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University Students' Need Satisfaction Trajectories: A Growth Mixture Analysis

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Abstract

This study examines trajectory profiles of University students over the course of a University semester defined based on global levels of psychological need satisfaction, as proposed by self-determination theory (SDT). This study also documents the implications of these trajectories for a variety of educational outcomes. A sample of 461 first-year undergraduates completed all measures three times over the course of a University semester. Longitudinal growth mixture analyses (GMA) revealed three distinct need satisfaction trajectories (Low-Decreasing, Moderate-Decreasing, and Moderate-Increasing). The Moderate-Increasing profile was associated with the highest levels of positive affect and effort. In contrast, the Low-Decreasing profile was associated with lower levels of positive affect, effort, and achievement, and higher levels of negative affect than the Moderate-Increasing profile.

Keywords: Need satisfaction trajectory profiles; Self-determination theory; Psychological needs; Undergraduate students; Achievement

Self-determination theory (SDT; Deci & Ryan, 2000) proposes that the satisfaction of the three psychological needs for autonomy (the need to experience a sense of volition and psychological freedom), competence (the need to feel effective in interacting with one's environment), and relatedness (the need to feel connected with others) plays a crucial role in the emergence of self-determined goal-directed behaviors. Variable-centered research has supported the existence of well-differentiated effects of the satisfaction of these psychological needs as well as autonomous (engaging in an activity out of pleasure and/or volition and choice) and controlled (engaging in an activity for internal or external pressures) motivations on multiple educational outcomes (Cordeiro, Paixão, Lens, Lacante, & Luyckx, 2016; Wang, Liu, Jiang, & Song, 2017). In particular, students' psychological need satisfaction appears to be able to explain important educational outcomes such as engagement and achievement (e.g., Jang, Reeve, Ryan, & Kim, 2009), in a variety of cultural contexts (e.g., Belgium, Canada, Korea), and to be even more strongly related to these outcomes than autonomous and controlled forms of motivation (e.g., De Meyer et al., 2016; Kanat-Maymon, Benjamin, Stavsky, Shoshani, & Roth, 2015). Unfortunately, the bulk of prior research has relied on designs precluding the consideration of how need satisfaction trajectories evolve over time, and how this evolution differs across distinct subgroups of students. Moreover, these need satisfaction trajectories may also differ from one another in terms of outcomes (Ratelle & Duchesne, 2014). Thus, the present study considers, through longitudinal growth mixture analyses (GMA), how the need satisfaction trajectories of distinct profiles of University students evolve over the course of a semester. In addition, we investigate how these distinct trajectory profiles are related to a broader range of time-varying educational outcomes (i.e., positive and negative affect, effort, expected achievement, and objective achievement) that has typically been taken into account in prior research.

Global Need Satisfaction

SDT proposes that the three psychological needs for autonomy, competence, and relatedness are essential nutriments for individuals' survival, growth, and integrity (Deci & Ryan, 2000), so that their satisfaction is seen as essential both for wellbeing and positive educational outcomes, an assertion that has been supported in a variety of studies and cultural contexts (e.g., Cordeiro et al., 2016; Sheldon & Filak, 2008). In contrast, when these needs are not satisfied, maladaptive outcomes (e.g., dropout intentions, burnout, psychological distress) are expected (e.g., Sulea, van Beek, Sarbescu, Virga, & Schaufeli, 2015; Taylor, Lekes, Gagnon, Kwan, & Koestner, 2012). These conclusions appear to hold irrespective whether researchers relied on a total score of need satisfaction encompassing the three psychological needs (e.g., Cheon, Reeve, & Song, 2016; Michou, Mouratidis, Ersoy, & Uğur, 2016), or on distinct measures of the needs for autonomy, competence, and relatedness (e.g., Johnston & Finney, 2010; Niemiec, Ryan, & Deci, 2009). The latter studies generally identified relations between need satisfaction and the outcomes of a similar magnitude across the three distinct measures of need satisfaction. This observation suggests that, at least from an outcomes perspective, the global level to which students' psychological needs are satisfied appears to be at least as critical as the extent to which each specific need is itself satisfied. This hypothesis is even consistent with SDT, which underscores the fact that "psychological health requires satisfaction of all three needs; one or two are not enough" (Deci & Ryan, 2000, p. 229).

Bifactor measurement models provide a way (e.g., Morin, Arens, & Marsh, 2016; Reise, 2012) to directly assess this hypothesis, by relying on an explicit partition of the covariance observed among need satisfaction ratings 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) exclusive to subsets of indicators but not explained by the global component. As such, bifactor models allow researchers to simultaneously consider students' global levels of need satisfaction, together with their specific needs for autonomy, competence, and relatedness. Indeed, recent research evidence has demonstrated that bifactor measurement models provide a more accurate representation of the complex multidimensionality associated with the measurement of psychological needs when compared to more traditional exploratory or confirmatory factor analytic models (Brunet, Gunnel, Teixeira, Sabiston, & Bélanger, 2016; Myers, Martin, Ntoumanis, Celimli, & Bartholomew, 2014; Sánchez-Oliva et al., 2017; Tóth-Király, Morin, Bőthe, Orosz, & Rigó, 2017). Interestingly, these studies all reported the presence of a well-defined global need satisfaction G-factor underlying responses to all ratings, whereas some of them found that at least one of the S-factors retained only a negligible amount of specificity once global levels of satisfaction were taken into account (e.g., competence: Tóth-Király et al., 2017; autonomy: Sánchez-Oliva et al., 2017). Perhaps even more importantly, these studies (e.g., Brunet et al., 2016; Sánchez-Oliva et al., 2017) also reported that participants' global levels of need satisfaction tended to be the key component responsible for associations between need satisfaction measures and a variety of covariates, underscoring the importance of considering global levels of need satisfaction in future research on the emergence, development, and consequences of need satisfaction.

Changes in Psychological Need Satisfaction

The bulk of research on students' need satisfaction has relied on cross-sectional designs, or short-term longitudinal designs precluding a clear understanding of the developmental trajectories occurring at the individual level (Ratelle & Duchesne, 2014). Longitudinal research is necessary not only to achieve a better understanding of the longitudinal stability and directionality of associations between variables, but also to achieve a proper understanding of how need satisfaction evolves over time for specific individuals (Grimm, Ram, & Estabrook, 2016). This last advantage of longitudinal research appears critical in the context of this study as SDT proposes need satisfaction to be partly situational in nature (Vallerand, 1997). In other words, need satisfaction is seen as emerging in part from the changing characteristics of the specific life context to which a person is exposed rather than to be an inherently stable individual characteristics. As such, the ability to study how need satisfaction evolves over time for specific subgroup of individuals would provide a rich window of opportunity into the various developmental mechanisms at play in the emergence of relations between need satisfaction and a variety of important developmental, educational, and professional outcomes. More precisely, the analytical approach (GMA) taken in the present study is specifically designed to examine how the need satisfaction trajectories of distinct profiles of University students evolve over the course of a semester, and to document how these distinct trajectory profiles are related to various educational outcomes. For instance, this study will help to respond to questions such as: Is a large proportion of University students characterized by initially low levels of need satisfaction coupled with a marked decreasing trajectory (*Low-Decreasing* profile)? What are the educational outcomes associated with this need satisfaction trajectory?

Among the few exceptions to this lack of longitudinal research, Wandeler and Bundick (2011) conducted a 3-year longitudinal study of 414 University students. Relying on autoregressive cross lagged models, these authors were mainly interested in obtaining a clearer picture of the longitudinal rank-order stability in students' levels of need satisfaction, and the directionality of the longitudinal associations between hope and need satisfaction. Interestingly, their results supported the idea that need satisfaction was mainly situational in nature and thus only moderately stable over time (r = .33 to .49), and that hope was only very minimally related to students' levels of need satisfaction over time. Marchand and Skinner (2007) reported a higher level of rank-order stability among a sample of children followed up over a 7-month period (r = .49 to .67), consistent with the ideas that children (Grades 3 to 6) tend to be exposed to a more stable environment than adults. Still, they also found significant relations between teachers' report of their own motivational practices, and later levels of need satisfaction among students, a result that has been replicated in a study focusing on the impact of coaching on female adolescents gymnasts measured twice seven months apart (Kipp & Weiss, 2015). In line with these results, Cheon et al. (2016) demonstrated that a teacher-focused intervention could result in a positive increase in middle and high school students' levels of need satisfaction over time, although estimates of rank-order stability obtained across four waves of measurement covering a school year remained of a similar magnitude (r = .55 to .69). Cox, Smith, and Williams (2008) obtained similar estimates of stability (r =.44 to .68) with sixth- and seventh-grade students who completed a survey containing a measure of need satisfaction on two occasions, one year apart.

Need Satisfaction Trajectories

Despite their interest, these studies are limited in their focus on rank-order stability in need satisfaction levels rather than on the estimation of individual trajectories. In particular, rank-order stability does not preclude the presence of normative increases or decreases in need satisfaction over time, and the observed levels of rank-order stability also remain low enough to suggest that substantial change still occurs over time for a substantial proportion of the students. This suggests that individual trajectories of need satisfaction may present substantial inter-individual heterogeneity which has yet to be specifically considered in research. Part of this heterogeneity may be explained by the presence of subpopulations characterized by different need satisfaction trajectories over time, which may be particularly important to identify for intervention purposes. It is noteworthy that previous studies all relied on variable-centered analyses, which rest on the assumption that all students are drawn from a single population following a similar trajectory. These investigations were thus not designed to test for the presence of developmental heterogeneity in psychological need satisfaction and to verify the extent to which this heterogeneity was related to the presence of unobserved subgroups of students following qualitatively distinct trajectories. Person-centered analyses, such as GMA, are specifically designed to explain longitudinal heterogeneity by separating a general population into profiles of students presenting qualitatively and quantitatively different trajectories (Muthén, 2002). GMA thus represents an alternative to traditional variable-centered analyses in addressing students' changes in psychological need satisfaction over time (Morin, Maïano, Marsh, Nagengast, & Janosz, 2013).

To our knowledge, a single study has so far relied on a person-centered approach of students' need satisfaction trajectories (Ratelle & Duchesne, 2014). In a study of 609 students followed annually from the end of elementary school to the end of secondary school, Ratelle and Duchesne (2014) relied on a restricted form of GMA to identify specific developmental trajectories of students' need satisfaction over time and confirmed the presence of substantial developmental heterogeneity. More precisely, these authors revealed that the trajectories depicting how the satisfaction of students' needs for competence, autonomy, and relatedness were each best represented according to five distinct profiles. Although each of these profiles presented differing levels of need satisfaction over time, they all tended to depict mostly stable trajectories, sometimes accompanied by slight increasing or decreasing tendencies with two noteworthy exceptions. These exceptions showed that 12% of the students reported a decrease in autonomy need satisfaction at the beginning of secondary school, whereas 6% of the students reported an increase in competence need satisfaction at the same moment. Ratelle and Duchesne (2014) further found that trajectory group membership was closely associated for the three needs, calling once again into question the true necessity of distinguishing among these three specific needs relative to a focus on global levels of need satisfaction. Perhaps even more importantly, they also demonstrated that all trajectory classes differed from one another in terms of academic, social, and emotional adjustment. This is important, since the only way to support a substantive interpretation of latent profiles is through a process of construct validation showing that these profiles present meaningful patterns of associations with theoretically significant covariates (Marsh, Lüdtke, Trautwein, & Morin, 2009; Morin, Morizot, Boudrias, & Madore, 2011).

The Present Study

Global Need Satisfaction Trajectories

Unfortunately, despite the pioneering nature of their study, Ratelle and Duchesne (2014) relied on a restricted form of GMA in which it was assumed that all students would correspond exactly to the average longitudinal trajectory identified in their own profile (i.e., latent class growth analysis: Nagin, 1999). This highly restrictive assumption has been shown to result in the possible over-extraction of latent profiles of students following trajectories of a similar shape but different levels (Bauer & Curran, 2004; Muthén & Muthén, 2000), to result in drastically different results than more flexible methods allowing for the representation of within- and between-profile heterogeneity (Morin, Maïano et al., 2011), and, more generally, to lead to biased conclusions relative to most alternative GMA specifications (Diallo, Morin, & Lu, 2016). As such, it is perhaps not so surprising to note that many of the profiles identified by Ratelle and Duchesne (2014) presented roughly the same shape, and differed from one another mainly in terms of their global levels of need satisfaction over time.

To address this limitation, we rely on a more flexible GMA approach to investigate University students' levels of global need satisfaction over the course of a semester. The decision to rely on a sample of University students is based on three distinct considerations. First, previously reviewed research suggests that need satisfaction levels may become less stable as students get older, thus possibly maximizing our ability to identify meaningfully distinct trajectory profiles. Second, SDT proposes that need satisfaction should be most relevant for self-determined activities (i.e., activities in which individuals engage out of pleasure and/or volition and choice; Vallerand, 1997). Given that University studies are more typically self-determined, relative to the mandatory nature of primary and secondary education, need satisfaction should thus be most relevant for the prediction of meaningful education outcomes at this level of education. Finally, persistence in University studies is a critically important consideration for educational systems worldwide, as higher education is associated with multiple social, economic, and psychological consequences for the students themselves as well as the society as a whole

(Voelkle & Sander, 2008). Among the key drivers of educational persistence and motivation, students' level of psychological need satisfaction appears to represent a particularly important mechanism to consider (Jang et al., 2009). Yet, despite the importance of University education in terms of professional, social, and vocational achievement and success, need satisfaction has received relatively little attention in prior longitudinal research.

Although prior longitudinal studies suggest that need satisfaction trajectories should exhibit some stability, they also suggest that change is possible over the course of a few months, and more likely among this older age group (Cheon et al., 2016; Cox et al., 2008; Kipp & Weiss, 2015; Ratelle & Duchesne, 2014; Wandeler & Bundick, 2011). Due to the scarcity of research using a person-centered approach to identify need satisfaction trajectories in the educational domain, it is difficult to propose specific hypotheses about the nature and number of the expected trajectory profiles. Still, based on Ratelle and Duchesne (2014), we expect these trajectories to follow distinct longitudinal profiles, although the reliance on a less restrictive GMA approach suggest that fewer than five profiles might be required to fully depict University students' need satisfaction trajectories. As such, we expect that between three and five profiles would be sufficient to adequately depict inter-individual heterogeneity in need satisfaction trajectories. Furthermore, to systematically test the assertion that need satisfaction is a mainly situational variable construct, we assess the extent to which these need satisfaction trajectory profiles depend on stable individual characteristics known to be relevant to the education area (i.e., sex, prior levels of achievement in college, grade repletion in college).

Outcomes of the Need Satisfaction Trajectories

Following from Ratelle and Duchesne (2014), and based on the idea that it is critical to demonstrate the criterion-related validity of the extracted trajectory profiles in relation to meaningful external covariates (Marsh et al., 2009; Morin, Morizot et al., 2011), we also seek to contrast the extracted latent trajectory profiles in relations to students' levels of positive and negative affect, effort, expected achievement level, and true achievement level at the end of the semester. These covariates were selected based on their documented importance in the educational area, their relevance to SDT, and results from prior research on students' need satisfaction. Thus, we focus on the key educational outcomes of effort and positive affect given mounting research evidence supporting their important role in academic success (Gillet, Vallerand, Lafrenière, & Bureau, 2013; Trautwein & Lüdtke, 2007). We also consider negative affect, as this outcome is known to be a strong predictor of school dropout behavior (Fortin, Royer, Potvin, Marcotte, & Yergeau, 2004), which is in turn associated with numerous negative life outcomes in terms of employment and criminality (Bjerk, 2012).

Consistent with SDT predictions (Deci & Ryan, 2000), prior studies have generally supported the idea that higher levels of need satisfaction tended to be associated with more adaptive academic outcomes. More specifically, research evidence has shown that psychological need satisfaction is positively related to positive affect, and negatively linked to negative affect (Martela & Ryan, 2016; Martela, Ryan, & Steger, 2017; Vandercammen, Hofmans, & Theuns, 2014). In addition, research has also shown that need satisfaction has positive effects on students' effort and achievement levels (Cerasoli, Nicklin, & Nassrelgrgawi, 2016; Taylor & Lonsdale, 2010). Ratelle and Duchesne (2014) also examined the effects of developmental trajectory membership on academic, social, and emotional adjustment at the end of high school. Overall, the best adjustment scores were observed for students with high levels of need satisfaction and an increasing trajectory, followed by those with moderate levels of need satisfaction, and finally those with low levels of need satisfaction. When we summarize all of the above, it seems that we can expect educational outcomes (i.e., positive and negative affect, effort, expected achievement, and observed achievement) to be differentially related to need satisfaction trajectory profiles. Specifically, we expect that profiles characterized by higher levels and/or by increasing levels of global need satisfaction would be associated with the most adaptive outcomes, whereas profiles characterized by lower and/or by decreasing levels of global need satisfaction would be associated with the least desirable outcomes.

Method

Participants and Procedure

The sample used in this study included a total of 461 first-year undergraduate psychology students (Mean age = 18.52; *SD* = 0.72), including 83 males and 378 females, enrolled in a French University. The educational context and undergraduate psychology curriculum to which students are exposed in this University are similar to those proposed in other French Universities, as well as to those implemented in most Western Universities. Specifically, the academic program presented in this University is based on an introduction to the field of psychology in general, as well as to its various subfields (clinical, developmental, educational, neuropsychological, etc.) and areas of applications (personality, behaviors, cognitions, etc.) and to quantitative research methods. As for the majority of French Universities, all the students who have a high-school diploma and want to apply for admission to this University can enroll in the undergraduate psychology program. The proportion of males and females, and age distribution of this sample is aligned with those of French undergraduate psychology students. Admission at the undergraduate level is not as restrictive in France as in other countries, and undergraduate studies are tuition-free, contributing to increase the representativeness of this sample. Participation was voluntary and all first-year students enrolled in the psychology program of this University were invited to complete a self-reported questionnaire two weeks after the beginning of the fall semester. Among these participants, 421 (91.3%) agreed to complete the questionnaire again at Time 2 (five weeks later) and 379 (82.2%) also completed the questionnaire at Time 3 (ten weeks after Time 1). At each data collection, we explained the general purpose of the study, participants provided informed consent, and then completed a 15 minutes questionnaire in class settings. Participants were ensured that their responses would be kept confidential and would not have any influence on their course grades. They were only required to provide a personal identification code to allow researchers to match their responses at each data collection point. All questionnaires were administered in French and instruments not already available in this language were adapted to French using a standardized back-translation procedure (Hambleton, 2005) by a panel of experts.

Measures

Need satisfaction. Participants' need satisfaction was assessed with a questionnaire initially developed and validated by Gillet, Rosnet, and Vallerand (2008) (see also Gillet, Fouquereau, Huyghebaert, & Colombat, 2016), which was slightly adapted to the educational context for purposes of the present study. This questionnaire includes 9 items scored using a 7-point Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree). It assesses three dimensions (3 items each) of students' psychological need satisfaction, including autonomy (e.g., "Generally, I feel free to express my ideas and opinions"; Time 1 $\alpha = .55$; Time 2 $\alpha = .65$; Time 3 $\alpha = .78$), competence (e.g., "Often, I feel that I am very efficient"; Time 1 $\alpha = .72$; Time 2 $\alpha = .81$; Time 3 $\alpha = .81$), and relatedness (e.g., "I have a lot of sympathy for the persons with whom I interact"; Time 1 $\alpha = .67$; Time 2 $\alpha = .75$; Time 3 $\alpha = .76$). As in previous research (Michou et al., 2016), we rely in the present study on a score of global need satisfaction (Time 1 $\alpha = .75$; Time 2 $\alpha = .82$; Time 3 $\alpha = .83$).

Positive and negative affect. Participants' levels of positive (3 items; i.e., "active", "determined", and "enthusiastic"; Time 1 $\alpha = .72$; Time 2 $\alpha = .80$; Time 3 $\alpha = .79$) and negative (3 items; i.e., "afraid", "nervous", and "scared"; Time 1 $\alpha = .66$; Time 2 $\alpha = .75$; Time 3 $\alpha = .79$) affect in their studies were assessed with the two relevant subscales from the Short Form of the Positive and Negative Affect Schedule (Thompson, 2007; Watson, Clark, & Tellegen, 1988). Responses were made on a 5-point Likert-type scale (1- not at all to 5- very much).

Effort. Participants' level of effort was assessed using five items (e.g., "I put a lot of effort in my classes"; Time 1 $\alpha = .87$; Time 2 $\alpha = .89$; Time 3 $\alpha = .90$) from the effort/importance subscale of the Intrinsic Motivation Inventory (McAuley, Duncan, & Tammen, 1989). Responses were given on 1 (strongly disagree) to 7 (strongly agree) Likert-type scale.

Expected achievement. At each time point, participants' were asked to report their expected grades (between 0 and 20) at the end of the fall semester on a 0 to 20 scale corresponding to the way class grades were provided in this University.

Observed achievement. At the end of the semester, grade transcripts were received from the administrative office of the University. The French grading system uses grades varying between 0 and 20 for each course.

Analyses

Model Estimation and Missing Data

All models estimated in the present study were estimated using Mplus 7.4 (Muthén & Muthén, 2015) using the robust Maximum Likelihood (MLR) estimator, which 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. These models were estimated in conjunction with Full Information Maximum Likelihood (FIML; Enders, 2010) procedures to account for the relatively limited amount of missing responses present at the item level for participants who completed each specific time point (0% to 2.5%). 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 listwise deletion strategy focusing only on those having answered all, or a subset, of the time waves (Enders, 2010; Graham, 2009). In total, 461 students provided a total of 1,237 time-specific ratings (M = 2.68 time-specific ratings per student), with 345 (74.8%) students completing all three time-points, 86 (18.7%) completing 2 time-points, and 30 (6.5%) completing a single time-point. FIML has comparable efficacy to multiple imputation, while being more efficient (Enders, 2010; Graham, 2009; Jeličič, Phelps, & Lerner, 2009; Larsen, 2011).

Preliminary Analyses

Rather than using scale scores (the mean or sum of the items) to estimate the trajectories and their relations with predictors and outcomes, factor scores (estimated in standardized units with $M = 0$, $SD = 1$) from preliminary measurement models were used as inputs for the analyses. The measurement models for the need satisfaction variables were estimated using bifactor confirmatory factor analyses (Holzinger & Swineford, 1937; Reise, 2012). This decision is based on recent evidence showing that bifactor measurement models are naturally suited to the representation of need satisfaction (Sánchez-Oliva et al., 2017) based on SDT (Deci & Ryan, 2000). Sánchez-Oliva et al. (2017) showed that a bifactor representation provided a way to obtain a direct and precise estimate of the global level of need satisfaction presented by participants across all three specific needs, which is used in this study to estimate participants' growth trajectories. To ensure comparability in the measures across time waves, these factors scores were saved from longitudinally invariant measurement models (Millsap, 2011). Although factor scores do not explicitly control for measurement errors the way latent variables do, they do provide a partial control for measurement errors (Skrondal & Laake, 2001) by giving more weight to more reliable items (i.e., items characterized by higher factor loadings and lower uniquenesses). Furthermore, factors scores are able to preserve the nature of the underlying measurement structure (e.g., invariance) better than scale scores (for additional discussions of factor scores, see Morin, Boudrias, Marsh, Madore, & Desrumaux, 2016; Morin, Meyer, Creusier, & Biétry, 2016). Details on these measurement models and their longitudinal invariance are reported in the online supplements. The correlations between all variables used in the main analyses (i.e., the factor scores saved from these final measurement models and single item measures) are reported in Table 1.

Growth Mixture Analyses (GMA)

In this study, linear GMA models[1] with one to eight latent trajectories of global need satisfaction were estimated and compared. GMA are built from latent curve models (Bollen & Curran, 2006), and aim to identify subgroups of participants following distinct longitudinal trajectories (Grimm et al., 2016; Morin, Maïano et al., 2011). Linear GMA summarize a series of repeated measures by the estimation of random intercepts and slope factors reflecting, respectively, the initial level of the growth trajectories and the rate of change over time. In the present study, time codes on the slope factors were set to 0 at Time 1 (to allow the intercept factors to reflect global need satisfaction levels at the initial time point), 1 at Time 2, and 2 at Time 3 to reflect the presence of three equally spaced measurement points. To avoid converging on a local maxima, all of these models were estimated using 10,000 random sets of start values, 1000 iterations, and 500 solutions for final stage optimization (Hipp & Bauer, 2006). A more technical presentation of GMA is provided in the online supplements.

Current recommendations from the statistical literature are that GMA should, whenever possible, be estimated while allowing all models parameters (intercept and slope means, intercept and slope variances and covariances, and time-specific residuals) to be freely estimated in all profiles (Diallo et al., 2016; Morin, Maïano et al., 2011). However, this recommendation comes with the recognition that

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[1] The decision to rely on linear models is based on the initial comparison of linear versus multibase latent curve models, which revealed no evidence of non-linearity. Multibase models provide a way to test for the presence of non-linearity in models including three time points through the free estimation of the second loading on the slope factor (i.e., time code). In addition, Metha and West (2000) showed that relying on uniform time codes when participants differ in age is proper when: (1) the regression of the intercept of a latent curve model on age is equal to the slope, and (2) the regression of the slope on age is equal to zero. In this study, participants are close in age, of the same grade level, and results supported both conditions, as shown by non-significant χ^2difference tests (condition 1: $\Delta\chi^2 = 0.101$, $df = 1$; Condition 2: $\Delta\chi^2 = 0.000$, $df = 1$; Conditions 1 and 2: $\Delta\chi^2 = 0.122$, $df = 2$).

this free estimation of all model parameters is not always possible due to the tendency of these more complex models to converge on improper solutions, or not to converge at all (Diallo et al., 2016), which is typically taken to reflect overparameterization and the need to rely on simpler models (Chen, Bollen, Paxton, Curran, & Kirby, 2001). This was the case in the present study. In such situations, the recommendation is to implement equality constraints across profiles on model parameters to achieve a more parsimonious representation (Diallo et al., 2016). Here, we relied on the Mplus default parameterization which sets the latent variance-covariance matrix to be invariant across latent profiles. We also allowed the time-specific residuals to be freely estimated in each classes, but homoscedastic across time points (Li & Hser, 2011; Enders & Tofighi, 2008). This specification of the residuals is consistent with a multilevel operationalization of growth models, and results in GMA which are assumed to provide an equally efficient representation of the all repeated measures, while allowing this explanatory power to differ across latent profiles.

Controls. Tests aiming to determine whether demographic control variables needed to be retained for the subsequent analyses were conducted.

Outcomes of Profile Membership. Time-varying outcomes levels measured at each time point (positive affect, negative affect, effort, expected achievement, and observed achievement) were contrasted across profiles using a model-based approach proposed by Lanza, Tan, and Bray (2013) and implemented through the Auxiliary (DCON) function (Asparouhov & Muthén, 2014).

Results

Unconditional Models

The results from the estimation of the alternative GMA solutions converged on a three-profile solution. The rationale supporting this solution is reported in the online supplements. This solution is graphically presented in Figure 1, and specific parameter estimates are reported in Table S5 of the online supplements. It is important to keep in mind that these trajectories were estimated on the basis of invariant factor scores with a mean of 0 and a standard deviation of 1 obtained on the global need satisfaction factor in the context of preliminary analyses reported in the online supplements. This means that 0 corresponds to the average level of global need satisfaction, and that deviations from this mean are expressed in standard deviation units.

In comparing the profiles, it is first informative to note that Profiles 1 and 2 are characterized by an initial level (i.e., the mean on the intercept factor) that are slightly higher than average by about .2 SD, and virtually identical. However, clear differentiations occur between these two profiles as the semester evolves leading to a difference of about .50 SD in global need satisfaction levels at the end of the semester. Profile 1 characterizes 11.50% of students with initially moderate levels of global need satisfaction, which are characterized by a slight decreasing tendency over time (corresponding to -.103 *SD* units per time point). In contrast, Profile 2 characterizes 61.39% of the students presenting initially moderate levels of global need satisfaction, which are characterized by a slight increasing tendency over time (.106 *SD* units per time point). Finally, Profile 3 is the most concerning, and characterizes 27.11% of students presenting an initially low levels of global need satisfaction coupled with a marked decreasing trajectory (-.305 *SD* units per year).

Statistics regarding the classification accuracy of the students into their most likely profile are reported in Table S6 of the online supplements, and indicate a relatively high level of classification accuracy for members of all three profiles, ranging from 80.2% for the *Low-Decreasing* profile (3), to 87.8% for members of the *Moderate-Decreasing* profile (1), and to 90.4% for members of the *Moderate-Increasing* profile (2), consistent with a relatively high entropy value (.717)[2].

Controls

Once the optimal number of profiles has been selected, we conducted a series of tests aiming to determine whether demographic controls assessed at Time 1 (sex, prior level of achievement, grade repetition) needed to be retained for subsequent analyses as time-invariant predictors (TIP). These controlled variables were included using the start values from the final retained unconditional GMA model (Diallo, Morin, & Lu, 2017; Morin, Meyer et al., 2016) and a series of alternative models were contrasted, following recommendations from Diallo et al. (2017) and previously implemented in applied

[2] The entropy indicates the precision with which the cases are classified into the various profiles. Higher entropy values (e.g., above .700) indicating a greater level of accuracy, whereas lower levels (e.g., under .500) indicate poorer levels of accuracy.

research by Morin and colleagues (Morin, Maïano et al., 2011; 2013; Morin, Rodriguez, Fallu, Maïano, & Janosz, 2012). First, a null effects model was estimated in which the effects of the controls on the probability of membership in all profiles, as well as on the growth factors, were constrained to be zero. Second, a first alternative model was estimated in which the controls were allowed to predict profile membership through a multinomial logistic regression. Tests were then conducted on additional models in which controls were also allowed to influence within-profile variation in the intercepts and slopes of the trajectories (via a multiple regression equation), and in which these effects were allowed to vary from one profile to another. Results from models incorporating controls are reported in the bottom section of Table S4 and support the null effects model. Examination of the detailed parameters estimates from these alternative models supports this conclusion regarding the lack of meaningful associations between the controls and the profiles, and the decision to exclude controls from further analyses.

Time-Varying Outcomes

Results from the comparison of the time-specific outcomes across profiles are reported in Table 2. These results reveal that the three profiles are very clearly differentiated on the outcomes considered, and that the pattern of associations between profiles and outcomes differs across outcome. Levels of negative affect are undistinguishable between the *Moderate-Decreasing* and *Moderate-Increasing* profiles, although both of these profiles present lower levels of negative affect than the *Low-Decreasing* profile. However, levels of positive affect are highest among the *Moderate-Increasing* profile, followed by the *Moderate-Decreasing* profile, and finally by the *Low-Decreasing* profile, with all pairwise comparisons being significant. Furthermore, levels of effort are undistinguishable between the *Moderate-Decreasing* and *Low-Decreasing* profiles, although both of these profiles present lower levels of effort than the *Moderate-Increasing* profile. Finally, it is interesting to note that expected achievement levels generally follow the same pattern of differences than observed achievement at the end of the semester, at least at the first and last time points where these outcomes are lower among the *Low-Decreasing* profile than among the other two profiles. It is however interesting to note that in the middle of the semester, students corresponding to the *Moderate-Decreasing* profile also report higher expected achievement levels than members of the *Low-Decreasing* profile.

With the sole exception of the aforementioned difference in expected achievement levels observed in the middle of the semester, most of these differences are stable over time. Taken together, these results suggest that, when compared to the other profiles, members of the *Moderate-Increasing* profile present higher levels of positive affect and invest more effort in their studies. In comparison to this *Moderate-Increasing* profile, members of the *Low-Decreasing* profile display less positive affect and more negative affect, invest less effort in their studies and, possibly as a result of these lower effort levels, present lower levels of achievement. Finally, members of the *Moderate-Decreasing* profile also present lower levels of positive affect and invest less effort in their studies, but display comparable levels of negative affect and achievement as members of the *Moderate-Increasing* profile.

Discussion

Prior studies have shown that the satisfaction of the three psychological needs for autonomy, competence, and relatedness tended to be associated with more positive academic outcomes (e.g. Cordeiro et al., 2016; Wang et al., 2017). However, in the educational area, prior research has largely ignored individual developmental trajectories (Ratelle & Duchesne, 2014). To better understand how need satisfaction evolves over time for specific subgroups of students, the present study was designed to inform how the need satisfaction trajectories of distinct profiles of University students evolved over the course of a semester and related to various educational outcomes (i.e., positive and negative affect, effort, expected achievement, and objective achievement).

Need Satisfaction Trajectories

Recently, Ratelle and Duchesne (2014) identified longitudinal trajectories of students' need satisfaction and confirmed the presence of substantial developmental heterogeneity (five distinct profiles for each specific need). However, they relied on a restricted form of GMA (i.e., latent class growth analysis) in which it was assumed that all students would correspond exactly to the average longitudinal trajectory identified in their own profile, and treated each need separately without considering evolution in students' global levels of need satisfaction. In the present study, we relied on a more flexible GMA approach and identified three distinct profiles of students' global need satisfaction: (1) Students with initially moderate levels of global need satisfaction, which are characterized by a slight decreasing tendency (*Moderate-Decreasing* profile); (2) students with initially moderate levels of global need satisfaction, which are characterized by a slight increasing tendency (*Moderate-Increasing* profile); and (3) students with initially low levels of global need satisfaction coupled with a marked decreasing trajectory (*Low-Decreasing* profile). Students' need satisfaction thus fluctuated in a heterogeneous fashion over the course of a University semester. Interestingly, our results also supported the idea that need satisfaction is at least partly situational in nature and thus fluctuates over time (Cheon et al., 2016; Cox et al., 2008; Marchand & Skinner, 2007).

These findings are the first to document longitudinal trajectories of University students' global need satisfaction over the course of a semester. Our participants were first-year undergraduate psychology students who have recently undergone the transition from high school to University, with the accompanying changes in teachers and learning structure, as well as classroom composition that changes over class. Some might even experience more than one simultaneous life transition when, for instance, they had to move to another neighborhood or city to enter University. More generally, the freshman year is known to represent a challenging life transition accompanied by major changes in students' educational and social environments, incorporating new and unfamiliar academic tasks and learning situations, and evolving social networks (De Clercq, Galand, & Frenay, 2017; Perry, Hladkyj, Pekrun, & Pelletier, 2001). These changes might influence students' psychological need satisfaction trajectories and explain why groups of students reported changing need satisfaction trajectories over the course of their first University semester. As such, the specific context of the freshman year might have generated slightly more elevated levels of instability in need satisfaction trajectories than what would be observed across more stable life contexts.

Future longitudinal research would be needed to more clearly address this possibility, and to better document the time-invariant (personal characteristics) and time-varying (associated with the academic and social life contexts) characteristics that predict membership into these various trajectory profiles. Interestingly, our results showed that these trajectory profiles were independent from students' demographic characteristics (sex, prior level of achievement, grade repetition), suggesting that changing life contexts might be particularly relevant to consider. For instance, in line with recent studies (Taylor & Lonsdale, 2010) showing that teachers' behaviors relate to students' levels of need satisfaction, these additional investigations might look at the impact of University teachers' autonomy-supportive and controlling behaviors. Similarly, following from studies supporting the key role of the social context in supporting students' need satisfaction in the academic area (Lu, Walsh, White, & Shield, 2017), it might be interesting to look at the role of changes in students' lives circumstances (moving away from family, integrating new peer groups, etc.) in predicting profile membership.

Outcomes of the Need Satisfaction Trajectories

Still, our findings clearly support the practical importance of the identified need satisfaction trajectories in the prediction of academic outcomes, showing well-differentiated associations between profile membership and the various outcomes considered in this study. First, the *Moderate-Increasing* profile was associated with the highest levels of positive affect and effort. Second, members of the *Low-Decreasing* profile tended to display less positive affect and more negative affect, invest less effort in their studies, and present lower levels of achievement than those from the *Moderate-Increasing* profile. Finally, the *Moderate-Decreasing* profile was associated with lower levels of positive affect and effort than the *Moderate-Increasing* profile, while these two profiles could not be distinguished from one another on negative affect and achievement. These results support SDT's propositions (Deci & Ryan, 2000) in demonstrating the positive effects of global levels of need satisfaction. They are also well aligned with those from prior studies conducted in the educational area showing that higher levels of global or specific need satisfaction were particularly beneficial in terms of social, academic, and personal–emotional adjustment (Jang et al., 2009; Ratelle & Duchesne, 2014).

It was interesting to note that the *Moderate-Increasing* profile tended to be associated with more positive outcomes, at least in terms of positive affect and effort, than the *Moderate-Decreasing* one. Furthermore, our findings demonstrate that students with comparable initial levels of need satisfaction ended up displaying similar levels of negative affect and achievement irrespective of whether their degree of satisfaction increased or decreased over the course of the semester. Future studies would be needed to verify the possibility that the negative effects of decreases in need satisfaction in terms of achievement and negative affect can be temporally lagged and only emerge in the following semester. Clearly, the adoption of a longer term longitudinal perspective would be useful in helping to unpack the mechanisms at play in these associations.

These results also show that pattern of associations between need satisfaction trajectories and outcomes differs as a function of the type of outcome, and are well aligned with those from Sheldon and Filak (2008) who similarly found that the effects of need satisfaction on performance and positive affect were not comparable. In this study, we focused on students' achievement (expected performance and objective grades), emotional engagement (positive and negative affect), and behavioral engagement (effort). To confirm the differential effects of need satisfaction trajectories on a wider range of educational outcomes, we encourage researchers to conduct additional research also considering markers of cognitive engagement, such as students' critical thinking. Indeed, mounting research evidence supports the role of students' engagement as a key determinant of academic success that is easier to target in intervention than achievement itself (e.g., van Rooij, Jansen, & van de Grift, 2017). Future research may also consider other outcomes representing, for instance, students' emotional (e.g., boredom), cognitive (e.g., disorganization), and behavioral (e.g., dropout intentions) disengagement from their studies. The importance of boredom and disorganization stems from research identifying these dimensions as negatively related to many desirable academic outcomes, including achievement (e.g., Pekrun, Hall, Goetz, & Perry, 2014). Moreover, dropout intentions are strongly related to school dropout behavior, which is in turn associated with numerous negative life outcomes such as decreased employment rates, and increased criminal activities (Bjerk, 2012).

Limitations and Directions for Future Research

The present study has some limitations. First, we relied on self-report measures, with the exception of observed achievement, and such measures can be impacted by social desirability and self-report biases. We thus encourage researchers to conduct additional research using more objective dropout data as well as informant-reported (e.g., teacher) measures of student engagement as ultimate outcomes. Second, although need satisfaction trajectory profiles were not found to be influenced by sex, prior levels of achievement in college, and grade repetition, it would be interesting for future research to consider a more diversified set of determinants of students' need satisfaction profiles. For instance, it would be interesting to determine the role of social agents within (e.g., teachers, friends) and outside (e.g., parents) the University in explaining the students' need satisfaction trajectories (Ratelle & Duchesne, 2014). Likewise, it would also be interesting to look more carefully at the possible impact of the course curriculum, learning context, and even pedagogical approach used in a greater diversity of University programs and country so as to be able to identify possible controllable levers for the improvement of students' need satisfaction. Third, the need satisfaction trajectories reported in the present study were observed in first-year undergraduate psychology students enrolled in a French University. Future research should examine whether the same trajectories emerge in samples from different academic levels (primary, secondary, graduate), countries, and cultural backgrounds.

Fourth, it is important to keep in mind that the current results are intimately related to the time lag that was considered in this study: One university semester (10 weeks). We found evidence that need satisfaction was quite stable over a period of five ($r = .894$ to $.889$) to ten ($r = .691$) weeks, which is in line with estimates reported in previous studies (e.g., Cheon et al., 2016; Marchand & Skinner, 2007), and supports the idea that studying change in need satisfaction requires relatively long time lags. Still, longitudinal research always needs to be interpreted in relation to a specific time frame (Cole & Maxwell, 2003). Thus, relying on a much shorter time frame (e.g., daily diary study) may have allowed us to detect finer associations occurring at the state level of the constructs being studied, whereas relying on longer time frames might have revealed relations occurring at a more fundamental trait level. Conversely, these alternative time frames might have hidden the currently observed relations. Ultimately, longitudinal evidence remains stronger in terms of clarifying the directionality of associations than cross-sectional research, but needs to be built incrementally from an accumulation of studies exploring alternative time frames. Finally, due to limitations posed by the sample size, the current study solely focused on students' trajectories of global need satisfaction, without simultaneously considering their more specific trajectories of competence, relatedness, and autonomy need satisfaction. Despite recent evidence providing tentative support to the key role played by global need satisfaction (Brunet et al., 2016; Sánchez-Oliva et al., 2017), it remains critical for future studies to more closely consider students more specific need satisfaction trajectories (e.g., Ratelle & Duchesne, 2014) and how they related to key developmental and educational outcomes.

Practical Implications

From a practical perspective, our findings suggest that teachers should be particularly attentive to students displaying low and decreasing levels of global need satisfaction (*Low-Decreasing* profile) as these appear to be at risk for a variety of educational difficulties. Such a trajectory might be identified by using a short version of a scale assessing psychological need satisfaction at the beginning of each semester for example, which could be presented as a request for feedback from the teacher. This way, teachers could easily become aware of students, or groups of students, displaying low levels of need satisfaction and attempt to intervene before the emergence of undesirable outcomes. For example, teacher-focused interventions and support systems might be made available for teachers in order to help them increase students' levels of need satisfaction over time (Cheon et al., 2016). In the existing literature, numerous studies have shown that autonomy-supportive teaching behaviors were positively related to psychological need satisfaction (Jang et al., 2009; Sheldon & Filak, 2008). Thus, having teachers displaying higher levels of autonomy-supportive behaviors could be associated with a greater likelihood of membership into the most desirable profile (*Moderate-Increasing*). Incorporating autonomy-supportive structure into classes may thus be an important pedagogical consideration. Jang, Reeve, and Halusic (2016) recently tested the educational utility of "teaching in students' preferred ways" as a new autonomy-supportive teaching strategy. Results revealed that students who received a preferred way of teaching (i.e., teachers take their students' perspective and adjust how they deliver a lesson plan so that it aligns with students' preferred ways of teaching) perceived their teacher as more autonomy-supportive and had more positive outcomes. Thus, "teaching in students' preferred ways" represents a way of teaching that may increase students' psychological need satisfaction.

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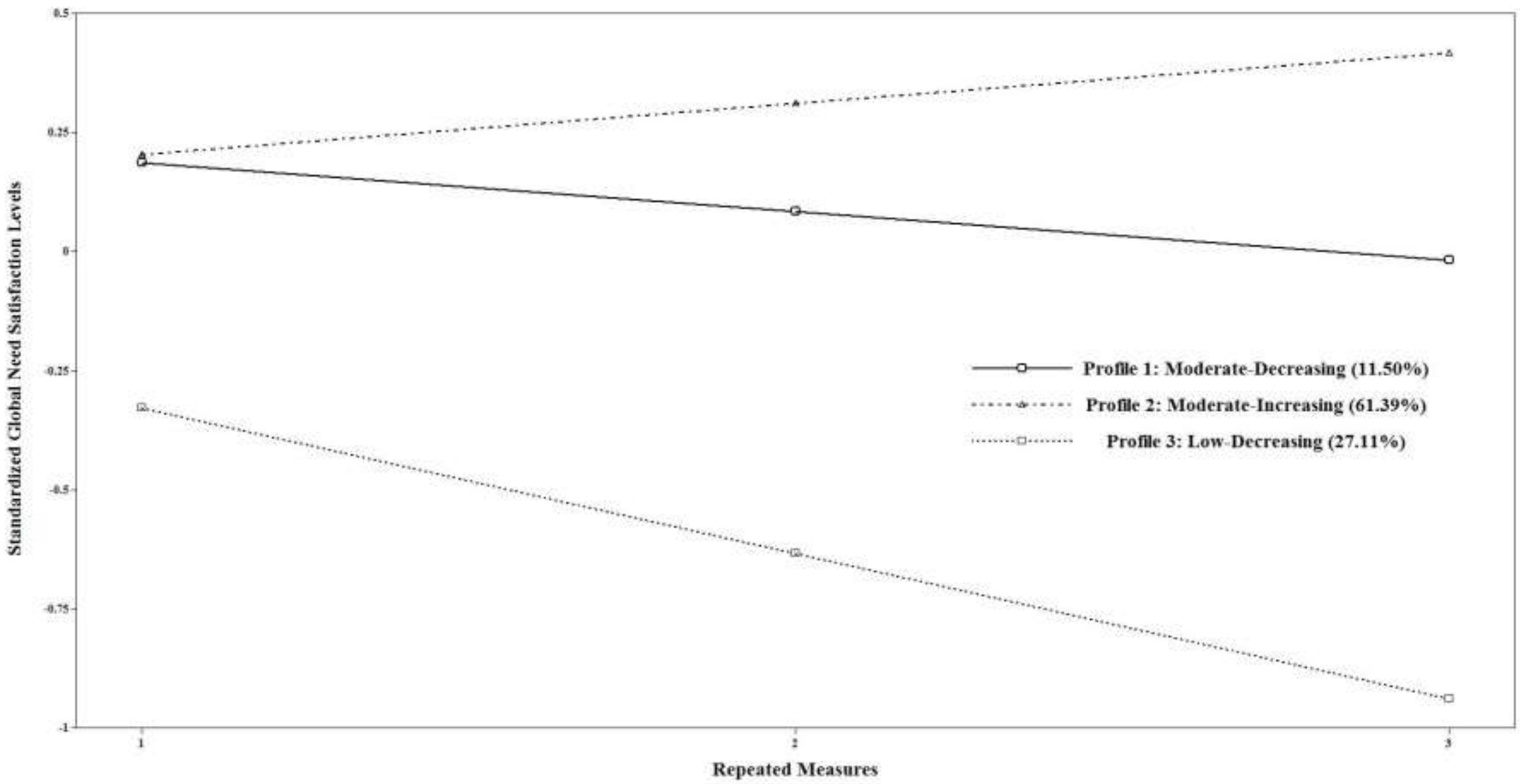

Figure 1. Estimated Growth Trajectories for the Three Need Satisfaction Profiles.

Note. Trajectories are estimated on the basis of invariant factor scores with a mean of 0 and a standard deviation of 1 obtained on the global need satisfaction factor in the context of preliminary analyses reported in the online supplements.

Table 1

Correlations between Variables Used in the Present Study

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Age	-																			
2. Sex	.148**	-																		
3. Repeating College Years	.611**	.058	-																	
4. College Achievement	-.199**	-.012	-.171**	-																
5. Need Satisfaction (T1)	-.025	.015	-.060	.036	-															
6. Positive affect (T1)	.009	-.141**	-.049	.089	.457**	-														
7. Negative affect (T1)	-.029	-.158**	-.008	.092	-.195**	.057	-													
8. Effort (T1)	.045	-.216**	.017	.006	.332**	.781**	.087	-												
9. Expected Achievement (T1)	-.041	.159**	-.117*	.328**	.157**	.285**	-.059	.136**	-											
10. Need Satisfaction (T2)	-.031	.020	-.066	.077	.894**	.439**	-.172**	.315**	.152**	-										
11. Positive affect (T2)	.008	-.079	-.070	.125**	.488**	.859**	-.029	.649**	.256**	.527**	-									
12. Negative affect (T2)	-.042	-.193**	-.070	.094	-.159**	.166**	.780**	.157**	-.029	-.177**	.026	-								
13. Effort (T2)	.060	-.183**	-.031	.074	.319**	.660**	-.011	.769**	.163**	.356**	.787**	.056	-							
14. Expected Achievement (T2)	-.110*	.106*	-.227**	.315**	.305**	.305**	-.124*	.146**	.685**	.338**	.369**	-.116*	.286**	-						
15. Need Satisfaction (T3)	-.021	.027	-.042	.063	.691**	.364**	-.164**	.254**	.143**	.889**	.460**	-.170**	.313**	.304**	-					
16. Positive affect (T3)	.029	-.067	-.037	.124**	.462**	.847**	-.055	.640**	.271**	.513**	.938**	-.033	.755**	.365**	.483**	-				
17. Negative affect (T3)	-.062	-.220**	-.064	.104*	-.150**	.138**	.742**	.119*	-.035	-.166**	-.007	.895**	.039	-.136**	-.161**	-.017	-			
18. Effort (T2)	.072	-.156**	-.028	.088	.307**	.659**	.051	.737**	.152**	.354**	.773**	.073	.912**	.267**	.341**	.793**	.086	-		
19. Expected Achievement (T3)	-.065	.167**	-.136**	.271**	.275**	.331**	-.017	.120*	.723**	.307**	.376**	.004	.237**	.848**	.314**	.398**	-.012	.261**	-	
20. Observed Achievement	-.155**	-.035	-.230**	.511**	.120*	.280**	.139**	.130**	.389**	.155**	.287**	.176**	.225**	.423**	.135**	.273**	.173**	.249**	.502**	-

Note. * $p < .05$; ** $p < .01$; T1: Time 1; T2: Time 2; T3: Time 3; for need satisfaction, positive and negative affect, and effort, scores are factor scores from preliminary models.

Table 2

Time-Varying Associations between Profile Membership and Outcomes

	Profile 1 (Moderate-Decreasing)	Profile 2 (Moderate-Increasing)	Profile 3 (Low-Decreasing)	Summary of Significant Differences
*Negative Affect**				
Time 1	-.328 [-.563; -.093]	-.120 [-.220; -.020]	.145 [-.008; .298]	1 = 2 < 3
Time 2	-.182 [-.449; .085]	-.015 [-.123; .093]	.353 [.182; .524]	1 = 2 < 3
Time 3	-.147 [-.410; .116]	-.019 [-.125; .087]	.326 [.161; .491]	1 = 2 < 3
*Positive Affect**				
Time 1	-.090 [-.327; .147]	.695 [.617; .773]	-.347 [-.449; -.245]	3 < 1 < 2
Time 2	-.118 [-.324; .088]	.596 [.527; .665]	-.762 [-.870; -.654]	3 < 1 < 2
Time 3	-.172 [-.417; .073]	.493 [.415; .571]	-.672 [-.784; -.560]	3 < 1 < 2
*Effort**				
Time 1	-.271 [-.565; .023]	.312 [.218; .406]	-.070 [-.215; .075]	1 = 3 < 2
Time 2	-.135 [-.431; .161]	.189 [.085; .293]	-.425 [-.588; -.262]	1 = 3 < 2
Time 3	-.278 [-.576; .020]	.207 [.107; .307]	-.583 [-.736; -.430]	1 = 3 < 2
Expected Performance				
Time 1	11.259 [10.885; 11.633]	11.422 [11.267; 11.577]	11.086 [10.874; 11.298]	1 = 2; 1 = 3; 2 > 3
Time 2	10.919 [10.315; 11.523]	11.621 [11.474; 11.768]	10.100 [9.851; 10.349]	3 < 1 < 2
Time 3	11.106 [10.547; 11.665]	11.527 [11.355; 11.699]	10.583 [10.367; 10.799]	1 = 2; 1 = 3; 2 > 3
Objective Grades				
Time 3	9.766 [8.798; 10.734]	10.698 [10.388; 11.008]	9.798 [9.357; 10.239]	1 = 2; 1 = 3; 2 > 3

Note. * Variables identified by an asterisk are factor scores saved in standardized units from preliminary measurement models.

Online Supplemental Materials for:

University Students' Need Satisfaction Trajectories: A Growth Mixture Analysis

Preliminary Measurement Models

Due to the complexity of the longitudinal models underlying all constructs assessed in the present study, these preliminary analyses were conducted separately for the need satisfaction variables and the multi-items outcomes measures (positive affect, negative affect, and effort). For the need satisfaction measure, a bifactor confirmatory factor analytic (CFA) model (e.g., Holzinger & Swineford, 1937; Reise, 2012) including one global factor (G-factor: global need satisfaction) and three specific orthogonal factors (S-factors: autonomy, competence, and relatedness) was estimated at each time point following Sánchez-Oliva et al.'s (2017) recommendations for the operationalization of need satisfaction measures based on self-determination theory (Deci & Ryan, 2000). For the outcomes model, a simple CFA model including three correlated first-order factors (positive affect, negative affect, and effort) was estimated at each time point.

Longitudinal models were directly estimated across all three time waves and included a total of 12 factors ([1 G-factor + 3 S-factors] x 3 time waves) for the need satisfaction measure and 9 factors for the outcome measures (3 factors x 3 time waves). All factors were freely allowed to correlate across time-points. A priori correlated uniquenesses between matching indicators of the factors utilized at the different time-points were included in the longitudinal models to avoid inflated stability estimates (e.g., Marsh, 2007). Before saving the factor scores for our main analyses, we verified that the measurement models operated in the same manner across time waves, through sequential tests of measurement invariance (Millsap, 2011). For the both models, we assessed (1) configural invariance; (2) weak invariance (loadings); (3) strong invariance (loadings and intercepts); (4) strict invariance (loadings, intercepts, and uniquenesses); (5) invariance of the latent variance-covariance matrix (loadings, intercepts, uniquenesses, and latent variances and covariances); and (6) latent means invariance (loadings, intercepts, uniquenesses, latent variances and covariances, and latent means).

Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications (e.g., Marsh, Hau, & Grayson, 2005), we relied on sample-size independent goodness-of-fit indices to describe the fit of the alternative models (Hu & Bentler, 1999): the comparative fit index (CFI), the Tucker-Lewis index (TLI), as well as the root mean square error of approximation (RMSEA) and its 90% confidence interval. Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .09 or .06 for the RMSEA respectively support acceptable and excellent model fit. Like the chi square, chi square difference tests present a known sensitivity to sample size and minor model misspecifications so that recent studies suggest complementing this information with changes in goodness-of-fit-indices (Chen, 2007; Cheung & Rensvold, 2002) in the context of tests of measurement invariance. A ΔCFI/TLI of .010 or less and a ΔRMSEA of .015 or less between a more restricted model and the previous one supports the invariance hypothesis.

The goodness-of-fit results from all models are reported in Table S1. These results support the adequacy of the a priori bifactor-CFA models underlying the need satisfaction measures (with all CFI $\geq$ .95, TLI $\geq$ .90, and RMSEA $\leq$ .09). Similarly, the results also support the adequacy of the CFA models underlying the outcomes measures (with all CFI/TLI $\geq$ .90 and RMSEA $\leq$ .09). Despite the fact that the RMSEA values (.081, .081, and .091) appear marginal in the time-specific outcome models, these value reach a fully satisfactory levels in the longitudinal models (RMSEA $\leq$ .06). The tests of measurement invariance conducted on both measurement models support their configural and weak invariance (ΔCFI $\leq$ .010; ΔTLI $\leq$ .010; ΔRMSEA $\leq$ .015; and overlapping RMSEA confidence intervals), but not their strong measurement invariance (ΔCFI/TLI $\geq$ .010). We thus pursued a model of partial strong invariance, in which the equality constraints across time points had to be relaxed on a single need satisfaction item, and on one outcome item at a single time point (one per factor). From this model of partial strong invariance, subsequent steps supported the invariance of the uniquenesses, latent variances, covariances, and latent means for the outcomes model. However, the strict invariance of the items uniquenesses was also not supported for the need satisfaction measure, leading us to a model of partial strict invariance in which equality constraints had to be relaxed on a total of 4 items across time points. From this model of partial strict invariance, subsequent steps supported the invariance of the latent variances, covariances, and latent means for the need satisfaction model. These results globally show that the measurement models underlying our constructs can be considered to be roughly equivalent across time points.

To ensure that the time-specific measures could be considered to be fully comparable across time points, the factor scores used in main analyses were saved from the most invariant models from the previous sequence (Need satisfaction: Latent mean invariance with partial strong and partial strict invariance; Outcomes: Latent mean invariance with partial strong invariance). Although only strict measurement invariance is required to ensure that measurement of the constructs remains equivalent across time waves for models based on factor scores (e.g., Millsap, 2011), there are advantages to saving factors scores from a model of complete measurement invariance, which provides time specific measures which are directly comparable based on a mean of 0 and a standard deviation of 1 at all time waves. The observation of latent mean invariance across time point for the need satisfaction measure indicates that, on the average, the sample is neither characterized by growth or decline in levels of global need satisfaction over time. However, observed levels of between-person variability in latent means and individual trajectories are consistent with the presence of substantial inter-individual variability in growth trajectories, supporting the use of methods specifically designed to model this variability (i.e., latent curve models) and specific growth profiles (i.e., growth mixture analyses). Figure S1 graphically represents observed individual trajectories.

The final invariant parameter estimates from these measurement models are reported in Tables S2 (need satisfaction) and S3 (outcomes). The outcome model resulted in factors that were well-defined through high factor loadings (λ = .400 to .874), resulting in fully acceptable model-based composite reliability coefficients (ω = .770 to .891; McDonald, 1970[3]). Although some of the need satisfaction S-factors were not well-defined, the global need satisfaction factor used in the estimation of the trajectories that form the core of this study were fully in line with Sánchez-Oliva et al.'s (2017) results, supporting its interpretation as a reliable (ω = .798 to .840) estimate of students' global levels of need satisfaction.

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[3] Composite reliability coefficients associated with each of the a priori factors are calculated from the model standardized parameters using McDonald (1970) omega (ω) coefficient:

$$\omega = \frac{(\sum|\lambda_i|)^2}{[(\sum|\lambda_i|)^2 + \sum\delta_i]}$$

where $|\lambda_i|$ are the standardized factor loadings associated with a factor in absolute values, and δi, the item uniquenesses. The numerator, were the factor loadings are summed, and then squared, reflects the proportion of the variance in indicators that reflect true score variance, whereas the denominator reflects total amount of variance in the items including both true score variance and random measurement errors (reflects by the sum of the items uniquenesses associated with a factor).

A bifactor exploratory structural equation modelling representation of the Basic Psychological Needs at Work Scale. *Journal of Vocational Behavior, 98, 173-187.*

A More Technical Presentation of Growth Mixture Analyses (GMA)

GMA aim to represent longitudinal heterogeneity by the identification of subgroups (i.e., profiles) of participants following distinct trajectories. A linear GMA for the repeated measure y_{it} for individual i at time t is estimated within k distinct levels (k = 1, 2, …, K) of an unobserved latent categorical variable c representing the profiles, with each individual having a probability (p) of membership in the k levels of this latent categorical variable.

$$y_{it} = \sum_{k=1}^{K} p_k[\alpha_{iyk} + \beta_{iyk}\lambda_t + \varepsilon_{yitk}] \tag{1}$$

$$\alpha_{iyk} = \mu_{\alpha yk} + \zeta_{\alpha yik} \tag{2}$$

$$\beta_{iyk} = \mu_{\beta yk} + \zeta_{\beta yik} \tag{3}$$

The k subscript indicates that most parameters can be freely estimated across profiles. In this equation, α_{iyk} and β_{iyk} represent the random intercept and random linear slope of the trajectory for individual i in profile k; $\mu_{\alpha yk}$ and $\mu_{\beta yk}$ represent the average intercept and linear slope in profile k, and $\zeta_{\alpha yik}$ and $\zeta_{\beta yik}$ represent the variability of the intercepts and slopes across cases within profiles. ε_{yitk} represents a diagonal matric of time- individual- and class- specific residuals. p_k defines the probability that an individual i belongs to class k with all $p_k \geq 0$ and $\sum_{k=1}^{K} p_k = 1$. The variance parameters ($\zeta_{\alpha yik}, \zeta_{\beta yik}$) have a mean of zero and a Φ_{yk} variance-covariance matrix:

$$\Phi_{yk} = \begin{bmatrix} \psi_{\alpha\alpha yk} & \\ \psi_{\alpha\beta yk} & \psi_{\beta\beta yk} \end{bmatrix} \tag{4}$$

In these models, Time is represented by λ_t, the factor loading matrix relating the time-specific indicators to the linear slope factor. Time is coded to reflect the passage of time and is thus a function of the intervals between measurement points. Given that the current study relies on three equally spaced located at the start, midpoint, and end of the semester, it is reasonable to set the intercept at Time 1 [$E(\alpha_{iyk}) = \mu_{y1k}$]. Thus, for a linear growth mixture model, time would be coded $\lambda_1 = 0$, $\lambda_2 = 1$, $\lambda_3 = 2$. As noted in the main manuscript, the current study relies on a more constrained estimation of GMA through which the latent variance-covariance matrix was specified as invariant across profiles, whereas the residuals were specified as homoscedastic but freely estimated across profiles, leading to:

$$y_{it} = \sum_{k=1}^{K} p_k[\alpha_{iyk} + \beta_{iyk}\lambda_t + \varepsilon_{yik}] \tag{5}$$

$$\alpha_{iyk} = \mu_{\alpha yk} + \zeta_{\alpha yi} \tag{6}$$

$$\beta_{iyk} = \mu_{\beta yk} + \zeta_{\beta yi} \tag{7}$$

$$\Phi_{y} = \begin{bmatrix} \psi_{\alpha\alpha y} & \\ \psi_{\alpha\beta y} & \psi_{\beta\beta y} \end{bmatrix} \tag{8}$$

Selection of the Final Solutions

Selection of the Final Unconditional Solution

A challenge in GMA is to determine the number of latent trajectory profiles in the data. Although the substantive meaning, theoretical conformity, and statistical adequacy of the solution are three critical elements to consider in this decision (Bauer & Curran, 2003; Marsh, Lüdtke, Trautwein, & Morin, 2009; Muthén, 2003), statistical indices support this decision (McLachlan & Peel, 2000): (i) The Akaïke Information Criterion (AIC), (ii) the Consistent AIC (CAIC), (iii) the Bayesian Information Criterion (BIC), (iv) the sample-size Adjusted BIC (ABIC), (v) the standard and adjusted Lo, Mendel, and Rubin's (2001) Likelihood Ratio Tests (LMR/aLMR, as these tests typically yield the same conclusions, we only report the aLMR); and (vi) the Bootstrap Likelihood Ratio Test (BLRT). A lower value on the AIC, CAIC, BIC, and ABIC suggests a better-fitting model. The aLMR and BLRT compare a *k*-class model with a *k-1*-class model. A significant *p* value indicates that the *k-1*-class model should be rejected in favor of a *k*-class model. Simulation studies indicate that four of these indicators (CAIC, BIC, ABIC, and BLRT) are particularly effective (e.g., Diallo, Morin, & Lu, 2016, 2017; Nylund, Asparouhov, & Muthén, 2007; Peugh & Fan, 2013; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008).

The results from the unconditional GMA models are reported in the top section of Table S4. Examination of the results reveal that the CAIC, BIC, and aLMR all clearly support the 3-profile solution. Despite the fact that the remaining indicators (AIC: 5 profiles; ABIC: 4 profiles; BLRT: 4 profiles) suggest that additional profiles might be present, the decrease in the values of all information criteria reaches a clear plateau when it reaches the 3-profile solution. Examination of the 3-profile solution and of the adjacent 2- and 4-profile solutions support this decision, showing that the 3-profile solution contributes to the addition of an additional meaningful, well-defined, and reasonably large profile, whereas the 4-profile solution only results in the arbitrary division of one of the profiles into two highly similar profiles. The 3-profile solution was thus retained.

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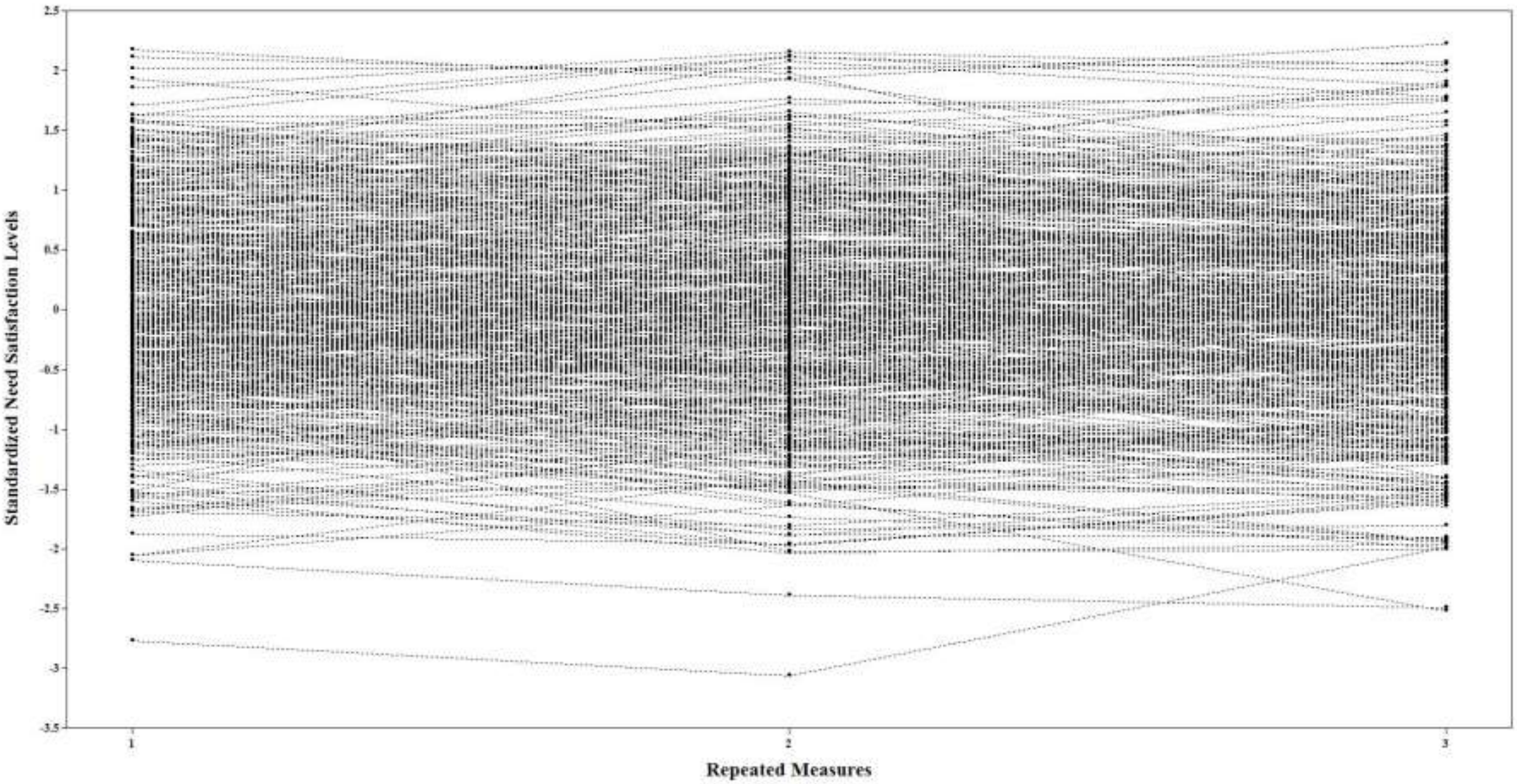

Figure S1. Observed Individual Trajectories of Student's Global Levels of Need Satisfaction.

Note. Global levels of need satisfaction are factor scores with a mean of 0 and a standard deviation of 1.

Table S1

Goodness-of-Fit Statistics for the Estimated Models

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Need Satisfaction: Time 1	38.482 (18)*	.973	.945	.051	[.028; .073]					
Need Satisfaction: Time 2	50.967 (18)*	.969	.937	.066	[.045; .087]					
Need Satisfaction: Time 3	53.737 (18)*	.967	.934	.072	[.050; .094]					
Outcomes: Time 1	161.257 (41)*	.928	.940	.081	[.068; .094]					
Outcomes: Time 2	155.799 (41)*	.943	.923	.081	[.068; .095]					
Outcomes: Time 3	173.206 (41)*	.932	.909	.091	[.078; .106]					
Measurement invariance (Need satisfaction)										
M5. Configural invariance	326.703 (240)*	.980	.971	.028	[.020; .035]	-	-	-	-	-
M6. Weak invariance	360.535 (268)*	.979	.973	.027	[.019; .034]	M5	34.168 (28)	-.001	+.002	-.001
M7. Strong invariance	417.239 (278)*	.969	.960	.033	[.026; .039]	M6	56.536 (10)	-.010	-.013	+.006
M7'. Partial strong invariance	399.269 (276)*	.972	.965	.031	[.024; .037]	M6	38.566 (8)	-.007	-.008	+.004
M8. Strict invariance	519.727 (294)*	.949	.939	.041	[.035; .046]	M7'	120.458 (18)	-.023	-.026	+.010
M8'. Partial strict invariance	436.327 (286)*	.966	.958	.034	[.027; .040]	M7'	37.058 (10)	-.006	-.007	+.003
M9. Var-Cov invariance	456.641 (294)*	.963	.956	.034	[.028; .040]	M8'	20.314 (8)	-.003	-.002	.000
M10. Latent means invariance	484.680 (302)*	.959	.952	.036	[.030; .042]	M9	28.039 (8)	-.004	-.004	+.002
Measurement invariance (Outcomes)										
M11. Configural invariance	727.102 (426)*	.962	.954	.039	[.034; .044]	-	-	-	-	-
M12. Weak invariance	769.663 (442)*	.959	.951	.040	[.035; .044]	M11	42.561 (16)	-.003	-.003	+.001
M13. Strong invariance	880.480 (458)*	.947	.939	.044	[.040; .049]	M12	110.817 (16)	-.012	-.012	+.004
M13'. Partial strong invariance	835.083 (457)*	.953	.946	.042	[.038; .047]	M12	65.420 (15)	-.006	-.005	+.002
M14. Strict invariance	930.766 (479)*	.944	.938	.045	[.041; .049]	M13'	95.683 (22)	-.009	-.008	+.003
M15. Var-Cov invariance	974.852 (491)*	.940	.935	.046	[.042; .050]	M14	44.086 (12)	-.004	-.003	+.001
M16. Latent means invariance	1052.096 (497)*	.931	.927	.049	[.045; .053]	M15	77.244 (6)	-.009	-.008	+.003

Note. * $p < .05$; χ^2: scaled 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; Var-Cov: variance-covariance; CM: comparison model; Δ: change in fit information relative to the CM.

Table S2

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Final Longitudinal Bifactor CFA Solution for the Measure of Need Satisfaction (Latent Means Invariance with Partial Strict and Partial Strong Measurement Invariance)

Items	Time 1 G λ	S-AS λ	S-CS λ	S-RS λ	δ	Time 2 G λ	S-AS λ	S-CS λ	S-RS λ	δ	Time 3 G λ	S-AS λ	S-CS λ	S-RS λ	δ
Autonomy															
Item 1	.555	*.048*			.689	.592	*.051*			.647	.661	*.057*			.560
Item 2	.576	.139			.649	.664	.160			.533	.711	.171			.465
Item 3	.615	*.223*			.573	.615	*.223*			.573	.615	*.223*			.573
ω		.081					.097					.113			
Competence															
Item 1	.405		.524		.562	.432		.559		.346	.455		.588		.337
Item 2	.468		.702		.288	.468		.702		.318	.468		.702		.318
Item 3	.481		.468		.549	.481		.468		.678	.481		.468		.678
ω			.672					.693					.696		
Relatedness															
Item 1	.411			.579	.496	.469			.659	.501	.471			.664	.447
Item 2	.401			.722	.318	.401			.722	.288	.401			.722	.288
Item 3	.439			.360	.678	.439			.360	.549	.439			.360	.549
ω	.798			.649		.824			.691		.840			.706	

Note. B-CFA = bifactor confirmatory factor analyses; G = global factor estimated as part of a bifactor model; S = specific factor estimated as part of a bifactor model; λ: factor loading; δ: item uniqueness; ω: omega coefficient of model-based composite reliability; AS = autonomy satisfaction; CS = competence satisfaction; RS = relatedness satisfaction; non-significant parameters ($p \geq .05$) are marked in italics.

Table S3

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Final Longitudinal First-Order CFA Solution for the Outcome Measures (Latent Means Invariance with Partial Strong Invariance)

	Time 1				Time 2				Time 3			
Items	NA λ	PA λ	EFF λ	δ	NA λ	PA λ	EFF λ	δ	NA λ	PA λ	EFF λ	δ
Negative affect												
Item 1	.400			.840	.400			.840	.400			.840
Item 2	.893			.203	.893			.203	.893			.203
Item 3	.833			.307	.833			.307	.833			.307
ω	.770				.770				.770			
Positive affect												
Item 1		.795		.368		.795		.368		.795		.368
Item 2		.734		.461		.734		.461		.734		.461
Item 3		.644		.585		.644		.585		.644		.585
ω		.770				.770				.770		
Effort												
Item 1			.803	.356			.803	.356			.803	.356
Item 2			.870	.243			.870	.243			.870	.243
Item 3			.874	.237			.874	.237			.874	.237
Item 4			.536	.712			.536	.712			.536	.712
Item 5			.828	.315			.828	.315			.828	.315
ω			.891				.891				.891	
Invariant Factor Correlations	NA	PA	EFF									
Negative affect												
Positive affect	.011											
Effort	.062	.699										

Note. λ: factor loading; δ: item uniqueness; ω: omega coefficient of model-based composite reliability; NA = negative affect; PA = positive affect; EFF = effort.

Table S4

Results from the Growth Mixture Analyses

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Growth Mixture Analyses										
1 Profile	-996.155	6	1.0061	2004.311	2035.111	2029.111	2010.069	Na	Na	Na
2 Profiles	-984.729	10	1.0089	1989.762	2040.792	2030.792	1999.055	.594	.0064	< .001
3 Profiles	-961.053	14	.9249	1950.106	2021.974	2007.974	1963.542	.717	< .001	< .001
4 Profiles	-954.977	18	.9730	1945.955	2038.356	2020.356	1963.229	.682	.1654	.0400
5 Profiles	-949.635	22	.9840	1943.269	2056.204	2034.204	1964.382	.743	.2406	.6667
6 Profiles	-947.976	26	1.0082	1947.951	2081.420	2055.420	1972.903	.762	.7117	.6667
7 Profiles	-946.591	30	1.0261	1953.182	2107.184	2077.184	1981.972	.766	.5249	1.000
8 Profiles	-944.834	34	.9661	1957.669	2132.204	2098.204	1990.298	.794	.6608	1.000
Models with Time-Invariant Predictors										
Null Effects	-890.713	14	.9230	1809.427	1880.352	1866.352	1821.924	.721	Na	Na
Effects on C	-886.960	20	.9923	1813.921	1915.243	1895.243	1831.774	.723	Na	Na
Effects on C, I (inv.)	-885.635	23	.9954	1817.270	1933.791	1910.791	1837.802	.726	Na	Na
Effects on C, I, S (inv.)	-885.450	26	1.0012	1822.899	1954.618	1928.618	1846.109	.726	Na	Na
Effects on C, I (var.)	-882.143	29	.9415	1822.287	1969.204	1940.204	1848.174	.727	Na	Na
Effects on C, I, S (var.)	-880.168	38	1.0260	1836.336	2028.848	1990.848	1870.258	.725	Na	Na

Note. LL: model loglikelihood; #fp: number of free parameters; scaling: scaling correction factor associated with robust maximum likelihood estimates; AIC: Akaïke information criteria; CAIC: constant AIC; BIC: Bayesian information criteria; ABIC: sample size adjusted BIC; aLMR: adjusted Lo-Mendel-Rubin likelihood ratio test; BLRT: bootstrap likelihood ratio test; Na: Not applicable; C: Profile membership; I: Intercept factor; S: Slope factor; inv.: predictions constrained to invariance across profiles; var.: predictions freely estimated across profiles.

Table S5

Parameters Estimates from the final Unconditional Growth Mixture Analysis Model

Parameter	Profile 1 (Moderate-Decreasing) Estimate (t)	Profile 2 (Moderate-Increasing) Estimate (t)	Profile 3 (Low-Decreasing) Estimate (t)
Intercept Mean	.186 (1.235)	.204 (3.101)**	-.329 (-3.575)**
Slope Mean	-.103 (-2.270)*	.106 (5.610)**	-.305 (-7.414)**
Intercept Variability ($SD = \sqrt{\sigma}$)	.791 (13.819)**	.791 (13.819)**	.791 (13.819)**
Slope Variability ($SD = \sqrt{\sigma}$)	.237 (8.566)**	.237 (8.566)**	.237 (8.566)**
Intercept-Slope Correlation	-.611 (-10.867)**	-.611 (-10.867)**	-.611 (-10.867)**
$SD(\varepsilon_{yi})$	.000 (4.214)**	.184 (12.395)**	.228 (8.074)**

Note. t = Estimate / standard error of the estimate (t value are computed from original variance estimate and not from their square roots); SD(ε_{yi}) = Standard deviations of the time-specific residuals; We present the square roots of the estimates of variability (trajectory factors, time-specific residuals) so that these results can be interpreted in the same units as the constructs used in these models (here, factor scores saved in standardized units from preliminary measurement models); * $p \leq .05$; ** $p \leq .01$

Table S6

Classification Accuracy: Classification Probability for Most Likely Profile Membership (Column) as a Function of the Profile Membership (Row)

	Profile 1 (Moderate-Decreasing)	Profile 2 (Moderate-Increasing)	Profile 3 (Low-Decreasing)
Profile 1 (Moderate-Decreasing)	.878	.090	.032
Profile 2 (Moderate-Increasing)	.042	.904	.054
Profile 3 (Low-Decreasing)	.033	.164	.802