Students' Need Satisfaction Profiles: Similarity and Change over the Course of a University Semester

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Abstract

Self-determination theory positions the satisfaction of students' needs for autonomy, competence, and relatedness as important determinants of various educational outcomes. In this study, we identify subpopulations of students characterized by distinct configurations of need satisfaction in the educational context, and assess the extent to which the nature of these configurations, and students' individual profiles, remain stable over the course of a university semester. We also examine the role of perfectionism in the prediction of profile membership, and how these profiles relate to a variety of educational outcomes. A total of 521 first-year undergraduate university students completed our measures at the beginning and end of a university semester. We identified five need satisfaction profiles, which remained unchanged over the course of the study. Students characterized by higher levels of self-oriented perfectionism were more likely to be a member of a profile characterized by high levels of relatedness and global needs satisfaction associated with average levels of competence need satisfaction ("Globally Satisfied and Highly Connected" profile) relative to the other ones, and into the "Globally Satisfied" profile relative to the "Globally Dissatisfied, Highly Connected, and Competence Deficient" profile. Finally, the "Globally Dissatisfied, Highly Connected, and Competence Deficient" profile was associated with the least desirable outcomes (the lowest levels of students' interest toward their studies, satisfaction, and attendance, and the highest levels of dropout intentions).

Keywords: Psychological needs satisfaction; Latent profiles; University students; Self-determination theory; Dropout

According to Self-Determination Theory (SDT; Deci & Ryan, 2000), the satisfaction of three basic psychological needs is proposed to play a central role in the prediction of a wide variety of desirable behaviors, and optimal functioning across life domains, including education (Jang, Reeve, Ryan, & Kim, 2009). These three basic needs refer to relatedness (i.e., expressed via feelings of having a positive connection with others) competence (i.e., expressed via feelings of being able to interact with the environment in an effective manner), and autonomy (i.e., expressed via feelings of psychological freedom and volition). Supporting this assertion, accumulating research evidence has revealed well-differentiated relations between the satisfaction of these needs and a variety of educational outcomes among samples of university students (Emery, Heath, & Mills, 2016; Martela & Ryan, 2016). However, despite their interest, these prior results are limited by their failure to consider the possible combinatory effects of autonomy, competence, and relatedness needs satisfaction. In particular, despite the recognition that individuals might particularly benefit from a balanced (i.e., equivalent) level of satisfaction across all three needs (e.g., Deci & Ryan, 2000; Sheldon & Niemiec, 2006), little is known about the typical configurations that characterize individuals' need satisfaction profiles (reflecting the need satisfaction configuration of specific students), their stability over time, and their effects on educational outcomes. The present study seeks to address this gap. More precisely, it seeks to extend current educational knowledge by: (1) examining the nature of university students' need satisfaction profiles in the educational context while considering their global levels of need satisfaction jointly with the more specific levels of satisfaction of their needs for relatedness, competence, and autonomy; (2) assessing the role of self-oriented and socially prescribed perfectionism in the prediction of these need satisfaction profiles; (3) assessing the impact of profile membership on a variety of outcomes variables related to students' interest toward their studies, dropout intentions, class attendance, and educational satisfaction; and (4) using a longitudinal design to assess the extent to which the nature of the profiles, as well individual membership in specific profiles, will remain unchanged over the course of a university semester (Kam, Morin, Meyer, & Topolnytsky, 2016).

The Critical Role of Need Satisfaction

Satisfaction of the basic psychological needs for relatedness, competence, and autonomy has often been described as a critical driver of wellbeing and desirable educational outcomes, such as students' interest toward their studies (Flunger, Pretsch, Schmitt, & Ludwig, 2013; Sheldon & Filak, 2008) and educational satisfaction (González-Cutre, Sicilia, Sierra, Ferriz, & Hagger, 2016). Conversely, undesirable consequences (e.g., dropout intentions, burnout) are expected for people experiencing a lack of satisfaction of these basic psychological needs (Sulea, van Beek, Sarbescu, Virga, & Schaufeli, 2015; Taylor, Lekes, Gagnon, Kwan, & Koestner, 2012). Empirical evidence has generally supported these expectations across samples of primary, secondary, and university students (Ryan & Deci, 2017). Likewise, these relations appear to hold regardless of whether need satisfaction was operationalized as a single global score (Cheon, Reeve, & Song, 2016; Vansteenkiste, Lens, Soenens, & Luyckx, 2006), or as distinct scores reflecting participants' needs for relatedness, competence, and autonomy (Johnston & Finney, 2010; Niemiec, Ryan, & Deci, 2009).

The Combined Effects of Need Satisfaction Components

According to SDT, all three needs should be satisfied for psychological wellbeing to occur (Deci & Ryan, 2000). More precisely, SDT proposes that students' functioning should be less optimal (Ryan, 1995) when only a subset of needs is met than when all three needs are satisfied. Sheldon and Niemiec (2006) argued that the benefits of need satisfaction should be greater when the satisfaction of all three psychological needs is in balance (i.e., at a same level). These theoretical perspectives clearly reinforce the importance for research to consider the combined effects of the satisfaction of all three needs using approach that goes beyond the simple investigation of their additive contribution.

So far, few studies have systematically scrutinised the combined effects of need satisfaction on a variety of outcome measures and in a variety of life contexts (Chang, 2012; Dysvik, Kuvaas, & Gagné, 2013; Sheldon & Filak, 2008; Sheldon & Niemiec, 2006; Vansteenkiste et al., 2006). These studies converged on the conclusion that all three needs have a desirable effect on a variety of outcomes ranging from intrinsic motivation to psychological wellbeing (Sheldon & Filak, 2008; Sheldon & Niemiec, 2006; Vansteenkiste et al., 2006). Vansteenkiste et al. (2006) also found that autonomy need satisfaction was most beneficial (i.e., lower levels depression and higher level of vitality) when levels of relatedness need satisfaction were low, but that the positive relation between competence need satisfaction and vitality was weaker when levels of autonomy need satisfaction were low. Chang (2012) reported a similar effect

in relation to leisure activities. Although Sheldon and Filak (2008) failed to replicate these results, Dysvik et al. (2013) similarly noted that: (a) competence and relatedness needs satisfaction was positively associated with intrinsic motivation only when the satisfaction of the need for autonomy was high; and (b) competence need satisfaction positively predicted intrinsic motivation only when relatedness need satisfaction was low. Finally, Sheldon and Niemiec (2006) reported positive associations between need balance and undergraduate university students' intrinsic motivation. Dysvik et al. (2013) reported similar effects of need balance in the prediction of workers' intrinsic motivation, but noted that need balance did not account for any additional variance in intrinsic motivation once the effects of need satisfaction levels and of their interactions were taken into account.

When considering these results, one should keep in mind that these studies relied on an indirect measurement of need balance via the calculation of difference scores. Differences scores have often been criticized for their high level of sensitivity to random measurement errors (Edwards, 2002). An additional flaw of the approach taken by Dysvik et al. (2013) for contrasting interaction and balance effects comes from their addition of the difference scores reflecting need balance to a regression equation already including interactions, which already incorporate an implicit representation of balance effects (e.g., Cheung, 2009; Edwards, 2009). This statistical redundancy could explain Dysvik et al.'s (2013) observation of the limited added-value of balance effects. Interestingly, recent research on the structure of need satisfaction suggests that a more direct measure of need balance is possible.

More precisely, despite the well-established conceptually-differentiated nature of the three basic needs for relatedness, competence, and autonomy, research shows that the degree to which all three needs are satisfied tends to be moderately inter-correlated (e.g., Jang et al., 2009; Vansteenkiste et al., 2006). This observation has led some researchers to conduct more extensive investigations of the measurement underpinnings of need satisfaction ratings. This new examination has revealed ratings of need satisfaction to simultaneously reflect respondents' global levels of need satisfaction across all three needs as well as the more specific satisfaction of their needs for relatedness, competence, and autonomy left unexplained by this global level. This conclusion appears to hold in the educational (Garn, Morin, & Lonsdale, 2019; Gillet et al., 2019), general life (Tóth-Király, Morin, Bőthe, Orosz, & Rigó, 2018), sport (Brunet, Gunnell, Teixeira, Sabiston, & Bélanger, 2016), and work (Bidee, Vantilborgh, Pepermans, Griep, & Hofmans, 2016; Sánchez-Oliva et al., 2017) domains. In practical terms, these studies show that it is possible to simultaneously obtain a direct estimate of participants' global need satisfaction levels encompassing all three needs, together with a non-redundant estimate of the unique satisfaction of each specific need over and above that global level (i.e., expressed as deviations from that global level, and thus providing a direct estimate of imbalance in the extent to which each need is satisfied relative to the other needs for a specific individual). Importantly, research in which these two layers of measurement cannot be disentangled risks leading to an overly similar assessment of the relative contribution of each psychological need, making it difficult to obtain a clear estimate of the unique contribution of each need over that of global need satisfaction levels (e.g., Sánchez-Oliva et al., 2017). We adopt this approach in the present study.

Need Satisfaction Profiles

All previously reviewed studies have relied on a *variable-centered* approach, which focus on average associations observed between sets of variables in the sample under study. Through its focus on average relations, the variable-centered approach generally fails to consider the possible existence of subpopulations of participants characterized by different types of relations among the variables under investigation. Variable-centered tests of interactions make it possible to verify whether some specific variable relations differ as a function of scores on another variable. However, such tests assume that the interactive effect applies equally to all participants. An even more direct way of looking at the combined effects of need satisfaction involves *person-centered* analyses, specifically designed to test for the presence of distinct students' profiles characterized by different configurations of need satisfaction components (Meyer & Morin, 2016). Person-centered analyses seek to identify qualitatively distinct subpopulations characterized by a similar configuration (or profile) of need satisfaction (Meyer & Morin, 2016; Morin & Wang, 2016).

No study has so far relied on a person-centered approach to study multidimensional profiles of need satisfaction in the education area. It is important to mention, however, previous studies conducted outside of the education area. Thus, in a study conducted in the context of geriatric care units, Souesme, Martinent, and Ferrand (2016) identified three need satisfaction profiles among patients: (a) one profile

characterized by low levels of autonomy and competence needs satisfaction, and moderate levels of relatedness need satisfaction (low-moderate satisfaction profile), (b) one profile characterized by high levels of relatedness need satisfaction, and moderate levels of autonomy and competence needs satisfaction (high-moderate satisfaction profile), and (c) one profile characterized by high levels of autonomy, competence, and relatedness needs satisfaction (high satisfaction profile). Ferrand, Martinent, and Charry (2015) similarly found three need satisfaction profiles among hospitalized elderly people: (a) a high satisfaction profile, (b) a profile characterized by high levels of autonomy and competence needs satisfaction, and moderate levels of relatedness need satisfaction, and (c) a profile characterized by low levels of autonomy, competence, and relatedness needs satisfaction. Finally, in a broader study focusing on both need satisfaction and frustration in the general life domain, Tóth-Király, Bőthe, Orosz, and Rigó (2018b) identified four profiles of need fulfillment characterized by different levels of need satisfaction and frustration toward life in general. Despite the broader scope of this study in which participants' levels of need satisfaction and frustration were considered, the identified profiles also shared similarities with those identified in the geriatric context revealing either a high level of satisfaction across all needs, a high level of frustration across all needs, a moderate level of satisfaction and frustration across all needs, or an imbalanced profile mainly characterized by relatedness need satisfaction.

In the educational context, Gillet et al. (2019) examined the evolution of longitudinal trajectories of global need satisfaction levels among a sample of university students followed over the course of a semester. Their results, despite focusing on a single global dimension of need satisfaction, revealed that students' global need satisfaction trajectories were best characterized by three distinct profiles presenting initially moderate levels that tended to increase over the course of the semester, initially moderate levels that tended to decrease over the course of the semester, and low levels that showed further decreases over the course of the semester. The present study was designed to build, among a new and independent sample of students, on these initial results in providing a more complete multidimensional perspective on the nature of students' multidimensional need satisfaction profiles in the educational context and their evolution over the course of a semester.

Of direct relevance to the present investigation, Morin, Boudrias et al. (2016, 2017) showed that when global constructs are known to co-exist with more specific constructs measured from the same indicators, person-centered analyses conducted while ignoring this global tendency were likely to artificially result in the estimation of profiles characterized by matching levels across indicators even when the true underlying set of profiles presents much clearer shape-related differences. This observation has led Morin, Boudrias et al. (2016, 2017) to note that, whenever this is the case, person-centered analyses should be directly estimated on the basis of indicators providing a proper disaggregation of these global (i.e., global levels of need satisfaction, reflecting need balance) and specific (i.e., unique levels of satisfaction of each need, reflecting need imbalance) components. In the present research, our first goal is to identify academic need satisfaction profiles in the educational context among a sample of first-year university students, while relying on a proper disaggregation of these two components. In the absence of prior studies relying on a multidimensional (properly disaggregated) person-centered investigation of students' need satisfaction profiles, hypotheses are hard to formulate. Yet, Gillet et al.'s (2019) results, as well as limited research conducted in other research areas (e.g., Ferrand et al., 2015; Souesme et al., 2016; Tóth-Király et al., 2018b), allow us to expect a relatively limited number of profiles (i.e., three to five).

Perfectionism and Need Satisfaction Profiles

A second goal of the present research is to document possible antecedents of students' need satisfaction profiles in the educational context by considering the role of two facets of perfectionism (Hewitt & Flett, 1991). Socially prescribed perfectionism refers to students' beliefs that others uphold high standards about them, and that they will only value them if they are able to meet these standards. Conversely, self-oriented perfectionism refers to students' own adherence to exceedingly high personal standards, often coupled with a high level of self-criticism. Past studies showed that students' personality traits (e.g., conscientiousness, agreeableness) presented statistically significant associations with their level of psychological need satisfaction (Demirbaş-Çelik & Keklik, 2019; Sulea et al., 2015). However, despite the well-documented importance of perfectionism in education (Bong, Hwang, Noh, & Kim, 2014), no variable- or person-centered research has yet looked at the possible relations between students' levels of socially prescribed and self-oriented perfectionism and their levels of need satisfaction.

Nevertheless, some research has looked at the effects of these two dimensions of perfectionism on conceptually-related constructs, namely autonomous and controlled motivations, which are assumed to be intimately related to the degree of satisfaction of the three needs considered here (Deci & Ryan, 2000).

Self-oriented perfectionists set high goals for themselves and invest substantial efforts in their attempts to achieve those goals (Hewitt & Flett, 1991). This form of perfectionism thus tends to involve higher levels of personal control (Mallinson & Hill, 2011), a component of competence and autonomy needs satisfaction. Likewise, the autonomous pursuit of challenging goals also fosters the development of self-efficacy (Bandura, 1997; Locke & Latham, 2002), a construct akin to competence need satisfaction. It thus appears logical to expect students characterized by strong self-referenced standards and a strong drive for perfection and improvement to display a higher level of psychological need satisfaction and autonomous motivation. In fact, research supports the idea that self-perfectionists display more autonomous motivation toward school (Harvey et al., 2015; Miquelon, Vallerand, Grouzet, & Cardinal, 2005), more autonomously-driven motivational profiles (Gillet, Morin, & Reeve, 2017), and higher levels of interpersonal adjustment (Hill, Zrull, & Turlington, 1997).

In contrast, students characterized by socially prescribed perfectionism tend to be motivated by a desire to approach rewards while avoiding punishments, and present a self-system that is less directly impacted by their school activities (Gaudreau, Franche, & Gareau, 2016). This second form of perfectionism can thus be seen as externalized or non-internalized because students with high levels pursue school activities mainly to respond to perceived social pressure (Gaudreau & Thompson, 2010). Socially prescribed perfectionism entails externally-driven standards that are typically seen as hard to modify or control (low autonomy need satisfaction), negative self-evaluative tendencies (low competence need satisfaction), and feelings of exposure to external pressures in order to avoid social rejection (low relatedness need satisfaction; Mallinson & Hill, 2011). In support of these assertions, research generally reveals negative relations between socially prescribed perfectionism, self-efficacy (Mills & Blankstein, 2000; Van Yperen, 2006), and more controlled forms of motivation (Miquelon et al., 2005; Stoeber, Feast, & Hayward, 2009).

These theoretical considerations and indirect sources of research evidence lead us to expect self-oriented perfectionism display positive associations with students' likelihood of membership into profiles characterized by high levels of psychological need satisfaction in the educational context. Similarly, we also hypothesized positive associations between socially prescribed perfectionism and students' likelihood of membership into profiles characterized by low levels of need satisfaction.

Educational Outcomes of Need Satisfaction Profiles

A third goal of this research is to consider the practical relevance of the need satisfaction profiles by an investigation of their relations with a series of educational outcomes. In accordance with SDT (Deci & Ryan, 2000), Ratelle and Duchesne (2014) found that students with high and increasing levels of relatedness, competence, and autonomy needs satisfaction tended to report a more positive school adjustment. However, conclusions regarding the relative importance of each need in the prediction of outcomes is not as clear. For instance, according to Sheldon and Niemiec's (2006) results, moderate levels of autonomy need satisfaction may not necessarily be harmful when combined with equivalently moderate levels of competence and relatedness needs satisfaction among undergraduate university students. In addition, autonomy need satisfaction appears to be less strongly related to wellbeing when relatedness need satisfaction is high (Vansteenkiste et al., 2006). Finally, numerous studies (e.g., Jang et al., 2009; Kashdan, Mishra, Breen, & Froh, 2009) reported differentiated relations between each need and various educational outcomes among university students, and showed that the functional significance of the need for competence could be greater than that of the other needs (i.e., autonomy and relatedness).

In sum, it seems that we can expect students' need satisfaction profiles in the educational context to display a well-differentiated pattern of associations with various educational outcomes. Thus, a profile demonstrating a globally high level of need satisfaction should result in the most desirable outcome levels, while a profile displaying low global levels of need satisfaction should result in the lowest levels of emotional and behavioral outcomes (Gillet et al., 2019; Ratelle & Duchesne, 2014). Based on prior research conducted among university students (Sheldon & Niemiec, 2006), we can also expect a profile displaying a mixture of high and low scores on different needs to be associated with less desirable outcomes than a profile characterized by moderate levels of psychological need satisfaction.

In this research, we consider the key educational outcomes of students' interest toward their studies, class attendance, and educational satisfaction given extensive empirical evidence of their role in academic success (e.g., Morrissey, Hutchison, & Winsler, 2014; Tosto, Asbury, Mazzocco, Petrill, & Kovas, 2016). Students' class attendance plays an important role in higher education, and has often been shown to be an important predictor of academic achievement (e.g., Silvestri, 2003). Attending classes makes it more likely for students to benefit from richer exchanges with the teacher and other students, and to benefit from an enriched exposure to the course material. These observation have led many universities to devise attendance policies, assuming that greater attendance will help students to reap greater benefits from their learning experiences. Moreover, educational satisfaction is an important outcome to consider given its influence on students' decisions to continue with, or drop out of, a course (e.g., Sinclaire, 2014). Satisfaction is also related to higher levels of academic performance, to the decision to enroll in additional classes, and to students' subjective assessments of their own wellbeing (Cummins & Tomyn, 2011). Similarly, students' levels of interest toward their studies represents another well-documented predictor of academic achievement, engagement, and persistence, as well as of positive affect (e.g., Gillet, Vallerand, Lafrenière, & Bureau, 2013).

Finally, throughout the world, university entry is highly-prized with a large number of applicants competing for a limited number of places. Although rates of student retention differ greatly across sectors, every year, students leave university either by choice or necessity (Maher et al., 2013). For instance, although cautious rates of dropout from higher education programs of 6.2% for the U.K. (Higher Education Statistics Agency, 2017) and 16% for Canada (Shaienks, Gluszynski, & Bayard, 2008) have been reported, the Organization for Economic Co-Operation and Development (OECD, 2017) reports an average dropout rate of 32% across 18 OECD countries. Persistence and dropout are critical outcomes for educational systems worldwide, and are associated with critically important psychological, social, and economic consequences for both the students and the society as a whole (Voelkle & Sander, 2008). In addition, a high rate of attrition can affect the reputation of the university itself, or even of a whole country as a provider of quality higher education, and may have financial consequences at the university and country levels. Dropout has also considerable financial, social, and emotional consequences for the students, and can be associated with distress, reduced professional opportunities, and increased levels of criminality (Bjerk, 2012; OECD, 2017). We thus also consider dropout intentions as one of the key predictor of school dropout behavior (Bjerk, 2012).

Stability and Change in Need Satisfaction Profiles

A last goal of this research is to assess the stability of students' need satisfaction profiles in the educational context over the course of a university semester (i.e., corresponding in France to a period of roughly twelve weeks). Although past longitudinal investigations suggest that need satisfaction profiles should exhibit some stability, they also suggest that change is possible over the course of a few months, and more likely among a sample of university students (Cheon et al., 2016; Cox, Smith, & Williams, 2008; Ratelle & Duchesne, 2014; Wandeler & Bundick, 2011). For instance, Gillet et al. (2019) found that a period of ten weeks was sufficient to identify evolutions in longitudinal trajectories of global need satisfaction levels among a sample of university students.

As noted by Meyer and Morin (2016; also see Meyer, Morin, & Wasti, 2018), it is critical to ascertain the stability of person-centered solutions in order to be able to support their utilization as guides for the development of intervention strategies tailored at distinct types, or profiles, of students. Two distinct forms of longitudinal stability can, and should, be considered (Gillet, Morin, & Reeve, 2017; Kam et al., 2016). A first form of longitudinal stability, within-sample stability, is related to the nature of the profiles themselves, which could change over time. For example, the number or structure of the profiles could change over time, which would suggest that the profiles have limited usefulness as intervention guides as they reflect highly transient phenomenon, or that the sample under consideration has recently been exposed to some rather important internal or external changes. Morin, Meyer, Creusier, and Biétry (2016) refer to these two subtypes of within-sample profile stability as configural (same number of profiles) and structural (profiles with the same nature) similarity. In contrast, changing circumstances may lead to a change in the degree of similarity among members of specific profiles (dispersion similarity), or in the relative size of the profiles (distributional similarity). These two subtypes of within-sample profile stability do not preclude the reliance on person-centered solutions as intervention guides, but simply suggest that the identified profiles show some degree of reactivity to internal or external changes.

A second form of longitudinal stability, within-person stability, is related to changes in the degree to which students correspond to specific profiles over time (Gillet, Morin, & Reeve, 2017; Kam et al., 2016) and can be observed in the absence of within-sample changes. For example, observing an average increase in levels of global need satisfaction at the sample level could alternatively be explained, at the profile level, by: (a) increases in the size of profiles presenting higher levels of global need satisfaction (within-sample distributional change); (b) changes in the nature of the profiles so that they become characterized by higher levels of global need satisfaction (within-sample structural change); and (c) a higher tendency for students to transition to profiles displaying greater levels of global need satisfaction (within-person change). Naturally, (c) could be a cause of (a). However, (a) could also happen due to the accumulation of multiple non-systematic transition patterns leading to changes in the size of multiple profiles.

To date, most research on need satisfaction has been cross-sectional in nature, and no research has yet looked at the critical issue of profile stability. Within a person-centered perspective, a single study has examined whether students' need satisfaction levels remained stable or fluctuated over time, but only considering a single need at a time (Ratelle & Duchesne, 2014). Prior variable-centered studies showed that psychological need satisfaction tends to display lower levels of rank-order stability in samples of more advanced students (vocational training, university) than at lower levels of education when children tend to experience more stable environments (Cheon et al., 2016; Cox et al., 2008). For instance, in a 3-year longitudinal study (with annual measurements) of 414 trainees, Wandeler and Bundick (2011) found need satisfaction to be only moderately stable over one-year intervals (r = .33 to .49). In contrast, higher levels of rank-order stability were reported over a period of 7-months by Marchand and Skinner (2007) among a sample of children (r = .49 to .67). Importantly, the freshman year is known to be accompanied with multiple major changes involving all facets of students' lifestyles and educational habits (e.g., moving to a new city, moving out of the parental house, starting part time work activities, new peer groups; De Clercq, Galand, & Frenay, 2017; Perry, Hladkyj, Pekrun, & Pelletier, 2001). Such important transformations are likely to impact students' need satisfaction in a way that might explain the lower levels of stability observed in this population.

Given that the first university semester provides freshman students with the occasion to integrate these various transitions and to become familiarized with university functioning and expectations, we decided to focus on this specific period. What remains unclear, however, is how and to which extent these previous results, all emerging from variable-centered studies, would translate to a person-centered perspective. For this reason, we leave open the question of whether, and to which extent, the identified need satisfaction profiles would display stability or change over the course of a university semester. Yet, on the basis of previous research evidence, we expect the profiles characterized by higher levels of need satisfaction in the educational context to display higher levels of stability over time (Gillet et al., 2019; Ratelle & Duchesne, 2014).

Method

Participants and Procedure

A convenience sample of 521 first-year undergraduate university students enrolled in a French university (M_{age} = 18.95; SD = 2.06; 101 males, 420 females) agreed to participate in this study via informed consent procedures. Two weeks after the beginning of the fall semester, these participants completed a first set of self-reported questionnaires in classroom settings (15 minutes). Of those, 423 (81.2%) also agreed to complete the same self-reported measures 10 weeks later (Time 2) near the end of the semester. Each time, the purpose of the study was explained to the participants, who were guaranteed confidentiality, and re-assured that they were entirely free to participate or not without any consequence. Due to the longitudinal nature of the study, participants were also asked to provide a personal identification code of their own choosing on their questionnaire in order to make it possible to link their responses across time points. Due to its non-interventional and non-invasive nature, this study was found exempt by our research ethics committee. All measures were administered in French. Questionnaires that were not already validated in this language were adapted to French by a panel of experts according to a standardized back-translation procedure (Hambleton, 2005; van de Vijver & Hambleton, 1996).

Measures

Need satisfaction. Need satisfaction levels were measured using a questionnaire developed by Gillet and colleagues (Gillet, Fouquereau, Huyghebaert, & Colombat, 2016; Gillet, Rosnet, & Vallerand,

2008). For purpose of this study, this nine-item questionnaire was minimally adapted to match the educational context. This questionnaire measures the satisfaction of students' basic psychological needs for relatedness (3 items; e.g., "I have a lot of sympathy for the persons with whom I interact"; Time 1 α = .69; Time 2 α = .75), competence (3 items; e.g., "Often, I feel that I am very efficient"; Time 1 α = .73; Time 2 α = .81), and autonomy (3 items; e.g., "Generally, I feel free to express my ideas and opinions"; Time 1 α[1] = .54; Time 2 α = .79). All items are rated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Perfectionism (Predictor). Self-oriented (3 items; e.g., "I am perfectionistic in setting my goals"; Time 1 α = .86; Time 2 α = .90) and socially prescribed (3 items; e.g., "My family expects me to be perfect"; Time 1 α = .77; Time 2 α = .84) perfectionism was assessed using the short form of the Multidimensional Perfectionism Scale (Cox, Enns, & Clara, 2002; Hewitt & Flett, 1991). All items are rated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Satisfaction (Outcome). Educational satisfaction was assessed with a single item measure (Gillet, Huyghebaert et al., 2017; Shimazu, Schaufeli, Kamiyama, & Kawakami, 2015) asking students to report the extent to which they were satisfied with their undergraduate courses using a 7-point Likert scale (1- strongly disagree to 7- strongly agree).

Interest (Outcome). Five items taken from the Intrinsic Motivation Inventory (McAuley, Duncan, & Tammen, 1989; e.g., "I would describe my classes as very interesting"; Time 1 α = .86; Time 2 α = .91) were used to assess participants' interest toward their studies. Responses are given on a 1 (strongly disagree) to 7 (strongly agree) Likert scale.

Dropout intentions (Outcome). Drop out intentions were captured using a three-item subscale created by combining two items previously used by Gillet, Berjot, Vallerand, and Amoura (2012; i.e., "I often intend to drop out of my studies" and "I am determined to pursue my college education"- reversed) with a single item previously used by Vallerand, Fortier, and Guay (1997; i.e., "I intend to drop out of university"). This three-item (Time 1 α = .89; Time 2 α = .95) combination was previously validated in French by Gillet, Huyghebaert et al. (2017). These items are rated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Class attendance (Outcome). Participants' self-reported their class attendance level over the course of the semester on a 6-point Likert-type scale (1- 0% to 6- 100%).

Analyses

Overview of the Analytic Procedures

Given the complexity of the analytical procedures utilized in the present study, we first provide a global overview of the main analytical steps, which we will then present in turn, that we followed in this study. First, in order to achieve a proper disaggregation of the global and specific components of the need satisfaction measures, as well as to verify the psychometric properties of all measures used in the present study and their measurement invariance over time, we conducted a series of preliminary measurement analyses to be described shortly. Factor scores were extracted from these analyses to serve as input for the main person-centered analyses in order to ensure that the various variable indicators used in this study retained the properties of the underlying measurement models estimated (bifactor structure, invariance, partial correction for measurement errors). Second, after briefly presenting the model estimation procedures utilized in the present study, latent profile analyses (LPA) were conducted in order to estimate the number of profiles required to reflect participants' need satisfaction configurations at each time point. Third, the two LPA solutions (one per time point) were combined into a single longitudinal model to verify the similarity of the profiles estimated over time. Fourth, the retained longitudinal LPA solution was converted to a latent transition analytic (LTA) model to estimate the within-person stability in profile membership. Fifth, predictors and outcomes were incorporated to

[1] Although we report scale score reliability estimates based on Cronbach alpha (α) associated with each of our measures in this section, more precise model based composite reliability coefficients (Dunn, Baguley, & Brunsden, 2014; Morin, Myers, & Lee, in press) are reported in the preliminary analysis section. These omega (ω; McDonald, 1970) coefficients were calculated from the absolute values of the standardized factors loadings ($|\lambda_i|$) and item uniquenesses (δi) taken from preliminary measurement models as:

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

the model.

This combination of advanced statistical procedures is likely to be unfamiliar, at the present time, for most readers. We refer readers interested at implementing similar analyses to the following user friendly introductions, which also include comprehensive sets of annotated analytic syntax. First, Morin, Boudrias et al. (2016, 2017) present an extensive introduction to the logic and estimation of LPA starting from indicators taken from preliminary bifactor measurement models in order to achieve a proper disaggregation of global versus specific ratings. Second, Morin and Litalien (2019) provide a very comprehensive introduction to person-centered analyses covering LPA, LTA, longitudinal tests of profile similarity, and covariate inclusion.

Preliminary Analyses

The psychometric properties of all measures were verified in a series of preliminary factor analyses realized using Mplus 7.4 (Muthén & Muthén, 2015). The main analyses conducted in the present study relied on longitudinally invariant factor scores (Millsap, 2011) saved from these preliminary models in standardized units (M = 0, SD = 1). When compared to scale scores created by simply averaging items, factor scores have the advantage of providing a partial control for measurement errors by giving more weight to more reliable items (Skrondal & Laake, 2001), of preserving more accurately the structure of the initial measurement models, and of ensuring comparability across time waves (e.g., measurement invariance). Readers interested in a more extensive discussion of the advantages of factor scores in the estimation of LPA are referred to Morin, Boudrias et al. (2016; also see Morin, Meyer et al., 2016).

Bifactor confirmatory factor analytic (CFA) models (e.g., Holzinger & Swineford, 1937) were utilized to represent the measurement structure for the need satisfaction variables. This decision is predicated on evidence from recent studies demonstrating the superiority of a bifactor representation for need satisfaction ratings based on SDT (Sánchez-Oliva et al., 2017; Tóth-Király, Morin et al., 2018). More precisely, these studies demonstrated how a bifactor model could be used to obtain a direct estimate of participants' global level of satisfaction across all needs, while also providing a direct estimate of the meaningful specificities (or imbalance) remaining in each of the specific needs. In these bifactor models, all need satisfaction items associated with the three subscales were used to define an overarching G-factor reflecting participants' global need satisfaction levels. Furthermore, all subscale-specific items were used to define a S-factor representing the unique variance associated with each need left unexplained by the G-factor (i.e., expressed as deviations from the global level). As noted in the online supplements, the bifactor model resulted in the estimation of a global need satisfaction factor that was well-defined (ω_{t1} = .794; ω_{t2} = .824), and of equally-well defined specific need satisfaction factors for competence ($\omega_{t1\text{-}2}$ = .679) and relatedness (ω_{t1} = .692; ω_{t2} = .719). However, these results showed that, once the variance explained by the G-factor was taken into account, there remained no meaningful specificity located at the level of the specific autonomy factor (ω_{t1} = .025; ω_{t2} = .036). As noted in the online supplements, this specific result was expected, and simply suggested that, among this specific sample of students, levels of autonomy need satisfaction were systematically found to be in balance, or alignment, with that of the other needs. As such, profiles will be estimated based on factor scores reflecting global need satisfaction (defined by all autonomy, competence, and relatedness items), specific competence satisfaction (defined from the competence items as the variance in competence need satisfaction left unexplained by the G-factor), and specific relatedness satisfaction (defined from the relatedness items as the variance in relatedness need satisfaction left unexplained by the G-factor). Although factor scores related to the specific autonomy satisfaction factor (defined from the autonomy items as the variance in autonomy need satisfaction left unexplained by the G-factor) were also saved as part of this process, they were simply not used in the following analyses due to very low level of composite reliability.

Results from all preliminary models, their invariance, and variable correlations are reported in the online supplements (pages S2 to S15). As shown in these supplements, composite reliability estimates for the multi-item predictors and outcomes proved to be fully equivalent across time points and equally satisfactory: Students' interest toward their studies ω = .891; dropout intentions ω = .923; socially prescribed perfectionism ω = .823; and self-oriented perfectionism ω = .876.

Model Estimation

All analyses were conducted with Mplus 7.4 (Muthén & Muthén, 2015) maximum likelihood robust (MLR) estimator and Full Information Maximum Likelihood (FIML) procedures to manage missing responses (Enders, 2010; Graham, 2009). FIML made it possible to use all respondents who participated

in at least one wave of data collection (N = 521) in the estimation of longitudinal models, without having to resort to a problematic listwise deletion strategy limited to respondents having participated in both waves (N = 423). When respondents were compared as a function of having completed both time waves or only the first one on all baseline measures, very few statistically significant differences emerged. These comparisons are reported in Table S7 of the online supplements (page S16) and only showed that slightly more males ($p \leq .01$) were lost through attrition, and that students lost through attrition tended to present slightly lower levels of class attendance ($p \leq .01$) and interest toward their studies ($p \leq .05$). FIML has been shown to perform as well as multiple imputation, even in the presence of large amounts of missing data (Enders, 2010; Graham, 2009; Jeličič, Phelps, & Lerner, 2009; Larsen, 2011). We note that FIML relies on missing at random (MAR) assumptions, making it robust to the presence of differences between participants related to attrition on any of the variables included in the model. Indeed, MAR allows missing responses to be conditioned on all variables included in the model (Enders, 2010; Graham, 2009).

Time-Specific Latent Profile Analyses (LPA)

Time-specific LPA solutions including one to eight latent profiles were first estimated using the need satisfaction factors as profile indicators. These initial analyses aimed to verify whether each time-specific solution would result in the identification of the same number of profiles. In each of these solutions, the profiles were defined while allowing for the free estimation of the means and variances of the indicators across profiles (Diallo, Morin, & Lu, 2016; Peugh & Fan, 2013). These analyses were conducted using 5000 sets of random start values (with 1000 iterations), and allowing the best 200 solutions to be retained for final optimization (Hipp & Bauer, 2006; McLachlan & Peel, 2000). In the more complex longitudinal models to be described shortly, these values were increased to 10000 (2000), and 500. Information on model comparison procedures used to select the optimal time-specific solution as well as for tests of profile similarity are provided in the online supplements (pages S17 to S24).

Longitudinal Tests of Profile Similarity

The optimal time-specific LPA solutions were integrated into a longitudinal LPA model. This model served as the baseline for the realization of systematic tests of profile similarity over time (Morin & Litalien, 2017; Morin, Meyer et al., 2016). These tests were conducted according to the following sequence: (a) configural similarity, which refers to the identification of the same number of profiles across time points; (b) structural similarity, which refers to the estimation of profiles having the same shape (i.e., within-profile means) across time waves; (c) dispersion similarity, which refers to the estimation of profiles characterized by the same level of within-profile variability across time waves; and (d) distributional similarity, which refers to the estimation of profiles having the same relative size across time points.

Latent Transition Analyses (LTA)

The most similar longitudinal LPA solution was converted to a LTA (Collins & Lanza, 2010) to investigate within-person stability and change in profile membership (Kam et al., 2016). This conversion was then used as a new baseline to investigate the predictive (relations with predictors) and explanatory (relations with outcomes) similarity of the profiles across time points. This conversion was done using the manual auxiliary 3-step approach (Asparouhov & Muthén, 2014; McLarnon & O'Neill, 2018) following the procedures outlined by Morin and Litalien (2017) for the LTA context.

Predictors and Outcomes of Profile Membership

The relations between predictors (self-oriented perfectionism, socially prescribed perfectionism, and sex) and profile membership were assessed using a multinomial logistic regression link function. The predictors were directly integrated into the LTA model and used to predict participants' likelihood of profile membership. Following the procedures advocated by Gillet, Morin, and Reeve (2017) in their study of the associations between perfectionism and motivational profiles, sex was allowed to predict the profiles at both time waves as a time-invariant controlled variable. This decision was predicated on the well-documented associations between sex, need satisfaction levels (Hollembeak & Amorose, 2005), and perfectionism (Shanmugam & Davies, 2015). This control was made particularly important given the specific composition of our sample, including a majority of females (80.6 %), in order to ensure that estimated relations would not be an artifact of sex.

In contrast, repeated measures of perfectionism were specified as related to membership into the profiles estimated at the same time point (i.e., perfectionism at Time 1 predicted profile membership at Time 1, etc.). We contrasted three alternative models (Ciarrochi, Morin, Sahdra, Litalien, & Parker,

2017; Gillet, Morin, & Reeve, 2017). In a first model, associations between the predictors and the profiles were estimated freely across time waves (i.e., the effects were allowed to change/differ over time), and the effects of the predictors on Time 2 profile membership were allowed to differ as a function of Time 1 profile membership (i.e., the predictors were allowed to predict specific profile-to-profile transitions). In a second model, associations between the predictors and the profiles were estimated freely across time waves (i.e., the effects were allowed to change/differ over time), but not across Time 1 profiles (i.e., the effects of predictors on profile membership were independent of profile membership at the previous time wave). A third model tested the predictive similarity of these relations by constraining the associations between the predictors and the profiles to be equal across time waves.

Finally, explanatory similarity was assessed by incorporating outcomes into the final LTA. Time-varying measures of the outcomes (dropout intentions, interest toward studies, satisfaction, and class attendance) were first allowed to differ across profiles and time waves. The explanatory similarity of these relations was then tested by constraining the within-profile means of these outcomes to be equal across time waves. Mplus' MODEL CONSTRAINT function, which relies on the multivariate delta method (Kam et al, 2016; Raykov & Marcoulides, 2004), was used to assess mean-level differences across profiles. Given the complexity of the models estimated here, it was not possible to simultaneously integrate predictors and outcomes into the same model. For this reason, predictors and outcomes were separately integrated (in two distinct analyses) into the final model of profile similarity. However, it must be noted that all of these models simultaneously included predictor or outcome measures taken at the two time points, so that the effects of Time 2 predictors can be considered to be controlled for Time 1 predictor measures, and the relations between profile membership and Time 2 outcomes can also be considered to be controlled for Time 1 outcome levels.

Results

Determination of the Number of Profiles and Longitudinal Tests of Profile Similarity

The procedures used to determine the optimal time specific LPA solutions, as well as for tests of profile similarity are fully reported in the online supplements (pages S17 to S24) and converged on a 5-profile solution at both time waves, thus evidencing configural similarity. This solution presents a moderately high classification accuracy, as captured by an entropy (and indicator of classification accuracy ranging from 0 to 1) value of .775 at Time 1 and .730 at Time 2. The results from the longitudinal LPA built from these two time-specific LPA solutions similarly provided evidence for the structural, dispersion, and distributional similarity of our solution.

Interpretation of the Final Profile Solution

The final retained model of distributional similarity is graphically represented in Figure 1 (exact within-profile means are reported in Table S10 of the online supplements), and served as the baseline for all upcoming analyses. Profiles 1 and 2 are both characterized by close to average levels of satisfaction of their specific needs for competence and relatedness. However, Profile 2 also presents average levels of global need satisfaction, whereas Profile 1 presents high levels of global need satisfaction. In the interpretation of these profiles, it is important to keep in mind that whereas scores on the global need satisfaction factors reflect participants' global levels of need satisfaction across all three needs, the specific factors reflect positive (higher levels) or negative (lower levels) imbalance in the satisfaction of the specific needs for relatedness, competence, and autonomy. Thus, which average scores on the specific factors, these two profiles can be considered to display a balanced level of need satisfaction (i.e., no evidence of imbalance). As such, Profile 1, which represents 13.64% of the sample, was labelled "*Globally Satisfied*". In contrast, the slightly larger (21.69%) Profile 2 was labelled "*Moderately Satisfied*". Profile 3 presents moderately low levels of global need satisfaction, accompanied by moderately high specific levels of relatedness need satisfaction (positive imbalance) and moderately low specific levels of competence need satisfaction (negative imbalance). This "*Globally Dissatisfied, Highly Connected, and Competence Deficient*" profile characterizes 17.94% of the respondents. Conversely, Profile 4 presents moderately low levels of global need satisfaction, coupled with moderately low specific levels of relatedness need satisfaction (negative imbalance), and average (i.e., balanced) specific levels of competence need satisfaction. This "*Globally Dissatisfied and Relatedness Deficient*" profile is the largest (37.86%). Finally, Profile 5 presents high levels of global need satisfaction associated with high specific levels of relatedness need satisfaction (positive imbalance) and average (i.e., balanced) specific levels of competence need satisfaction. This "*Globally Satisfied and Highly Connected*" profile is the smallest, corresponding to 8.87% of the respondents.

Latent Transitions

The transition probabilities associated with the LTA model build from this final model of distributional similarity are reported in Table 1. Membership into Profiles 3 (*Globally Dissatisfied, Highly Connected, and Competence Deficient*: stability of 99.0%) and 4 (*Globally Dissatisfied and Relatedness Deficient*: 97.8%) are the most stable. Similarly, membership into Profiles 1 (*Globally Satisfied*: 65.9%) and 2 (*Moderately Satisfied*: 64.8%) is also relatively stable. Conversely, membership into Profile 5 (*Globally Satisfied and Highly Connected*: 26.1%) displays a high level of instability over time.

Not surprisingly, transitions are rare for participants initially corresponding to Profiles 3 and 4. However, transitions are more frequent for members of the other profiles. When transitions befall members of Profile 1 (*Globally Satisfied*) at Time 1, they primarily involve Profile 2 (*Moderately Satisfied*; 20.1%), although some members of Profile 1 also transition to Profiles 3 (*Globally Dissatisfied, Highly Connected, and Competence Deficient*; 5.4%) or 5 (*Globally Satisfied and Highly Connected*; 8.7%). For members of Profile 2 (*Moderately Satisfied*) at Time 1, the dominant transitions involve Profiles 4 (*Globally Dissatisfied and Relatedness Deficient*; 15.0%) and 5 (*Globally Satisfied and Highly Connected*; 12.4%), although some transitions also occur toward Profile 1 (*Globally Satisfied*; 7.8%). Finally, members of Profile 5 (*Globally Satisfied and Highly Connected*) at Time 1 only transition toward Profiles 1 (*Globally Satisfied*; 30.8%) or 2 (*Moderately Satisfied*; 43.1%) at Time 2.

Predictive Similarity (Predictors)

As noted in the online supplements (see page S18 and Table S9), the results supported the equivalence of the predictions across time periods (predictive similarity), and a lack of relations between predictors and specific profile transitions. The results from this final predictive model are reported in Table 2[2]. No statistically significant association was noted between profile membership and participants' sex. Results further revealed that higher levels of self-oriented perfectionism were related to a higher likelihood of membership into Profile 5 (*Globally Satisfied and Highly Connected*) relative to all other profiles, and into Profile 1 (*Globally Satisfied*) relative to Profile 3 (*Globally Dissatisfied, Highly Connected, and Competence Deficient*). In contrast, socially prescribed perfectionism showed an almost exactly opposite pattern of associations with the profiles relative to self-oriented perfectionism. More precisely, socially prescribed perfectionism levels predicted a lower likelihood of membership into Profile 5 (*Globally Satisfied and Highly Connected*) relative to Profiles 2 (*Moderately Satisfied*), 3 (*Globally Dissatisfied, Highly Connected, and Competence Deficient*), and 4 (*Globally Dissatisfied and Relatedness Deficient*), and into Profile 1 (*Globally Satisfied*) relative to Profile 3 (*Globally Dissatisfied, Highly Connected, and Competence Deficient*).

Explanatory Similarity (Outcomes)

As noted in the online supplements (see page S19 and Table S9), the model in which the outcome levels were specified to be equal over time was supported by the data (explanatory similarity). The within-profile means of the outcomes, together with their 95% confidence intervals, are reported in Table 3, and graphically illustrated in Figure 2. These results were highly consistent across outcomes, showing the most desirable outcome levels (higher levels of interest toward one's studies, educational satisfaction, and attendance, and the lowest levels of dropout intentions) to be equally associated with Profiles 1 (*Globally Satisfied*) and 5 (*Globally Satisfied and Highly Connected*), followed equally by Profiles 2 (*Moderately Satisfied*) and 4 (*Globally Dissatisfied and Relatedness Deficient*), with the least desirable outcomes observed in Profile 3 (*Globally Dissatisfied, Highly Connected, and Competence Deficient*). However, levels of class attendance were lower in Profile 3 (*Globally Dissatisfied, Highly Connected, and Competence Deficient*) relative to the other profiles, and slightly higher in Profile 5 (*Globally Satisfied and Highly Connected*) relative to Profile 4 (*Globally Dissatisfied and Relatedness Deficient*).

Discussion

Many studies have shown that the satisfaction of the three basic needs for relatedness, competence, and autonomy tended to be moderately to strongly interrelated (e.g., Sheldon & Filak, 2008). Yet, our

[2] Models including interactions between sex and perfectionism were also estimated. These models similarly resulted in a conclusion of *predictive* similarity. However, none of the added interactions was statistically significant in the prediction of profile membership.

understanding of how these three needs combine into specific profiles of students remains understudied, particularly in the educational area (e.g., Vansteenkiste et al., 2006). In particular, the value of considering the satisfaction of each specific need, once students' global level of need satisfaction is considered, remains essentially unknown (Sánchez-Oliva et al., 2017). The adoption of a person-centered approach appeared to naturally suited to this question, as it provided us with a way to assess how global and specific (imbalance) components of need satisfaction in the educational context are most commonly combined for specific profiles of students, and the educational consequences of these profiles.

Characteristics of Students' Need Satisfaction Profiles

Five distinct profiles best reflected the need satisfaction configurations in the educational context of the French university students forming the current sample: (a) *Globally Dissatisfied, Highly Connected, and Competence Deficient* (moderately low global satisfaction, moderate levels of positive imbalance in specific relatedness satisfaction, and moderate levels of negative imbalance in specific competence need satisfaction); (b) *Globally Satisfied and Highly Connected* (high global satisfaction, high levels of positive imbalance in specific relatedness satisfaction, and no imbalance in specific competence satisfaction); (c) *Globally Satisfied* (high global satisfaction, and no imbalance in specific relatedness and competence satisfaction); (d) *Moderately Satisfied* (average global satisfaction, and no imbalance in specific relatedness and competence satisfaction); and (e) *Globally Dissatisfied and Relatedness Deficient* (moderately low global satisfaction, moderate levels of negative imbalance in specific relatedness satisfaction, and no imbalance in specific competence satisfaction). These profiles support the value of a finer-grained representation of need satisfaction incorporating both the global extent to which all three needs are met, and the specificity associated with each individual need over and above this global level of satisfaction (need imbalance, expressed as deviations from the global level), rather than simply focusing on a global satisfaction score (Vansteenkiste et al., 2006). Still, additional person-centered research is needed to increase the generalizability of our results. For instance, tests of profile similarity (Morin, Meyer et al., 2016) could also be used to assess the generalizability of the current profiles across distinct samples of students (e.g., primary, secondary, and higher education) or individuals (e.g., youth, working adults, aging adults, athletes). Such evidence of generalizability would greatly reinforce the robustness of our conclusions and the possibility to use them to guide the development of person-centered intervention strategies.

It is imperative to keep in mind that these profiles were considered based on three indicators reflecting global (a global factor score assessed from all autonomy, competence, and relatedness items), competence (a specific factor reflecting what is unique to competence satisfaction ratings once the global factor is taken into account), and relatedness (a specific factor reflecting what is unique to relatedness satisfaction ratings once the global factor is taken into account) needs satisfaction. Indeed, the preliminary analyses used to generate the factor scores representing these indicators resulted in the estimation of well-defined global, specific competence, and specific relatedness needs satisfaction factors. However, once the variance in need satisfaction ratings explained by global levels of need satisfaction was taken into account, there remained no meaningful specificity in the indicators of the autonomy factor. This result suggests, as in previous studies (Sánchez-Oliva et al., 2017; Tóth-Király, Bőthe, Orosz, & Rigó, 2018a), that scores on the three items used to assess autonomy need satisfaction provided a clearer indication of students' global need satisfaction than of the specific level of satisfaction of their need for autonomy (revealing no discrepancies or imbalance between students' reports of their autonomy need satisfaction relative to their global need satisfaction). This finding is also in line with the suggestion that autonomy is a "meta-need" or a "general need" (Assor, 2018) and has a special status relative to the competence and relatedness needs because autonomy is relevant to the regulation and satisfaction of these two needs (Ryan & Deci, 2017).

Given that this study focused on higher education, an educational context in which student's autonomy is particularly important, this result is not surprising. For instance, university students must learn to assume responsibility for, and take control of, their overall learning experience, ranging to making decisions related to what they choose to learn, but also in how they will proceed to learn it. This process involves a high level of self-direction, and requires the development of an autonomous and proactive approach in the context of a reduced amount of classroom contact time. Thus, university students must become self-reliant learners and develop an approach to learning allowing them to maintain efforts outside of the classroom context while remaining able to adequately address their own

individual needs. Although our results are aligned with those obtained in previous studies showing that need satisfaction is a hierarchically-ordered construct best represented by a bifactor model (e.g., Sánchez-Oliva et al., 2017), future investigations relying on bifactor models and using other measures of psychological need satisfaction (e.g., Ntoumanis, 2005; Standage, Duda, & Ntoumanis, 2005) are needed. Such studies would make it possible to assess whether more specificity could remain associated with autonomy need satisfaction within distinct age groups or populations.

Due to its longitudinal nature, the current study was also able to contribute to our understanding of the joint issues of within-person and within-sample stability in need satisfaction profiles in the educational context over the course of a university semester (Kam et al., 2016). In this regard, our results first showed that the profiles identified in this study were essentially unchanged, and thus generalizable, over the course of a university semester (within-sample stability). Indeed, the results from our tests of profile similarity led to the identification of the same number of profiles (configural), presenting the same shape (structural), within-profile variability (dispersion), and size (distributional) across time points.

Second, our results showed that it was possible for within-person changes in profile membership to occur over the course of a semester (within-person stability). More precisely, membership into four (*Globally Dissatisfied, Highly Connected, and Competence Deficient*, *Globally Dissatisfied and Relatedness Deficient*, *Globally Satisfied*, and *Moderately Satisfied*) of the five need satisfaction profiles remained moderately to highly stable over time (with stability rates ranging from 64.8% and 99.0% over the course of the semester). In contrast, membership into the *Globally Satisfied and Highly Connected* profile was far more unstable over time (26.1%). Thus, it appears harder to maintain over time a need satisfaction profile presenting such a high levels of satisfaction across all needs. It is important to keep in mind that respondents were first-year undergraduate psychology students. These students only recently experienced the transition into university. In itself, this transition involves multiple changes related to classroom composition, teachers (who are now professors), teaching and learning structure, etc. In addition, this educational transition is itself also associated, for a substantial number of students, with additional important life transitions (De Clercq et al., 2017; Perry et al., 2001). These multiple transformations (e.g., new peer groups) are likely to have a major impact on students' levels of need satisfaction, which could explain why it appeared to be so difficult for students to maintain initially very high levels of need satisfaction across this first university semester as they face, for the first time, the specific expectations of university studies.

In sum, the results obtained in this study revealed that the need satisfaction profiles displayed a high level of within-sample stability, coupled with a moderate to high level of within-person stability for four out of five profiles, over the course of a university semester. It is true that this level of stability could possibly be due, at least in part, to the relatively short time period (one university semester) considered in the present study. Yet, the fact that we were able to observed a considerable level of within-person changes over this time period suggests that changes at the individual level do happen, and can be investigated, over the course of a university semester. Vallerand's (1997) hierarchical representation of human motivation proposes that motivation can be best understood when considered at different levels of analyses (i.e., the global, contextual, and situational levels). When transposed to need satisfaction by Milyavskaya, Philippe, and Koestner (2013), this model thus suggests that it might be useful for future research to similarly disentangle which levels of need satisfaction present the greatest levels of stability or change over shorter and longer time periods. Critically, longitudinal studies are still needed to better identify the mechanisms involved in profile stability and change, and particularly the role of changes occurring in the familial, academic, and personal lives of students.

Perfectionism and Need Satisfaction Profiles

Despite this recognition that changing characteristics of students' life contexts could play an important role in profile membership, this research was more specifically designed to consider the role played by arguably more stable characteristics of students' personality reflected in their levels of socially prescribed and self-oriented perfectionism (Gaudreau & Thompson, 2010). To the best of our knowledge, no educational research has yet been conducted to ascertain the role of personality-like characteristics in the development of students' need satisfaction profiles in the educational context. Our results revealed that self-oriented perfectionism presented positive associations with students' likelihood of membership into the *Globally Satisfied and Highly Connected* profile relative to all other profiles, and into the *Globally Satisfied* profile relative to the *Globally Dissatisfied, Highly Connected, and*

Competence Deficient profile. Thus, this facet of perfectionism appears to be particularly important for students' corresponding to profiles characterized by high levels of global need satisfaction. This result is aligned with previous studies in which self-oriented perfectionism was found to contribute to autonomous motivation (Gillet, Morin, & Reeve, 2017; Harvey et al., 2015; Miquelon et al., 2005) as self-oriented perfectionists tended to rely on self-referenced criteria (Hewitt & Flett, 1991).

In contrast, socially prescribed perfectionism was associated with a decreased likelihood of membership into the *Globally Satisfied and Highly Connected* profile relative to the *Moderately Satisfied, Globally Dissatisfied, Highly Connected, and Competence Deficient*, and *Globally Dissatisfied and Relatedness Deficient* profiles, and into the *Globally Satisfied* profile relative to the *Globally Dissatisfied, Highly Connected, and Competence Deficient* profile. Socially prescribed perfectionism was thus associated with a higher likelihood of membership into profiles with low to moderate levels of global need satisfaction. This finding is consistent with research conducted among samples of students (Stoeber, Feast, & Hayward, 2009) and athletes (Gaudreau & Antl, 2008) showing that socially prescribed perfectionism tends to be connected with controlled motivation. This association is consistent with the idea that students presenting high levels of socially prescribed perfectionism are driven, in great part, by their perceptions of a high level of pressure emerging from their social environment (Gaudreau & Thompson, 2010). Finally, results revealed that sex was not significantly related to the likelihood of profile membership. Contrary to those found by Hollembeak and Amorose (2005), these findings suggest, as demonstrated in past studies (Sánchez-Oliva et al., 2017), that sex did not predict psychological need satisfaction in the educational domain.

More generally, the relations found in the present study were particularly robust. Indeed, these relations not only generalized over the course of a university semester, they were also found to be independent from prior profile membership and to emerge even when controlling for sex. However, it would be interesting to confirm these relations between perfectionism and profile membership when controlling for students' level of education, country of origin, or culture. Moreover, future research should examine whether additional time-changing characteristics might also influence profile membership and be involved in the prediction of more specific profile transitions over time such as, goal striving, a promotion mindset, achievement motivation, or a possible self.

Outcomes of Students' Need Satisfaction Profiles

Another goal of this research was to better document the affective and behavioral outcomes (i.e., students' interest toward their studies, class attendance, satisfaction, and dropout intentions) of membership into various need satisfaction profiles in the educational context. In this regard, our results revealed a generally well-differentiated pattern of associations between the need satisfaction profiles and various educational outcomes. They also revealed that these associations could be generalized over the course of a university semester. More precisely, students presenting the highest levels of global need satisfaction (*Globally Satisfied, and Globally Satisfied and Highly Connected*), regardless of their levels of satisfaction of their more specific needs for relatedness and competence, displayed the greatest levels of interest toward their studies, satisfaction, and attendance, and the lowest levels of dropout intentions. These results thus suggest that the key determinant of positive educational outcomes seems to be the presence of high levels of global need satisfaction, rather than the degree of imbalance in the satisfaction of specific needs over and above that global level.

In demonstrating the positive implications of global need satisfaction, these results are also well aligned with SDT's propositions (Deci & Ryan, 2000), as well as with the results from prior educational studies which also supported these propositions (Jang et al., 2009; Ratelle & Duchesne, 2014). One might have anticipated that the *Globally Satisfied and Highly Connected* profile would yield better outcomes than the *Globally Satisfied* profile as students characterized by a *Globally Satisfied and Highly Connected* profile also tended to experience higher levels of satisfaction of their specific need for relatedness whereas the *Globally Satisfied* profile only presented average levels of relatedness and competence need satisfaction (Sheldon & Niemiec, 2006). However, this pattern of results was not replicated in the present study as the outcomes associated with the *Globally Satisfied* profile could not be differentiated from those of the *Globally Satisfied and Highly Connected* profile. Thus, the combination of high levels of global need satisfaction and specific relatedness need satisfaction does not lead to better outcomes than high levels of global need satisfaction coupled with average levels of specific relatedness need satisfaction. More generally, our findings suggest that the key drivers of the outcomes considered in the present study are really the presence of balanced levels of need satisfaction

of at least a moderate magnitude across the psychological needs considered here.

Furthermore, the *Moderately Satisfied* and *Globally Dissatisfied and Relatedness Deficient* profiles did not differ in terms of educational outcomes but were both equally associated with more desirable outcome levels than the *Globally Dissatisfied, Highly Connected, and Competence Deficient* profile. These three profiles presented moderately low levels of global need satisfaction. However, the *Moderately Satisfied* and *Globally Dissatisfied and Relatedness Deficient* profiles also presented similarly high levels of competence need satisfaction. In contrast, the *Globally Dissatisfied, Highly Connected, and Competence Deficient* profile presented high levels of relatedness need satisfaction. These differences observed between these three profiles on the educational outcomes suggests that the satisfaction of the specific need for competence in the educational area may thus help to offset the negative effects of a low level of global need satisfaction, whereas this is not the case for relatedness. These results confirm that specific needs may exhibit differential relations with educational outcomes and are in line with recent bifactor investigations (Sánchez-Oliva et al., 2017; Tóth-Király, Bőthe, Orosz, & Rigó, 2018a) and prior studies showing than competence need satisfaction is a more reliable predictor of educational outcomes than relatedness (Jang et al., 2009; Kashdan et al., 2009). These results are also consistent with Dysvik et al.' (2013) findings, who showed that competence need satisfaction was positively related to intrinsic motivation only when relatedness need satisfaction was low. More generally, these results highlight the importance of exploring synergistic relations between psychological needs and argue for the added-value of jointly considering the global and specific components of psychological need satisfaction. However, future research is needed to assess whether our results would generalize across linguistic and cultural groups.

Limitations and Directions for Future Research

Limitation have to be considered when interpreting our results. First, this study relied on self-report measures. Such measures can be influenced by various forms of self-report biases (e.g., social desirability). We encourage researchers to build on the present research by incorporating objective achievement and dropout data to their studies, and external ratings (e.g., teacher) of creativity, engagement, and learning strategies as additional outcomes. Second, we used a single item to assess educational satisfaction, which could have made it harder to differentiate the profiles on this outcome variable. When compared to multi-item measures, single-item measures tend to be less reliable to provide a more restricted content coverage. Future research should seek to expand on the previous results via the incorporation of solid measurement scales to their studies. Third, theoretical considerations (e.g., Taylor et al., 2012) guided our treatment of the covariables as predictors (i.e., perfectionism) or outcomes (i.e., students' interest toward their studies, dropout intentions, class attendance, and educational satisfaction) (Meyer & Morin, 2016). Despite the fact that this approach allowed us to rule out possible effects of predictors on profile transitions, our design and limitations of current analytical possibilities made it impossible to rule out the possibility of reciprocal influences, reverse causality or even spuriousness, as well as the possibility that profile transitions could impact changes in outcome levels. It thus seem important for future longitudinal studies to seek to uncover with greater precision the true directionality of the associations among profiles, outcomes, and predictors, as well as the mechanisms underpinning these associations.

Fourth, as noted above, we relied on a relatively short time interval (one semester), which could have amplified our estimates of profile stability. Yet, our results still revealed that changes did occur over this shorter time interval. Arguably, the stability of the identified need satisfaction profiles is likely to be attenuated, both at the within-sample and within-person levels, if longer time intervals (multiple semesters or a full degree) are considered. In this context, a semester might not be enough to achieve a comprehensive consideration of stability and change in need satisfaction profiles in the educational context.

Fifth, we considered only two types of perfectionism (i.e., socially prescribed and self-oriented) as determinants of students' need satisfaction profiles. It thus appears important for future investigations to consider a broader and more comprehensive set of determinants of need satisfaction profiles among student populations (e.g., teachers' autonomy-supportive behaviors). For instance, future studies might consider student's motives to succeed or to avoid failure, as well as contingent self-esteem, as possible determinants of need satisfaction profiles on the basis of recent research evidence supporting the role of motive dispositions (Lang & Fries, 2006) in the prediction of autonomous and controlled forms of motivation (Michou, Matos, Gargurevich, Gumus, & Herrera, 2016; van der Kaap-Deeder et al., 2016).

Sixth, the present results are limited by the fact that they were obtained in a single sample of first-year undergraduate students enrolled in a psychology program in a French university. Future research is need to assess the generalizability of the present results to student samples with different ages and developmental levels, and from different cultural backgrounds and countries. Sixth, our preliminary analyses revealed a weakly defined S-factor (low factor loadings, low reliability) reflecting students' autonomy need satisfaction once their global levels of need satisfaction were considered. Although, as noted above, this result makes sense given the importance of autonomy for university students, this result made it impossible for us to analyze latent profiles defined using the complete spectrum of global and specific need satisfaction considered to be relevant according to SDT. Clearly, future studies are needed to examine how the present results generalize, or are complemented, when focusing on more diversified samples of younger students, workers, athletes, etc.

Finally, SDT has recently demonstrated that need satisfaction and frustration could be two separate psychological experiences that have different antecedents and consequences over-time (Chen et al., 2015; Vansteenkiste & Ryan, 2013). Toth-Kiraly, Morin et al. (2018) offered a joint exploration of need satisfaction and frustration in two samples of Hungarian adults, which also supported a bifactor representation. Yet, their results also showed that a single global factor was required to represent participants' global levels of need fulfillment, thus suggesting that these two facets (satisfaction and frustration) might rather form a single underlying continuum rather than really referring to conceptually distinct experiences. Yet, it could be fruitful to also investigate how such bifactor measurement models apply to need satisfaction and frustration in the work domain, and to resort to person-centered analyses to assess need frustration and satisfaction profiles, and their respective associations with work-related antecedents and employee functioning.

Practical Implications

Despite these limitations and pending replication, our results highlight the importance for teachers to be attentive to students experiencing low global levels of need satisfaction in the educational context, especially when those low global levels are coupled with similarly low levels of competence need satisfaction (*Globally Dissatisfied, Highly Connected, and Competence Deficient* profile). Indeed, in this study, these students were found to present a higher level of risk for multiple educational difficulties, including the intention to drop out of their program. Numerous studies have previously documented the benefits of autonomy-supportive teaching behaviors in terms of students' need satisfaction (e.g., Jang et al., 2009; Sheldon & Filak, 2008). Thus, encouraging teachers to display, or to display more, autonomy-supportive behaviors could possibly result in a higher prevalence of the two most desirable profiles among students (*Globally Satisfied and Highly Connected* and *Globally Satisfied*). Obviously, future research would be needed to ascertain the validity of this suggestion. Interestingly, a recent study revealed that students taught in their "preferred ways" (an autonomy-supportive teaching strategy) not only perceived their teacher as being more autonomy-supportive, but also displayed more desirable educational outcomes (Jang, Reeve, & Halusic, 2016).

The present findings showed that self-oriented perfectionism was associated with a greater likelihood of membership into the *Globally Satisfied and Highly Connected* profile relative to all of the other profiles, while an almost exactly opposite pattern of relations was found for socially prescribed perfectionism. These results thus suggest that decreasing socially prescribed perfectionism and promoting self-oriented perfectionism might help to enhance students' levels of need satisfaction in the educational context, leading in turn to more desirable affective and behavioral outcomes (e.g., students' interest toward their studies, satisfaction). In this regard, Harvey, Moore, and Koestner (2017) showed that parental expectations were positively related to self-oriented perfectionism. Stoeber, Otto, and Dalbert (2009) also found that conscientiousness plays a role in the development of self-oriented perfectionism. In contrast, neuroticism was positively related to socially prescribed perfectionism. Interestingly, certain behavioral and mental health interventions (e.g., behavioral and cognitive–behavioral therapies, metacognitive techniques for setting and achieving goals, cognitive remediation therapies) may prove useful for increasing conscientiousness (Javaras, Williams, & Baskin-Sommers, 2019), and thus leading to higher levels of self-oriented perfectionism.

Attempts to encourage self-oriented perfectionism and decrease socially prescribed perfectionism should be mainly directed at students presenting the lowest levels of global need satisfaction (i.e., *Moderately Satisfied, Globally Dissatisfied and Relatedness Deficient,* and *Globally Dissatisfied, Highly Connected, and Competence Deficient* profiles). It also appears important to enhance, in priority,

competence need satisfaction rather than relatedness need satisfaction, at least among university students. Indeed, moderately low levels of global need satisfaction lead to more negative outcomes when relatedness need satisfaction is high (i.e., *Globally Dissatisfied, Highly Connected, and Competence Deficient* profile) than when competence need satisfaction is moderate to high (i.e., *Globally Dissatisfied and Relatedness Deficient* profile).

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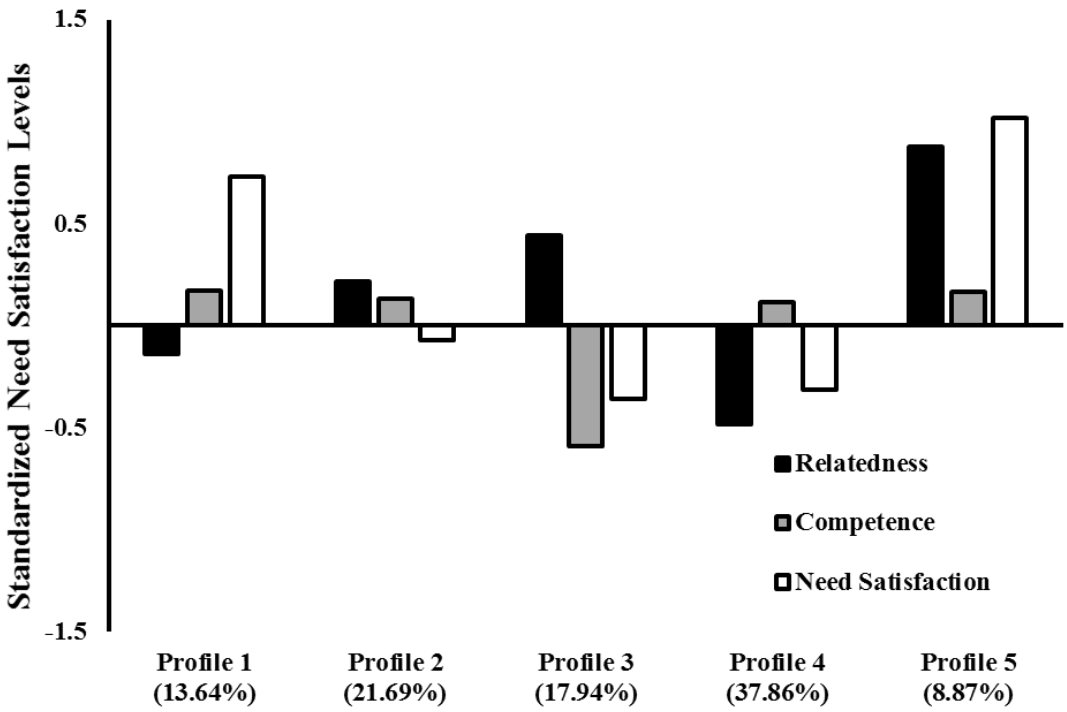

Figure 1. Five-profile solution.
Note. Profile 1: Globally Satisfied; Profile 2: Moderately Satisfied; Profile 3: Globally Dissatisfied, Highly Connected, and Competence Deficient; Profile 4: Globally Dissatisfied and Relatedness Deficient; Profile 5: Globally Satisfied and Highly Connected; Profile indicators are factor scores with a mean of 0 and a standard deviation of 1.

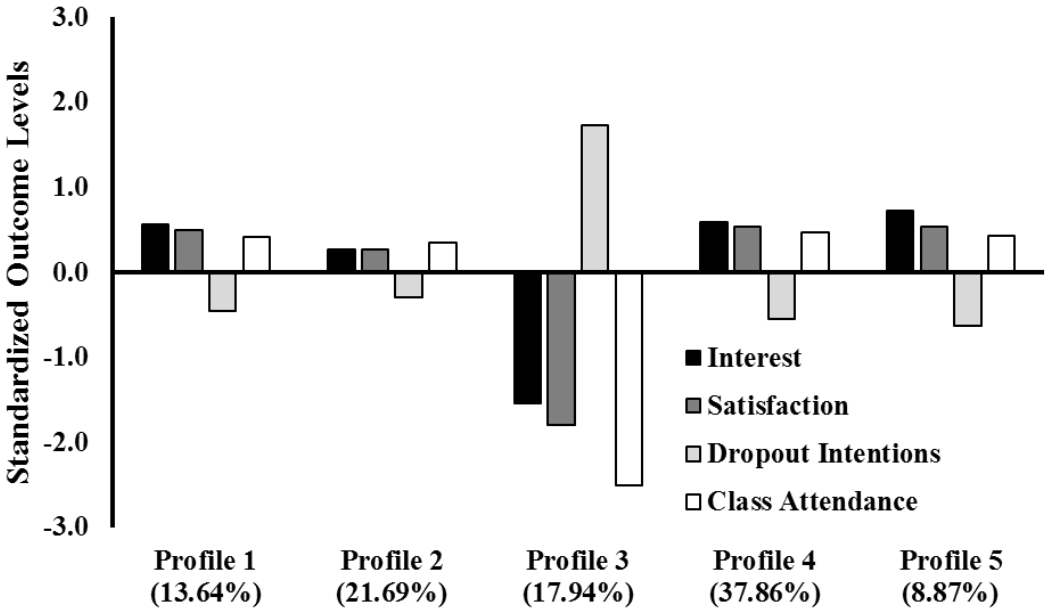

Figure 2. Standardized outcome levels for the five-profile solution of explanatory similarity (equal across time points).
Note. Profile 1: Globally Satisfied; Profile 2: Moderately Satisfied; Profile 3: Globally Dissatisfied, Highly Connected, and Competence Deficient; Profile 4: Globally Dissatisfied and Relatedness Deficient; Profile 5: Globally Satisfied and Highly Connected; Indicators of students' interest toward their studies and dropout intentions are factor scores with a mean of 0 and a standard deviation of 1, whereas those for satisfaction and class attendance were standardized for this figure.

Table 1

Size of the Profiles and Transitions Probabilities

	Time 2 Profiles				
	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
Time 1 Profiles					
Profile 1	.659	.201	.054	.000	.087
Profile 2	.078	.648	.000	.150	.124
Profile 3	.010	.000	.990	.000	.000
Profile 4	.000	.022	.000	.978	.000
Profile 5	.308	.431	.000	.000	.261

Note. Profile 1: Globally Satisfied; Profile 2: Moderately Satisfied; Profile 3: Globally Dissatisfied, Highly Connected, and Competence Deficient; Profile 4: Globally Dissatisfied and Relatedness Deficient; Profile 5: Globally Satisfied and Highly Connected.

Table 2

Effects of the Predictors on the Likelihood of Profile Membership into the First Listed Profile Relative to the Second Listed One (Model of Predictive Similarity)

	Profile 1 vs. Profile 5		Profile 2 vs. Profile 5		Profile 3 vs. Profile 5		Profile 4 vs. Profile 5		Profile 1 vs. Profile 4	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
SOP	-.636 (.249)**	.530	-.802 (.226)**	.448	-1.947 (.686)**	.143	-.996 (.259)**	.369	.360 (.257)	1.434
SPP	.476 (.280)	1.609	.563 (.266)*	1.756	1.353 (.520)**	3.869	.876 (.279)**	2.402	-.401 (.222)	.970
Sex	.026 (.359)	1.027	-.125 (.336)	.883	-.550 (.618)	.577	-.302 (.353)	.740	.333 (.369)	1.388
	Profile 2 vs. Profile 4		Profile 3 vs. Profile 4		Profile 1 vs. Profile 3		Profile 2 vs. Profile 3		Profile 1 vs. Profile 2	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
SOP	.194 (.232)	1.214	-.951 (.720)	.386	1.311 (.660)*	3.710	1.145 (.617)	3.141	.167 (.216)	1.181
SPP	-.313 (.205)	.731	.477 (.496)	1.610	-.877 (.442)*	.416	-.790 (.426)	.454	-.088 (.202)	.916
Sex	.177 (.333)	1.193	-.249 (.645)	780	.577 (.587)	1.780	.426 (.579)	1.531	.151 (.358)	1.163

Note. * $p < .05$; ** $p < .01$; SE: Standard Error of the coefficient; OR: Odds Ratio; SOP: Self-Oriented Perfectionism; SPP: Socially Prescribed Perfectionism. The coefficients and OR reflect the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile. Profile 1: Globally Satisfied; Profile 2: Moderately Satisfied; Profile 3: Globally Dissatisfied, Highly Connected, and Competence Deficient; Profile 4: Globally Dissatisfied and Relatedness Deficient; Profile 5: Globally Satisfied and Highly Connected.

Table 3

Outcomes of Profile Membership (Model of Explanatory Similarity)

	Profile 1 M [CI]	Profile 2 M [CI]	Profile 3 M [CI]	Profile 4 M [CI]	Profile 5 M [CI]	Summary of Statistically Significant Differences
Students' interest toward their studies	.569 [.454; .683]	.268 [.109; .427]	-1.539 [-1.889; -1.189]	.081 [-.080; .243]	.593 [.428; .759]	1 = 5 > 2 = 4 > 3
Satisfaction	5.765 [5.615; 5.916]	5.494 [5.296; 5.692]	3.090 [2.690; 3.489]	5.338 [5.161; 5.516]	5.817 [5.602; 6.031]	1 = 5 > 2 = 4 > 3
Dropout Intentions	-.460 [-.556; -.364]	-.293 [-.429; -.156]	1.737 [1.454; 2.019]	-.305 [-.415; -.195]	-.553 [-.625; -.480]	3 > 2 = 4 > 1 = 5
Class Attendance	95.540 [93.406; 97.675]	94.252 [32.023; 96.481]	46.083 [37.726; 54.439]	93.324 [91.633; 95.015]	96.276 [94.550; 98.002]	3 < 1 = 2 = 4; 1 = 2 = 5; 3 < 4 < 5

Note. M: Mean; CI: 95% Confidence Interval. Indicators of students' interest toward their studies and dropout intentions are factor scores with a mean of 0 and a standard deviation of 1. Profile 1: Globally Satisfied; Profile 2: Moderately Satisfied; Profile 3: Globally Dissatisfied, Highly Connected, and Competence Deficient; Profile 4: Globally Dissatisfied and Relatedness Deficient; Profile 5: Globally Satisfied and Highly Connected.

Online Supplemental Materials for:

Students' Need Satisfaction Profiles: Similarity and Change over the Course of a University Semester

Authors' note:

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

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

Preliminary Measurement Models

A Bifactor Operationalization of Global and Specific Levels of Need Satisfaction

As noted in the main manuscript, accumulating research evidence suggests that ratings of need satisfaction are best represented as simultaneously reflecting respondents' global levels of need satisfaction across all three needs as well as the more specific levels of satisfaction of their needs for competence, relatedness, and autonomy left unexplained by this global level of need satisfaction. This conclusion appears to hold in the educational (Garn, Morin, & Lonsdale, 2018; Gillet et al., 2018), work (Bidee, Vantilborgh, Pepermans, Griep, & Hofmans, 2016; Sánchez-Oliva et al., 2017), sport (Brunet, Gunnell, Teixeira, Sabiston, & Bélanger, 2016), and general life (Tóth-Király, Morin, Bőthe, Orosz, & Rigó, 2018) domains. In practical terms, these studies show that it is possible to simultaneously obtain a direct estimate of participants' global levels of need satisfaction across all three needs (thus providing an explicit estimate of the extent to which the satisfaction of all three needs is balanced for a specific individual), together with a non-redundant estimate of the unique satisfaction of each specific need over and above that global level (i.e., expressed as deviations from that global level, and thus directly reflecting imbalance in the satisfaction of each need relative to all others for a specific individual). Importantly, research in which these two layers of measurement cannot be properly disentangled carries the risk of leading to an overly similar assessment of the relative contribution of each psychological need, making it impossible to clearly identify the unique contribution of each need over and above that of global levels of need satisfaction (Sánchez-Oliva et al., 2017; Tóth-Király et al., 2018).

This multidimensional operationalization of need satisfaction is typically achieved via the estimation of bifactor measurement models (e.g., Holzinger & Swineford, 1937; Morin, Arens, & Marsh, 2016; Reise, 2012). In bifactor models, all need satisfaction items associated with the three subscales were used to define an overarching G-factor reflecting participants' global levels of need satisfaction. In addition, all subscale-specific items were used to define a S-factor reflecting the unique variance associated with each need left unexplained by the G-factor (i.e., expressed as deviations from the global level). When considering the adequacy of a bifactor solution, Morin et al. (2016) highlight that, whereas the observation of a well-defined G-factor is critical, it is only necessary for some of the S-factors to be similarly well-defined. Morin, Myers, and Lee (in press) add that the observation of weakly defined S-factors simply suggests that the items associated with these specific factors only retain a limited amount of specificity once the variance explained by the global factor is taken into account, and illustrate that bifactor models are notably robust to such "vanishing" S-factors. In terms of need satisfaction, observing a weakly-defined specific factor would thus simply indicate that the items used to assess the satisfaction of the need associated with this specific factor provide a clearer reflection of students' global levels of need satisfaction than of that more specific need. More precisely, this would reveal that, among the sample under study, this specific need tends to present only negligible amounts of discrepancies or imbalance relative to students' global levels of need satisfaction.

The previous discussion on "vanishing" S-factors is important as it appears to be the norm in the previous studies in which a bifactor operationalization of need satisfaction has been considered. If we ignore two studies in which need satisfaction and frustration have been simultaneously considered, that have both resulted in the identification of multiple "vanishing" S-factors (Bidee et al., 2016; Tóth-Király et al., 2018), it is interesting to note that the nature of the "vanishing" S-factors identified in the remaining studies appears to be context-specific. Thus, in a study of adolescent students involved in mandatory physical education classes, Garn et al. (2018) reported a "vanishing" relatedness S-factor. In contrast, in a study focusing on adolescents extracurricular sport involvement, Brunet et al. (2016) reported more weakly-defined competence and autonomy S-factors. However, and in direct relevance to the present study, research conducted on older populations of University students (Gillet et al., 2018) or working adults (Sánchez-Oliva et al., 2017) systematically reported a "vanishing" S-factor. If we focus on the University context of the present study, this can easily be explained by the fact that, in this higher education context (just like the work context), student's autonomy is particularly important. For instance, university students must learn to take control and responsibility for their own learning, both in terms of what they learn and how they learn it. They must be capable of self-direction and develop an independent proactive approach to their studies in the context of a reduced amount of classroom contact time. It is therefore important for them to become self-reliant learners who can continue learning efficiently outside the classroom as they can address their own individual needs. In line with these previous results, we also expect to find support for a bifactor operationalization of need satisfaction

resulting in well-defined G-factor, competence S-factor, and relatedness S-factor, but a more weakly-defined autonomy S-factor.

Analyses: Measurement Model Estimation

Preliminary measurement models 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 limited amount of missing responses present at the item level for participants who completed each specific time point (0% to 2.50%). 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 participated at both time waves (Enders, 2010; Graham, 2009). In total, 521 students participated in this study, with 423 (81.2%) students completing both questionnaires and 98 (18.8%) completing only Time 1 questionnaires. FIML has comparable efficacy to multiple imputation, while being more efficient (Enders, 2010; Graham, 2009; Jeličič, Phelps, & Lerner, 2009; Larsen, 2011).

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 measure and the multi-items predictor (self-oriented and socially prescribed perfectionism) and outcome (students' interest toward their studies and dropout intentions) measures. 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. Given our expectation of observing a more weakly-defined autonomy S-factor, a few additional preliminary verifications were conducted in order to reinforce our confidence in the obtained results. First, we first systematically contrasted the results from time-specific CFA and bifactor-CFA models to ensure that: (a) the "vanishing" S-factor was not a function of problematic item ratings (i.e., we expected the first-order CFA autonomy factor to be well-defined); (b) the bifactor-CFA model was indeed superior (in terms of model fit) than the CFA model; and (c) the results would be replicated across two distinct time-specific sets of analyses. For the covariates, a CFA model including four correlated first-order factors (students' self-oriented perfectionism, socially prescribed perfectionism, dropout intentions, and interest toward their studies) was estimated at each time point.

Longitudinal models were directly estimated across all three time waves and included a total of 8 factors ([1 G-factor + 3 S-factors] x 2 time waves) for the need satisfaction measure and 8 factors for the outcome measures (4 factors x 2 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 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 .08 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 CFIs and RMSEAs (Chen, 2007; Cheung & Rensvold, 2002) in the context of tests of measurement invariance. A ΔCFI of .010 or less, a ΔTLI of .010 or less, and a ΔRMSEA of .015 or less between a more restricted model and the previous one supports the invariance hypothesis.

Results: Preliminary Measurement Models

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/TLI ≥ .95, and RMSEA ≤ .06) and their superiority relative to the CFA models (Time 1: $\Delta\chi^2$ = 18.557, Δdf = 6, $p \leq .01$, ΔCFI = +.016, ΔTLI = +.014; ΔRMSEA = -.007; Time 2: $\Delta\chi^2$ = 17.158, Δdf = 6, $p \leq .01$, ΔCFI = +.013, ΔTLI = +.012; ΔRMSEA = -.004). The CFA results, reported in Table S2, revealed that all first-order need satisfaction factors are well-defined at both time points (λ = .513 to 884), supporting the idea that these items work well at representing their a priori factors. When interpreting a bifactor solution, it is important to keep in mind that, because bifactor models rely on two factors to explain the covariance present at the item level for each specific item, factor loadings on G- and S-Factors are typically lower than their first-order counterparts (e.g., Morin et al., 2016). As such, the critical question to ask when interpreting a bifactor solution 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 meaningful S-factors.The bifactor results, reported in Table S4, reveal a reasonably well-defined G-factor (λ = .318 to .762) at both time points, as well as well-defined competence (λ = .363 to 791) and relatedness (λ = .333 to .806) S-factors. Likewise, these results match our expectations in revealing that only a negligible level of specificity remains associated with the autonomy S-factor, which does not appear to be related to any problems related to the performance of these items in the estimation of the previous CFA model, and which fully replicated across two independent analyses performed at each time point (Time 1: λ = .124 to .348; Time 2: λ = .116 to .457). We come back to these bifactor parameter estimates shortly, when we discuss the longitudinally invariant results. Finally, the results also support the adequacy of the CFA models underlying the covariates measures (with all CFI/TLI ≥ .90 and RMSEA ≤ .08).

The tests of measurement invariance conducted on responses to the covariate measures supports their complete measurement invariance across time points (ΔCFI ≤ .010; ΔTLI ≤ .010; ΔRMSEA ≤ .015; and overlapping RMSEA confidence intervals). For responses to the need satisfaction measure, the results also support the configural and weak invariance of the model, but not its strong invariance (ΔCFI/TLI ≥ .010; ΔRMSEA ≥ .015). We thus pursued tests of partial strong invariance, in which the equality constraints across time points had to be relaxed on three need satisfaction items across time points (one per factor). From this model of partial strong invariance, the results also fail to support the complete strict invariance of the model (ΔCFI/TLI ≥ .010; ΔRMSEA ≥ .015), but support a model of partial strict invariance in which equality constraints had to be relaxed on a total of 3 items across time points. Subsequent steps support the invariance of the latent variances, covariances, and latent means of this 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; Covariates: Latent mean invariance). Although only (partial) 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 final invariant parameter estimates from these measurement models are reported in Tables S4 (need satisfaction) and S5 (covariates). The covariate model resulted in factors that were well-defined through high factor loadings (λ = .629 to .930), resulting in fully acceptable model-based composite reliability coefficients (ω = .823 to .923; McDonald, 1970). For the need satisfaction measure, the invariant global need satisfaction factor is well-aligned with Sánchez-Oliva et al.'s (2017) results, supporting its interpretation as a well-defined (λ =.311 to .731) and reliable (ω = .794 at Time 1 and .824 at Time 2) estimate of students' global levels of need satisfaction. Similarly, over and above students' global levels of need satisfaction, the S-factors referring to their feelings of competence (λ =.422 to .722; ω = .679 at Times 1 and 2) and relatedness (λ =.429 to .804; ω = .692 at Time 1 and .719 at Time 2) also appear to retain a meaningful amount of specificity. In contrast, the autonomy S-factor does not appear to retain any meaningful specificity, resulting in the estimation of very small (λ =.054 to .097) and non-significant factor loadings, suggesting that responses to autonomy items mainly serve

to define students' global levels of need satisfaction (i.e., the G-factor) in this study. As such, factor scores on this factor were not retained for further analyses. The correlations between all variables used in the main analyses (i.e., the factor scores from these final measurement models and single item measures) are reported in Table S6.

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Table S1

Goodness-of-Fit Statistics for the Estimated Measurement Models

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Need Satisfaction									
Time 1: CFA	53.245 (24)*	.965	.948	.048	[.031; .066]	-	-	-	-
Time 1: Bifactor CFA	34.012 (18)*	.981	.962	.041	[.019; .062]	18.557 (6)*	+.016	+.014	-.007
Time 2: CFA	55.862 (24)*	.965	.943	.056	[.037; .075]	-	-	-	-
Time 2: Bifactor CFA	38.356 (18)*	.978	.955	.052	[.029; .074]	17.158 (6)*	+.013	+.012	-.004
Longitudinal: Configural invariance	131.097 (92)*	.983	.973	.029	[.016; .039]	-	-	-	-
Longitudinal: Weak invariance	138.305 (106)*	.986	.980	.024	[.010; .035]	7.208 (14)	+.003	+.007	-.005
Longitudinal: Strong invariance	209.347 (111)*	.958	.943	.041	[.033; .050]	71.042 (5)	-.028	-.037	+.017
Longitudinal: Partial strong invariance	150.062 (108)*	.982	.975	.027	[.016; .037]	11.757 (2)	-.004	-.005	+.003
Longitudinal: Strict invariance	208.326 (117)*	.961	.950	.039	[.030; .047]	58.264 (9)	-.021	-.025	+.012
Longitudinal: Partial strict invariance	175.237 (114)*	.974	.966	.032	[.022; .041]	25.175 (6)	-.008	-.001	+.005
Longitudinal: Variance-Covariance invariance	193.866 (118)*	.968	.958	.035	[.026; .044]	18.269 (4)	-.008	-.008	+.003
Longitudinal: Latent means invariance	221.076 (122)*	.958	.948	.039	[.031; .048]	27.210 (4)	-.010	-.010	+.004
Predictors and Outcomes									
Time 1: First-Order CFA	211.147 (71)*	.952	.938	.062	[.052; .071]	-	-	-	-
Time 2: First-Order CFA	149.984 (71)*	.973	.966	.051	[.040; .063]	-	-	-	-
Longitudinal: Configural invariance	559.979 (308)*	.967	.959	.040	[.034; .045]	-	-	-	-
Longitudinal: Weak invariance	579.410 (318)*	.966	.959	.040	[.035; .045]	19.431 (10)	-.001	.000	.000
Longitudinal: Strong invariance	621.757 (328)*	.961	.956	.042	[.037; .046]	42.347 (10)	-.005	-.003	+.002
Longitudinal: Strict invariance	659.400 (342)*	.958	.954	.042	[.037; .047]	37.643 (14)	-.003	-.002	.000
Longitudinal: Var-Cov invariance	711.964 (352)*	.953	.949	.044	[.040; .049]	52.564 (10)	-.005	-.005	+.002
Longitudinal: Latent means invariance	764.140 (356)*	.946	.943	.047	[.042; .052]	52.176 (4)	-.007	-.006	+.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; Δ: change in fit information relative to the previous model.

Table S2

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Final Time-Specific CFA Solutions (Need Satisfaction)

	Time 1				Time 2			
Items	AS λ	CS λ	RS λ	δ	AS λ	CS λ	RS λ	δ
Autonomy								
Item 1	.521			.728	.700			.510
Item 2	.513			.737	.773			.403
Item 3	.578			.666	.767			.412
Competence								
Item 1		.651		.577		.708		.498
Item 2		.781		.391		.884		.219
Item 3		.638		.593		.734		.461
Relatedness								
Item 1			.738	.455			.754	.431
Item 2			.801	.359			.804	.354
Item 3			.514	.735			.617	.619

Note. λ: factor loading; δ: item uniqueness; 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 Time-Specific Bifactor-CFA Solutions (Need Satisfaction)

	Time 1					Time 2				
Items	G λ	S-AS λ	S-CS λ	S-RS λ	δ	G λ	S-AS λ	S-CS λ	S-RS λ	δ
Autonomy										
Item 1	.486	*.164*			.737	.652	*.457*			.367
Item 2	.520	*.124*			.714	.762	*.116*			.407
Item 3	.527	*.348*			.601	.743	*.129*			.431
Competence										
Item 1	.422		.492		.580	.447		.516		.534
Item 2	.486		.656		.333	.523		.791		.101
Item 3	.520		.363		.598	.547		.458		.492
Relatedness										
Item 1	.350			.600	.517	.372			.616	.482
Item 2	.336			.806	.237	.318			.805	.250
Item 3	.440			.333	.696	.374			.480	.630

Note. 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; AS = autonomy satisfaction; CS = competence satisfaction; RS = relatedness satisfaction; non-significant parameters ($p \geq .05$) are marked in italics.

Table S4

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Final Longitudinal Bifactor-CFA Solution (Need Satisfaction)

	Time 1					Time 2				
Items	G λ	S-AS λ	S-CS λ	S-RS λ	δ	G λ	S-AS λ	S-CS λ	S-RS λ	δ
Autonomy										
Item 1	.607	*.084*			.671	.731	*.097*			.556
Item 2	.568	*.054*			.629	.659	*.065*			.461
Item 3	.681	*.077*			.531	.681	*.077*			.531
ω		.025					.036			
Competence										
Item 1	.388		.549		.548	.388		.549		.548
Item 2	.483		.722		.245	.483		.722		.245
Item 3	.509		.422		.563	.509		.422		.563
ω			.679					.679		
Relatedness										
Item 1	.330			.594	.538	.362			.652	.444
Item 2	.311			.804	.257	.311			.804	.257
Item 3	.359			.429	.687	.359			.429	.687
ω	.794			.692		.824			.719	

Note. 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 S5

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Completely Invariant Longitudinal First-Order CFA Solution (Predictors and Outcomes)

Items	DI λ	INT λ	SOP λ	SPP λ	δ
Dropout intentions					
Item 1	.871				.241
Item 2	.880				.225
Item 3	.930				.135
ω	.923				
Students' interest toward their studies					
Item 1		.873			.238
Item 2		.897			.195
Item 3		.700			.510
Item 4		.664			.559
Item 5		.790			.376
ω		.891			
Self-oriented perfectionism					
Item 1			.852		.275
Item 2			.844		.287
Item 3			.818		.330
ω			.876		
Socially prescribed perfectionism					
Item 1				.629	.604
Item 2				.810	.344
Item 3				.885	.216
ω				.823	
Factor Correlations	DI	INT	SOP	SPP	
Dropout intentions					
Students' interest toward their studies	-.584				
Self-oriented perfectionism	-.145	.206			
Socially prescribed perfectionism	-.008	-.033	.612		

Note. CFA = confirmatory factor analyses; λ: factor loading; δ: item uniqueness; ω: omega coefficient of model-based composite reliability; DI = dropout intentions; INT = students' interest toward their studies; SOP = self-oriented perfectionism; SPP = socially prescribed perfectionism.

Table S6

Correlations between Variables Used in the Present Study

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1. Sex	-											
2. Self-oriented perfectionism (T1)	-.030	-										
3. Socially prescribed perfectionism (T1)	-.022	.661**	-									
4. Competence need satisfaction (T1)	.083	.122**	.008	-								
5. Relatedness need satisfaction (T1)	-.007	.080	.023	-.128**	-							
6. Global need satisfaction (T1)	.045	.225**	.024	.232**	.146**	-						
7. Class attendance (T1)	-.130**	.093*	-.016	.176**	.019	.146**	-					
8. Study satisfaction (T1)	-.058	.079	-.071	.146**	.016	.275**	.178**	-				
9. Students' interest toward their studies (T1)	-.034	.207**	-.036	.178**	.044	.407**	.281**	.671**	-			
10. Dropout intentions (T1)	-.016	-.126**	.003	-.258**	-.027	-.335**	-.315**	-.313**	-.561**	-		
11. Self-oriented perfectionism (T2)	-.049	.861**	.629**	.140**	.028	.204**	.072	.112*	.205**	-.175**	-	
12. Socially prescribed perfectionism (T2)	-.009	.553**	.860**	.060	-.018	.013	-.004	-.066	-.014	-.063	.686**	-
13. Competence need satisfaction (T2)	.119**	.158**	.069	.868**	-.133**	.217**	.166**	.103*	.166**	-.292**	.182**	122**
14. Relatedness need satisfaction (T2)	-.035	.017	-.034	.048	.579**	-.081	.060	.023	.045	-.019	-.018	-.066
15. Global need satisfaction (T2)	-.001	.157**	-.045	-.079	.111*	.715**	.106*	.283**	.367**	-.239**	.170**	-.057
16. Class attendance (T2)	-.088	.103*	-.018	.117*	.092	.113*	.494**	.141**	.256**	-.345**	.135**	-.004
17. Study satisfaction (T2)	-.044	.157**	-.018	.157**	.081	.331**	.226**	.493**	.537**	-.338**	.166**	-.047
18. Students' interest toward their studies (T2)	-.013	.232**	-.023	.158**	.136**	.426**	.263**	.532**	.751**	-.559**	.242**	-.050
19. Dropout intentions (T2)	.003	-.133**	.012	-.264**	-.085	-.353**	-.297**	-.258**	-.439**	.796**	-.180**	-.003

Table S6 (Continued)

	13	14	15	16	17	18	19
13. Competence need satisfaction (T2)	-						
14. Relatedness need satisfaction (T2)	-.018	-					
15. Global need satisfaction (T2)	-.035	-.001	-				
16. Class attendance (T2)	.184**	.116*	.160**	-			
17. Study satisfaction (T2)	.162**	.096*	.462**	.329**	-		
18. Students' interest toward their studies (T2)	.181**	.107*	.478**	.421**	.733**	-	
19. Dropout intentions (T2)	-.323**	-.054	-.334**	-.485**	-.476**	-.675**	-

Note. T1: Time 1; T2: Time 2; for students' psychological need satisfaction, perfectionism, interest toward their studies, and dropout intentions, scores are factor scores from preliminary models. * $p < .05$; ** $p < .01$.

Table S7

Attrition Analyses: Mean Comparison of Time 1 Levels between Students Lost or Not through Attrition

Variable	M_{T1}	SD_{T1}	M_{T1-T2}	SD_{T1-T2}	F	p-value
Sex	1.29 (71% females)	.45	1.17 (83% females)	.38	6.574	.011
Relatedness need satisfaction (T1)	-.05	1.05	-.00	.83	.293	.589
Competence need satisfaction (T1)	.04	.81	.01	.81	.082	.775
Global need satisfaction (T1)	-.03	.81	.01	.81	.235	.628
Class attendance (T1)	90.20	15.79	94.88	10.44	12.813	.000
Study satisfaction (T1)	4.89	1.37	5.10	1.15	2.560	.110
Dropout intentions (T1)	.07	.98	-.11	.85	3.092	.079
Students' interest toward their studies (T1)	-.14	1.05	.07	.85	4.375	.037
Self-oriented perfectionism (T1)	.06	.92	.06	.93	.001	.974
Socially prescribed perfectionism (T1)	-.04	.94	.03	.93	.511	.475

Note. M_{T1} = mean level among students who only completed Time 1; SD_{T1} = standard deviation among students who only completed Time 1; M_{T1-T2} = mean level among students who completed Time 1 and Time 2; SD_{T1-T2} = standard deviation among students who completed Time 1 and Time 2.

Selecting the Optimal Number of Profiles

Model Comparison and Selection

Selecting the optimal number of profiles that best represents the data is a challenge for any person-centered study. This selection needs to consider various sources of information. First and foremost among these sources are related to the theoretical conformity and meaningfulness of the extracted profiles, coupled with an examination of the statistical adequacy of each solution (Bauer & Curran, 2003; Marsh, Lüdtke, Trautwein, & Morin, 2009; Muthén, 2003). This mainly procedure can be guided by a series of statistical indicators (McLachlan & Peel, 2000). In the present study, we report the Akaïke Information Criterion (AIC), the Consistent AIC (CAIC), the Bayesian Information Criterion (BIC), and the sample-size Adjusted BIC (ABIC). A better-fitting model is suggested by the observation of a lower value on these information criteria. We also report the adjusted Lo, Mendel, and Rubin's (2001) Likelihood Ratio Test (aLMR), and the Bootstrap Likelihood Ratio Test (BLRT). A statistically significant result in these tests supports the value of a solution relative to one including fewer profiles.

Statistical research has supported the utility of the CAIC, BIC, ABIC, and BLRT, but not that of the AIC and ALMR (Diallo, Morin, & Lu, 2017; Henson, Reise, & Kim, 2007; Nylund, Asparouhov, & Muthén 2007; Peugh & Fan, 2013; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008; Yang, 2006). In the present study, we thus do not rely on these additional indicators (AIC and aLMR) to guide the selection of the optimal solution, but still disclose them for purposes of transparency and to permit comparisons with previously published research. Importantly, a recent statistical study has led to the recommendation that BIC and CAIC should be favored when the entropy of the model (an indicator of classification accuracy) is high (e.g., $\geq .800$), whereas the ABIC and BLRT should be favored when the entropy is low (e.g., $\leq .600$; Diallo et al., 2017). Despite these recommendations, all of these indicators present a strong sample size dependency (Marsh et al., 2009) and sometimes simply fail to converge on any specific solution. When this happens, the point at which these indicators appear to reach a plateau, when graphically displayed as part of elbow plots, can be considered to reflect a possible optimal solution (Morin et al., 2011).

In test of profile similarity, alternative models can be compared using the Consistent Akaïke Information Criterion (CAIC), the Bayesian Information Criterion (BIC), and the sample-size Adjusted BIC (ABIC). Morin, Meyer, Creusier, and Biétry (2016) note that at least two of these indicators should decrease in order to support the more "similar" model in any pairwise model comparison.

Results: Time-Specific Model Selection

The fit indices associated with the alternative time-specific latent profile analyses (LPA) are reported in Table S8, and graphically displayed in Figures S1 and S2. Across time waves, the entropy values associated with the solutions including four profiles and more are all relatively high (.700 and above), suggesting that more attention should be given to the CAIC and BIC, which supported the five-profile solution at Time 1. At Time 2 however, both the BIC and CAIC were lower for the three-profile solution, although the BIC and CAIC values associated with the two- to five-profile solutions are essentially equivalent to one another. Importantly, examination of the alternative solutions revealed that all solutions were statistically proper, and showed profiles characterized by a very similar shape at both time waves. These results provide initial support to the generalizability of the solution over time.

Furthermore, adding latent profiles to the solution at both time waves resulted in the addition of theoretically meaningful, interpretable, and distinct profiles up to the five-profile solution. In contrast, including a sixth profile resulted in the arbitrary division of an already identified profile into smaller ones (i.e., 38% at Time 2). For instance, when we consider the retained five-profile solution illustrated in Figure 1 of the main manuscript, its added value is well-illustrated by the fact that moving from three to four profiles added the current first profile to the data, while adding a fifth profile resulted in the current third profile to the solution. Conversely, adding a sixth profile resulted in the division of Profile 1 into two smaller profiles of the same general shape. For all of these considerations, a solution including five profiles was retained at both time waves, evidencing the configural similarity of this solution.

Results: Tests of Profile Similarity

The fit indices associated with the final time-specific LPA, as well as those associated with all longitudinal solutions are reported in Table S9. The results from the longitudinal LPA provide evidence for the structural, dispersion, and distributional similarity of our solution, as each of these solutions resulted in lower BIC and CAIC values.

For models including predictors, the results reported in Table S9 revealed that the lowest values for all information criteria were found to be associated with the model of predictive similarity, thus supporting the equivalence of the predictions across time periods, and a lack of relations between predictors and specific profile transitions.

Finally, for models including outcomes, the results reported in Table S9 revealed that the model in which the outcome levels were specified to be equal over time resulted in lower values for the BIC and CAIC, thus supporting the explanatory similarity of the solution.

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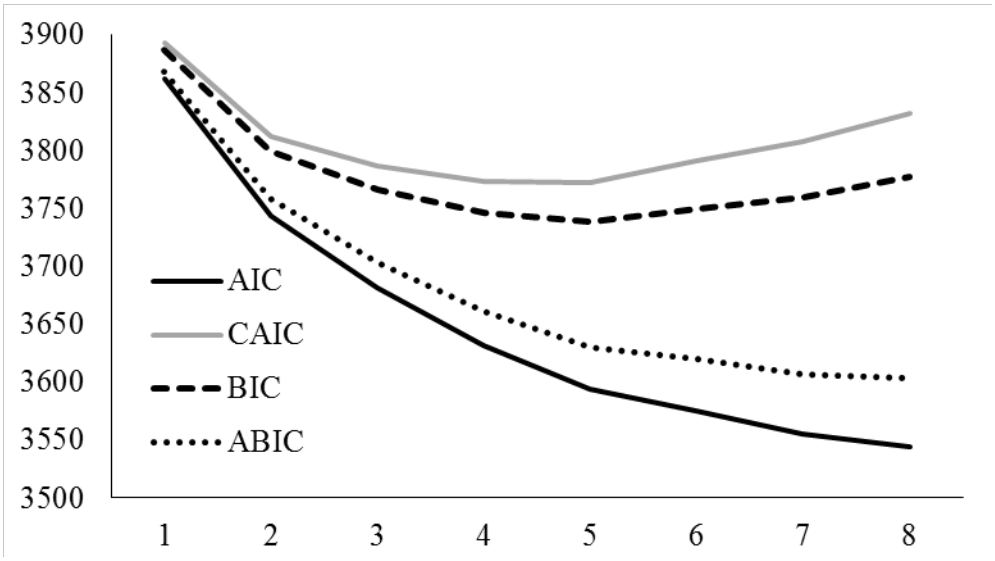

Figure S1
Elbow Plot of the Information Criteria for the Latent Profile Analyses (Time 1)

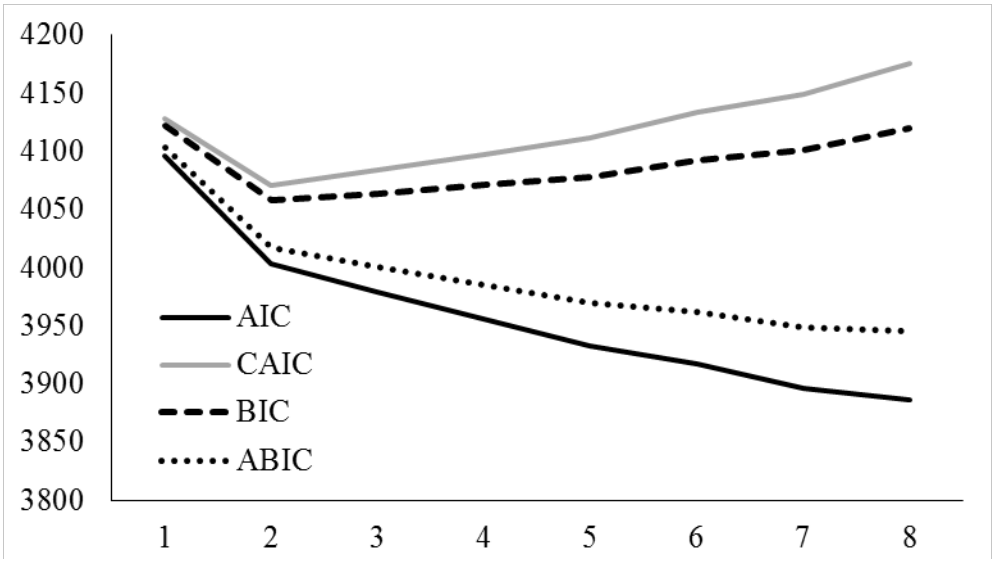

Figure S2
Elbow Plot of the Information Criteria for the Latent Profile Analyses (Time 2)

Table S8

Results from the Time-Specific Latent Profile Solutions

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Time 1 (N = 521)										
1 Profile	-1925.120	6	1.172	3862.240	3893.774	3887.774	3868.729	Na	Na	Na
2 Profiles	-1859.135	13	.940	3744.271	3812.596	3799.596	3758.331	.491	< .001	< .001
3 Profiles	-1820.681	20	1.218	3681.361	3786.476	3766.476	3702.992	.654	.105	< .001
4 Profiles	-1788.906	27	1.334	3631.813	3773.718	3746.718	3661.014	.751	.296	< .001
5 Profiles	-1762.952	34	1.231	3593.905	3772.600	3738.600	3630.677	.775	.064	< .001
6 Profiles	-1746.708	41	1.145	3575.417	3790.902	3749.902	3619.759	.724	.134	< .001
7 Profiles	-1729.646	48	1.091	3555.292	3807.568	3759.568	3607.205	.770	.008	< .001
8 Profiles	-1716.915	55	1.040	3543.831	3832.897	3777.897	3603.315	.781	.240	1.000
Time 2 (N = 423)										
1 Profile	-2042.231	6	1.282	4096.462	4127.996	4121.996	4102.951	Na	Na	Na
2 Profiles	-1988.482	13	1.232	4002.965	4071.289	4058.289	4017.025	.476	.012	< .001
3 Profiles	-1969.484	20	1.345	3978.967	4084.082	4064.082	4000.598	.662	.294	< .001
4 Profiles	-1950.960	27	1.199	3955.921	4097.826	4070.826	3985.122	.737	.049	.013
5 Profiles	-1932.558	34	1.173	3933.117	4111.812	4077.812	3969.889	.730	.277	< .001
6 Profiles	-1917.921	41	1.135	3917.841	4133.327	4092.327	3962.184	.766	.368	< .001
7 Profiles	-1900.309	48	1.329	3896.618	4148.894	4100.894	3948.531	.786	.715	< .001
8 Profiles	-1888.123	55	1.047	3886.246	4175.313	4120.313	3945.730	.725	.961	< .001

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.

Table S9

Latent Profile and Latent Transition Analyses

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC
Final Latent Profile Analyses							
Time 1 (n = 521)	-1762.952	34	1.231	3593.905	3772.600	3738.600	3630.677
Time 2 (n = 423)	-1932.558	34	1.173	3933.117	4111.812	4077.812	3969.889
Longitudinal Latent Profile Analyses							
Configural Similarity	-3701.833	68	1.174	7539.666	7897.057	7829.057	7613.210
Structural Similarity	-3732.420	53	1.155	7570.840	7849.394	7796.394	7628.161
Dispersion Similarity	-3759.382	38	1.420	7594.763	7794.482	7756.482	7635.861
Distributional Similarity	-3768.426	34	1.505	7604.852	7783.548	7749.548	7641.624
Latent Transition Analysis	-1440.073	24	.583	2928.145	3054.283	3030.283	2954.102
Predictive Similarity							
Profile-Specific Free Relations with Predictors	-1370.518	108	.483	2957.036	3524.241	3416.241	3073.427
Free Relations with Predictors	-1403.501	48	.911	2903.002	3155.094	3107.094	2954.732
Equal Relations with Predictors	-1415.025	36	.805	2902.050	3091.118	3055.118	2940.847
Explanatory Similarity							
Free Relations with Outcomes	-8997.411	72	1.332	18138.822	18517.236	18445.236	18216.692
Equal Relations with Outcomes	-9033.686	52	1.470	18171.372	18444.671	18392.671	18227.611

Note. LL: Model LogLikelihood; #fp: Number of free parameters; Scaling: Scaling factor associated with MLR loglikelihood estimates; AIC: Akaïke Information Criteria; CAIC: Constant AIC; BIC: Bayesian Information Criteria; ABIC: Sample-Size adjusted BIC.

Table S10

Detailed Results from the Final Longitudinal Latent Profile Analytic Solution (Distributional Similarity)

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
	Mean [CI]	Mean [CI]	Mean [CI]	Mean [CI]	Mean [CI]
Relatedness	-.137 [-.252; -.021]	.219 [.105; .332]	.445 [.124; .767]	-.486 [-1.104; .132]	.875 [.812; .937]
Competence	.171 [-.089; .432]	.133 [-.031; .298]	-.588 [-1.948; .773]	.116 [-.021; .254]	.166 [-.071; .402]
Global Need Satisfaction	.730 [.369; 1.090]	-.070 [-.275; .135]	-.358 [-.825; .109]	-.316 [-.513; -.119]	1.017 [.745; 1.289]
	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]
Relatedness	.029 [.014; .045]	.039 [.018; .059]	.533 [.157; .910]	1.069 [.902; 1.237]	.030 [.013; .046]
Competence	.571 [.369; .773]	.393 [.156; .630]	1.319 [.854; 1.784]	.550 [.362; .739]	.579 [.364; .793]
Global Need Satisfaction	.233 [.093; .372]	.188 [.082; .294]	1.130 [-.115; 2.375]	.690 [.335; 1.046]	.248 [.017; .478]

Note. CI = 95% Confidence Interval*;* the profile indicators are estimated from factor scores with mean of 0 and a standard deviation of 1; Profile 1: Globally Satisfied; Profile 2: Moderately Satisfied; Profile 3: Globally Dissatisfied, Highly Connected, and Competence Deficient; Profile 4: Globally Dissatisfied and Relatedness Deficient; Profile 5: Globally Satisfied and Highly Connected.