**	.876	-.007	-.101	.294**	**.496****	-.059	.121*	.749
Item 8	**.775**	.400	-.184**	.094*	.037	**.756****	.048	-.046	.329
Item 14	**.805**	.352	.058	-.041	-.014	**.874****	-.093	.104*	.253
Item 20	**.756**	.429	-.079	.068	-.206**	**.393****	.264**	-.020	.506
Relatedness frustration (R-Fr)									
Item 4	**.768**	.410	-.040	-.112*	.052	.017	**.574****	.239**	.446
Item 10	**.835**	.302	-.075	-.157**	.065	.073	**.720****	.010	.272
Item 16	**.834**	.305	-.167**	.051	.102*	-.027	**.891****	.083	.199
Item 22	**.766**	.413	.126*	-.313**	-.042	.108*	**.455****	.149**	.435
Competence frustration (C-Fr)									
Item 6	**.884**	.218	-.147**	.070	-.093	.171**	.151**	**.613****	.232
Item 12	**.803**	.356	.083*	.018	-.173**	.137**	.247**	**.564****	.339
Item 18	**.828**	.314	.064	-.042	-.252**	.183**	.046	**.596****	.296
Item 24	**.837**	.299	.123**	.055	-.328**	.101*	.304**	**.516****	.247

Note. CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; S: Need satisfaction; Fr: Need frustration; A: Need for autonomy; C: Need for competence; R: Need for relatedness; λ: Factor loading; δ: Item uniqueness; Target factor loadings are in bold; *$p < .05$; **$p < .01$.

Table S5

Latent Factor Correlations from the Six-Factor CFA and ESEM for the BPNSFS

	A-S	R-S	C-S	A-Fr	R-Fr	C-Fr
Autonomy satisfaction (A-S)	—	.451**	.358**	-.428**	-.260**	-.422**
Relatedness satisfaction (R-S)	.557**	—	.184**	-.206**	-.484**	-.235**
Competence satisfaction (C-S)	.812**	.464**	—	-.414**	-.400**	-.401**
Autonomy frustration (A-Fr)	-.668**	-.289**	-.610**	—	.523**	.404**
Relatedness frustration (R-Fr)	-.571**	-.687**	-.573**	.640**	—	.274**
Competence frustration (C-Fr)	-.597**	-.327**	-.879**	.710**	.673**	—

Note. CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; Values above the diagonal are from the ESEM model; Values below the diagonal are from the CFA model.; * $p < .05$; ** $p < .01$.

Table S6

Parameter estimates for the bifactor-ESEM solution of need fulfillment including one general factor and six specific factors

	N-Fu (λ)	A-S (λ)	R-S (λ)	C-S (λ)	A-Fr (λ)	R-Fr (λ)	C-Fr (λ)	δ
Autonomy satisfaction (A-S)								
Item 1	**.506****	**.303****	.103*	.236**	-.116	.053	.179**	.537
Item 7	**.654****	**.596****	.078**	.080	-.005	.012	.038	.203
Item 13	**.636****	**.519****	.101**	-.067	.017	.024	.095**	.302
Item 19	**.690****	**.207****	-.133**	-.208**	-.100	.055	-.033	.406
Relatedness satisfaction (R-S)								
Item 3	**.487****	.098*	**.513****	.051	-.101*	-.090*	.053	.466
Item 9	**.411****	.148**	**.822****	-.042	.122**	-.062*	.030	.112
Item 15	**.516****	-.038	**.705****	-.027	.128**	-.093**	.090**	.202
Item 21	**.590****	-.085*	**.507****	.039	.091*	-.217**	.195**	.292
Competence satisfaction (C-S)								
Item 5	**.726****	.132**	-.027	**.438****	.098	.178*	-.191**	.185
Item 11	**.738****	.085*	-.083*	**.088**	.181**	.210**	-.171**	.327
Item 17	**.748****	.119**	-.044	**-.202**	.102	.111*	-.078	.354
Item 23	**.774****	-.001	-.094**	**-.025**	.136**	.215**	-.174**	.296
Autonomy frustration (A-Fr)								
Item 2	**-.251****	.033	-.023	-.199*	**.387****	.039	-.026	.744
Item 8	**-.564****	-.139**	.161**	.060	**.544****	.068	.009	.333
Item 14	**-.596****	.022	.120**	.063	**.601****	-.012	.130**	.248
Item 20	**-.610****	-.001	.156**	.184**	**.224****	.157**	-.009	.494
Relatedness frustration (R-Fr)								
Item 4	**-.593****	.040	-.117**	-.040	.017	**.409****	.131**	.447
Item 10	**-.589****	-.069	-.230**	.111	.094*	**.571****	.092*	.239
Item 16	**-.636****	-.014	-.048	.024	.024	**.623****	.006	.203
Item 22	**-.635****	.231**	-.185**	.020	.014	**.341****	-.046	.391
Competence frustration (C-Fr)								
Item 6	**-.756****	.019	.188**	-.208*	.061	.010	**.337****	.233
Item 12	**-.620****	.015	.054	-.011	.070*	.124**	**.598****	.235
Item 18	**-.693****	.088**	.112**	-.060	.038	-.062*	**.442****	.295
Item 24	**-.719****	.166**	.175**	.062	-.021	.115**	**.394****	.252

Note. Fu: Global (G-Factor) representing need fulfillment; S-Factors: Specific factors from the bifactor model; S: Need satisfaction; Fr: Need frustration; A: Need for autonomy; C: Need for competence; R: Need for relatedness; λ: Factor loading; δ: Item uniqueness; Target factor loadings are in bold.; *$p < .05$; **$p < .01$.

Table S7

Parameter estimates for the Subjective Vitality Scale

	Vit (λ)	δ
Vitality		
Item 1	**.789****	.378
Item 2	**-.687****	.527
Item 3	**.737****	.457
Item 4	**.935****	.126
Item 5	**.774****	.401
Item 6	**.785****	.384
Item 7	**.890****	.208

Note. Vit: Vitality; λ: Factor loading; δ: Item uniqueness; Target factor loadings are in bold.; *$p < .05$; **$p < .01$

Table S8

Correlations and reliability indices for the variables of the study

	ω	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. IMOT	.681	—															
2. EMIN	.556	.630**	—														
3. EMID	.527	.750**	.684**	—													
4. EMIJ	.511	.589**	.737**	.685**	—												
5. EMER	.788	-.245**	-.008	-.089*	.048	—											
6. AMOT	.770	-.468**	-.453**	-.382**	-.530**	.581**	—										
7. N-Fu	.975	.455**	.407**	.362**	.326**	-.369**	-.526**	—									
8. A-Sa	.449	.304**	.314**	.348**	.307**	.015	-.135**	.096*	—								
9. R-Sa	.738	.027	-.020	.016	.008	-.011	.023	.020	.007	—							
10. C-Sa	.131	.035	.102*	.089*	.022	-.070	-.068	.015	.025	.011	—						
11. A-Fr	.495	-.015	.047	.024	.035	.091*	.049	-.034	-.004	.083	.048	—					
12. R-Fr	.560	.058	.196**	.157**	.140**	.193**	.114*	-.019	.110*	-.054	.089*	.071	—				
13. C-Fr	.497	.058	.004	.076	.063	.039	.097*	-.103*	.199**	.154**	-.056	-.052	-.047	—			
14. VIT	.927	.459**	.414**	.406**	.408**	-.271**	-.445**	.613**	.126**	-.060	.088*	-.050	.061	-.057	—		
15. Duration	—	.271**	.270**	.197**	.221**	.012	-.097*	.136**	.069	.037	.075	-.002	.043	.031	.152**	—	
16. Length	—	.155**	.374**	.129**	.203**	.029	-.074	.126**	.080	-.015	.072	.063	.183**	-.036	.113*	.278**	—
17. Frequency	—	.239**	.376**	.199**	.354**	.033	-.235**	.120**	.176**	-.090*	.021	.056	.125**	.001	.201**	.125**	.291**

Note. IMOT: intrinsic motivation; EMIN: extrinsic motivation integrated regulation; EMID: extrinsic motivation identified regulation; EMIJ: extrinsic motivation introjected regulation; EMER: extrinsic motivation external regulation; AMOT: amotivation; N-Fu: need fulfillment global factor; A-Sa: autonomy satisfaction; R-Sa: relatedness satisfaction; C-Sa: competence satisfaction; A-Fr: autonomy frustration; R-Fr: relatedness frustration; C-Fr: competence frustration; VIT: vitality; ω = McDonald's model-based omega reliability coefficient; *$p < .05$; **$p < .01$.

Table S9

Classification Probabilities for the Most Likely Latent Profile Membership (Column) by Latent Profile (Row)

	Average motivated	Introjected self-determined	Amotivated	Non-self-determined
Average motivated	0.880	0.028	0.025	0.067
Introjected self-determined	0.037	0.924	0.000	0.040
Amotivated	0.034	0.000	0.910	0.056
Non-self-determined	0.076	0.019	0.037	0.868

Table S10

Exact means of the different motivations in the final retained 4-profile solution

	Average motivated (Profile 1)		Introjected self-determined (Profile 2)		Amotivated (Profile 3)		Non-self-determined (Profile 4)	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
1. IMOT	0.046	0.496	0.922	0.328	-1.037	0.306	-0.089	0.313
2. EMIN	-0.123	0.270	0.996	0.228	-1.100	0.352	0.064	0.311
3. EMID	-0.082	0.369	0.985	0.257	-1.104	0.301	0.051	0.310
4. EMIJ	-0.085	0.258	0.938	0.223	-1.008	0.364	0.037	0.287
5. EMER	-0.532	0.227	-0.103	0.483	0.228	0.581	0.716	0.449
6. AMOT	-0.447	0.143	-0.615	0.326	0.774	0.484	0.556	0.343

Note. IMOT: intrinsic motivation; EMIN: extrinsic motivation integrated regulation; EMID: extrinsic motivation identified regulation; EMIJ: extrinsic motivation introjected regulation; EMER: extrinsic motivation external regulation; AMOT: amotivation; Factors were estimated from factor scores with a mean of 0 and a standard deviation of 1.

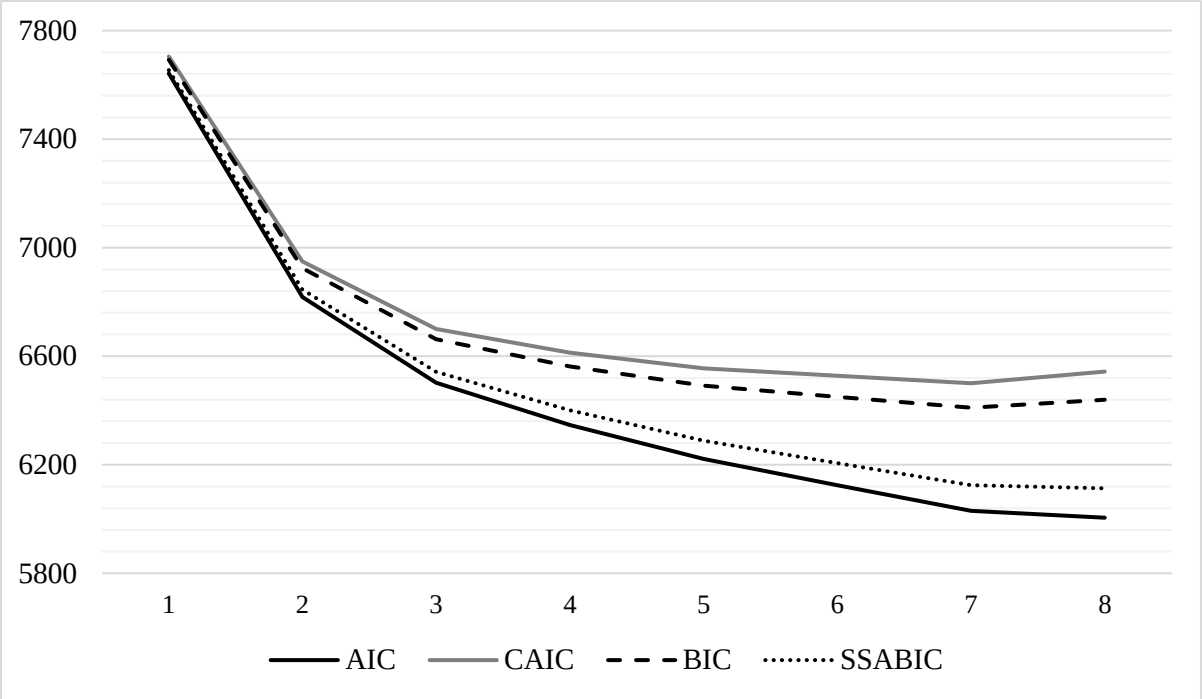

Figure S1
Elbow plot for the information criteria used in class enumeration

Note. AIC: Akaike Information Criterion; BIC: the Bayesian Information Criterion; CAIC: Constant AIC; SSABIC: Sample-Size-Adjusted BIC.