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ORIGINAL RESEARCH

Students' Motivational Profiles in the Physical Education Context

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The purpose of the current study is to test the self-determination theory (SDT) continuum hypothesis of motivation using latent profile analysis (LPA). A total of 3,220 school students took part in the study. We compared LPA solutions estimated using the four motivation types versus the two higher-order dimensions to assess their degree of correspondence to the SDT continuum hypothesis. To examine the concurrent validity of the profiles, we also verified their associations with three predictors (age, gender, perception of physical education teachers' autonomy-supportive behaviors) and two outcomes variables (perceived competence and intentions to be physically active). The results showed that profiling using the four motivation types provides more differentiated and meaningful description of responses to the Perceived Locus of Causality Scale, compared with profiling using two higher-order factors. In general, the results of the current study were consistent with the SDT continuum hypothesis of human motivation.

Keywords*:* perceived locus of causality, latent profile analysis, self-determination continuum, continuum hypothesis

Studies of motivation in physical activity and sport often address questions such as "Why do I take part in physical activity/sport?," "Why I choose soccer rather than basketball?," or "Why do I exert so much effort in exercising?" These are fundamental questions since the reasons given will affect the consequences and outcomes of involvement in physical activities and sports. Deci and Ryan (1985) suggest that people may be involved in physical activity and sport for different types of motives. For example, one basketball player may play because he or she truly loves basketball, while another may play because he or she strives to achieve a sufficient level of performance to be nominated as the team representative for an event. In the sport psychology literature there is an assumption that intrinsic motivation (i.e., doing something for its own sake) is more advantageous than extrinsic motivation (i.e., doing something as a means to an end). Self-determination theory (SDT) is an organismic theory of motivation and assumes that humans have the natural tendency to grow, learn, and integrate their experiences into a coherent sense of self (Deci & Ryan, 1985, 2000). However Ryan and Deci (2000) temper that conclusion by arguing that some types of extrinsic motivation are more internalized and autonomous than others and, thus, more advantageous.

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Behavioral Regulations

Although intrinsic motivation is the drive to pursue an activity for the sheer pleasure that it procures, Deci and Ryan (1985) further propose that extrinsic motivation can take many forms differing from one another according to their levels of self-determination. For example, certain activities occurring in the context of physical education classes may not be interesting in and of themselves. Participation in these activities is therefore extrinsically motivated. Thus, in addition to intrinsic regulation, where behavior is regulated by the pleasure it procures, Deci and Ryan (1985) propose to consider at least three other types of behavioral regulations corresponding to more extrinsic forms of motivations, with each type reflecting a qualitatively different "reason" for engaging in the behavior (e.g., Ntoumanis, 2001; Ryan & Connell, 1989). *External regulation* refers to behaviors that are fully controlled by external means such as rewards, punishments, or authority. *Introjected regulation* refers to behaviors that are self-imposed as a way to reduce negative feelings (e.g., guilt, shame) or to induce positive feelings (e.g., pride, self-esteem). Overall, introjected regulation refers to activities that one feels "ought" to be done. In contrast, *identified regulation* refers to activities that are aligned to one's own personal goals and values. Identified regulation thus refers to activities that one "wants" to do because they are personally meaningful and worthy. These four main types of behavioral regulations (external regulation, introjected regulation, identified regulation, and intrinsic regulation) in sport and physical education settings have been assessed through several different measures, including the Perceived Locus of Causality Scale (PLOCS; Goudas, Biddle, & Fox, 1994), which was adapted from the Academic Self-Regulation Scale (Ryan & Connell, 1989).

Organismic integration theory describes the processes through which extrinsically motivated behaviors can become more autonomous as individuals realize the value of the behaviors and their conformity with their own goals and values. This process, through which behavioral regulation shifts from an external to internal locus of causality, is referred to as *internalization* (Deci & Ryan, 1991). The more internalized a behavioral regulation, the more it is experienced as self-determined (Ryan & Connell, 1989).

The Continuum Hypothesis

According to SDT, these four types of regulations are assumed to form a continuum representing the degree to which a behavior becomes internalized (Deci, Vallerand, Pelletier, & Ryan, 1991). Ryan and Connell (1989) showed that the four types of behavioral regulations were correlated according to a simplex-like correlation structure, supporting this underlying continuum of internalization. That is, higher positive correlations were evident between conceptually adjacent subscales (e.g., external and introjected regulations) than between more distal subscales (e.g., external and identified regulations), with either very low or even negative correlations observed between the subscales theoretically located at each end of the continuum (e.g., external and intrinsic regulations).

This hypothesized continuum structure of motivation was recently questioned by Chemolli and Gagné (2014). Using Rasch analyses, these authors suggested that the different motivation regulations measured via the Multidimensional Work Motivational Scale (Gagné et al., 2015) and the Academic Motivation Scale (AMS; Vallerand et al., 1992) did not follow the hypothesized continuum structure as closely as could be expected from theory. In parallel to Chemolli and Gagné (2014), Guay, Morin, Litalien, Valois, and Vallerand (2014; also see Litalien, Guay, & Morin, 2015) independently conducted a different test of this hypothesis, contrasting confirmatory factor analytic (CFA) and exploratory structural equation modeling (ESEM) representations of responses to the AMS. Their results first showed that the CFA solution was more in line with Chemolli and Gagné's (2014) conclusions in failing to support the presence of an underlying continuum of motivation. In contrast, the ESEM solution provided a much closer approximation of the expected simplex factor correlation pattern. The key difference between these two representations is that ESEM allows for cross-loadings between items and nontarget, yet conceptually related, motivation factors to represent the fact that each item seldom provides an exact reflection of a single construct. For this reason, accumulating statistical evidence shows that ESEM tends to provide more accurate estimates of factor correlations relative to CFA when cross-loadings are indeed present in the population model yet tends to remain unbiased otherwise (for more extensive discussion of these issues, see Asparouhov, Muthén, & Morin, 2015; Morin, Arens, & Marsh, 2016). Other studies have supported the continuum using methods such as multidimensional scaling (MDS; e.g., Roth, Assor, Kanat-Maymon, & Kaplan, 2006). Unfortunately, none of these studies was conducted in a sport or physical activity context.

A Person-Centered Approach to Tests of the Continuum Hypothesis

An alternative approach to examine the continuum structure of motivation involves the use of person-centered latent profile analysis (LPA). LPA identifies relatively homogeneous subgroups of participants, called latent profiles, that differ qualitatively and quantitatively from one another in relation to their configuration on a series of indicators (e.g., motivation types) (Morin & Marsh, 2015; Morin & Wang, 2016). LPA is thus similar to CFA, except that the latent variable is categorical (reflecting profiles, or groupings of persons) rather than continuous (reflecting factors, or groupings of variables) (Lubke & Muthén, 2005). In LPA, all individuals correspond to each profile based on their degree of similarity to each of the prototypical configurations represented by the latent categorical variable. Thus, latent profiles are not fixed or rigid groupings of persons, but rather prototypical configurations allowing for substantial levels of within-profile variation. In other words, each individual corresponding to each profile can differ from this average prototypical configuration on each of the various indicators considered separately.

Typical tests of SDT's continuum hypothesis have involved the examination of correlations among the different types of behavioral regulations to see whether they followed the expected simplex pattern. LPA provides an alternative view of the same underlying reality, representing these same correlations through the estimation of a finite set of latent profiles. Furthermore, in addition to anchoring this analytical process on the examination of these correlations, LPA further takes into account the full multivariate distribution of the behavioral regulation scales themselves, to identify latent profiles presenting a meaningful level of within-profile variability and following multivariate normality assumptions. Thus, for any pattern of variable-centered correlations observed among a series of subscales, there exists an underlying person-centered solution that provides a mirror image of the observed correlations. This is why variable- and person-centered research are generally positioned as providing complementary perspectives on the same research questions (e.g., Marsh, Lüdtke, Trautwein, & Morin, 2009; Morin & Wang, 2016).

Thus, should SDT motivation types form a single underlying continuum, one would expect to mainly observe profiles corresponding to different positions on this continuum. For instance, one prototypical profile may describe individuals presenting high levels of external regulation, moderate levels of introjected regulation, low levels of identified regulation, and very low levels of intrinsic regulation. Another profile could be dominated by a high level introjected regulation, moderately low levels of external and identified regulations, and low levels of intrinsic regulation. Variations around these prototypical configurations are to be expected, supporting the added value of each specific motivation type over and above their aggregation into a single continuum score (e.g., Morin & Marsh, 2015). However, the observation of profiles dominated by motivation types located at different endpoints of the continuum, such as by high levels of external or introjected regulation coexisting with high levels of identified or intrinsic regulations would argue against the continuum hypothesis.

Alternative Representations of the Behavioral Regulations

In applied SDT research, rather than separately studying the four motivation types, many have simply relied on two summary indices (or higher-order dimensions) reflecting autonomous (combining identified and intrinsic regulations) versus controlled (combining external and introjected regulations) motivation (e.g., Gagné et al., 2010, 2015; Williams, Grow, Freedman, Ryan, & Deci, 1996). The fact that results have generally shown these two higher-order dimensions to be negatively correlated to one another apparently supports the continuum hypothesis. However, a key question that remains is whether using this approach results in a loss of valuable information. The possible impact of using different scoring protocols is an important consideration in research examining the relations between motivation and physical activity behavior. In particular, results from prior variable-centered research have shown that the reliance on more global scoring protocols tended to result in the loss of potentially important information (Wilson, Sabiston, Mack, & Blanchard, 2012).

In a previous person-centered cluster analyses conducted on these two higher-order dimensions, Vansteenkiste, Sierens, Soenens, Luyckx, and Lens (2009) identified four distinct subgroups (clusters) of individuals. Two of these clusters included individuals presenting matching levels of autonomous and controlled motivation (high and high vs. low and low) while the remaining clusters presented levels of autonomous and controlled motivation convergent with SDT continuum hypothesis (high and low, low and high). Although the first two profiles, if they were to be commonly identified in research, would argue against the idea that motivation types are arrayed along an underlying continuum, the reliance on cluster analyses represents a potentially serious limitation of this study. Among the key limitations of cluster analyses are their sensitivity to the clustering algorithm and to the response scale of the indicators, their reliance on a series of rigid assumptions (e.g., exact assignment of participants to a single profile, conditional independence, equality of the indicators' variances across clusters), and the fact that they are a standalone analytical procedure that cannot accommodate the inclusion of predictors/outcomes, or the consideration of the multilevel structure of multiple data sets. Model-based LPA provide a way to address most of these limitations (for additional details, see Magidson & Vermunt, 2002; Meyer & Morin, 2016; Morin & Wang, 2016; Vermunt & Magidson, 2002). Despite this limitation, recent reports suggesting that the combination of autonomous and controlled forms of regulation might be beneficent in some contexts supports the need for further research in this area (Brunet, Gunnell, Gaudreau, & Sabiston, 2015).

The Present Study

The purpose of the current study is to examine the SDT continuum of motivation using LPA within a sport and physical activity context using the PLOCS. LPA solutions using either the four motivation types assessed in the PLOCS or the two higher-order dimensions will be contrasted to assess their degree of correspondence to the SDT continuum hypothesis, and whether valuable information can be brought to the profiles through a consideration of the four motivation types.

We used three predictors (gender, age, and perception of the autonomy support provided by the physical education teacher considered both at the individual and classroom levels) and two outcomes (perceived competence and intentions to be physically active) to examine the concurrent validity of the latent profiles gained from these two methods. In terms of predictors, research has found that female students tend to correspond more frequently to the less adaptive motivational profiles while male students tend to correspond more frequently to the more adaptive motivational profiles (Wang & Biddle, 2001). It is also known that as children grow older, they tend to become less physically active, which could be due to a decrease of more autonomous sources of motivation (Wang, Koh, Biddle, Liu, & Chye, 2011). Previous results have shown that autonomy-supportive classroom teacher behaviors tend to predict more autonomous forms of motivation for physical activity (Hagger, Chatzisarantis, Barkoukis, Wang, & Baranowski, 2005). However, there has been little consideration of whether these effects occur at the classroom level (i.e., reflecting the effects of more objective teacher behaviors, or at least students' shared perceptions) or at the individual student levels (i.e., reflecting deviations in student idiosyncratic perceptions relative to class averages).

In terms of outcomes, results also tend to show that more autonomous forms of regulations tend to result in higher levels of perceived competence (Thill & Mouanda, 1990; Wang & Liu, 2007) and intentions to be physically active (Hagger et al., 2005; Wang & Biddle, 2001), which is also in line with the transcontextual model of motivation (Hagger, Chatzisarantis, Culverhouse, & Biddle, 2003). These variables will be used to verify the concurrent validity of the profiles: Gender, age, and autonomy-supportive classroom teacher behaviors will be used to predict profile membership whereas perceived competences and intentions to be physically active will be considered as outcomes of the profiles.

Methods

Participants and Procedures

A sample of 3,220 students (1,257 boys and 1,963 girls) ages 10–21 years (M = 14.17, SD = 2.64) from 128 classroom located in 28 schools took part in the study. The students were attending Grade 4 in primary school to the second year of junior college in the Singapore school system. The data were collected as part of a larger study examining teaching and learning in physical education from a multidisciplinary perspective (pedagogy, psychology, physiology). The primary aim of the project was to examine the current state of teaching and learning in physical education classes using Huitt's (2003) transactional framework of teaching and learning processes. The data on PLOCS, perceived competence, and teachers' autonomy-supportive behaviors has not been published before. Ethical approval for this project was granted by the university's Ethical Review Board. Permission to collect data with the students was obtained from the Ministry of Education and the principals of the participating schools. Questionnaires were administered to all students in English by trained research assistants in quiet classroom settings. Before the administration of the questionnaires, students were informed of the nature of the project, that their participation was voluntary, and that they could withdraw at any time. The students were told that their confidentiality would be maintained, and their informed consent was obtained. The participants took 15 min to complete the questionnaire.

Measures

Motivation. The PLOCS, developed by Goudas et al. (1994), based on the Academic Self-Regulation Scale originally developed by Ryan and Connell (1989), was employed to assess four types of behavioral regulation in the physical education context. The common stem used for all items was "I take part in PE [physical education] . . . ," followed by the items. External regulation (α = .79; e.g., "because I'll get into trouble if I don't") and introjection (α = .66; e.g., "because I'll feel bad about myself if I didn't") were assessed through four items each. Identification (α = .82; e.g., "because it is important for me to do well in PE") and intrinsic regulation (α = .87; e.g., "because PE is fun") were measured through three items each. All items were rated on a 7-point Likert-type scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Previous studies have supported the psychometric properties of responses to this instrument in samples of Singaporean children and adolescents (Wang, Biddle, & Elliot, 2007; Wang & Liu, 2007).

Perception of Autonomy-Support. Students' perceptions of the level of autonomy support provided by their teacher in physical education classes were measured using the 15-item (α = .94; e.g., "I feel that my PE teacher provides me choices and options") Learning Climate Questionnaire (LCQ; Williams & Deci, 1996). Students responded to the questionnaire in accordance to the degree to which they perceived their physical education teacher to have an autonomy-supportive interpersonal style. Responses were given on a 7-point Likert-type scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*).

Perceived Competence. Students' perceptions of competence in physical education activities were assessed with an adapted version of the Sport Competence subscale of the Physical Self-Perception Profile (Fox & Corbin, 1989; five items; α = .87; e.g., "I feel that I am among the best when it comes to PE"). Responses were made on a 7-point Likert-type scales ranging from 1 (*strongly disagree*) to 7 (*strongly agree*).

Intentions to Exercise During Leisure Time. Three items (α = .82) were used to measure intentions to exercise during leisure time (Hagger et al., 2007, Wang et al., 2008). The students were asked to rate the item "I intend to do active sports and/or vigorous physical activities for at least 30 minutes, 3 days per week during my leisure time, over the next 2 weeks" on three distinct 7-point response scales: (a) 1 (*very unlikely*) to 7 (*very likely*); (b) 1 (*not at all*) to 7 (*every day*); (c) 1 (*definitely not*) to 7 (*definitely*). Our decision to rely on intentions to be physically active in the context of leisure time, relative to physical education, is related to the fact that physical education participation is mandatory in the Singaporean education system. Thus, because students cannot "intend" to participate or not in physical education, we elected to focus on intentions to be physically active in self-determined activities.

Data Analysis

All analyses were conducted using Mplus 7.3's (Muthén & Muthén, 2014) robust maximum likelihood (MLR) estimator, which is robust to nonnormality. These analyses are also robust to students' nesting within classrooms (N = 128 classroom including between 6 and 50 students each,

M = 25) as they were implemented conjunction with the Mplus COMPLEX function (Asparouhov, 2005). Full information maximum likelihood (Enders, 2010) was used to handle the few missing responses present at the item (0–.85%; M = .32%) or scale (0–.09%; M = .01%) levels.

Preliminary CFAs were first conducted to ascertain the psychometric properties of our measures. In a first model, all constructs were specified as defined by their respective items, no cross-loadings was allowed, and all constructs were allowed to correlate. Three a priori correlated uniquenesses were included to control for the parallel wording of two items from the perceived competence instrument ("I feel that I am among the best when it comes to physical education" and "I feel that I am one of the best when it comes to physical education"), two items from the introjection scale ("because I want the coach/teacher to think I'm a good student" and "because I want the other students to think I'm good"), and two items from the intrinsic scale ("because PE is fun" and "because PE is exciting"). This CFA model included a total of seven correlated factors (intrinsic regulation, identified regulation, introjected regulation, external regulation, autonomy support, perceived competence, and intentions). Then, a second model was assessed in which the four motivation types were used to assess two higher-order dimensions (autonomous and controlled regulation). To assess the fit of these models, we used the Tucker–Lewis index (TLI), the comparative fit index (CFI), and the root mean square error of approximation (RMSEA). Values greater than .90 and .95 for the TLI and CFI are considered to indicate adequate and excellent fit to the data, while values smaller than .08 or .06 for the RMSEA are taken to reflect acceptable and excellent model fit (Hu & Bentler, 1999; Marsh, Hau, & Wen, 2004, Marsh, Hau, & Grayson, 2005).

For the main analyses, two series of LPAs were conducted using either the four types of regulations (intrinsic, identified, introjected, and extrinsic), or the two higher-order dimensions of motivation (autonomous and controlled) as profile indicators.[1] For each series of LPA, solutions including one to eight profiles were estimated. The number of initial stage random starts was set at 10,000 with the 500 best solutions retained for final stage optimization, with 1,000 iterations.

The selection of the optimal number of profiles followed a series of recommendations presented recently by Morin and Wang (2016). This selection thus first relied on the examination of a series of statistical indicators: the Akaike's information criterion (AIC), the constant AIC (CAIC), the Bayesian information criterion (BIC), the sample-size adjusted BIC (ABIC), the adjusted Lo–Mendell–Rubin likelihood ratio test (aLMR), and the bootstrap likelihood ratio test (BLRT) (e.g., Marsh et al.,2009; Morin & Wang, 2016). For the first four indicators, a lower value suggests a better fit. The aLMR and BLRT compare the estimated model including k profiles with a model that has one less profile (k – 1). Nonsignificant p values support the k – 1 profile model. However these tests remain variations of tests of statistical significance and can still be heavily influenced by sample size so that given a large enough sample, they will tend to support the more complex model (i.e., the one with the most profiles; e.g., Marsh et al., 2009). In these situations, information criteria (AIC, CAIC, BIC, and ABIC) should be examined through "elbow plots" to locate the point at which the improvement becomes negligible (Morin & Wang, 2016; Petras & Masyn, 2010). This examination should also be complemented by a more detailed examination of theoretical meaningfulness and statistical adequacy of the parameter estimates obtained from the most likely alternative solution. Finally, although it should not be used to determine the optimal number of profiles, the entropy provides a useful descriptive summary of the classification accuracy of the retained solution, ranging from 0 to 1 with higher value indicating greater accuracy (Lubke & Muthén, 2007).

As noted by Morin and Wang (2016) and demonstrated by Chen, Kwok, Luo, and Willson (2010), controlling or not for the nested structure of the data has no impact on the class enumeration performance of LPA (i.e., the selection of the optimal number of profiles in the data). For this reason, and given that the BLRT cannot be computed when using the Mplus COMPLEX function, the class enumeration procedure was conducted without controlling for the nesting of students within classrooms. However, failure to control for nesting may still result in biased results in terms of standard errors and classification accuracy. For this reason, the final retained solutions, as well as all models including covariates, were re-estimated while incorporating this control implemented via the COMPLEX function. Thus, all parameters estimates reported in this study can be considered to be robust to nesting.

Once the final solution was identified, the relation between demographic predictors (age and gender) as well as students' perceptions of the level of autonomy support provided by their teacher in physical education classes and their likelihood of membership in the various profiles was estimated using a multilevel logistic regression approach. In this model, predictors were directly entered in the final retained solution, specified as an individual-level (L1) LPA solution. Gender, age, and group-mean-centered perceptions of autonomy support (reflecting deviations between students' individual perceptions of their physical education teachers and the class-average perceptions of all students forming a class) were used to predict the likelihood of membership in the various latent profiles at L1. Furthermore, class averages of students' perceptions of their teachers' autonomy support were used as a classroom-level (L2) predictor of classroom-level variations in the relative frequency of the various latent profiles.

Finally, the final set of profiles was compared on the basis of two outcomes (perceived competence and intentions) using Mplus's Auxiliary (BCH) function (Asparouhov & Muthén, 2014; Vermunt, 2010). This method estimates the associations between profiles and continuous outcomes directly included in the model in a single step without allowing them to change the nature of the profiles (e.g., Marsh et al., 2009; Morin & Wang, 2016).

Results

Descriptive Statistics

Based on the aforementioned interpretation guidelines, the results support the adequacy of both the first-order (scaled χ^2 = 4,032.19; *df* = 605; $p \leq .001$; CFI = .922; TLI = .914; RMSEA = .042) and higher-order (scaled χ^2 = 4,505.51; *df* = 612; $p \leq .001$; CFI = .911; TLI = .903; RMSEA = .044) measurement models of motivation. The parameter estimates from the higher-order model are reported in the appendix (the parameter estimates from the first-order model were essentially equivalent). These parameter estimates support the factor validity of responses to these instruments. The descriptive statistics including means, standard deviations, and correlations for all variables are presented in Table 1. The observed correlations between subscales, and between subscales and outcomes, generally followed theoretical expectations, showing that more self-determined forms of motivation (intrinsic, identified, and autonomous) were positively related to autonomy support, perceived competence, and intentions. Conversely, less self-determined forms of motivation constructs (external, introjected, and controlled) were either negatively related or not related to autonomy support, perceived competence, and intentions.

Latent Profile Analysis

The fit results for the various LPA models are reported in Table 2, and the elbow plots associated with the LPA based on the four motivation types and the two higher-order dimensions are, respectively, presented in Figures 1 and 2. For models based on the four motivation types, the values of AIC, CAIC, BIC, ABIC, and BLRT decreased as the number of profiles increased. However, the aLMR reached nonsignificance after the five-profile solution, corresponding also to the point where the increment in fit became negligible on the other indicators. The elbow plot also reached a plateau at the five-profile solution. Examination of the parameter estimates (mean levels of regulation types in the various profiles, and relative size of the profiles) of the five-profile solution, and of bordering four- and six-profile solutions, further supported our decision to retain the five-profile solution as the final model. Indeed, this examination revealed that adding a fifth profile always resulted in the addition of a well-defined qualitatively distinct and theoretically meaningful profile to the solution, whereas adding a sixth profile often resulted in the arbitrary division of one of the existing profiles into two distinct profiles differing only quantitatively from one another. For models based on the higher-order dimensions, none of the indicators converged on a clear preferable solution. However, examination of the elbow plot tends to support the five-profile solution, which was retained for comparison purposes and re-estimated as the final model with Mplus design-based correction of standard errors. Both of these models resulted in high levels of classification accuracy, as illustrated by entropy values of .836 and .803.

Description of the Profiles

Figure 3 provides a graphical representation of the five-profile solution based on standardized scores for the models based on the four motivation types. The exact means of the indicators and their confidence intervals in each of the profiles are reported in Table 3. The first profile characterizes 19.90% of the sample (67.4% of whom were girls; M_{age} = 15.41) presenting, relative to the levels observed in the total sample, moderately high levels of external regulation, average levels of introjected regulation, and low levels of identified and intrinsic regulations. We labeled this profile as reflecting *Moderate Controlled Motivation*. The second profile is the largest and describes 34.56% of the sample (60.7% girls; M_{age} = 13.24); it is characterized by relatively low levels of external regulation, average levels of introjected regulation, and high levels of identified and intrinsic regulations. This profile was labeled as reflecting *Autonomous Motivation*. The third profile represents 14.14% of the sample (47.7% girls; M_{age} = 13.00) presenting, again relative to the levels observed in the total sample, very high levels of introjected regulation, together with high levels of identified and intrinsic regulations, and moderately high levels of external regulation. We labeled this profile as reflecting *Internalized Regulation*. Because it is characterized by differing levels of introjected (very high) and external (moderately high) regulations, this profile clearly shows the value of differentiating between these two forms of regulations, rather than merging them into a single indicator of controlled motivation and simply contrasting them with the more autonomous motives. The fourth profile is the smallest and describes 4.82% of the sample (64.8% girls; M_{age} = 15.23) relatively presenting very high levels of external regulation, extremely low levels of identified and intrinsic regulations, and low levels of introjected motivation. This profile has been labeled as reflecting a *Strong Controlled Motivation*. Finally, the fifth characterizes 26.58% of the sample (62.8% girls; M_{age} = 14.85) and is characterized by close to average levels on all four motivation types. This profile has been labeled as reflecting *Moderate Motivation*. It is interesting to note that all of these profiles are aligned with the hypothesized continuum structure of motivation insofar as they demonstrate configurations of behavioral regulations located at different positions on this continuum, while also showing the value of considering the four distinct motivation types.

Figure 4 provides a graphical representation of the five-profile solution based on standardized scores for the models based on the two higher-order dimensions (see Table 3 for exact mean values and confidence intervals). The first profile characterizes 8.75% of the sample (46.2% girls; M_{age} = 12.91) presenting, relative to the levels observed in the total sample, high levels of controlled and autonomous motivation—which is unexpected according to the expected continuum structure of motivation. This profile was labeled as reflecting *High Motivation*. The

Table 1 Descriptive Statistics and Zero-Order Correlations Between All Variables of the Overall Sample

	M	*SD*	1	2	3	4	5	6	7	8
1. External regulation	3.26	1.62								
2. Introjected regulation	3.09	1.34	.44**							
3. Identified regulation	5.30	1.45	–.31**	.16**						
4. Intrinsic regulation	5.49	1.50	–.46**	.01	.80**					
5. Autonomous motivation	5.39	1.40	–.41**	.09**	.95**	.95**				
6. Controlled motivation	3.17	1.26	.88**	.82**	–.12**	–.29**	–.22**			
7. Autonomy support	4.46	1.09	–.28**	.03	.48**	.50**	.52**	–.16**		
8. Perceived competence	3.89	1.42	–.25**	.16**	.46**	.49**	.50**	–.07**	.34**	
9. Intentions	3.94	1.50	–.24**	.05**	.38**	.39**	.41**	–.13**	.22**	.42**

**$p < .01$.

Table 2 Latent Profile Fit Statistics for Models Based on the Four Motivation Types

Model	LL	Scaling	No. of FP	AIC	CAIC	BIC	ABIC	aLMR	BLRT	Entropy
Models based on the four motivation types										
1 profile	–18273.25	.946	8	36562.51	36619.13	36611.13	36585.71	—	—	—
2 profiles	–16548.37	1.21	13	33122.74	33214.74	33201.74	33160.44	≤.001	≤.001	.847
3 profiles	–15900.28	1.43	18	31836.57	31963.95	31945.95	31888.76	≤.001	≤.001	.875
4 profiles	–15521.96	1.27	23	31089.92	31252.69	31229.69	31156.61	≤.001	≤.001	.883
5 profiles	–15201.48	1.33	28	30458.97	30568.16	30540.16	30540.16	≤.001	≤.001	.835
6 profiles	–15002.55	1.59	33	30071.11	30199.80	30166.80	30166.80	≤.053	≤.001	.817
7 profiles	–14881.12	2.06	38	29838.23	29986.42	29948.42	29948.42	≤.509	≤.001	.814
8 profiles	–14785.83	1.84	43	29657.67	29825.35	29782.35	29782.35	≤.206	≤.001	.819
Final 5 profiles	–15189.73	1.89	28	30435.46	30633.60	30605.60	30516.63	—	—	.836
Models based on the two higher-order dimensions										
1 profile	–10963.25	.94	4	21934.50	21962.81	21958.81	21946.10	—	—	—
2 profiles	–10685.17	1.12	7	21384.33	21433.87	21426.87	21404.63	≤.001	≤.001	.734
3 profiles	–10523.89	1.12	10	21067.78	21138.55	21128.55	21096.77	≤.001	≤.001	.824
4 profiles	–10401.68	1.10	13	20829.35	20921.35	20908.35	20867.05	≤.001	≤.001	.844
5 profiles	–10312.42	1.08	16	20656.83	20770.07	20754.07	20703.23	≤.001	≤.001	.802
6 profiles	–10265.71	1.10	19	20569.43	20703.89	20684.89	20624.52	≤.001	≤.001	.803
7 profiles	–10198.28	1.13	22	20440.56	20596.26	20574.26	20504.35	≤.001	≤.001	.824
8 profiles	–10157.04	1.11	25	20364.09	20541.08	20516.08	20436.58	≤.002	≤.001	.843
Final 5 profiles	–10305.82	1.70	16	20643.64	20756.87	20740.87	20690.028	—	—	.803

Note. LL = model loglikelihood; Scaling = scaling correction factor associated with the Robust Maximum Likelihood (MLR) estimator; FP = free parameters; AIC = Akaike information criterion; CAIC = constant AIC; BIC = Bayesian information criterion; ABIC = sample-size adjusted BIC; aLMR = adjusted Lo–Mendell–Rubin likelihood ratio test; BLRT = bootstrap likelihood ratio test.

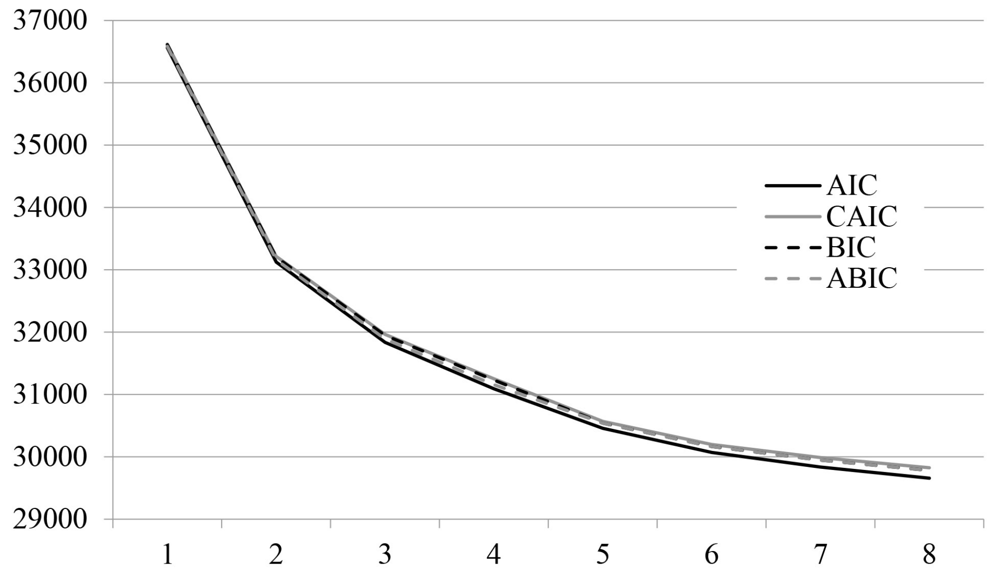

Figure 1 — Elbow plot of the information criteria for latent profile models based on the four motivation dimensions. AIC = Akaike information criterion; CAIC = constant AIC; BIC = Bayesian information criterion; ABIC = sample-size adjusted BIC.

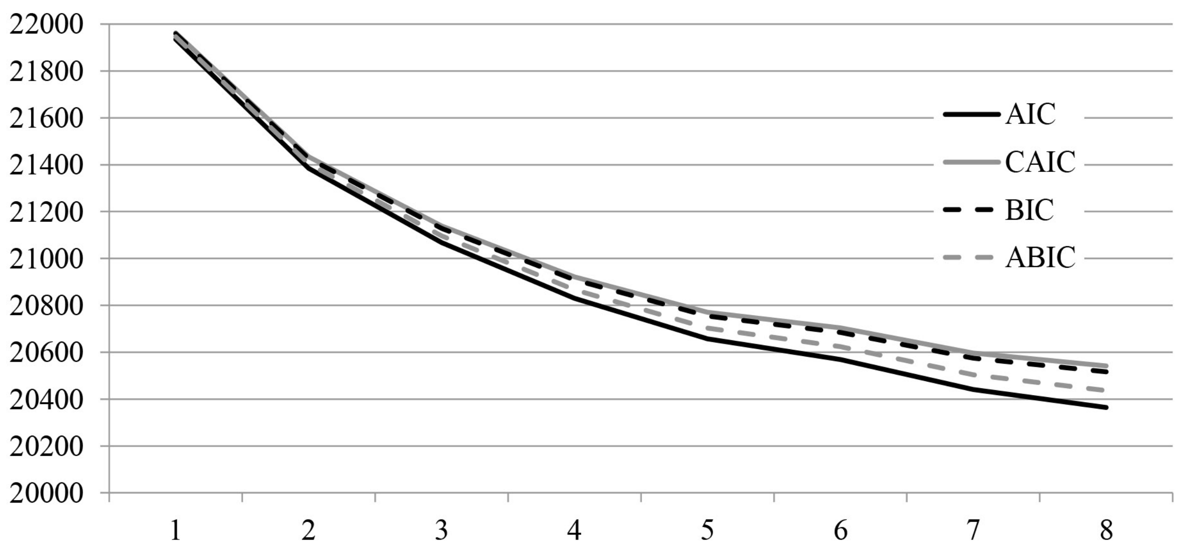

Figure 2 — Elbow plot of the information criteria for latent profile models based on the two higher-order motivation dimensions. AIC = Akaike information criterion; CAIC = constant AIC; BIC = Bayesian information criterion; ABIC = sample-size adjusted BIC.

second profile characterizes 4.03% of the sample (65.3% girls; M_{age} = 15.23) presenting relatively high levels of autonomous motivation and very low levels of controlled motivation. This profile was labeled as reflecting *Marked Autonomous Motivation* due to this high level of discrepancy between levels of autonomous and controlled motivation. The third profile describes 19.07% of the sample (67.9% girls; M_{age} = 15.37) presenting, relative to the levels observed in the total sample, moderate levels of autonomous motivation and moderately low levels of controlled motivation. This profile has been labeled as reflecting *Moderate Autonomous Motivation*. The fourth profile is similar to the fifth profile from the preceding solution and describes 28.37% of the sample (63.0% girls; M_{age} = 14.87) presenting close to average levels of autonomous and controlled motivation. This profile has been labeled as reflecting *Moderate Motivation*. The fifth profile is the largest and describes 39.80% of the sample (59.0% girls; M_{age} = 13.25) presenting the lowest levels of controlled motivation and high levels of autonomous motivation. This profile has been labeled as reflecting *Controlled Motivation*.

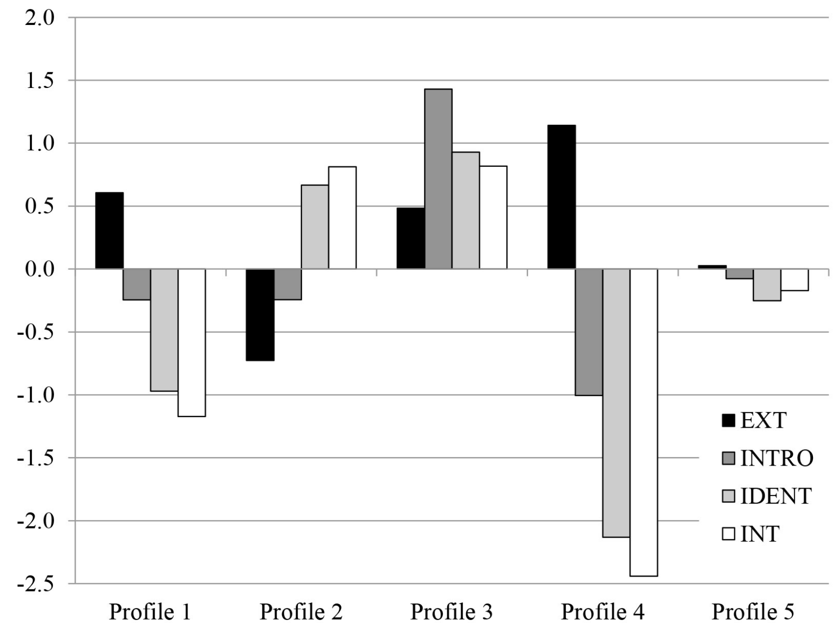

Figure 3 — Graphical representation of profiles based on four motivation types. *Note*. The results were standardized to help in the interpretation of this histogram. EXT = external regulation; INTRO = introjected regulation; IDENT = identified regulation; INT = intrinsic regulation. Profile 1: Moderate Controlled Motivation; Profile 2: Autonomous Motivation; Profile 3: Internalized Regulation; Profile 4: Strong Controlled Motivation; Profile 5: Moderate Motivation.

When this solution based on the two higher-order dimensions is compared with the preceding one based on the four distinct motivation types, the relative loss of information is obvious, both in terms of achieving a less balanced repartition of participants (including one very large profile, and two very small profiles), and in terms of extracting profiles that are not as clearly differentiated from one another (e.g., Profiles 2–3–4 have the same shape, differing only in level). Furthermore, Profile 1 is unexpected according to theory but appears to correspond to Profile 3 from the previous solution so that the high levels of controlled motivation observed here may simply reflect the lack of differentiation between introjected and controlled regulations. Overall, this solution also supports the value of differentiating among four motivation types rather than relying on two higher-order dimensions. For this reason, this solution was not retained for further analyses.

Predictors of Profile Membership

The results from the multilevel multinomial regression analyses describing the relations between the predictors and participants' likelihood of being a member of each profile are reported in Table 4. These results show that girls present a higher likelihood of membership in Profile 1 (Moderate Controlled Motivation) relative to all other profiles with the exception of the fourth (Strong Controlled Motivation). They were also more likely to be members of Profile 4 (Strong Controlled Motivation) relative to Profiles 2 (Autonomous Motivation) and 3 (Internalized Regulation), but not to 5 (Moderate Motivation). Girls also appeared less likely to be members of Profile 3 (Internalized Regulation) relative to Profiles 2 (Autonomous Motivation) and 5 (Moderate Motivation). Essentially, these results suggest that girls tend to present a greater likelihood than boys of being members of profiles characterized by higher levels of external regulation (Profiles 1 and 4), and a lower likelihood of membership in profiles characterized by higher levels of the more autonomous forms of regulations (Profiles 2 and 3). Particularly interesting is the fact that girls appear more likely to be members of Profile 2 (Autonomous Motivation) relative to 3 (Internalized Regulation), which essentially differ from one another on the levels of introjection.

In terms of age, the results show that younger participants have a greater likelihood of membership in Profiles 2 (Autonomous Motivation) and 3 (Internalized Regulation) relative to all other profiles. They are also more likely to be members of Profile 5 (Moderate Motivation) relative to 1 (Moderate Controlled Motivation), but equally likely to be members of Profiles 1 (Moderate Controlled Motivation) and 4 (Strong Controlled Motivation). Essentially, these results suggest that age seems to be accompanied by a greater likelihood of membership in profiles characterized by higher levels of external regulation (Profiles 1 and 4), and a lower likelihood of membership into profiles characterized by higher levels of autonomous regulations (Profiles 2 and 3).

Table 3 Mean Level of the Indicators in the Final Profile Solutions and Confidence Intervals (CIs)

	Profile 1		Profile 2		Profile 3		Profile 4		Profile 5	
Variable	*M*	95% CI	*M*	95% CI	*M*	95% CI	*M*	95% CI	*M*	95% CI
Models based on the four motivation types										
External regulation	4.24	[4.06, 4.42]	2.08	[1.98, 2.19]	4.04	[3.53, 4.56]	5.11	[4.80, 5.42]	3.30	[3.14, 3.47]
Introjected regulation	2.76	[2.63, 2.89]	2.76	[2.58, 2.95]	5.01	[4.81, 5.20]	1.74	[1.47, 2.02]	2.99	[2.86, 3.12]
Identified regulation	3.89	[3.75, 4.03]	6.27	[6.17, 6.36]	6.65	[6.59, 6.70]	2.21	[1.98, 2.44]	4.93	[4.85, 5.02]
Intrinsic regulation	3.73	[3.62, 3.84]	6.71	[6.66, 6.75]	6.72	[6.65, 6.78]	1.83	[1.69, 1.97]	5.23	[5.13, 5.34]
Models based on the two higher-order dimensions										
Controlled	4.85	[4.64, 5.06]	3.87	[3.66, 4.09]	3.65	[3.53, 3.77]	3.20	[3.08, 3.32]	2.49	[2.40, 2.58]
Autonomous	6.64	[6.58, 6.70]	1.86	[1.71, 2.01]	3.70	[3.60, 3.81]	5.06	[4.97, 5.15]	6.53	[6.48, 6.58]

Note. Profile 1: Moderate Controlled Motivation; Profile 2: Autonomous Motivation; Profile 3: Internalized Regulation; Profile 4: Strong Controlled Motivation; Profile 5: Moderate Motivation.

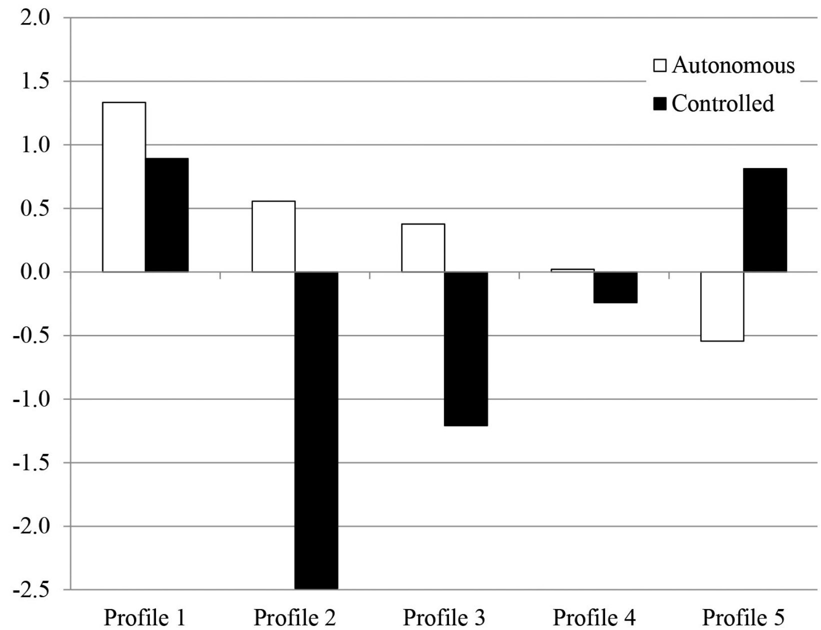

Figure 4 — Graphical representation of profiles based on two higher-order dimensions. *Note*. The results were standardized to help in the interpretation of this histogram. Profile 1: High Motivation; Profile 2: Marked Autonomous Motivation; Profile 3: Moderate Autonomous Motivation; Profile 4: Moderate Motivation; Profile 5: Controlled Motivation.

Finally, the results show a completely parallel pattern of associations between respondents' perceptions of their physical education teachers' autonomy-supportive behaviors at the individual level as well as the classroom level and the likelihood of membership into the various profiles. In other words, the effects of group average students' perceptions of physical education teachers' autonomy-supportive behaviors, which is likely to provide a more exact approximation of true teacher's behaviors, on students' motivational profiles is essentially equivalent, and complementary, to the effects of students' interindividual differences in perceptions of their teachers' autonomy-supportive behaviors relative to the group average. These results show that higher levels of perceived autonomy-supportive behaviors tend to be associated with a higher likelihood of membership to the two profiles characterized by the highest levels of autonomous regulation (Profiles 2 and 3) relative to all other profiles. Perceived physical education teachers' autonomy-supportive behaviors also predicted a higher likelihood of membership into the moderately motivated profile (Profile 5) relative to the more externally motivated profiles (1 and 4). Particularly interesting was the fact that higher levels of perceived autonomy-supportive behaviors also predicted a higher likelihood of membership in Profile 1 (Moderate Controlled Motivation) relative to 4 (Strong Controlled Motivation).

Profile Differences on Key Outcomes

The results from the analyses comparing the extracted profiles on the two outcome variables considered in the current study are reported in Table 5. These results are pretty consistent across outcomes considered. Thus, the highest levels of outcomes are observed in the second (Autonomous Motivation) and third (Internalized Regulation) profiles. It is noteworthy that, even though the third profile is dominated by introjected regulation, these two profiles are those presenting the highest levels of identified and intrinsic regulations of all profiles. Interestingly, these two profiles also differ from one another on their levels of perceived competence, with Profile 3 presenting higher levels than Profile 2 on perceptions of competence, showing the advantages of a profile that includes high levels of introjection for activities including at least some aspects that that are not necessarily pleasant for everyone. These two profiles then present higher levels on all covariates than Profile 5 (Moderate Motivation), which itself presents higher levels on all covariates than Profile 1 (Moderate Controlled Regulation). Finally, the lowest levels on all covariates are observed in Profile 4 (Strong Controlled Regulation), which only remains undistinguishable from Profile 1 on intentions to be physically active. Taken together, these results show the value of differentially considering all four types of motivation, as well as the risk of being primarily driven by externally regulated motives.

Discussion

The purpose of the current study was to test the SDT continuum hypothesis of motivation using person-centered LPA methods. Results from previous studies using Rasch

Table 4 Results From Multilevel Multinomial Logic Regressions for the Effects of Predictors on Profile Membership

	Latent Profile 1 vs. 5		Latent Profile 2 vs. 5		Latent Profile 3 vs. 5		Latent Profile 4 vs. 5		Latent Profile 1 vs. 4	
	Coef. (*SE*)	OR	Coef. (*SE*)	OR	Coef. (*SE*)	OR	Coef. (*SE*)	OR	Coef. (*SE*)	OR
Individual level (L1)										
Gender	0.37 (0.15)*	1.45	–0.27 (0.15)	0.77	–1.10 (0.19)**	0.33	0.34 (0.23)	1.47	0.033 (0.233)	1.03
Age	0.24 (0.08)**	1.28	–0.84 (0.09)**	0.43	–1.07 (0.12)**	0.34	0.22 (0.17)	1.25	0.025 (0.144)	1.03
Autonomy support	–0.62 (0.07)**	0.54	0.85 (0.07)**	2.33	1.00 (0.11)**	2.73	–1.23 (0.15)**	0.29	0.614 (0.139)**	1.85
Classroom level (L2)										
Autonomy support	–0.90 (0.16)**	0.41	0.69 (0.18)**	1.99	0.69 (0.22)**	1.99	–1.58 (0.32) **	0.21	0.679 (0.252)**	1.97
	Latent Profile 2 vs. 4		Latent Profile 3 vs. 4		Latent Profile 1 vs. 3		Latent Profile 2 vs. 3		Latent Profile 1 vs. 2	
Individual level (L1)										
Gender	–0.61 (0.26)*	0.54	–1.44 (0.29)**	0.24	1.47 (0.21)**	4.37	0.83 (0.17)**	2.30	0.64 (0.11)**	1.90
Age	–1.05 (0.20)**	0.35	–1.29 (0.22)**	0.28	1.31 (0.15)**	3.72	0.24 (0.14)	1.26	1.08 (0.11)**	2.94
Autonomy support	2.08 (0.17)**	8.00	2.24 (0.19)**	9.37	–1.62 (0.12)**	0.20	–0.16 (0.12)	0.85	–1.47 (0.09)**	0.23
Classroom level (L2)										
Autonomy support	2.27 (0.40)**	9.63	2.27 (0.44)**	9.64	–1.59 (0.29)**	0.20	–0.01 (0.25)	1.00	–1.59 (0.24)**	0.20

Note. *SE* = standard error of the coefficient (Coef.); OR = odds ratio. The coefficients and ORs reflect the effects of the predictors on the likelihood of membership in the first listed profile relative to the second listed profile. Profile 1: Moderate Controlled Motivation; Profile 2: Autonomous Motivation; Profile 3: Internalized Regulation; Profile 4: Strong Controlled Motivation; Profile 5: Moderate Motivation.

*$p < .05$. **$p < .01$.

Table 5 Mean-Level Differences Across Profiles on the Outcomes

Variable	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Sample *M*	Sample *SD*	Differences between profiles
Perceived competence	3.01	4.39	4.87	2.28	3.67	3.89	1.42	3 > 2 > 5 > 1 > 4
Intentions	3.15	4.51	4.66	2.97	3.59	3.94	1.50	2 = 3 > 5 > 1 = 4

Note. Profile 1: Moderate Controlled Motivation; Profile 2: Autonomous Motivation; Profile 3: Internalized Regulation; Profile 4: Strong Controlled Motivation; Profile 5: Moderate Motivation.

analyses to test for the presence of a single dimension of human motivation underlying all motivation types (Chemolli & Gagné, 2014) failed to support this hypothesis. In contrast, results from studies relying on ESEM (Guay et al., 2014; Litalien et al., 2015) provided stronger support to the continuum hypothesis. Results from a more recent application relying on a bifactor-ESEM approach bridging these two perspectives provided stronger evidence in favor of the continuum hypothesis of human motivation in the work area (Howard, Gagné, Morin, & Forest, 2016), although results obtained using a similar approach in the physical activity area provided a slightly weaker support for the continuum hypothesis (Gunnell & Gaudreau, 2015). Finally, results obtained using an alternative MDS approach also supported the continuum hypothesis in the academic area (e.g., Roth et al., 2006). Altogether, these results support the need to rely on a variety of methodological approaches to achieve a proper test of the continuum hypothesis of motivation, which may possibly be expressed differently in various domains (work, school, physical activity, etc.). Even more importantly, these results clearly demonstrate the fact that the various types of motivation proposed by SDT possess meaningful specificity that warrants consideration, especially when the goal is to achieve a complete picture of an individual's motivation.

Motivational Profiles and the Continuum Hypothesis of Motivation

The present study extends this body of research by relying on a different methodological approach, LPA, within the physical activity area. LPA provides a way to identify prototypical profiles of participants presenting well-defined and clearly differentiated configurations of behavioral regulations (e.g., Morin & Wang, 2016). Within the LPA framework, motivation configurations can be specifically isolated and inspected to see if they follow the expected continuum structure. Thus, support for the continuum hypothesis would come from the observation that the extracted profiles characterize individuals located at different positions on this continuum. More precisely, each profile should be characterized by varying levels of behavioral regulations showing an ordering aligned with the continuum hypothesis, such as a high level of external regulation, followed by the moderately high level of introjected regulation, and then by moderately low, and low, levels of identified and intrinsic regulations. Another advantage of relying on a LPA approach is that it is also well-aligned with another key principle of SDT, which is that "most intentional acts involve some combination of the varied types of regulation" (Ryan, Williams, Patrick, & Deci, 2009, p. 113) by providing an explicit representation of how these types of regulation combine within specific subgroups of individuals. In contrast, alternative variable-centered representations of the continuum hypothesis typically ignore these combinations in the prediction of key behavioral outcomes.

To more explicitly test the value of considering the various motivation types proposed in SDT, relative to another approach frequently used in SDT research and consisting of aggregating motivation types into two higher-order dimensions, we also contrasted LPA solutions obtained using either the four motivation types assessed in the PLOCS (external, introjected, identified, and intrinsic regulations) or the two higher-order dimensions (autonomous vs. controlled motivation). Across both sets of analyses, the results converged on a five-profile solution. Using the four motivation types, this solution revealed five profiles of students, which followed the proposed continuum structure of motivation. Thus, the largest profile (34.56%) referred to participants with Autonomous Motivation. The second largest profile (26.58%) referred to participants with Moderate Motivation across all subscales. Two other profiles appeared to be dominated by more external forms of regulations, characterized by Moderate Controlled Motivation (19.90%) and Strong Controlled Motivation (4.82%). Finally, the remaining profile appeared to be dominated by high levels of Internalized Regulation (14.14%), supporting the value of differentiating introjection from measures of external regulation.

This last observation appears particularly important as it may explain the key difference between the LPA solutions based on the four motivation types and the two higher-order dimensions. Indeed, four of the profiles identified using the two higher-order dimensions appeared to match those from the LPA based on the four regulation types, showing Moderate Motivation (28.37%), Controlled Motivation (39.80%), Moderate Autonomous Motivation (19.07%), and Marked Autonomous Motivation (4.03%). In contrast, a small profile (8.75%) extracted in this solution was characterized by high levels of both controlled and autonomous forms of motivation and did not appear to match either SDT's continuum hypothesis or the results from the more complete LPA solution. This result appears to reflect the fact that the solution merges into a single higher-order dimension, whereas these two dimensions were Introjection and External Regulation, which were associated with well-differentiated profiles in the more complete solution based on the four regulation types. Further arguing against this more restricted solution based on the two higher-order dimensions is the observation that it resulted in a substantial loss of information, as illustrated by the extraction of a less balanced repartition of participants into profiles. Thus, in addition to providing support to SDT continuum hypothesis of motivation, our results are well aligned with results from previous studies (e.g., Howard et al., 2016), demonstrating the value of relying on a finer grained representation of motivation and the risk of relying on more global and less precise scoring protocols (e.g., Wilson et al., 2012).

Predictors of Profile Membership

Our results further showed that girls and older participants had a higher likelihood of membership in the less desirable profiles (Moderate Controlled Regulation, Strong Controlled Regulation, and Moderate Motivation), supporting the results from previous research conducted in the physical education, physical activity, and sport settings (e.g., Wang & Biddle, 2001; Weiss, Ebbeck, & Horn, 1997). This result highlights the need to increase the motivation of older students and girls with respect to physical education. It is important for physical education classes to provide an enjoyable experience so that students come to want to participate in the lessons. In addition, there is a need to examine whether physical education activities are appealing to all students. Physical education teachers should aim to promote more self-determined forms of motivation and competence in students during their lessons. This, in turn, may enhance intentions to engage in physical activity outside physical education (Wang & Liu, 2007). Future studies are needed to further examine age and gender differences in profile composition, as well as the mechanisms involved in the emergence of these differences.

In addition to these demographic predictors, we also examined the predictive role of students' perceptions of their physical education teachers' autonomy-supportive behaviors while properly disaggregating the classroom-level component of these ratings (reflecting more "objective" teacher behaviors as reflected in class average perceived ratings) from the student-level component of these ratings (reflecting deviations in students' idiosyncratic individual perceptions from the class average). Interestingly, our results showed that the effects of these two components on the likelihood of membership in the various motivational profiles were identical. More precisely, these results showed that having teachers perceived as displaying higher levels of autonomy-supportive behaviors in the classroom, as well as having more positive perceptions of one's teacher autonomy-supportive behaviors than one's classmates, were both related to a greater likelihood of membership in the two most desirable profiles (Internalized Regulation and Autonomous Motivation) as well as allowing for a clear differentiation between the three remaining profiles characterized by lower or average levels of controlled motivation. These findings lend support to the existing literature that autonomy-supportive teaching tends to be related to more self-determined motivation (Hagger et al., 2005; Wang & Liu, 2007). This affirms that incorporating autonomy-supportive structure into physical education lessons may be an important pedagogical consideration.

Outcomes of Profile Membership

Finally, to further document the convergent validity of the extracted motivational profiles, we also examined their associations with two key outcomes (perception of perceived competence and intentions to be physically active). Taken together, our results supported the convergent validity of the extracted profiles and were well aligned with prior results (e.g., Hagger et al., 2005; Thill & Mouanda, 1990; Wang & Liu, 2007). More precisely, the present results showed differences between profiles that were relatively consistent across outcomes in supporting the greater desirability of profiles characterized by higher levels of the more autonomous forms of regulations relative to the more controlled forms of regulations.

One of our most interesting finding was that those who were high on the Internalized Regulation profile, which included high levels of introjection, reported high levels of autonomy-supportive behaviors from their physical education teachers that could not be differentiated from the levels reported by students from the Autonomous Motivation profile, and also presented the highest levels of perceived competence and intentions to be physically active out of all profiles. One notes, however, that this profile was also characterized by levels of autonomous motivation comparable in magnitude to those observed in the Autonomous Motivation profile. This result nonetheless demonstrates that introjection can co-occur with more autonomous forms of motivation without diminishing its positive impact on involvement in physical activities, a result that may have been missed in studies relying on higher-order dimensions. It may be interesting to examine the cross-cultural generalizability of this finding, which occurred within a Singaporean context. For instance, Nie, Chua, Yeung, Ryan, and Chan (2015) recently found positive associations between introjection and perceived autonomy support from supervisors in Chinese teachers. While introjection also predicted some positive outcomes in that study as well, it was also associated with more frequent undesirable somatic symptoms. In contrast, Brunet et al. (2015), relying on response surface analyses of three distinct samples of Canadian participants, also found that the combination of autonomous and controlled forms of motivation could yield positive outcomes. Thus, the positive and negative role of introjection within individuals' configurations of motivation warrants further research, both within and across cultural contexts.

Limitations

A few limitations warrant recognition in this study. First, this is a cross-sectional study, and therefore causality cannot be inferred. Second, while this study has shown the contributions of LPA to the understanding of students' motivation profiles, there is a need for longitudinal research to more fully understand how motivational processes vary within a person, between persons, and across time as a function of a variety of life contexts, situations, and circumstances. Third, although our results showed highly consistent and interpretable results supporting profiles that were well differentiated in terms of outcomes, both outcomes were self-reported variables and would have benefited from the addition of more objective measures of physical activity. Finally, this study only examined four motivation types, suggesting that future research should also consider integrated regulation and amotivation.

Methodological Considerations and Directions for Future Research

Although we relied on a state-of-the-art approach to LPA (e.g., Morin & Wang, 2016) to identify distinct configurations of behavioral regulations in a sample of physical education students, coupled with a multilevel approach to the incorporation of predictors, a few interesting areas of future methodological developments are worthy of note. First, it is important to keep in mind that a key limitation of mixture models (including LPA) is the reliance on the assumption that all extracted profiles follow multivariate normal distributions (McLachlan & Peel, 2000). Violation of this assumption, which is impossible to test in practice, could possibly result in the extraction of spurious latent profiles (Bauer & Curran, 2003; Guerra-Peña, & Steinley, 2016; Sen, Cohen, & Kim, 2016). As new methods emerge to test this assumption or to estimate mixture models without relying on this assumption (e.g., Muthén & Asparouhov, 2015), emerging person-centered evidence will likely need to be reassessed. Similarly, a typical limit of many LPA applications is the reliance on scale scores uncorrected for measurement errors as profile indicators. Even though the impact of measurement error has yet to be more systematically documented in the LPA context, we note the availability of fully latent methods to the estimation of LPA (e.g., Morin, Scalas, & Marsh, 2015), which may provide an interesting alternative. However, these methods are highly computer intensive and may not always be possible to implement, even with large sample sizes such as in the current study.

Second, it is also well-documented that a *k*-profile and a $k-1$-factor models have identical covariance implications (Bartholomew, 1987; Steinley & McDonald, 2007), so that the decision to rely on one, or the other, is typically theoretical in nature and involves a paradigmatic shift between analyzing how variables relate to one another to how these variables are grouped together in subgroups of participants (Meyer & Morin, 2016; Morin & Wang, 2016). In the current study, we relied on LPA to identify which different configurations of continuous behavioral regulations would emerge in distinct subpopulations and the extent to which these configurations followed the expected continuum structure of motivation. As future evidence accumulates to support the development of even more precise hypotheses regarding the way this continuum is likely to be expressed across subpopulations of participants, confirmatory applications of LPA (Finch & Bronk, 2011) might represent an interesting area for future research. Furthermore, indirect applications of LPA are also possible to directly test the underlying continuous, ordered, or nominal nature of motivation and other psychological constructs (Borsboom et al., 2016; Clark et al., 2013).

Third, as noted by Morin and Marsh (2015), whenever there is a global overarching construct underlying the profile indicators (such as global teaching efficacy in their example), then profiles will emerge showing pronounced quantitative (or "level") differences to account for the presence of this global overarching construct. In the current study, the idea that motivation types follow an underlying continuum suggests the presence of such an underlying construct. Indeed, Howard et al. (2016), as well as Gunnell and Gaudreau (2015) have recently demonstrated that this continuum can indeed be modeled as an overarching construct reflecting a global "quantity of self-determination." In the current study, given our objective to verify whether the extracted profiles would indeed support the continuum structure of motivation, it was not necessary to control for these overarching global tendencies. However, an interesting direction for future research would be to rely on models taking into account this global "quantity of self-determination" and the specific qualities inherent in each form of behavioral regulation properly disaggregated from this global continuum to identify profiles differing from one another both in terms of global motivation and specific regulations (e.g., Morin, Boudrias, Marsh, Madore, & Desrumaux, 2016; Morin, Boudrias, Marsh, McInerney, et al., 2016).

Conclusion

Overall, our results support the reliance on models that can consider the specific qualities of each different motivation type, as well as of the underlying continuum of autonomy that may be associated with them (e.g., Howard et al., 2016). In addition, the correlational results and profile analyses support the SDT viewpoint that different subtypes and configurations of motivation differentially predict students' engagement and experience of physical education. It is not only how motivated students are, but in what ways they are motivated, that helps explain their persistence in physical activities.

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Appendix Standardized Parameter Estimates From the Preliminary Confirmatory Factor Analytic Model

	Intrinsic		Identified		Introjected		External		Autonomy support	
Indicator	λ	δ	λ	δ	λ	δ	λ	δ	λ	δ
Item 1	.74	.45	.82	.33	.52	.73	.74	.45	.67	.55
Item 2	.84	.29	.66	.57	.57	.67	.55	.70	.74	.45
Item 3	.78	.39	.88	.23	.50	.75	.75	.44	.72	.48
Item 4					.53	.72	.75	.43	.72	.48
Item 5									.74	.46
Item 6									.67	.55
Item 7									.67	.56
Item 8									.79	.37
Item 9									.75	.43
Item 10									.71	.50
Item 11									.78	.40
Item 12									.79	.38
Item 13									.42	.82
Item 14									.70	.51
Item 15									.63	.61
ω	.83		.83		.61		.80		.94	

	Competence		Intentions		HO-autonomous		HO-controlled	
Indicator	λ	δ	λ	δ	λ	δ	λ	δ
Item 1	.83	.31	.86	.27				
Item 2	.69	.53	.63	.61				
Item 3	.86	.27	.90	.20				
Item 4	.65	.58						
Item 5	.60	.64						
Factor 1					.99	.02	.50	.76
Factor 2					.98	.03	.97	.06
ω	.85		.84		.99		.85	

Note. All parameters are statistically significant ($p \leq .01$); λ = standardized factor loading; δ = standardized item uniqueness; HO = higher-order factor; ω = omega coefficient of composite reliability computed using omega: $\omega = (\sum|\lambda_i|)^2/[(\sum|\lambda_i|)^2 + \sum\delta_{ii}]$ (McDonald, 1970).

[1]The variables' means were freely estimated in all profiles. There are advantages to models in which the indicators' variances are also freely estimated in all profiles (Morin, Maïano, et al., 2011; Peugh & Fan, 2013). However, in this study, models in which means and variances were freely estimated tended to converge on improper solutions (negative variance estimates, nonpositive definite Fisher information matrix, etc.) or not to converge at all. This suggests the inadequacy of these models (Bauer & Curran, 2003; Chen, Bollen, Paxton, Curran, & Kirby, 2001), which may have been overparameterized, and the superiority of our more parsimonious models (Morin & Wang, 2016).