Basic Psychological Need Satisfaction Toward Learning: A Longitudinal Test of Mediation using Bifactor Exploratory Structural Equation Modeling

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Abstract

Student motivation research seeks to uncover greater understanding of when, how, and why students succeed or fail in school settings. Self-determination theory has been at the forefront of helping educational stakeholders answer questions on student motivation. This study investigates the motivation mediation model proposed by self-determination theory using a longitudinal research design. A total of 1,789 Grade 8 Australian physical education students reported perceptions of their teacher's motivational style (antecedent), their levels of basic psychological need satisfaction (mediator), their motivation (outcome), and their affect (outcome) across three time points. Bifactor exploratory structural equation modeling (bifactor-ESEM) was used to simultaneously test the mediating roles of students' global levels of basic psychological need satisfaction and of the specific satisfaction of their basic psychological needs for autonomy, competence, and relatedness. A longitudinal autoregressive cross-lagged model, allowed us to achieve a systematic disaggregation of the cross-sectional and longitudinal associations between constructs. Findings first supported the superiority of the bifactor-ESEM representation of students' need satisfaction ratings over alternative measurement models, as well as their longitudinal measurement invariance. Second, the longitudinal predictive model revealed that only students' global levels of basic psychological need satisfaction mediated the relations observed between the theoretical antecedents and outcomes in the motivation mediation model. However, meaningful relations between specific factors and outcomes were also identified.

Keywords: autonomy support, basic psychological needs, bifactor models, longitudinal, self-determination theory

Classroom learning contexts often create highly diversified learning experiences for students. Some students are able to explore their own interests, to engage in class activities, and to achieve substantial levels of success whereas other students may suffer from boredom, cause disruptions, and endure failure. These contrasting dynamics are of great interest to educational researchers and practitioners alike given their potential to represent key mechanisms involved in the determination of student motivation (Martin & Elliot, 2016), adjustment (Ratelle & Duchesne, 2014), and achievement (Marsh & Martin, 2011).

Self-determination theory (SDT) is a macro-theory of human motivation that may help to explain the role of school-based interactions as determinants of students' goal-driven behaviors and academic success (Deci & Ryan, 1985, 2000). Motivation is broadly defined as the energy and direction of behavior (Pintrich, 2003) and SDT researchers postulate that all students possess inherent growth tendencies that contribute to energize and direct their learning engagement and behavior (Reeve, 2006). Within SDT (Deci & Ryan, 1985, 2000), basic psychological needs and behavioral regulation processes are theorized as core internal motivational resources. Basic psychological needs for autonomy, competence and relatedness are conceptualized as innate and universal nutriments that must be satisfied, if optimal development and wellbeing are to be achieved. Autonomy is the need to self-organize and regulate behavior in accordance with one's sense of self. Competence is the need to develop personal capabilities and interact effectively with one's environment. Relatedness is the need to feel socially connected and cared for by others.

Behavioral regulation processes are delineated as underlying motives for engaging in volitional behavior (Ryan & Deci, 2000). Autonomous forms of motivation encompass (a) intrinsic motivation for activities that are fully endorsed and driven by the inherent satisfaction and pleasure of participation, and (b) identified regulation for activities that fulfill one's personal goals and values. Controlled forms of motivation encompass (a) external regulation in activities that are associated with external contingencies such as rewards, praise, or punishment, and (b) introjected regulation in activities that are regulated by internal (e.g., guilt) and/or external (e.g., social) pressures that are not fully self-endorsed. Research has found autonomous motivation to be associated with a variety of adaptive learning outcomes, while controlled motivation rather tends to be associated with more maladaptive outcomes (Guay, Valois, Falardeau, & Lessard, 2016; Owen, Smith, Lubans, Ng, & Lonsdale, 2014; Ryan & Deci, 2000).

Using a large longitudinal dataset of Australian physical education students, the present study addresses current issues associated with the conceptualization and study of students' basic psychological needs for autonomy, competence, and relatedness, and demonstrates the usefulness of emerging statistical methods to resolve these issues. We argue that the common practices of focusing on *either* a global composite score of basic psychological needs satisfaction (BPNS) (Bartholomew, Ntoumanis, Ryan, Bosch, & Thogersen-Ntoumani, 2011; Chen et al., 2015, Study 2; Quested et al., 2011; Standage, Duda, & Ntoumanis, 2005; Tian, Chen, & Huebner, 2014) *or* on the independent effects of the separate needs for autonomy, competence, and relatedness (Chen et al., 2015, Study 1; Howard, Gagne, Morin, Wang, & Forest, 2016; Jang, Reeve, Ryan, & Kim, 2009; Taylor & Lonsdale, 2010) are both limited.

In this study we demonstrate that it is possible to have one's cake and eat it too. More precisely, we demonstrate how bifactor exploratory structural equation modeling (bifactor-ESEM) provides a way to simultaneously consider physical education students' global levels of need satisfaction disaggregated from the specific degree of satisfaction for the needs for autonomy, competence, and relatedness (Myers, Martin, Ntoumanis, Celimli, & Bartholomew, 2014; Sànchez-Oliva et al., 2017). Using the bifactor-ESEM framework (Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, & Caci, 2016), we also address a second gap in the literature associated with the examination of the role of students' basic psychological needs as a key mechanism involved in explaining the relations between characteristics of the learning environment and motivational outcomes (Jang, Kim, & Reeve, 2012; Oga-Baldwin, Nakata, Parker, & Ryan, 2017). SDT researchers rarely test such mediation effects using a proper longitudinal framework allowing for a clear examination of the directionality of the associations between the various constructs involved in the theoretical mediation chain. In the present study we demonstrate that the bifactor-ESEM framework provides a way to do so while simultaneously considering the role of students' global, versus specific (i.e., autonomy, competence, and relatedness), levels of need satisfaction.

Physical Education in the Australian Context

SDT has been successfully applied to numerous educational settings across the school curriculum. Students in this study were enrolled in compulsory physical education classes. Health and physical education is a core academic subject in the Australian Curriculum and aims to develop students' knowledge, understanding, and skills related to health and movement (Australian Curriculum, Assessment and Reporting Authority [ACARA], 2015). Health literacy promotion with emphasis on higher-order thinking skills such as application, analysis, and evaluation is a key learning objective of the Australian Curriculum (MacDonald, 2013). Health and physical education present unique motivational phenomenon compared to more classical course subjects such as mathematics, language, or sciences. For example, content in health and physical education often integrates movement and cognitive competencies. Performance and learning are generally public in nature, where success and failure are observable by peers. Students are often not restricted to desks in health and physical education classes, which often creates greater social interaction opportunities and constraints, and freedom of movement compared to other classes. These are a few examples of how students are exposed to different motivational opportunities in health and physical education compared with other key learning areas. Despite contextual differences between physical education and other school subjects, generalizations of SDT tenets including need satisfaction are well supported across diverse learning contexts (Chen et al., 2015; Jang et al., 2012) including physical education (Standage et al., 2005).

Basic Psychological Needs Theory

Basic psychological needs theory (BNT) is a subcomponent of SDT that focuses on understanding variations in optimal functioning based on the fulfilment of basic psychological needs (Qusted, Duda, Ntoumanis, & Maxwell, 2013; Ryan & Deci, 2007). It is hypothesized in BNT that human beings are inherently growth-oriented and benefit from social contexts that support feelings of autonomy, competence, and relatedness. In schools, student beliefs about their teachers' motivational style represents an important element of the learning context that impacts the satisfaction of their basic psychological needs (Standage et al., 2005). In this study we focus on two motivational styles; autonomy supportive and controlling. Autonomy supportive teaching behaviors are considered an effective motivational teaching style that facilitates students' basic need satisfaction, wellbeing, and autonomous engagement in the learning process. Autonomy supportive teaching strategies include giving students choices, reducing classroom pressure, and providing explanations and encouragement toward learning (Jang et al., 2012). A controlling style undermines students' need satisfaction and leads to less autonomous forms of engagement in the learning process. Controlling strategies include giving directives, making praise contingent on performance, and cultivating classroom pressure (Reeve, 2009). In the present study, we focus more specifically on a key component of such controlling strategies, the reliance on negative conditional regard practices by the teacher. Conditional regard practices are commonly used in adult–child relationships including teacher–student interactions and occur when teachers withhold attention and affect in order to control behaviors (Assor, Kaplan, Kanat-Maymon, & Roth, 2005). Furthermore, previous research suggests that negative conditional regard is a controlling strategy with the strongest opposition (r = -.50) to autonomy support (Bartholomew, Ntoumanis, & Thogersen-Ntoumani, 2010).

The Motivation Mediation Model

In BNT, basic psychological needs are considered the causal mechanisms that connects teachers' motivational style to student educational outcomes (Jang et al., 2012; Reeve, 2009; Ryan & Deci, 2007). Jang et al. (2012) refers to this proposed causal mechanism as the *motivation mediation model*. Typically, research focusing on BNT tends to focus on indices of human growth and wellbeing as key outcomes based on the assumption that basic psychological needs are universal nutriments for all human beings (Deci & Ryan, 2000; Quested & Duda, 2010). From the perspective of the motivation mediation model, the current study focuses on student autonomous and controlled motivation for learning as outcomes related to human growth (Ryan & Deci, 2007) and on positive and negative affect as outcomes related to wellbeing (Quested & Duda, 2010). Because physical education provides a unique motivational context, we use a general measure of student affect in order to test the impact of need satisfaction in physical education on a more universal student outcome. Previous research suggests that domain level need satisfactions are powerful motivators that transfer to general measures of well-being (Deci et al., 2001).

An important goal of any mediation model is to establish the temporal dynamics of proposed antecedents (predictors, i.e., teachers' motivational style), mechanisms (mediators, i.e., need satisfaction), and outcomes (i.e., motivation and affect) (Cole & Maxwell, 2003; Jang et al., 2012). In order to properly assess such a mediation model, a minimum of three different time points is desirable so as to be able to clearly establish the directionality of the proposed relations and the temporal precedence of each link in the proposed causal chain (Little, 2013; Marsh, Hau, Wen, Nagengast, & Morin, 2013). Despite the fact that the present study is designed to assess the motivation mediation model, Cole and Maxwell (2003) highlight the importance of testing alternative representations of the data, through the inclusion of reciprocal effects aiming to assess the underlying temporal dynamics.

Prior research has already assessed and found tentative support for the motivation mediation model. However, this research has either focused on the mediating role of specific psychological needs (Adie, Duda, & Ntoumanis, 2012; Jang et al., 2012; Quested & Duda, 2010; Taylor & Lonsdale, 2010; Taylor & Ntoumanis, 2007) or the mediating role of a global level of basic need satisfaction (Jang, Kim, & Reeve, 2016; Sheldon & Krieger, 2007; Standage et al., 2005). Although Jang et al. (2016) also employed a longitudinal design, only Jang et al. (2012) have used an analytical design allowing them to disentangle the directionality of the observed relations. In addition, researchers have not yet tested this motivation mediation model while simultaneously considering both students' global levels of basic need satisfaction *and* their specific psychological need for autonomy, competence, and relatedness. This approach can provide useful information about the unique contributions to students' overall levels of need satisfaction, and the ability of specific psychological needs to contribute to the mediation mechanism over and above this global level of need satisfaction.

The Bifactor-ESEM Framework

Bifactor models (Morin, Arens, & Marsh, 2016) are well suited for reproducing the complex multidimensionality associated with the measurement of basic psychological needs (Brunet et al., 2016; Myers et al., 2014; Sànchez-Oliva et al., 2017). Bifactor models are explicitly designed to partition the covariance among various measurement indicators into that explained by a global latent factor (the G-factor: global need satisfaction) underlying responses to all indicators and a series of specific components (the S-factors: satisfaction of the needs for autonomy, competence, and relatedness) specific to subsets of indicators but not explained by the global component. Bifactor models provide a solution to the dilemma presented above by providing a measurement model able to simultaneously consider students' global levels of basic need satisfaction, together with their specific psychological need for autonomy, competence, and relatedness.

Bifactor models can be applied in either exploratory (EFA) or confirmatory (CFA) factor analytic frameworks (Gignac, 2016; Morin, Arens, & Marsh, 2016; Myers et al., 2014). However, the restrictive nature of the independent cluster assumption inherent in CFA models (i.e., no cross-loadings on non-target factors are allowed) has been questioned for measures tapping into conceptually-related constructs (for a review, see Marsh, Morin, Parker, & Kaur, 2014). Given the naturally fallible nature of the indicators that are typically used in psychological research, at least some degree of construct-relevant associations can be expected between items and non-target conceptually-related constructs (Morin, Arens, & Marsh, 2016). This assumption can be lifted through the reliance on EFA. Importantly, statistical simulation studies show that whenever cross-loadings (even as small as .100) exist in the population model, relying on CFA results in inflated estimates of the factor correlations (for a review, see Asparouhov, Muthén, & Morin, 2015). Alternatively relying on EFA when no cross-loadings are present still results in unbiased estimates of factor correlations. Given that the true meaning of any psychological constructs lies in the way it relates to other constructs, CFA may thus lead to construct misspecification and multicollinearity due to the inflation of factor correlations (Asparouhov et al., 2015; Marsh et al., 2014; Morin, Arens & Marsh, 2016).

In SDT research, it is common for researchers to rely exclusively on CFA (Bartholomew et al., 2011; Quested & Duda, 2010; Standage et al., 2005), and to observe moderate-to-strong positive latent correlations among measures of autonomy, competence, and relatedness (Bartholomew et al., 2011; Chen et al., 2015). Given that such measures tap into conceptually-related constructs, cross-loadings are to be expected, suggesting that some items ay simultaneously tap into the satisfaction of more than one basic need, albeit at different levels. This is consistent with the idea that autonomy may help individuals to maintain strong relationships or to express their competencies, just like having strong relationships or competencies may help one to achieve greater levels of autonomy.

EFA has now been incorporated with CFA and structural equation modeling (SEM) into exploratory structural equation modeling (ESEM: Asparouhov & Muthén, 2009; Marsh et al., 2014; Morin, Marsh, & Nagengast, 2013). Target rotation and bifactor target rotation even makes it possible to rely on a "confirmatory" approach when estimating ESEM and bifactor-ESEM factors, allowing for the specification of the main loadings in a confirmatory manner while cross-loadings are "targeted" to be as close to zero as possible (Asparouhov & Muthén, 2009; Morin, Arens & Marsh, 2016; Reise, 2012). The ability to combine these approaches (bifactor and ESEM) into a single framework is important given the demonstrated ability of each of these alternative models (CFA, bifactor-CFA, ESEM, bifactor-ESEM; illustrated in Figure 1) at absorbing the sources of multidimensionality that are not explicitly incorporated. More precisely (e.g., Asparouhov et al., 2015; Morin, Arens, & Marsh, 2016; Murray, & Johnson, 2013): (a) unmodelled cross-loadings lead to inflated factor correlations in CFA, or inflated G-factor loadings in bifactor-CFA; (b) an unmodelled G-factor leads to inflated factor correlations in CFA, or inflated cross-loadings in ESEM. Recent research conducted within the SDT framework in the work (Sànchez-Oliva et al., 2017) and sport (Myers et al., 2014) settings have demonstrated the conceptual and empirical advantages of a bifactor-ESEM representation of basic need satisfaction measures. In the present study, we extend this verification to the educational area.

The Present Study

The purposes of the present study are twofold. First, we test competing CFA, ESEM, bifactor-CFA, and bifactor-ESEM representations of students' ratings of basic psychological needs satisfaction. Regarding this objective we make the following hypothesis based on SDT and BNT theory (Deci & Ryan, 1985, 2000; Reeve, 2006, 2009) and related evidence to bifactor modeling (Brunet et al., 2016; Myers et al., 2014; Sànchez-Oliva et al., 2017) and the motivation mediation model (Jang et al., 2012; Quested & Duda, 2010):

H_1: The bifactor-ESEM representation would provide a better representation of students' rating of need satisfaction compared to the alternative measurement models (CFA, bifactor-CFA, ESEM; the detailed sequential strategy used for the estimation and comparison of these models is described below, in the Analysis section).

Second, we test the SDT motivation mediation model. More precisely, based on this model, we hypothesize that:

H_2: Students perceptions of their teachers' autonomy supportive behaviors will positively predict their levels of need satisfaction.

H_3: Students perceptions of their teachers' conditional regard will negatively predict their levels of need satisfaction.

H_4: Students' levels of need satisfaction will positively predict their levels of autonomous motivation and positive affect.

H_5: Students' levels of need satisfaction will negatively predict their levels of controlled motivation and negative affect.

H_6: Students' basic needs satisfaction will mediate the relation between their perceptions of their teachers' motivational style, and their levels of autonomous motivation, controlled motivation, positive affect, and negative affect.

However, in the absence of prior guidance, we leave as an open research question the relative contribution of students' global levels of need satisfaction and of their specific levels of autonomy, competence, and relatedness satisfaction.

Methods

Sample and Procedure

English-Speaking Australian adolescents (N = 1,789) recruited from 14 government-funded schools (including 72 physical education classes) located in the greater Western Sydney area were included in the present study. At each wave of data collection, all students from the participating classes had the possibility to participate, or not, in the data collection. The initial data collection point occurred in Grade 8 during the first school term (February-April in Australia) of the 2014 school year. At this baseline measurement point, the sample included a total of 1452 students (45% females; 55% males), aged between 11 and 15 years (M= 12.94, SD = .54) and mainly born in Australia (72.7%). The ethnic background of students included English/European (66.8%), Asian (16.4%), Middle Eastern (10.6%), and South Pacific (5.2%). At the first follow-up, occurring in Term 4 of the same school year (September-December of 2014, about 7-8 months after the baseline measurement point), 1,489 students completed the questionnaires. Then, 1,276 students participated in the second follow-up, which occurred in Grade 9, 14-15 months after the baseline measurement point. The gender, age at baseline, and ethnicity distribution of the sample who completed the questionnaires at the first and second follow-up period was essentially identical to that of the baseline sample.

This project was approved by the human research ethic committee of the Western Sydney University, the Australian Catholic University, and the NSW Department of Education. Authorization to perform the study was first obtained from school principals. Appropriate consent procedures were then followed, with permission obtained from the participants' parents prior to the data collection. All participants volunteered and the confidentiality of their responses was guaranteed.

Measures

Need satisfaction. Autonomy need satisfaction in physical education (PE) classes was measured with five items (α = .772 at Baseline, .806 at Follow-Up 1, and .838 at Follow-Up 2) including "In this PE class, I can decide which activities I want to do" and "In this PE class, I have a say regarding what skills I want to practice" (Standage et al., 2005). Competence need satisfaction was measured with five items (α = .845 at Baseline, .871 at Follow-Up 1, and .873 at Follow-Up 2) including "I think I am pretty good at this PE class" and "I am satisfied with my performance in this PE class" (McAuley, Duncan, & Tammen, 1989). Relatedness need satisfaction was measured with four items (α = .856 at Baseline, .865 at Follow-Up 1, and .889 at Follow-Up 2) including "In this PE class I feel understood" and "In this PE class I feel listened to" (Richer & Vallerand, 1998). All 14 need satisfaction items were rated on a 7-point scale ranging from (1) strongly disagree to (7) strongly agree and have been used extensively in SDT research.

Motivation style. Students' perceptions of teacher autonomy support in their PE classes were measured with the Teacher as Social Context Questionnaire (Belmont, Skinner, Wellborn, & Connell, 1988). Using a 7-point Likert scale ranging from (1) strongly disagree to (7) strongly agree, students completed four items (α = .757 at Baseline, .757 at Follow-Up 1, and .863 at Follow-Up 2) including "My teacher gives me choices about how I do tasks in PE" and "My teacher talks about the how I can use the things I learn in PE". Students' perceptions of teacher control were measured with the conditional regard subscale of the Controlling Interpersonal Style Scale (Bartholomew et al., 2010). Using a 7-point scale, students completed four items (α = .823 at Baseline, .832 at Follow-Up 1, and .931 at Follow-Up 2) including "My teacher is less friendly with me if I don't make the effort to see things his/her way" and "My teacher is less accepting of me if I have disappointed him/her".

Behavioral regulation. The Perceived Locus of Causality Questionnaire in PE (Goudas, Biddle, & Fox, 1994; Lonsdale, Sabiston, Taylor, & Ntoumanis, 2011) was used to assess autonomous and controlled motivation. Autonomous motivation (α = .915 at Baseline, .920 at Follow-Up 1, and .784 at Follow-Up 2) was measured with the 4-items intrinsic motivation and identified regulation subscales. Students were given the following stem: "Why do you participate in PE?" and answer questions such as "because PE is fun" (intrinsic motivation) and "because I want to learn sports skills" (identified regulation). Controlled regulation (α = .764 at Baseline, .774 at Follow-Up 1, and .784 at Follow-Up 2) was measured with the 4-item external and introjected regulation subscales. Using the same stem, students answered questions such as "because I'll get into trouble if I don't" (external regulation) and "because I want the teacher to think I'm a good student" (introjected regulation). Each question was answered on a five-point Likert scale, ranging from strongly disagree (1) to strongly agree (5).

Positive and negative affect. Positive and negative affect were measured with the Positive and Negative Affect Scale for Children (Ebesutani et al., 2012). Students were asked how they generally felt in the last few weeks and completed two five-item subscales including adjective-based items aiming to assess positive (α = .835 at Baseline, .857 at Follow-Up 1, and .873 at Follow-Up 2; e.g., joyful, cheerful, happy), and negative (α = .794 at Baseline, .788 at Follow-Up 1, and .801 at Follow-Up 2; e.g., miserable, mad, afraid) affect. All items were answered on a 5-point scale ranging from "not at all" (1) to "extremely" (5).

Analyses

Model Estimation and Evaluation

All analyses were conducted using Mplus 8.0's (Muthén & Muthén, 2017) robust maximum likelihood (MLR) estimator and design-based correction of standard errors for nesting (Asparouhov, 2005). This estimator provides parameter estimates, standard errors, and goodness-of-fit indices that are robust to the non-normality of the response scales used in the present study as well as to students' nesting within classes. Full Information Maximum Likelihood (FIML; Enders, 2010) procedures were used to account for the limited amount of missing responses present at the item level for participants who completed each specific time-point (Baseline: .82% to 4.48%, *M* = 2.58%; Follow-Up 1: 1.48% to

3.83%; *M* = 2.60%; Follow-Up 2: .78% to 4.39%, *M* = 2.73%). FIML also allowed us to estimate all longitudinal models using the data from all respondents who completed at least one wave of data rather than using a problematic quasi-listwise deletion strategy focusing only on those having answered all, or a subset, of the time waves (Enders, 2010; Graham, 2009). In total, 1,789 students provided a total of 4,217 time-specific ratings (M = 2.36 time-specific ratings per student), with 992 (55.4%) students completing all three time-points, 444 (24.8%) completing 2 time-points, and 353 (19.7%) completing a single time-point. When participants where compared on all of the baseline measures as a function of the number of time points completed, no significant differences emerged between participants who completed one, two, or all three times points. The results from these comparisons are reported in Table S5 of the online supplements. FIML has comparable efficacy to multiple imputation, while being more efficient (Enders, 2010; Graham, 2009; Jeličič, Phelps, & Lerner, 2009; Larsen, 2011). We note that FIML relies on missing at random (MAR) assumptions, so that it would be robust to the presence of difference between participants related to attrition, as it allows the missing response process to be conditioned on all variables included in the model.

We relied on a combination of absolute and relative fit indices to evaluate model fit (Hu & Bentler, 1999). The robust chi-square (χ^2) test of exact fit and degrees of freedom (*df*) are provided for all models. However, because this test tends to be oversensitive to sample size and minor model misspecifications, common goodness-of-fit indices were also interpreted: the comparative fit index (CFI), the Tucker-Lewis Index (TLI), the root mean square error of approximation (RMSEA). Values $\geq .90$ and .95 for the CFI and TLI are respectively considered to indicate adequate and excellent fit to the data, whereas values $\leq .08$ or .06 for the RMSEA respectively support acceptable and excellent model fit (e.g., Hu & Bentler, 1999; Marsh, Hau, & Grayson, 2005). Nested models comparisons used in the context of tests of measurement invariance, were conducted using changes (Δ) in goodness-of-fit indices and scaled chi square difference tests ($\Delta\chi^2$; Satorra & Bentler, 2001). Decreases in CFI and TLI of $\geq .010$ or increases in RMSEA of $\geq .015$ between a model and a more restricted one (e.g., a more invariant one) are generally taken to support the least restricted model (e.g., to reject the invariance hypothesis) (Chen, 2007; Cheung & Rensvold, 2002). Goodness-of-fit indices corrected for parsimony (TLI, RMSEA) can improve with the addition of model constraints. Although χ^2 and CFI should be monotonic with complexity, they can still improve with added constraints when the MLR scaling correction factors differ across models. These improvements should be considered to be random. It is important to note that, when comparing complex longitudinal models such as those used in the present studies, fluctuations in goodness-of-fit indices much smaller than those recommended for tests of measurement invariance (i.e., those noted above) may reflect meaningful differences across models. So, as others before us (e.g., Morin, Arens et al., 2017; Morin, Meyer et al., 2016), we conducted predictive model comparisons while considering any change in goodness-of-fit and $\Delta\chi^2$ as indicative of possible model differences, and reached conclusions through a combined examination of model fit and parameter estimates. However, due to the number of model comparisons, $\Delta\chi^2$ significance levels were set at $p \leq .01$.

Measurement Models

We started by comparing and contrasting the underlying factor structure of students' responses to the 14-items measuring their basic psychological needs of autonomy, competence, and relatedness using CFA, bifactor-CFA, ESEM, and bifactor-ESEM measurement models illustrated in Figure 1. In the CFA model (Figure 1a), a correlated three-factor model was tested whereby paths were specified from each factor (Autonomy, Competence, Relatedness) to its a priori indicators with all cross-loadings and correlated uniquenesses constrained to be zero. In the bifactor-CFA model (Figure 1b), all items were allowed to define a G-factor representing students global levels of need satisfaction, as well as one out of three a priori S-factors (Autonomy, Competence, Relatedness). In this model, all factors were specified as orthogonal (Morin, Arens, & Marsh, 2016; Reise, 2012), and no cross-loading or correlated uniqueness was allowed. The ESEM model (Figure 1c) was similar to the CFA model, with the exception that all cross-loadings were freely estimated but "targeted" to be as close to zero as possible through oblique target rotation (Browne, 2001). Finally, the bifactor-ESEM model (Figure 1d) was similar to the bifactor-CFA model, with the exception that all cross-loadings between the S-factors were freely estimated but "targeted" to be as close to zero as possible through orthogonal bifactor target rotation (Reise, 2012).

These four models were independently estimated at each of the three measurement points and contrasted following Morin et al.'s recommendations (Morin, Arens, & Marsh, 2016; Morin, Arens, Tran et al., 2016; Morin, Boudrias, Marsh, McInerney et al., 2017). Given the ability of these models to absorb unmodelled sources of multidimensionality, these authors noted that the examination of goodness-of-fit indices is not sufficient, and needs to be complemented by a comparison of parameter estimates and theoretical conformity. They suggest that CFA and ESEM measurement models should be compared first. In this comparison, it is important to ascertain whether the factors remain well-defined by strong target loadings. However, the key comparison should involve the factor correlations, based on statistical evidence showing that ESEM produces more exact estimates of factor correlations when cross-loadings are present in the population model, but unbiased estimates otherwise (Asparouhov et al., 2015). As long as the observed pattern of factor correlations differs across these two models, then the ESEM solution should be favored. Then, the second comparison should be conducted between the retained ESEM or CFA solution and its bifactor counterpart. In this second comparison, a G-factor well-defined by strong factor loadings, and the observation of reduced cross-loadings following the incorporation of the G-factor both argue in favor of the bifactor representation.

Using the final retained need satisfaction measurement model, tests of measurement of invariance across time points were realized in the following sequence (Millsap, 2011; Morin, Arens, & Marsh, 2016): (1) configural invariance; (2) weak invariance (invariance of the factor loadings/cross-loadings); (3) strong measurement (invariance of the factor loadings/cross-loadings, and intercepts); (4) strict invariance (invariance of the factor loadings/cross-loadings, intercepts, and uniquenesses). In predictive latent variable models estimated at the item level, such as those used in the present study, only the first 2 steps (configural and weak invariance) are required to ensure comparability of the constructs over time, although strong and strict invariance remain useful to establish as strictly invariant models involve the estimation of fewer parameter estimates (parsimony), leading to increases in statistical power. In all longitudinal models, factors were freely allowed to correlate across time waves, and a priori correlated uniquenesses between matching indicators utilized at the different time-points were included to avoid inflated stability estimates (Marsh, 2007).

Before moving on to the main predictive model, we also ascertained that the complete measurement models, including student's ratings of need satisfaction, behavioral regulation, motivation style, and affect performed adequately separately at each measurement point, as well as across measurement points (including test of measurement invariance corresponding to the previously described sequence). In these models the need satisfaction measurement model was specified based on the conclusions from the prior analyses, whereas the remaining constructs were specified as six confirmatory factor analytic factors (i.e., autonomy support, conditional regard, autonomous motivation, controlled regulation, positive affect, negative affect), allowed to correlate within and across time waves. In these models one *a priori* correlated uniqueness was included between the conceptually similar "afraid" and "scared" items of the affect measure, as well as among matching indicators of the factors utilized at the different time-points in the longitudinal models (Marsh, 2007). For all measurement models, we also reported the associated model-based omega coefficients of composite reliability, calculated as (McDonald, 1970): $\omega = (\Sigma|\lambda_i|)^2 / ([\Sigma|\lambda_i|]^2 + \Sigma\delta_{ii})$ where λ_i are the factor loadings and δ_{ii} the error variances.

Predictive Model

The potential mediating role of BPNS in the relation between teacher motivation styles and student's behavioral regulation, and affect were tested using a fully latent longitudinal mediation autoregressive cross-lagged model (Little, 2013; Morin, Arens et al., 2017; Morin, Meyer et al., 2016). Figure 2 provides a visual presentation of this model. In this figure, sets of factors assumed to occupy distinct roles in the theoretical predictive sequence are enclosed in boxes marked by dotted lines. The theoretical predictors (perceptions of teachers' motivational style) are placed in the top section of the Figure. The theoretical mediators (need satisfaction) are in the middle section of the Figure. Finally, theoretical outcomes (behavioral regulation and affect) are in the bottom section of the Figure. These variables were all integrated in the predictive model as sets of latent factors estimated at the item level. The measurement components of these predictive models were specified as invariant across time-waves on the basis of the previous stages of analyses, and operationalized as described above. In all of the alternative predictive models described below, all factors forming a single set of factors were similarly specified to be related to all other factors forming the other sets of factors according to the specific predictive model under evaluation.

We started with a baseline autoregressive model (Model 0) in which each latent construct measured at a specific time point was allowed to predict itself at the next time point (the dotted arrows in Figure 2). Then, we estimated a first model (Model 1: The full black arrows) corresponding to our a priori mediational predictions that the predictors (perceptions of teacher autonomy support and conditional regards) at a specific time point would predict the mediators (need satisfaction) at the following time point, and that the same mediators at a specific time point would likewise predict the outcomes at the next time point (autonomous motivation, controlled motivation, positive affect, and negative affect). In a second model (Model 2: The full greyscale arrows), we tested the reciprocal predictions corresponding to the opposite of our a priori model to control for the possible effects of students' affect and behavioral regulations at a specific time point in the prediction of their levels of need satisfaction at the following time point, and of their levels of need satisfaction at a specific time point in the prediction of their perceptions of their teachers' motivational practices at the following time point. In a third model (Model 3: The dashed black arrows), we included direct paths between the theoretical predictors at a specific time point and the outcomes at the next time point. Finally, in a fourth model (Model 4: The dashed greyscale arrows), we included reciprocal direct paths between the theoretical outcomes at a specific time point and the predictors at the next time point.

This sequence was designed to systematically test the longitudinal relations occurring across distinct constructs over and above their longitudinal stability and potential reciprocal effects– providing a clear disaggregation of the cross-sectional and longitudinal associations between the constructs. Doing so provided a direct test of the directionality of the associations between constructs (Morin et al., 2011; Morin, Meyer et al., 2016). At each step, we started with a model in which all predictive paths were freely estimated, and contrasted it with a model in which the Baseline-Follow-Up 1 paths were constrained to be equal to the matching Follow-Up 1- Follow-Up 2 paths. This was designed to test the predictive equilibrium of the system (Cole & Maxwell, 2003) in order to systematically assess whether the pattern of associations between constructs remained the same across time periods, showing that the results can generalize across time periods (Morin, Arens et al., 2017). In addition, a predictive model that has reached equilibrium has the advantage of being more parsimonious, maximising the statistical power of the analyses and the stability of the estimates.

The predictive models tested in the present study involved mediation, which was statistically tested via the calculation of indirect effects of predictors on the outcomes as mediated by the mediators. These indirect effects, calculated as the product of the paths coefficients associated with both components of the mediational chain (predictor → mediator and mediator →outcome) were assessed via bias-corrected bootstrap (based on 500 bootstrap samples) confidence intervals (CI; e.g., Cheung & Lau, 2008; MacKinnon, Lockwood, & Williams, 2004), which should exclude zero to be considered to be statistically significant.

Results

Measurement Models: Need Satisfaction

The goodness-of-fit statistics of the alternative measurement models estimated based on participants' need satisfaction responses are reported in Table 1. The first-order CFA failed to achieve an acceptable level of fit to the data based on the TLI (≤ .900) and RMSEA (≥ .080) across all measurement points. In contrast, the remaining models (bifactor-CFA, ESEM, bifactor-ESEM) all achieved an adequate degree of fit to the data (CFI and TLI ≥ .900; RMSEA ≤ .080). However, the ESEM solution achieved a higher degree of fit to the data than both the CFA (ΔCFI = .076 to .086; ΔTLI = .083 to .094; ΔRMSEA = -.039 to -.045) and bifactor-CFA (ΔCFI = .008 to .020; ΔTLI = .010 to .021; ΔRMSEA = -.007 to -.012). Similarly, the bifactor-ESEM solution itself achieved a higher degree of fit to the data higher than that of the ESEM model (ΔCFI = .007 to .015; ΔTLI = 008 to .024; ΔRMSEA = .008 to -.019). This statistical information appears to support the superiority of the bifactor-ESEM solution. However, as noted above this information needs to be complemented by an examination of the parameter estimates from the alternative models. The time-specific bifactor-ESEM solutions are reported in Table 2 whereas the CFA, ESEM, and Bifactor-CFA solutions are reported in Tables S1 to S3 of the online supplements.

Initial comparisons between CFA and ESEM solutions revealed that both resulted in factors that, with few exceptions, are generally well-defined by their target factor loadings (CFA: λ = .521 to .865, M = .749; ESEM: λ = .128 to .996, M = .663). Among the few exceptions, the ESEM solution revealed that three items (Autonomy 3 "*I feel that I do this PE class because I want to*"; Competence 3 "*When I have participated in this PE class for a while, I feel pretty competent*", and Relatedness 1 "*In* *this PE class I feel understood*") presented weak factor loading on their a priori factor (λ = .128 to .481, *M* = .320), and cross-loadings of a similar magnitude on at least one of the remaining factor (λ = .015 to .473, *M* = .249), suggesting that these items may be more suitable to the assessment of a global level of need satisfaction than to the satisfaction of any specific need. Apart from these three items, the remaining items presented high target loadings (λ = .582 to .996, *M* = 766) and reasonably low cross-loadings (|λ| = .002 to .247, *M* = .069). In addition, the results also revealed lower factor correlations in the ESEM (*r* = .478 to .680, *M* = .588), relative to CFA (*r* = .559 to .782, *M* = .693), solutions. These results appear to support the statistical information provided by the goodness-of-fit indices in supporting the superiority of the ESEM, relative to CFA, solutions, but also suggest the interest of exploring a bifactor solution.

Examination of the parameter estimates from the bifactor-ESEM solution, reported in Table 2, support this suggestion. When interpreting bifactor results it is important to keep in mind that, because these models rely on two factors to explain the item-level covariance associated with each item, factor loadings on G-factors and S-Factors are typically lower than their first-order counterparts (e.g., Morin, Arens, & Marsh, 2016)[1]. As such, the critical question is whether the G-factor really taps into a meaningful amount of covariance shared among all items, and whether there remains sufficient covariance at the subscale level unexplained by the G-factor to result in the estimation of at least some meaningful S-factors. In the present study, apart from one item (Autonomy 1 "*In this PE class I can decide which activities I want to practice*" which only has a low level of correspondence to students global levels of need satisfaction (λ =.243 to .368, *M* = .304), the results reveal a strong G-factor, well-defined by all of the remaining items (λ =.454 to .850, *M* = .666). This global need satisfaction factor appears to be well-aligned with Sánchez-Oliva et al.'s (2017) results supporting its interpretation as a well-defined and reliable (ω = .919 to .946) estimate of students' global levels of need satisfaction. In addition, and as expected from the ESEM model results the items Autonomy-3 and Competence-3 appear to provide a much clearer reflection of the G-factor (λ =.589 to .781, *M* = .695) than of their a priori S-factors (λ =.046 to .206, *M* = .116). Apart from these items, over and above students' global levels of need satisfaction, the S-factors referring to their feelings of autonomy (λ =.468 to .625, M = .553, ω = .669 to .726) and competence (λ =.385 to .688, M = .546, ω = .675 to .737) also retain a meaningful amount of specificity. In contrast, the relatedness S-factors only retain a limited amount of specificity (λ =.007 to .321, M = .165, ω = .209 to .265) once students' global levels of need satisfaction are taken into account. This suggests that relatedness ratings may play a critical role in defining global need satisfaction in this population. Despite the fact that this weak reliability and factor loadings argue against the use of any manifest scale scores (e.g., taking the average of items on this factors) based on this S-factors, it remains important to keep in mind that latent scores on the relatedness S-factors can still be considered to be perfectly reliable in this study as they are estimated based on latent variable models incorporating a control for measurement errors (Bollen, 1989).

Altogether our results supported H_1 that a bifactor-ESEM would provide the most optimal representation of students' ratings of need satisfaction. This representation was retained for longitudinal tests of measurement invariance, as well as for the next stages. The goodness-of-fit results from the tests

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[1] This observation raises the question of what is an "acceptable" factor loading. This question is difficult to answer with precision as the correct response is that it depends, and that it is important to keep in mind that any guideline proposed should be applied flexibly, and not turned into a golden rule. In a factor analytic model, the size of the target factor loadings should ideally be large enough to support their interpretation as proper construct indicators. Classical guidelines differ between .300 and .500. Our view is that target factor loadings greater than .500 are typically fully satisfactory, whereas those lower than .300 call into question the adequacy of the indicator. However, these guidelines cannot be directly translated to bifactor models given that these involve the estimation of two target loadings for each indicator. In this case, at least one of those two target loadings should meet our recommendations. Perhaps more importantly, each S-factor should, ideally, remain satisfactorily defined by at least a few indicators in order to be considered to retain meaningful specificity once the G-factor is taken into account. However, as noted by Morin, Arens, and Marsh (2016), it is frequent for bifactor applications to result in the estimation of at least one weakly defined S-factor. In these cases, these weaker factors should still be retained in the model, but interpreting their associations with other constructs should be done with caution.

of measurement invariance are reported in the top section of Table 3 and supported the weak and strong measurement invariance of students' ratings of need satisfaction across time (ΔCFI/TLI ≤ .010 and ΔRMSEA ≤ .015). However, the ΔCFI and ΔTLI both exceeded .010 for the test of strict measurement invariance, suggesting that the unreliability of some items ratings fluctuate across time. Although strict measurement invariance is not a pre-requisite to comparisons of latent constructs corrected for measurement errors (e.g., Millsap, 2011), we still pursued a model of partial invariance to achieve a greater level of precision and parsimony. To achieve partial invariance, we carefully examined the parameter estimates from the model of strong invariance as well as the modification indices associated with the model of strict invariance in order to locate item uniqueness displaying strong differences across time points. In total, six longitudinal invariance constraints had to be relaxed suggesting minor fluctuation in item reliability over time in order to achieve a model of partial strict invariance supported by the data.

Measurement Models: Global

The goodness-of-fit statistics associated with the global measurement models estimated separately at each specific time points are reported in the bottom section of Table 1. This model incorporated a bifactor-ESEM representation of need satisfaction ratings as well as six additional CFA factors reflecting perceptions of teacher autonomy support and conditional regard, autonomous motivation, controlled motivation, positive affect, and negative affect. As shown in Table 1, these models all achieve a satisfactory level of fit to the data. Tests of longitudinal measurement invariance conducted on this global model are reported in the middle section of Table 3, and supported the weak, and strong measurement invariance of students' ratings across time (ΔCFI/TLI ≤ .010 and ΔRMSEA ≤ .015). The ΔCFI reached.010 for tests of strict measurement invariance, suggesting that the unreliability of some items ratings tended to fluctuate across time. As above, we pursued a model of partial invariance to achieve a greater level of precision and parsimony in the estimation of the predictive models. To achieve partial invariance we simply had to relax the same six longitudinal invariance constraints that already had to be relaxed in the need satisfaction model. The parameter estimates associated with the additional factors included in this final longitudinal model of partial strict measurement invariance are reported in Table S4 of the online supplements and reveal well-defined latent factors. Latent variable correlations estimated as part of this final model, as well as estimates of scale score (α) and composite (ω) reliability are reported in Table 4, and reveal that all new (i.e., antecedents and outcomes) latent factors are associated with satisfactory estimates of scale score (α = .757 to .931) and composite (ω = .762 to .922) reliability. This final global model of partial strict invariance was retained as the baseline for further predictive analyses.

Longitudinal Mediation Models

The goodness-of-fit statistics associated with the various predictive models are reported in the bottom section of Table 3. It is first interesting to note that the baseline autoregressive model (Model 0) provide a level of fit to the data almost comparable to that of the final retained longitudinal measurement model (ΔCFI = -.004; ΔTLI = -.003; ΔRMSEA = .000). This result suggests that the stability paths seem able to explain most of the longitudinal associations among constructs, but not all of them – an interpretation that was supported by the relatively large $\Delta\chi^2$ associated with this comparison (683.604, df = 256, $p \leq .01$). Constraining these autoregressive paths to equality across time periods (Model 0 with equilibrium) resulted in a completely equivalent degree of fit to the data (ΔCFI/TLI/RMSEA = .000; $\Delta\chi^2$ = 24.129, df = 22, *ns*), supporting the equivalence of the autoregressive paths across the two time intervals considered in the present study. Adding the a priori predictive paths to this model (Model 1) resulted in a small increase in model fit according to the ΔCFI (.001), ΔTLI (.001), and $\Delta\chi^2$ (166.809, df = 48, $p \leq .01$) which is supported by the observation of multiple statistically significant predictive paths in this model. The equilibrium of these predictive paths is also supported by the data, and even resulted in a slight increase in model fit according to the ΔTLI (.001). This model (Model 1 with equilibrium) is retained.

Adding the reciprocal predictive paths (Model 2) or the direct paths (Model 3) to this model resulted in a small increase in model fit for Model 2 (ΔCFI = .001), and no increase at all for Model 3. Examination of the parameter estimates associated with both of these models showed that neither of them is associated with the addition of meaningful predictive paths to the model. These models are rejected, a decision supported by the non-significant $\Delta\chi^2$. Adding reciprocal direct paths to this model (Model 4), which proved to be equivalent across time periods (Model 4 with equilibrium), also resulted in a small increase in model fit (ΔCFI = .001) that is accompanied by a statistically significant $\Delta\chi^2$ (106.635, *df* = 16, *p* ≤ .01) and the addition of meaningful paths to the model. This model (Model 4 with equilibrium) is retained for interpretation.

The parameter estimates from this final retained model are reported in Table 5. The predictive equilibrium of this model signifies that the non-standardized predictive paths can be considered identical across time periods. However, because the standardized predictive paths are also a function of the latent variance-covariance matrix, which was still allowed to differ across time periods, small differences in the magnitude of these paths are to be expected. Starting with the auto-regressions, the results show that most constructs display a moderate to high level of stability over time (β = .416 to .712), with the sole exception of students' levels of autonomous motivation for which the stability coefficient proved to be non-significant. Given that the longitudinal correlations observed in Table 4 for this construct proved to be moderately high (r = .618 to .694) and statistically significant, this results suggests that stability in students' levels of autonomous motivation can be entirely explained by their levels of need satisfaction, which are the only variables included in the model and allowed to predict autonomous motivation. This interpretation is supported by the observation of stability paths of a magnitude comparable to that of the longitudinal correlations as part of the simple autoregressive model (Model 0: β = .620 to .666).

Turning our attention to the predictive relation most directly related to our research objectives, our results first show a single significant longitudinal relation between students' perceptions of their teachers' motivational styles and their levels of need satisfaction. Students' perceptions of their teachers' autonomy supportive behaviors predicted higher levels of global need satisfaction over time, supporting H_2. Conditional regard did not negatively predict need satisfaction, failing to support H_3. In constrast, multiple statistically significant relations emerge in the prediction of the various outcome measures. Students' global levels of need satisfaction presented significant longitudinal associations with higher levels of autonomous motivation and positive affect (supporting H_4), as well as with lower levels of controlled motivation and negative affect (supporting H_5).

Additional relations also emerge between the S-factors representing students' levels of competence, relatedness and autonomy need satisfaction. First, levels of competence need satisfaction tended to be associated with higher levels of positive affect and lower levels of controlled motivation and negative affect. However, levels of autonomy and relatedness need satisfaction both proved to be longitudinally associated with lower levels of autonomous motivation while relatedness need satisfaction also predicted lower levels of positive affect.

Finally, reciprocal direct effects are present between some of our theoretical outcome variables and students' perceptions of their teachers' motivational style. Students' with higher levels of autonomous motivation tended to report a higher level of autonomy supportive behaviors among their teachers, whereas those with higher levels of controlled motivation rather tended to report higher levels of conditional regard among their teachers.

Taken together the results from these predictive analyses suggested the presence of five distinct mediation paths, which all are associated with indirect effects significantly different from zero (partially supporting H_6). First, the relations between students' perceptions of their teacher autonomy supportive behaviors and all four outcomes variables proved to be significantly mediated by students' global levels of need satisfaction [(autonomous motivation: indirect effect = .094; CI = .037 to .145); (controlled motivation: indirect effect = -.011; CI = -.021 to -.004); (positive affect: indirect effect = .018; CI = .009 to .031); (negative affect: indirect effect = -.009; CI = -.019 to -.003)]. Second, due to the presence of reciprocal direct effects, a significant indirect effect also emerged between students' levels of autonomous motivation and their global levels of need satisfaction, as mediated by their perceptions of teachers' autonomy supportive behaviors (indirect effect = .017; CI = .008 to .030).

Discussion

The Structure of Basic Need Satisfaction Ratings

Grounded in SDT, we first investigated the underlying structure of students' reports of basic psychological need satisfaction over time. In accordance with H_1, we found support for the superiority of a bifactor-ESEM representation of these ratings. A key advantage of this representation is that it provides researchers with a way to achieve a direct estimate of participants' global levels of need satisfaction while still being able to account for their specific levels of satisfaction of their needs for autonomy, competence, and relatedness disaggregated from these global levels. Another advantage of this approach lies in the incorporation of cross-loadings to the model, which provide a way to directly reflect the overlap in indicators' content that commonly occurs in the assessment of conceptually related multidimensional constructs (Marsh et al., 2014; Morin, Arens, & Marsh, 2016) including basic psychological needs (Myers et al., 2014; Sanchez-Olivia et al., 2017). This incorporation of cross-loadings results in more accurate parameter estimates in terms of construct depiction (Asparouhov et al., 2015; Morin, Arens, & Marsh, 2016). The present study supports emerging research evidence favoring a bifactor representation of ratings of participants basic psychological need satisfaction as providing a clearer alignment with SDT theoretical underpinnings in the sport (Myers et al., 2014), exercise (Brunet et al., 2016), and work (Sanchez-Olivia et al., 2017) contexts.

Unlike these previous studies, however, our findings also highlight the longitudinal invariance of the bifactor-ESEM structure of students' basic psychological need satisfactions. There was support for strong longitudinal invariance, an essential element for examining change in longitudinal investigations because it provides evidence of true change in students' basic psychological need satisfaction rather than change associated with measurement bias (e.g., Cole & Maxwell, 2003; Little, 2013; Marsh et al., 2014). Examination of the autoregressive paths present in the final predictive models supports the longitudinal stability of ratings of both global levels of need satisfaction (the G-factor) and of specific need satisfactions (the S-factors), with test-retest stability estimates ranging from $\beta = .439$ to .712 over a 6 to 8 month period.

Close examination of parameter estimates in the bifactor-ESEM solution also offers important information about the structure of students' ratings of basic psychological need satisfaction. Factor loadings provided strong support for the strength of the G-factor underlying students' global levels of need satisfaction. Interestingly, relatedness indicators were found to load strongly on the G-factor while retaining only trivial loadings on the S-factor. This suggests that they retain almost no residual specificity once their relation to global levels of need satisfaction are taken into account. Relatedness need satisfaction appears to be crucial for students' global levels of basic psychological need satisfaction. This may reflect the nature of the physical education learning contexts. Physical education classes rely heavily on teacher and peer interactions, which makes relatedness a key motivational construct in this context (Sparks, Lonsdale, Dimmock, & Jackson, 2017; Sparks, Dimmock, Lonsdale, & Jackson, 2016). Students consistently engage in both small and large group activities and unlike many other learning subjects teachers and students move around freely without being restricted to desks. In contrast, the S-factors related to students' autonomy and competence need satisfaction remained well-defined once the variance in ratings explained by the G-factor is taken into account, evidencing the possibility of discrepancies in the satisfaction of these specific needs in relation to more global levels of need satisfaction.

The Motivation Mediation Model

A second objective of the present study, in accordance with H_2-H_6, was to systematically assess the motivation mediation model (Jang et al., 2012; Ryan & Deci, 2007; Sheldon & Krieger, 2007). Although the present study is not the first to apply a bifactor representation to ratings of basic need satisfaction (Brunet et al., 2016; Myers et al., 2014; Sanchez-Olivia et al., 2017), it is the first to extend this approach to systematic tests of longitudinal mediation. Current findings match the conclusions from these earlier studies in terms of relations with covariates. These earlier studies (Brunet et al., 2016; Sànchez-Oliva et al., 2017) showed that global levels of need satisfaction emerged as the key construct responsible for cross-sectional associations between need satisfaction and a variety of covariates. The present study extends these conclusions to longitudinal predictions and provides partial support for H_2, H_4, H_5, and H_6. Global levels of need satisfaction significantly mediated the relations between students' perceptions of their teachers' autonomy supportive behaviors and the four outcomes considered in the present study in the expected direction (positive for autonomous motivation and positive affect and negative for controlled motivation and negative affect). Contrary to H_3, no significant predictive relations were found between students' perceptions of their teachers' conditional regard and any of the mediators or outcomes considered here. This reflects recent longitudinal findings by Jang et al. (2016), who found that teacher control increased changes in students' need frustration, but had no effect on changes in need satisfaction. Still, it is important to note that students' with higher levels of controlled motivation tended to report higher levels of conditional regard among their teachers. Controlled motivation is closely associated with a lack of student internalization of the importance or intrinsic value of a subject (Deci & Ryan, 2000). In other words, some students did not find physical education interesting or important. The directional link from controlled motivation to conditional regard may reflect teachers' typical reactions toward unmotivated students such as ignoring them or withholding praise and affection (Reeve, 2009).

Similarly, students' with higher levels of autonomous motivation tended to report a higher level of autonomy supportive behaviors among their teachers. Although the effect of autonomous motivation on autonomy support gets much less attention than its reciprocal effect in the SDT literature (Jang et al., 2016; Standage et al., 2005), motivation research clearly demonstrates that relations between teachers and students exist in both directions (Skinner & Belmont, 1993; Taylor & Ntoumanis, 2007). Autonomously motivated learners demonstrate high levels of curiosity, interest, engagement, and self-direction (Ryan & Deci, 2000). This likely increases teachers' comfort and willingness to rely on autonomy supportive strategies (Reeve, 2006). Teachers may not feel the need to manipulate highly engaged students' behavior (Reeve, 2009).

In addition to these relations involving the G-factor, some additional relations emerge in relation to the S-factors. In accordance with H_4 and H_5, levels of competence need satisfaction were associated with higher levels of positive affect, and with lower levels of controlled motivation and negative affect. Contrary to H_4, levels of autonomy and relatedness need satisfaction were both associated with lower levels of autonomous motivation. Relatedness need satisfaction also predicted lower levels of positive affect.

It is important to keep in mind two critical pieces of information when interpreting results. First, the relatedness satisfaction S-factor retained almost no meaningfull residual specificity once students' levels of global need satisfaction were controlled for, casting doubts on the true relevance of the relations identified here and involving the relatedness S-factor. Second, the results involving the autonomy S-factor are harder to dismiss. In order to properly interpret these findings, one has to consider the meaning of this S-factor once the variance explained by students' global levels of need satisfaction are taken into account. In a bifactor-ESEM representation of students' ratings of need satisfaction, the S-factors do not reflect absolute levels of satisfaction of the specific needs for autnomy, relatedness and competence, but rather what is specific to students' ratings of these needs once their global levels of need satisfaction are controlled for. As such, they can be tentatively interpreted as suggesting some kind of imbalance in the satisfaction of one need relative to all others.

From an SDT perspective, researchers have theorized that students in physical education often face imbalances in basic psychological need satisfactions (Sun & Chen, 2010). High levels on the autonomy S-factors may suggest the presence of too much autonomy in the absence of sufficient levels of competence and relatendess to support the expression of that autonomy. The inability to properly act on this high level of autonomy may in turn limit the students' levels of autonomous motivation relative to what they would have been had the three needs been properly balanced with one another. The opposite type of imbalance is also likely. As noted above, physical education learning contexts are often inherently relational in nature (Cox, Duncheon, & McDavid, 2009) and focused on the development of sport competence – which may explain the previously mentioned role of compentence need satisfaction in the prediction of the various outcomes. These lessons are also often paradoxically set up in a manner that fails to maximize students' need for competence (Cothran & Ennis, 1999) with units of instruction that are typically delivered in short one-to-two week intervals (Rink & Hall, 2008). The continually shifting content focus could make learning and skill development difficult, requiring high levels of autonomy on the parts of the students. This imbalance interpretation needs to be more thoroughly investigated in future studies. However, based on the observed negative relation between this S-factor and students' perceptions of their teacher's autonomy supportive behaviors, this interpretation appears plausible.

A final unexpected result is noteworthy of discussion. Initial results showed that students' levels of autonomous motivation were to be quite stable over time based on the longitudinal correlations estimated as part of the measurement model ($r = .618$ to $.694$) and the autoregressive paths estimated in the purely autoregressive model ($\beta = .620$ to $.666$). However, these stability coefficients became small and non-significant in the final predictive model suggesting that the longitudinal stability of autonomous motivation levels may be entirely explained by longitudinal fluctuations in global levels of need satisfaction. This aligns with the SDT assumption that satisfaction of all three basic psychological needs is essential for sustaining autonomous motivation (Deci & Ryan, 2000; Ryan & Deci, 2000). It would be interesting for future researchers to examine this longitudinal relation across different time-periods, ranging from daily fluctuations to major school transitions.

Educational Implications

Our results suggest that nurturing students' need satisfaction by using autonomy supportive teaching styles may be an effective pedagogical approach for increasing future autonomous motivation and positive affect, and decreasing controlled motivation and negative affect. In addition, autonomy supportive teaching styles appear to represent an efficient way of increasing students' global levels of need satisfaction in a balanced manner. An important practice of autonomy supportive teachers is endorsing and incorporating student perspectives into the classroom. For example, obtaining student input, providing students with meaningful choices, and creating interactive learning sessions are all practical strategies teachers can use to enhance autonomy support (Reeve, 2006). Emphasizing student initiated actions and accepting self-initiated mistakes are also practical strategies teachers can use to increase autonomy support. Systematic and sustained professional development that allows teachers to learn how to consistently implement autonomy supportive practices such as explaining why learning activities are important, giving meaningful choices, cultivating personal interest, and reducing pressure-oriented language would likely translate to adaptive student outcomes by fulfilling basic psychological need satisfaction.

The prominence of the G-factor in our model reiterates "…that psychological health requires satisfaction of all three needs; one or two are not enough" (Deci & Ryan, 2000, p. 229). Still, our results also suggest that teachers should remain aware of the need for balance, to ensure that students' levels of autonomy are well matched by their levels of relatedness and competence satisfaction. For example, teachers need to confirm that learning choices fit into a clear structure for developing feelings of competence rather than overwhelming students with choices that may result in limited success. This seems especially prudent for physical education classes because student performance is often observable and highly public. Clearly, balancing students' need satisfaction is a complex aspect of effective teaching that may be improved through teacher reflection and intensive pedagogical training (Reeve, 2006; Sun & Chen, 2010).

Limitations and Future Directions

This study relied on a robust methodological approach to testing the motivation mediation modeling using bifactor representation of students' basic psychological need satisfaction. Key procedures included: (1) comparing theoretically-relevant representations of students' ratings of basic psychological need satisfaction in order to better document the superiority of the bifactor-ESEM approach; (2) testing the longitudinal measurement invariance of this representation to ensure that the observed relations remained untainted by changes in measurement properties; (3) examining a comprehensive pattern of relations allowing for the systematic disaggregation of the cross-sectional and longitudinal associations between the constructs under study corrected for measurement errors; and (4) establishing predictive equilibrium in order to demonstrate stability of the observed relations across two distinct time intervals. Substantively, our results also provide meaningful contributions to the SDT research literature. Our results showed that students' global levels of need satisfaction significantly mediated the relations between teachers' autonomy support practices and learning motivation and affect, whereas the S-factors were only associated with changes in the outcomes levels. These observations suggest that, while both the G- and S-factors appear to be clearly important to our understanding of student motivation and learning affect, the G-factor is the only component that appears reactive to teachers' motivational practices.

Still, this study is not without limitations. First, we focused on autonomy support and conditional regard as two teacher motivational styles; however, there are other important dimensions of teachers' motivational style that have not been considered in the present study, such as structure, involvement, controlling use of rewards, and intimidation. Therefore, investigating a more comprehensive set of teacher motivational styles may be required to achieve a more precise understanding of the mechanisms involved in the motivation mediation model. Similarly, teacher motivational style was self-reported by students, which can also be considered a limitation. We advocate for future researchers to incorporate teacher observations of their own motivation style. Second, we solely focused on students' basic psychological need satisfaction. Including basic psychological need frustration (Bartholomew et al., 2011; Jang et al., 2016) into the motivation mediation model (i.e., the dual process model) is also likely to result in an enriched perspective on the mechanisms at play in these relations. Third, the outcomes considered in this study remained related to learning motivation and affect. Examining student achievement as an outcome in future research would increase the utility value of the motivation mediation model. Fourth, many of the indirect effects observed in this study were small in magnitude, suggesting that mediation might be less important than direct effects. Fifth, we relied on self-report measures rated on Likert type response scales. Future researchers could consider the use of visual analog scales, which is a format that may provide greater flexibility and precision than Likert scales. Finally, we tested the motivation mediation model in secondary physical education classes in Australian schools, which may affect the generalizability of findings to different learning domains, cultures, and developmental stages.

Conclusion

This study provided further evidence supporting the usefulness of a bifactor-ESEM representation of the underlying structure of students' basic psychological need satisfaction. This approach allows SDT researchers to better capture the complexity of basic psychological need satisfaction, while avoiding the reliance on a measurement strategy that focuses either on a general factor or on specific factors. Instead, both general and specific factors can be explored simultaneously. This approach also reduces the extent of the conceptual overlap between the assessed constructs, thereby enhancing their discriminant validity. When considering the motivation mediation model, the general factor of basic psychological need satisfactions was most conducive to explaining longitudinal relations between antecedents and outcomes. However, specific factors of autonomy, competence, and relatedness need satisfaction did explain additional variance in changes in student outcomes such as learning motivation and affect. Further stringent testing of the motivation mediation model across diverse students and learning contexts is needed to advance the generalizability of our findings.

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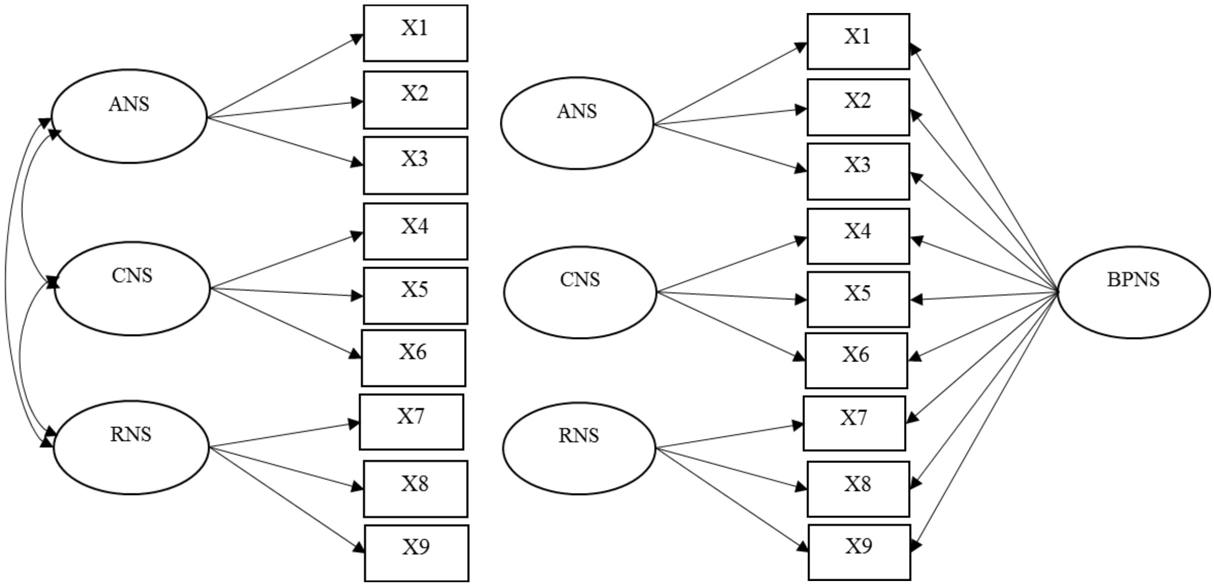
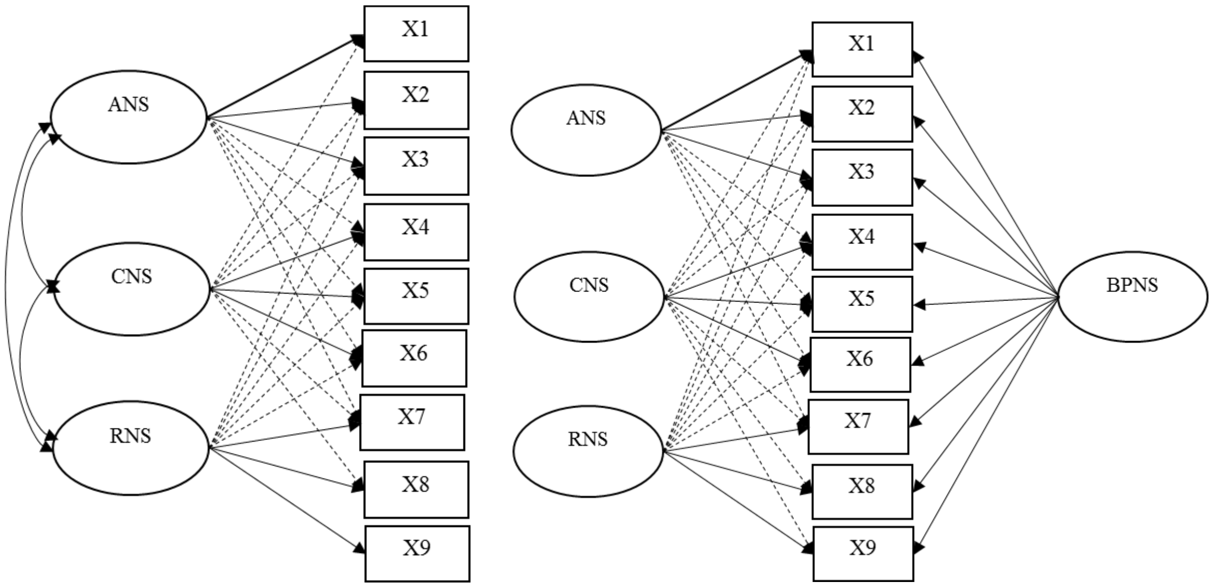


A. Confirmatory Factor Analysis (CFA) **B. bifactor-CFA**



C. Exploratory Structural Equation Modeling (ESEM) **D. Bifactor- ESEM**

Figure 1. Alternative Measurement Model for the Need Satisfaction Ratings.

Note. ANS: Autonomy need satisfaction; CNS: Competence need satisfaction; RNS: Relatedness need satisfaction; BPNS: Global levels of basic psychological need satisfaction; Ovals represent latent factors, rectangles represent observed indicators (X1 to X9); Full directional arrows represent factor loadings; Dashed directional arrows represent cross-loadings; double-headed arrows represent factor correlations; factor variances and item uniqueness are not included in the figure for purposes of simplicity.

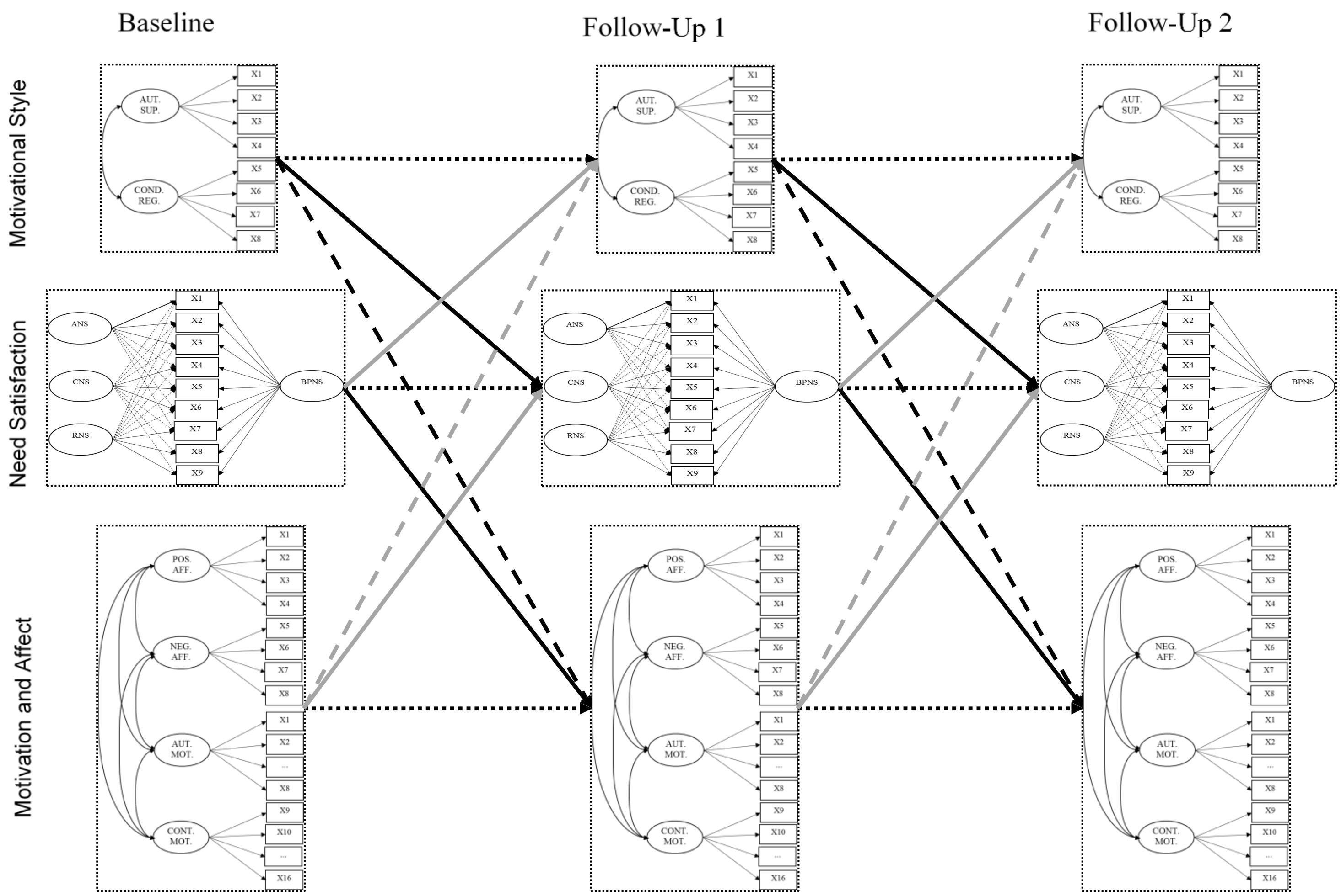


Figure 2. Conceptual Representation of the Alternative Predictive Models Tested in the Present Study.

Note. Sets of factors with a distinct role in the theoretical predictive sequence are enclosed in dotted boxes. Theoretical predictors (perceptions of teacher autonomy support and conditional regard) are in the top section, mediators (need satisfaction, defined as in Figure 1) are in the middle, and outcomes (autonomous motivation, controlled motivation, positive affect, and negative affect) are in the bottom section. Dotted arrows are autoregressive paths (Model 0); full black arrows are theoretical predictive paths (Model 1); full greyscale arrows are reciprocal predictive paths (Model 2); dashed back arrows are direct paths between predictors and outcomes (Model 3); dashed greyscale arrows are reciprocal direct paths between outcomes and predictors (Model 4).

Table 1
Alternative Need Satisfaction Measurement Models.

Model	χ^2	*df*	CFI	TLI	RMSEA	RMSEA 90% CI
Need Satisfaction						
Baseline (*N*= 1419)						
CFA	619.429*	62	.912	.890	.080	.074 - .085
B-CFA	181.867*	52	.980	.969	.042	.035 - .049
ESEM	115.570*	42	.988	.979	.035	.028 - .043
B-ESEM	65.195*	32	.995	.987	.027	.018 - .036
Follow-Up 1 (*N*= 1454)						
CFA	754.512*	62	.903	.878	.088	.082 - .093
B-CFA	327.291*	52	.961	.942	.060	.054 - .067
ESEM	190.551*	42	.979	.961	.049	.042 - .057
B-ESEM	74.732*	32	.994	.985	.030	.021 - .039
Follow-Up 2 (*N*= 1219)						
CFA	779.524*	62	.890	.862	.097	.091 - .104
B-CFA	337.329*	52	.956	.935	.067	.060 - .074
ESEM	198.446*	42	.976	.956	.055	.048 - .063
B-ESEM	87.784*	32	.991	.979	.038	.028 - .047
Complete Measurement Model						
Baseline	2655.982*	961	.929	.920	.035	.033-.036
Follow-Up 1	2973.325*	961	.923	.913	.037	.036-.039
Follow-Up 2	3263.127*	961	.914	.903	.043	.042-.045

Note. *$p < .01$; CFA: confirmatory factor analysis; B-CFA: Bifactor-CFA; ESEM: Exploratory structural equation modeling; B-ESEM: Bifactor-ESEM; 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.

Table 2

Need Satisfaction Parameter Estimates (Bifactor-Exploratory Structural Equation Modeling).

Items	Baseline					Follow-Up 1					Follow-Up 2				
	GF λ	SF1 λ	SF2 λ	SF3 λ	δ	GF λ	SF1 λ	SF2 λ	SF3 λ	δ	GF λ	SF1 λ	SF2 λ	SF3 λ	δ
Autonomy 1	**.243**	**.550**	.026	.091	.630	**.301**	**.598**	.016	.146	.530	**.368**	**.586**	.031	.204	.479
Autonomy 2	**.454**	**.468**	.051	.175	.541	**.501**	**.533**	-.004	.186	.430	**.546**	**.500**	-.010	.121	.437
Autonomy 3	**.589**	**.075**	.157	.021	.623	**.610**	**.062**	.182	.036	.590	**.708**	**.046**	.137	.074	.473
Autonomy 4	**.578**	**.543**	-.074	-.156	.341	**.643**	**.510**	-.064	-.191	.287	**.638**	**.554**	-.064	-.135	.263
Autonomy 5	**.459**	**.625**	.005	-.045	.397	**.546**	**.581**	-.037	-.102	.353	**.580**	**.589**	-.028	-.115	.304
Competence 1	**.559**	.048	**.626**	.074	.297	**.594**	.010	**.679**	.092	.177	**.585**	-.009	**.688**	.121	.170
Competence 2	**.605**	-.025	**.385**	.029	.484	**.607**	-.058	**.391**	.016	.475	**.657**	-.008	**.387**	.029	.418
Competence 3	**.736**	-.045	**.148**	-.010	.434	**.746**	-.039	**.206**	.024	.398	**.781**	-.053	**.157**	-.066	.359
Competence 4	**.622**	-.001	**.589**	-.087	.259	**.654**	-.021	**.582**	-.096	.224	**.637**	-.025	**.588**	-.124	.233
Relatedness 1	**.687**	.040	.118	**.297**	.425	**.697**	.075	.182	**.321**	.373	**.754**	.048	.154	**.265**	.335
Relatedness 2	**.736**	.055	-.101	**.219**	.397	**.764**	.081	-.080	**.190**	.367	**.773**	.137	-.071	**.251**	.315
Relatedness 3	**.796**	-.035	-.107	**.079**	.348	**.813**	-.038	-.132	**.189**	.284	**.844**	-.044	-.103	**.111**	.263
Relatedness 4	**.819**	-.021	-.004	**.035**	.328	**.800**	-.014	-.012	**.007**	.359	**.850**	-.043	-.024	**.020**	.275
Reliability (ω)	.919	.669	.675	.209		.934	.704	.730	.265		.946	.726	.737	.261	

Note. GF: Global Factor; SF: Specific Factor; λ: Loadings (target loadings are in bold); δ: Uniquenesses.

Table 3

Goodness-of-Fit of the Longitudinal Models Estimated in the Present Study

Model	χ^2	df	CFI	TLI	RMSEA	RMSEA 90% CI	$\Delta\chi^2$	Δdf	ΔCFI	ΔTLI	ΔRMSEA
Measurement Invariance: Need Satisfaction											
Configural	683.111*	516	.993	.990	.014	.011-.017					
Weak	755.254*	588	.993	.991	.013	.010-.016	74.050	72	.000	.001	-.001
Strong	793.232*	606	.992	.991	.014	.011-.016	39.332*	18	-.001	.000	+.001
Strict	1200.799*	632	.977	.973	.023	.021-.025	313.892*	26	-.015	-.018	+.009
Partial Strict (6)	947.596*	626	.987	.984	.017	.015-.020	118.810*	20	-.005	-.007	+.003
Measurement Invariance: Global Models											
Configural	15922.559*	9069	.924	.917	.021	.021-.022					
Weak	16044.808*	9197	.924	.918	.021	.020-.021	143.245	128	.000	+.001	.000
Strong	16253.046*	9271	.922	.917	.021	.020-.022	207.568*	74	-.002	-.001	.000
Strict	17213.822*	9365	.912	.908	.022	.022-.023	727.759*	94	-.010	-.009	+.001
Partial Strict (6)	16946.113*	9359	.915	.911	.022	.021-.022	553.788*	88	-.007	-.006	+.001
Predictive Models											
Model 0	17630.389*	9615	.911	.908	.022	.022-.023					
Model 0 with Equilibrium	17652.528*	9637	.911	.908	.022	.022-.023	24.129	22	.000	.000	.000
Model 1	17477.196*	9589	.912	.909	.022	.021-.022	166.809*	48	+.001	+.001	.000
Model 1 with Equilibrium	17488.335*	9613	.912	.910	.022	.021-.022	15.112	24	.000	+.001	.000
Model 2	17389.637*	9565	.913	.910	.022	.021-.022	97.826	48	+.001	.000	.000
Model 2 with Equilibrium	17422.455*	9589	.913	.910	.022	.021-.022	33.534	24	.000	.000	.000
Model 3	17474.082*	9597	.912	.910	.022	.021-.022	15.684	16	.000	.000	.000
Model 3 with Equilibrium	17474.394*	9605	.912	.910	.022	.021-.022	2.585	8	.000	.000	.000
Model 4	17413.791*	9597	.913	910	.022	.021-.022	106.635*	16	+.001	.000	.000
Model 4 with Equilibrium	17433.593*	9605	.913	.910	.022	.021-.022	19.940	8	.000	.000	.000

Note. *$p < .01$; 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; Δ: Change in fit indices from the preceding model in the sequence; $\Delta\chi^2$: Robust chi-square difference tests (calculated from loglikelihoods for greater precision) (Satorra & Bentler, 2001).

Table 4

Latent Correlations and Reliability Estimates.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	BPNS	1.000															
2	ANS	.000	1.000														
3	CNS	.000	.000	1.000													
4	RNS	.000	.000	.000	1.000												
5	Aut. Support	.628**	.101**	-.086*	.119	1.000											
6	Cond. Regard	-.165**	.034	.158**	.022	-.243**	1.000										
7	Aut. Motiv.	.652**	-.044	.254**	.147**	.458**	-.135**	1.000									
8	Cont. Motiv.	-.003	.087*	-.040	.083	.046	.210**	.020	1.000								
9	Pos. Affect	.502**	-.028	.116**	.118**	.414**	-.040	.446**	.021	1.000							
10	Neg. Affect	-.216**	.127**	-.146**	-.037	-.107**	.148**	-.201**	.158**	-.370**	1.000						
11	F1 BPNS	.522**	.060	.142**	.011	.400**	-.118**	.448**	-.127**	.304**	-.208**	1.000					
12	F1 ANS	.003	.420**	-.021	.033	.104**	-.024	-.022	-.035	-.025	.039	.000	1.000				
13	F1 CNS	.195**	-.012	.632**	-.061	.002	.133**	.250**	-.015	.137**	-.080	.000	.000	1.000			
14	F1 RNS	.174**	-.056	-.058	.210**	.155	-.091	.071	.126**	.173**	-.001	.000	.000	.000	1.000		
15	F1 Aut. Support	.401**	.001	.004	.041	.565**	-.165**	.332**	-.065	.290**	-.134**	.600**	.205**	-.042	.129	1.000	
16	F1 Cond. Regard	-.137**	-.020	.066	-.038	-.193**	.404**	-.129**	.143**	-.069	.154**	-.218**	-.104*	.106**	-.006	-.291**	1.000
17	F1 Aut. Motiv.	.470**	.032	.234**	.065	.339**	-.079	.641**	-.075	.347**	-.138**	.662**	.028	.307**	.113	.421**	-.135**
18	F1 Cont. Motiv.	-.073	.061	-.103*	.082	-.024	.109**	-.065	.553**	-.008	.189**	-.079	.063	-.084*	.090	-.052	.204**
19	F1 Pos. Affect	.322**	.030	.142**	.100*	.250**	-.041	.313**	-.018	.477**	-.204**	.497**	-.005	.176**	.023	.438**	-.083*
20	F1 Neg. Affect	-.157**	.051	-.128**	-.010	-.091**	.075	-.131**	.116**	-.185**	.477**	-.244**	.037	-.144**	.043	-.150**	.163**
21	F2 BPNS	.467**	.010	.209**	.064	.410**	-.110**	.424**	-.013	.293**	-.222**	.558**	.064	.209**	.095	.457**	-.168**
22	F2 ANS	.010	.271**	-.101*	.062	.140**	-.077	.022	.103*	-.039	.064	.003	.476**	-.067	.117	.107*	-.032
23	F2 CNS	.167**	.028	.640**	.012	-.016	.152**	.273**	-.056	.154**	-.101*	.171**	-.065	.674**	-.025	-.034	.116**
24	F2 RNS	.064	.088	-.032	.271**	.224**	-.068	.182**	.099	.116	-.096	.110	.003	-.011	.238**	.152	-.104
25	F2 Aut. Support	.406**	.083*	.044	.113	.514**	-.157**	.339**	.006	.262**	-.126**	.441**	.169**	.035	.125	.492**	-.156**
26	F2 Cond. Regard	-.061	-.016	.043	-.082	-.159**	.328**	-.025	.126**	-.087	.100**	-.074	-.056	.059	-.015	-.139**	.425**
27	F2 Aut. Motiv.	.433**	.046	.251**	.148**	.399**	-.103**	.618**	-.031	.326**	-.131**	.538**	.053	.278**	.071	.374**	-.132**
28	F2 Cont. Motiv.	-.077	.038	-.088*	.104	-.058	.078	-.069	.500**	-.037	.219**	-.127**	-.035	-.094	.103	-.070	.151**
29	F2 Pos. Affect	.268**	.031	.095*	.085	.213**	-.007	.263**	-.024	.379**	-.123**	.338**	-.001	.182**	.067	.267**	-.083*
30	F2 Neg. Affect	-.157**	.051	-.107*	.039	-.078	.020	-.151**	.061	-.190**	.373**	-.196**	.050	-.178**	-.007	-.125**	.097*
	Alpha (α)	.903	.772	.845	.856	.757	.823	.915	.764	.835	.794	.915	.806	.871	.865	.757	.832
	Omega (ω)	.919	.669	.675	.209	.790	.846	.919	.784	.855	.780	.934	.704	.730	.265	.762	.835

Note. ** $p < .01$; * $p < .05$. B: Baseline; F1: Follow-Up 1; F2: Follow-Up2; ANS: Autonomy need satisfaction; CNS: Competence need satisfaction; RNS: Relatedness need satisfaction; BPNS: Global levels of basic psychological need satisfaction.

Table 4 (Continued)

	17	18	19	20	21	22	23	24	25	26	27	28	29	30
17 F1 Aut. Motiv.	1.000													
18 F1 Cont. Motiv.	-.065	1.000												
19 F1 Pos. Affect	.453**	-.032	1.000											
20 F1 Neg. Affect	-.187**	.170**	-.447**	1.000										
21 F2 BPNS	.445**	-.098*	.371**	-.230**	1.000									
22 F2 ANS	.003	.129**	-.043	.069	.000	1.000								
23 F2 CNS	.281**	-.039	.217**	-.140**	.000	.000	1.000							
24 F2 RNS	.120	.050	-.006	-.013	.000	.000	.000	1.000						
25 F2 Aut. Support	.357**	-.002	.299**	-.134**	.711**	.299**	-.029	.233**	1.000					
26 F2 Cond. Regard	-.044	.174**	-.043	.079	-.137**	-.139**	.117*	-.050	-.282**	1.000				
27 F2 Aut. Motiv.	.694**	-.121**	.434**	-.187**	.713**	.103*	.307**	.244**	.533**	-.072	1.000			
28 F2 Cont. Motiv.	-.096*	.575**	-.037	.205**	-.069	.097	-.096*	.105	-.004	.208**	-.470	1.000		
29 F2 Pos. Affect	.327**	-.059	.570**	-.347**	.439**	-.027	.172**	.082	.382**	-.072	.417**	-.024	1.000	
30 F2 Neg. Affect	-.193**	.133**	-.307**	.622**	-.304**	.090	-.141**	-.062	-.203**	.086*	-.237**	.234**	-.464**	1.000
Alpha (α)	.920	.774	.857	.788	.926	.838	.873	.889	.832	.863	.931	.784	.873	.801
Omega (ω)	.920	.773	.856	.775	.946	.726	.737	.261	.787	.841	.922	.762	.866	.793

Note. ** $p < .01$; * $p < .05$. B: Baseline; F1: Follow-Up 1; F2: Follow-Up2; ANS: Autonomy need satisfaction; CNS: Competence need satisfaction; RNS: Relatedness need satisfaction; BPNS: Global levels of basic psychological need satisfaction.

Table 5

Parameter Estimates from the Final Predictive Model (Model 4 with Equilibrium)

Predictor	*Outcome*	*b (S.E.)*	*Baseline → Follow Up 1* *ß (E.S.)*	*Follow Up 1 → Follow Up 2* *ß (E.S.)*
Autoregressive paths				
BPNS	BPNS	.565 (.035)**	.559 (.035)**	.516 (.038)**
ANS	ANS	.434 (.032)**	.457 (.032)**	.439 (.034)**
CNS	CNS	.694 (.027)**	.712 (.029)**	.644 (.060)**
RNS	RNS	.634 (.054)**	.668 (.073)**	.611 (.185)**
Aut. Support	Aut. Support	.470 (.034)**	.505 (.036)**	.446 (.034)**
Cond. Regard	Cond. Regard	.402 (.028)**	.416 (.030)**	.398 (.030)**
Aut. Motiv.	Aut. Motiv.	-.036 (.171)	-.035 (.169)	-.036 (.173)
Cont. Motiv.	Cont. Motiv.	.560 (.025)**	.577 (.026)**	.584 (.026)**
Pos. Affect	Pos. Affect	.462 (.031)**	.450 (.030)**	.461 (.033)**
Neg. Affect	Neg. Affect	.511 (.032)**	.500 (.031)**	.521 (.036)**
Predictive paths				
Aut. Support	BPNS	.142 (.034)**	.141 (.033)**	.120 (.028)**
Cond. Regard	BPNS	-.037 (.020)	-.036 (.020)	-.032 (.018)
Aut. Support	ANS	.058 (.045)	.061 (.048)	.057 (.046)
Cond. Regard	ANS	.002 (.025)	.002 (.026)	.002 (.026)
Aut. Support	CNS	-.092 (.050)	-.094 (.052)	-.081 (.044)
Cond. Regard	CNS	.063 (.032)	.064 (.033)	.058 (.031)
Aut. Support	RNS	.072 (.057)	.075 (.062)	.068 (.061)
Cond. Regard	RNS	-.022 (.040)	-.024 (.042)	-.022 (.041)
BPNS	Aut. Motiv.	.658 (.136)**	.648 (.140)**	.661 (.135)**
ANS	Aut. Motiv.	-.103 (.040)**	-.101 (.040)**	-.097 (.038)**
CNS	Aut. Motiv.	.016 (.029)	.016 (.028)	.016 (.028)
RNS	Aut. Motiv.	-.387 (.087)**	-.381 (.088)**	-.365 (.096)**
BPNS	Cont. Motiv.	-.074 (.022)**	-.076 (.023)**	-.080 (.024)**
ANS	Cont. Motiv.	-.022 (.023)	-.023 (.023)	-.022 (.023)
CNS	Cont. Motiv.	-.056 (.020)**	-.057 (.021)**	-.058 (.022)**
RNS	Cont. Motiv.	.017 (.029)	.018 (.030)	.018 (.030)
BPNS	Pos. Affect	.123 (.027)**	.120 (.026)**	.121 (.026)**
ANS	Pos. Affect	.002 (.025)	.002 (.024)	.002 (.023)
CNS	Pos. Affect	.051 (.025)*	.049 (.024)*	.048 (.024)*
RNS	Pos. Affect	-.059 (.029)*	-.057 (.028)*	-.054 (.027)*
BPNS	Neg. Affect	-.064 (.023)**	-.062 (.022)**	-.064 (.023)**
ANS	Neg. Affect	.019 (.028)	.019 (.027)	.018 (.027)
CNS	Neg. Affect	-.069 (.024)**	-.067 (.023)**	-.067 (.023)**
RNS	Neg. Affect	.016 (.031)	.016 (.030)	.015 (.030)
Aut. Motiv.	Aut. Support	.119 (.029)**	.127 (.031)**	.123 (.030)**
Cont. Motiv.	Aut. Support	-.026 (.018)	-.028 (.020)	-.025 (.018)
Pos. Affect	Aut. Support	.035 (.026)	.038 (.028)	.037 (.027)
Neg. Affect	Aut. Support	-.002 (.023)	-.002 (.025)	-.002 (.024)
Aut. Motiv.	Cond. Regard	-.012 (.026)	-.012 (.027)	-.012 (.027)
Cont. Motiv.	Cond. Regard	.071 (.027)**	.074 (.027)**	.071 (.026)**
Pos. Affect	Cond. Regard	-.038 (.030)	-.039 (.031)	-.040 (.032)
Neg. Affect	Cond. Regard	.008 (.026)	.009 (.027)	.009 (.027)

Note. ** $p < .01$; * $p < .05$. The final predictive model had reached equilibrium, which explains why the unstandardized coefficients (*b*) are invariant across time periods. Conversely, the standardized coefficients (*ß*) are a function of the latent variance-covariance on which no constraints were imposed, and thus differ slightly across time periods. S.E.: Standard error of the coefficient; ANS: Autonomy need satisfaction; CNS: Competence need satisfaction; RNS: Relatedness need satisfaction; BPNS: Global levels of basic psychological need satisfaction.

Online Supplements for:

Basic Psychological Need Satisfaction Toward Learning: A Longitudinal Test of Mediation using Bifactor Exploratory Structural Equation Modeling

Table S1

Need Satisfaction Parameter Estimates (Confirmatory Factor Analysis).

	Baseline				Follow-Up 1				Follow-Up 2			
Items	F1 λ	F2 λ	F3 λ	δ	F1 λ	F2 λ	F3 λ	δ	F1 λ	F2 λ	F3 λ	δ
Autonomy 1	**.529**			.720	**.584**			.659	**.628**			.606
Autonomy 2	**.654**			.572	**.717**			.486	**.740**			.453
Autonomy 3	**.521**			.729	**.531**			.718	**.599**			.641
Autonomy 4	**.781**			.390	**.816**			.334	**.841**			.293
Autonomy 5	**.738**			.455	**.783**			.387	**.806**			.351
Competence 1		**.786**		.382		**.851**		.276		**.825**		.319
Competence 2		**.734**		.461		**.733**		.463		**.787**		.381
Competence 3		**.708**		.499		**.735**		.460		**.746**		.444
Competence 4		**.820**		.328		**.865**		.253		**.840**		.295
Relatedness 1			**.729**	.469			**.760**	.422			**.796**	.366
Relatedness 2			**.754**	.431			**.792**	.373			**.808**	.348
Relatedness 3			**.786**	.382			**.799**	.361			**.829**	.313
Relatedness 4			**.819**	.329			**.789**	.377			**.842**	.292
Factor Correlations	F1	F2	F3		F1	F2	F3		F1	F2	F3	
F1		.579	.697			.559	.741			.592	.762	
F2			.772				.755				.782	
Reliability (ω)	0.784	0.848	0.855		0.820	0.875	0.865		0.848	0.877	0.890	

Note. F: Factor; λ: Loadings (target loadings are in bold); δ: Uniquenesses.

Table S2

Need Satisfaction Parameter Estimates (Exploratory Structural Equation Modeling).

Items	Baseline				Follow-Up 1				Follow-Up 2			
	F1 λ	F2 λ	F3 λ	δ	F1 λ	F2 λ	F3 λ	δ	F1 λ	F2 λ	F3 λ	δ
Autonomy 1	**.674**	-.029	-.154	.650	**.736**	-.032	-.152	.590	**.742**	.009	-.140	.557
Autonomy 2	**.582**	.047	.069	.579	**.673**	-.018	.083	.485	**.695**	.002	.066	.453
Autonomy 3	**.139**	.301	.275	.622	**.132**	.333	.273	.588	**.128**	.291	.406	.470
Autonomy 4	**.718**	-.059	.142	.400	**.740**	-.009	.105	.352	**.810**	-.041	.078	.293
Autonomy 5	**.832**	-.017	-.066	.377	**.843**	-.021	-.035	.341	**.855**	-.012	-.031	.312
Competence 1	.047	**.906**	-.152	.303	.027	**.967**	-.140	.205	-.008	**.996**	-.159	.204
Competence 2	-.004	**.626**	.136	.480	-.018	**.634**	.141	.472	.040	**.639**	.143	.412
Competence 3	.015	**.339**	.469	.442	.026	**.404**	.424	.402	.037	**.356**	.473	.384
Competence 4	.017	**.895**	-.082	.276	.049	**.896**	-.075	.241	.030	**.902**	-.092	.266
Relatedness 1	.085	.240	**.481**	.486	.104	.305	**.436**	.440	.111	.309	**.466**	.379
Relatedness 2	.139	-.034	**.701**	.417	.156	-.017	**.695**	.374	.247	-.002	**.626**	.353
Relatedness 3	.051	-.009	**.787**	.344	.006	-.074	**.898**	.270	.036	-.017	**.854**	.251
Relatedness 4	.065	.140	**.678**	.333	.085	.126	**.638**	.385	.058	.110	**.727**	.288
Factor Correlations	F1	F2	F3		F1	F2	F3		F1	F2	F3	
F1		.485	.554			.478	.626			.504	.635	
F2			.661				.670				.680	
Reliability (ω)	0.767	0.836	0.816		0.806	0.864	0.829		0.833	0.869	0.849	

Note. F: Factor; λ: Loadings (target loadings are in bold); δ: Uniquenesses.

Table S3

Need Satisfaction Parameter Estimates (Bifactor-Confirmatory Factor Analysis).

Items	Baseline					Follow-Up 1					Follow-Up 2				
	GF λ	SF1 λ	SF2 λ	SF3 λ	δ	GF λ	SF1 λ	SF2 λ	SF3 λ	δ	GF λ	SF1 λ	SF2 λ	SF3 λ	δ
Autonomy 1	**.266**	**.523**			.656	**.336**	**.544**			.592	**.408**	**.511**			.573
Autonomy 2	**.480**	**.431**			.584	**.530**	**.477**			.491	**.565**	**.468**			.461
Autonomy 3	**.636**	**.041**			.594	**.654**	**.015**			.572	**.749**	**.004**			.440
Autonomy 4	**.547**	**.546**			.403	**.609**	**.525**			.354	**.621**	**.576**			.282
Autonomy 5	**.453**	**.650**			.372	**.530**	**.623**			.332	**.565**	**.611**			.308
Competence 1	**.601**		**.567**		.318	**.638**		**.616**		.214	**.623**		**.610**		.239
Competence 2	**.635**		**.337**		.483	**.627**		**.361**		.477	**.676**		**.366**		.409
Competence 3	**.757**		**.087**		.420	**.760**		**.168**		.394	**.781**		**.135**		.372
Competence 4	**.638**		**.581**		.255	**.663**		**.574**		.231	**.637**		**.601**		.233
Relatedness 1	**.707**			**.142**	.479	**.748**			**.083**	.434	**.793**			**.059**	.368
Relatedness 2	**.686**			**.320**	.427	**.732**			**.284**	.383	**.760**			**.240**	.365
Relatedness 3	**.716**			**.406**	.323	**.745**			**.433**	.257	**.789**			**.368**	.243
Relatedness 4	**.779**			**.238**	.337	**.760**			**.195**	.384	**.810**			**.252**	.294
Reliability (ω)	0.917	0.648	0.626	0.439		0.931	0.671	0.692	0.404		0.944	0.695	0.701	0.399	

Note. GF: Global Factor; SF: Specific Factor; λ: Loadings (target loadings are in bold); δ: Uniquenesses.

Table S4

Motivation Style, Behavioral Regulation, and Affect Factor Loadings and Uniquenesses

	Baseline			Follow-Up 1			Follow-Up 2		
Items	Factor 1 λ	Factor 2 λ	δ	Factor 1 λ	Factor 2 λ	δ	Factor 1 λ	Factor 2 λ	δ
Autonomy Support 1	.606		.633	.574		.670	.602		.637
Autonomy Support 2	.677		.542	.646		.583	.673		.547
Autonomy Support 3	.748		.440	.720		.481	.745		.444
Autonomy Support 4	.749		.440	.721		.481	.746		.444
Conditional Regard 1		.627	.606		.611	.626		.620	.615
Conditional Regard 2		.762	.419		.749	.440		.756	.428
Conditional Regard 3		.829	.313		.817	.332		.824	.322
Conditional Regard 4		.814	.337		.802	.357		.809	.346

	Baseline			Follow-Up 1			Follow-Up 2		
Items	Factor 1 λ	Factor 2 λ	δ	Factor 1 λ	Factor 2 λ	δ	Factor 1 λ	Factor 2 λ	δ
Autonomous 1	.782		.389	.784		.386	.787		.380
Autonomous 2	.678		.540	.680		.537	.685		.531
Autonomous 3	.772		.404	.774		.401	.777		.396
Autonomous 4	.747		.443	.749		.440	.752		.434
Autonomous 5	.741		.451	.743		.448	.747		.442
Autonomous 6	.811		.343	.812		.340	.815		.335
Autonomous 7	.778		.395	.780		.392	.783		.387
Autonomous 8	.816		.334	.818		.331	.821		.326
Controlled 1		.622	.613		.609	.629		.597	.644
Controlled 2		.571	.674		.557	.689		.545	.703
Controlled 3		.677	.542		.664	.559		.652	.575
Controlled 4		.667	.556		.654	.572		.642	.588
Controlled 5		.594	.647		.581	.663		.568	.677
Controlled 6		.432	.813		.420	.823		.409	.833
Controlled 7		.531	.718		.518	.732		.505	.745
Controlled 8		.353	.876		.342	.883		.332	.890

Note. CFA: Confirmatory Factor Analysis; λ = Loadings (target loadings are in bold); δ = Uniquenesses.

Table S4 (Continued)

Items	Baseline Factor 1 λ	Baseline Factor 2 λ	Baseline δ	Follow-Up 1 Factor 1 λ	Follow-Up 1 Factor 2 λ	Follow-Up 1 δ	Follow-Up 2 Factor 1 λ	Follow-Up 2 Factor 2 λ	Follow-Up 2 δ
Positive Affect 1	.772		.404	.773		.403	.786		.383
Positive Affect 2	.792		.372	.793		.371	.805		.352
Positive Affect 3	.781		.391	.781		.389	.794		.369
Positive Affect 4	.670		.551	.671		.550	.686		.529
Positive Affect 5	.660		.564	.661		.563	.677		.542
Negative Affect 1		.699	.511		.693	.519		.713	.491
Negative Affect 2		.562	.684		.556	.691		.577	.667
Negative Affect 3		.552	.695		.546	.702		.567	.678
Negative Affect 4		.569	.677		.563	.683		.584	.659
Negative Affect 5		.822	.324		.818	.331		.832	.307

Note. CFA: Confirmatory Factor Analysis; λ = Loadings (target loadings are in bold); δ = Uniquenesses.

Table S5

Analysis of Variance Tests at Baseline based on Number of Missing Data Time Points.

Variable	F-value	p-Value
B_ANS	2.207	0.110
B_CNS	0.304	0.738
B_RNS	1.379	0.252
B_AS	1.733	0.177
B_CR	0.791	0.454
B_AM	1.572	0.208
B_CM	0.462	0.630
B_PA	1.899	0.150
B_NA	2.040	0.130
Gender	0.569	0.566
Age	1.814	0.163

Note. Three levels of independent variable, 0 missing time points, 1 missing time point, two missing time points; ANS = autonomy need satisfaction; CNS = competence need satisfaction; RNS = relatedness need satisfaction; AS = autonomy support; CR = conditional regard; AM = autonomous motivation; CM = controlled motivation; PA = positive affect; NA = negative affect.