Undergraduate Students' Motivational Profiles Before and During the COVID-19 Pandemic: The Role of Educational Climate and Trait Self-Control

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Abstract

Background: Universities faced important and sudden changes following the lockdown measures imposed during the COVID-19 pandemic. Traditional educational practices were disrupted as campuses were closed while distance learning was hastily adopted. **Aims**: This study documents the evolution of university students' autonomous and controlled motivation for their studies following campus closures by relying on a person-centered perspective. More specifically, it examines motivation profiles and their temporal stability across two-time points taken before and during the pandemic, while also considering the role of educational climate, trait self-control, and control variables (sex and age) as predictors of profile membership. **Sample**: A total of 1940 university students participated in this study by responding to online questionnaires at two time points, before (Time 1) and after (Time 2) the pandemic. **Methods**: We relied on latent profile and latent transition analyses to estimate motivation profiles, their temporal stability, and their predictors. **Results**: A 4-profile solution (*Self-Determined*, *Moderately Motivated*, *Extrinsically Motivated*, *Amotivated*) was selected and replicated at both time points. We observed a low degree of variability in profile membership over time, especially for the *Amotivated* profile. A need-supportive educational climate and trait self-control consistently predicted a greater likelihood of membership into more adaptative profiles (*Self-Determined*, *Moderately Motivated)*. **Conclusions**: The COVID-19 pandemic did not drastically change the motivational profiles of university students. Nevertheless, educational climate and self-control appeared to "protect" students against the endorsement of more problematic motivation profiles both before and during the pandemic, making them important targets for intervention.
Keywords: COVID-19; Academic motivation; Educational climate; Self-control; Latent transition analysis.

Early 2020 was marked by unprecedented shifts in university functioning caused by the onset of the COVID-19 pandemic. To limit the spread of COVID-19, campuses were closed, and distance learning was abruptly implemented in most universities (Marinoni et al., 2020). Campus closures lasted throughout 2020 in many countries, resulting in a forced prolonged exposure to suboptimal teaching and learning conditions which contributed to increased levels of distress among many students (Pokhrel & Chhetri, 2021). Many researchers raised concerns about the consequences of the pandemic for students' academic outcomes, including their motivation. Rapidly disseminated findings suggested negative developmental trends in students' motivation after the onset of the pandemic (Janke et al., 2022; Usher et al., 2022). However, other studies contradicted this trend, observing no significant decrease in university students' motivation (Bolatov et al., 2022; Pasion et al., 2020).

This heterogeneity in results calls for additional research on whether and how students' motivation changed as a result of the COVID-19 pandemic. The present study provides new insights on this important topic through the adoption of a person-centered perspective focused on the nature and one-year stability of students' motivation profiles before and during the COVID-19 pandemic. The role of contextual (educational climate) and individual (trait self-control, sex, age) factors as predictors of students' likelihood of profile membership is also examined.

Academic Motivation

According to Self-Determination Theory (SDT; Ryan & Deci, 2017), academic motivation is a multidimensional construct encompassing different types of behavioural regulation organized along a continuum of self-determination. At one end of this continuum is intrinsic motivation, which occurs when students enjoy their educational tasks. This is considered to reflect the most autonomous, or self-determined, form of motivation. Then, identified regulation occurs when students feel that their education is important and coherent with their personal values and goals. Next on the continuum, introjected regulation occurs when students feel internally pressured to engage in their studies to preserve their positive self-image or to avoid feelings of shame or guilt. External regulation then occurs when students feel externally pressured to engage in their studies to attain rewards or to avoid punishments. Lastly, amotivation is a state that describes a complete lack of reason to engage in academic work (non-regulation). More globally, intrinsic motivation and identified regulation can be classified as autonomous types of motivation, whereas external and introjected regulations can be considered as controlled types of motivation. Numerous studies have supported the presence of well-differentiated associations between these various types of behavioral regulation and important educational outcomes. For instance, autonomous forms of motivation have been positively linked to students' engagement, persistence, and achievement while controlled forms of motivation and amotivation have been found to be associated with school dropout, academic dishonesty, and anxiety (Guay et al., 2008; Howard et al., 2021). These results thus highlight the important role played by academic motivation in general, in addition to highlighting the importance of finding ways to support autonomous motivation while limiting controlled motivations and amotivation as students undergo important changes in their academic trajectories, such as those imposed by the COVID-19 pandemic.

A Person-Centered Perspective on Academic Motivation

Previous studies of academic motivation conducted during the COVID-19 pandemic have mostly relied on variable-centered approaches to assess general changes in students' levels of motivation during the pandemic, assuming that their results would generalize to the whole student population. Despite their relevance, these studies fail to acknowledge that students' motivational experiences tend to be rooted in a dynamic combination of diverse types of behavioral regulation (Litalien et al., 2019; Vallerand, 1997). By ignoring the presence of subpopulations of students displaying qualitatively distinct configurations of behavioral regulations, these studies did not grasp the full heterogeneous reality of students' academic motivation. Adopting a person-centered perspective is necessary to capture this heterogeneity. Indeed, person-centered analyses are designed to uncover the various ways in which various types of behavioral regulations are combined within different subpopulations (or profiles) of students (Litalien et al., 2019).

In this study, we rely on a person-centered approach to identify the various types of motivation profiles among students exposed to the COVID-19 pandemic, as well as the stability of these profiles before and during the pandemic. In doing so, we adopt a recently advocated bifactor operationalization of academic motivation (Howard et al., 2018, 2020; Litalien et al., 2017; See Figure 1) allowing us to jointly obtain an estimate of students' global level of self-determined motivation (an estimate anchored in their ratings of all types of behavioral regulation) together with a non-redundant estimate of the extent to which each type of behavioral regulation deviates from, or is aligned with, this global level. Indeed, statistical research has demonstrated that it was necessary to account for this global/specific duality, when present, to properly identify meaningful latent profile solutions (Morin et al., 2016a, 2017).

Predictors of Academic Motivation

SDT assumes that the social environment in which students evolve helps shape the nature of their academic motivation (Ryan & Deci, 2017). More precisely, SDT suggests that educational contexts helping to support the satisfaction of students' psychological needs for autonomy (a sense of volition), competence (a sense of effectiveness and mastery), and relatedness (a sense of connection with meaningful others) should help foster more autonomous forms of motivation, whereas a context that thwarts these needs should foster more controlled forms of motivation and amotivation (Ryan & Deci, 2020). These propositions have been supported by recent meta-analyses, which have also helped to position students' psychological need satisfaction as the most proximal driver of autonomous types of motivation (Bureau et al., 2022; Vasconcellos et al., 2019).

Unfortunately, the lockdown measures imposed by the COVID-19 pandemic are likely to have interfered with students' need satisfaction. Indeed, prolonged campus closures imposed external restrictions on students who were forced to take all their courses online, thus interfering with the fulfillment of their need for autonomy (Janke et al., 2022). Likewise, the sudden switch to distance learning disrupted learning processes, as many instructors were not prepared to move their classes online (Carrillo & Flores, 2020), just like many students did not have access to an optimal home setting for distance learning (Falardeau et al., 2022). This suboptimal learning environment is thus likely to have interfered with the fulfillment of students' need for competence. Lastly, campus closures and distance learning both resulted in diminished possibilities for social interactions between students, their peers, and their instructors, thus directly interfering with the fulfillment of students' need for relatedness (Janke et al., 2022).

Gilbert et al. (2021; 2022) identified a variety of need-supporting and need-thwarting components (collectively referred to as need nurturing; Tóth-Király et al., 2020) of universities' educational climate that could help students maintain adequate levels of autonomous motivation while limiting controlled motivation and amotivation, even within otherwise unfavorable learning conditions such as those imposed by the COVID-19 pandemic. Examples of these components include the provision of relevant course options, clear and accessible information on the curriculum, and networking opportunities among students and between students and instructors (Gilbert et al., 2021). Importantly, Gilbert et al. (2022) showed that programs which provided students with such need-nurturing conditions during the first wave of the COVID-19 pandemic were more efficient in helping students maintain satisfactory levels of need satisfaction. Conversely, failing to do so seemed to interfere with need satisfaction (Gilbert et al., 2022). These results thus suggest, albeit indirectly, that the need supportive and need thwarting components of universities' educational climate have potentially played an important role in minimizing or amplifying the impact of campus closure on students' self-determined motivational profiles.

Some stable personality characteristics could also have helped students maintain adequate motivation profiles during the COVID-19 pandemic by influencing their natural tendencies to adopt more or less self-determined forms of motivation (e.g., Gillet et al., 2017; Komarraju et al., 2009). For instance, trait self-control (i.e., the ability to exert control over one's thoughts, feelings, and behaviours to prioritize long-term goals over instant gratification; Baumeister & Heatherton, 1996) has recently been identified as a strong determinant of motivation quality, being linked to increased levels of autonomous motivation and decreased levels of controlled motivation over time (Converse et al., 2019; Holding et al., 2019). Trait self-control may have been particularly important during the COVID-19 pandemic since distance learning requires students to be actively involved in their learning process (e.g., managing their learning schedule, avoiding procrastination; Eberle & Hobrecht, 2021). Moreover, self-control is a proactive capacity believed to help students assess and understand their needs, values, and interests, thus facilitating the endorsement of autonomous forms of motivation (Holding et al., 2019), even despite unfavorable learning conditions (e.g., forced distance learning).

The Present Study

The first goal of this study was to investigate the nature and temporal stability of university students' academic motivation profiles before and during the COVID-19 pandemic while relying on a proper disaggregation of their global and specific levels of motivation. Results from previous person-centered research (e.g., Litalien et al., 2019; Tóth-Király et al., 2022) suggest that a relatively small (3 to 5) number of motivation profiles should be identified (Hypothesis 1). Based on the negative impact of the pandemic on students' motivation and psychological need satisfaction reported in some previous studies

(Falardeau et al., 2022; Janke et al., 2022; Usher et al., 2022), we also postulated that membership into profiles characterized by high levels of self-determined motivation would be less stable over time than membership into less desirable motivation profiles (Hypothesis 2). Second, this study aimed to investigate the role of the need-nurturing characteristics of the program educational climate and students' trait self-control in the prediction of profile membership, while controlling for sex and age. These two demographic characteristics have been previously shown to relate to motivation, with female and older university students generally having a more self-determined motivational orientation than male and younger university students (Brouse et al., 2010; Gillet et al., 2017; Stynen et al., 2014; Vallerand et al., 1989; 1992). As our sample (see next section) includes a majority of women and slightly older students than we expected, we considered it important to consider these controls in our analyses. Based on the aforementioned theoretical and empirical considerations (e.g., Gilbert et al., 2021, 2022; Holding et al., 2019), we postulated that need-nurturing study programs and high trait self-control would predict membership into profiles characterized by higher levels of autonomous motivation at both time points, while also possibly predicting transitions to profiles characterized by higher levels of autonomous motivation across time points, beyond the role played by sex and age (Hypothesis 3). From a practical perspective, this study was thus designed to help identify whether and how the COVID-19 pandemic might have interfered with students' motivation, and whether characteristics of the educational climate and students' trait self-control might have helped limit these effects.

Method

Procedure and Participants

During the 2019 Fall semester (before the COVID-19 pandemic), we contacted the entire population (N = 12,153) of first-year undergraduate students registered in disciplinary baccalaureates (i.e., programs focusing on a specific field of study) from two large French-speaking Canadian universities. Of these students, 1425 (participation rate: 11.73%; Female = 80.1%, M_{age} = 21.56; SD_{age} = 4.99) agreed to participate by completing an online questionnaire. During the 2020 Fall semester (during the COVID-19 lockdown), all potential participants (N = 12,153) were re-invited to complete a follow-up questionnaire. A total of 882 students agreed to do so (participation rate: 7.26%; Female = 79.2%, M_{age} = 22.61; SD_{age} = 4.86). At each measurement occasion, student participation was voluntary, and an incentive was offered to encourage participation (i.e., a chance to win one of five $50 gift cards). Participation was also completely anonymous, meaning that only general invitations were sent to all students at T2, including those who initially completed the T1 questionnaire (data from students who responded to both time points were merged using a unique identifier generated by the respondents). As a drawback, fewer students participated in both measurement occasions (n = 367).

Measures

Academic Motivation

Students' academic motivation was measured using the original French version of the Academic Motivation Scale (AMS; Vallerand et al., 1992). Following a stem asking "Why do you go to university?", this scale measures intrinsic motivation (only the subscale of intrinsic motivation to know was used in this study; e.g., *Because I experience pleasure and satisfaction while learning new things*), identified regulation (e.g., *Because I think that a high-school education will help me better prepare for the career I have chosen*), introjected regulation (e.g., *To prove to myself that I am capable of completing my university degree*), external regulation (e.g., *In order to obtain a more prestigious job later on*) and amotivation (e.g., *I once had good reasons for going to school; however, now I wonder whether I should continue*). Each subscale includes four items answered on a 7-point scale (1 = *completely false* to 7 = *completely true*). Cronbach's alphas[1] were adequate, ranging from .72 to .92 at Time 1 (T1; M_α = .84) and .73 to .95 at Time 2 (T2; M_α = .87).

Educational Climate

Participants' perceptions of the educational climate of their program were assessed using the original French version of the College Need Support/Thwarting Questionnaire (CNSTQ; Gilbert et al., 2021). Following a stem stating "In my study program…", this instrument measures autonomy support (e.g., *A variety of options (courses, teachers, length of study) is available to students*), competence support (e.g., *Information about the program is easily and quickly accessible*), relatedness support (e.g., *There are*

[1] We also report more precise coefficients of composite reliability (omega: McDonald, 1970) as part of our preliminary measurement analyses (Section 1 of the online supplements).

events that allow students to get to know their teachers better), autonomy thwarting (e.g., *Students cannot make choices to influence the content of their studies*), competence thwarting (e.g., *Administrative officials do not communicate to students the important decisions that affect their progress*), and relatedness thwarting (e.g., *The workload is so intense that students' social relationships suffer*). Each subscale includes four items answered on a 7-point scale (1 = *completely false* to 7 = *completely true*). Cronbach's alphas were adequate, ranging from .73 to .91 at T1 (M_α = .80) and .75 to .90 at T2 (M_α = .81). In this study, we rely on a single global indicator of exposure to a need nurturing educational climate estimated from all items (α_{T1} = .81; α_{T2} = .92)

Trait Self-Control

Trait self-control was measured using the French version (Brevers et al., 2017) of the Brief Self-control Scale (BSCS; Tangney et al., 2004). With 13 items, this scale assesses participants' capacity to resist short-term gratification and achieve long-term goals (e.g., *I am able to work effectively toward long-term goals*) using a 5-point scale (1 = *not at all* to 5 = *very much*). Cronbach's alpha for this scale was .84 (T1) and .85 (T2).

Analyses

Preliminary Analyses

Preliminary factor analyses were conducted using Mplus 8.8 (Muthén & Muthén, 2017) to evaluate the psychometric properties and longitudinal invariance of all measures. Factor scores estimated in standardized units (M = 0, SD = 1) were saved from these preliminary models and used in the main analyses (for a discussion on the advantages of factor scores, see Morin et al., 2016a). Details on these models and their longitudinal invariance are reported in the online supplements (see Section 1). Correlations between all variables included in this study are presented in Table 1. Finally, results from a MANOVA revealed no significant differences between participants who completed both time points versus those who only participated at Time 1 on all variables included at T1 (main effect; F [10, 1332] = 1.451, p = .153; Wilk's Λ = .989).

Latent Profile and Transition Analyses

Latent profile analyses (LPA) and latent transition analyses (LTA) were estimated in Mplus 8.8 with the robust maximum likelihood (MLR) estimator (Muthén & Muthén, 2017), and full information maximum likelihood (FIML) to handle missing data. FIML allowed us to include all participants (N = 1940) who completed at least one wave of data (Enders, 2010; Graham, 2009). We first estimated LPA models including 1 to 8 profiles separately at T1 and T2 using the six motivation factors obtained as part of our preliminary analyses (global self-determined motivation, intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation). The global self-determined motivation factor was defined based on all motivational items, with loadings corresponding to the position of these items on the theoretical continuum of motivation proposed by SDT (high and positive for intrinsic, moderately high and positive for identified regulation, moderately low and positive for introjected regulation, low and positive for external regulation, and moderately high and negative for amotivation), which thus reflect the extent to which student motivation can be considered to be self-determined (Howard et al., 2020). The mean and variance of all six motivation indicators were allowed to vary over time (Morin & Litalien, 2019). To ensure convergence on a true maximum likelihood, these analyses relied on 5000 random start values each allowed 1000 iterations, and 200 final optimizations (Hipp & Bauer, 2006). These values were increased to 10000, 1000 and 500 for the longitudinal analyses (Morin & Litalien, 2019).

After selecting the optimal LPA solution at both time points, and assuming the same number of profiles over time, these solutions were combined into a longitudinal LPA to assess their longitudinal similarity in the following sequence (Morin et al., 2016b): (1) configural similarity (same number of profiles); (2) structural similarity (same within-profile means); (3) dispersion similarity (same within-profile variances), and (4) distributional similarity (same profile size). Similarity is confirmed when lower values are observed on at least two information criteria out of the Bayesian Information Criterion (BIC), Sample-Size-Adjusted BIC (ABIC), and Constant Akaike Information Criterion (CAIC) from one step to the next (Morin et al., 2016b). The most similar model was then converted into our final LTA to investigate within-person stability and transitions using the manual 3-step approach advocated by Morin and Litalien (2017, 2019) for this conversion.

Predictors of Profile Membership

Predictors were directly included into the final LTA via a multinomial logistic regression link, allowing us to assess their associations with participants' likelihood of profile membership at T1 and T2.

Three models of prediction were tested and contrasted using the same aforementioned information criteria. First, the associations between predictors and profile membership were freely estimated at both time points, and the predictions of profile membership at T2 were free to vary across T1 profiles to assess the links between predictors and specific profile-to-profile transitions. Second, the associations between predictors and profile membership were free to vary across time points but not as a function of Time 1 profiles. Third, the associations between predictors and profile membership were set to be equal over time (predictive similarity).

Results

Latent Profile Solution

Matching our first hypothesis, our results converged on the selection of a 4-profile solution at T1 and T2. The procedure and results leading to this section are reported in Section 2 of the online supplements. The results from the test of longitudinal similarity conducted on this solution are reported in the top section of Table 2 and revealed that each step resulted in a lower value on at least two of the information criteria, thus supporting the complete distributional similarity of this solution over time. The model of distributional similarity, retained for interpretation, is illustrated in Figure 2 (within-profile means are presented in Table S3 of the online supplements).

Profile 1 (*Self-Determined*) was the smallest (17.42%) and described students with very high levels of global levels of self-determined motivation, high levels of intrinsic motivation and moderately high levels of identified regulation. This profile also displayed average levels of introjected and external regulations coupled with low levels of amotivation. Profile 2 (*Moderately Motivated*) corresponded to 23.54% of the sample presenting moderately high levels of global self-determined motivation, moderate levels of intrinsic and identified regulations, moderately low levels of introjected and external regulations, and average levels of amotivation. Profile 3 (*Extrinsically Motivated*) was the largest (31.47%) and described students presenting average global levels of self-determined motivation, intrinsic motivation, identified regulation, and introjected regulation, coupled with moderately high levels of external regulation and low levels of amotivation. Finally, Profile 4 (*Amotivated*) corresponded to 27.5% of the sample presenting very low global levels of self-determined motivation, low levels of intrinsic motivation and identified regulation, moderate levels of introjected motivation, average levels of external regulation, and very high levels of amotivation.

Latent Transitions

The latent transition probabilities estimated from the final LTA solution (based on the longitudinal LPA of distributional similarity) are reported in Table 3. The *Amotivated* profile was the most stable, with 85.1% of students belonging to this profile at T1 remaining in this profile at T2. As for the other profiles, membership was also quite stable: 71.8% for the *Moderately Motivated* profile, 70.7% for the *Self-Determined* profile, and 68.8% for the *Extrinsically Motivated* profile. In terms of profile transitions, the main transition for *Self-Determined* students at T1 was toward the *Moderately Motivated* profile (15.5%) at T2, followed by the *Extrinsically Motivated* profile (13.8%). No student transitioned from the *Self-Determined* profile at T1 to the *Amotivated* profile at T2. For *Moderately Motivated* students at T1, the main transition was toward the *Extrinsically Motivated* profile (17.2%) at T2, followed by the *Self-Determined* (6.5%) and *Amotivated* (4.6%) profiles. For *Extrinsically Motivated* students at T1, the main transition was toward the *Self-Determined* profile (13.8%) at T2, followed by the *Moderately Motivated* (9.1%) and *Amotivated* (8.3%) profiles. Finally, 10.5% of *Amotivated* students at T1 transitioned to the *Moderately Motivated* profile at T2, whereas only 3.9% of them transitioned to the *Extrinsically Motivated* profile (3.9%). Very few students (.6%) transitioned from this profile to the *Self-Determined* profile at T2. Overall, these results did not fully support our second hypothesis as the stability of profile membership was similar across all four profiles.

Predictors of Profile Membership

The results from the predictive models are reported in the bottom of Table 2 and revealed that the lowest values on all information criteria were associated with the model of predictive similarity, which was retained for interpretation. These results suggest that the relations between predictors and profiles are equivalent across T1 and T2, and that the predictors do not contribute to specific profile-to-profile transitions (Morin & Litalien, 2019). The final set of predictive results taken from this model is reported in Table 4 and is consistent with our third hypothesis. These results show that students who report being exposed to high levels of need nurturing characteristics from their program, as well as those displaying high levels of trait self-control, were more likely to belong to the *Self-Determined* profile relative to the other profiles, and to the *Moderately Motivated* and *Extrinsically Motivated* profiles relative to the *Amotivated* profile. Next, older students were more likely to belong to the *Self-Determined* profile relative to the other profiles. Finally, male students were less likely to belong to the *Extrinsically Motivated* profile relative to the *Moderately Motivated* and *Amotivated* profiles.

Discussion

This study sought to document the nature and stability of university students' academic motivation profiles before and during the COVID-19 pandemic, as well as the role played by the need nurturing characteristics of the educational program and of trait self-control as possible predictors of profile membership. Our results revealed four academic motivation profiles, which remained identical over time, and showed that student membership in these profiles remained highly stable between T1 (before the pandemic) and T2 (12 months later, during the pandemic). Consistent with our hypotheses, our results also highlighted the key roles of the need nurturing educational climate of the program and of trait self-control in predicting membership to more adaptative profiles.

Academic Motivation Profiles

Supporting Hypothesis 1, our results revealed that four profiles best represented the configurations of academic motivation among our sample of university students. First, the *Self-Determined* profile was the most adaptative, and represented students who attend university primarily for autonomously driven reasons. Next, the *Moderately Motivated* profile described students who primarily experience autonomous forms of motivation which, however, coexist with a certain degree of amotivation. Thus, although these students seem to enjoy their schoolwork, they also sometimes appear to question the reasons that lead them to pursue their studies. In contrast, the *Extrinsically Motivated* profile represented students who are mainly driven by controlled forms of motivation. Importantly, this profiles also displays low levels of amotivation coupled with average levels on all other motivational indicators, suggesting a certain degree of adaptivity. Finally, the *Amotivated* profile described students who experience very high levels of amotivation combined with very low levels of autonomous motivations. This profile is therefore highly maladaptive and represents students who seem to lack a reason to engage and persevere in their studies. Overall, the nature and shape of these four profiles are aligned with previous person-centered results in the education domain (e.g., Bechter et al., 2018; Gillet et al., 2017; Tóth-Király et al., 2022; Wang et al., 2016).

Importantly, this 4-profile solution was completely replicated at both time points, supporting its longitudinal within-sample stability. Thus, despite the turmoil caused by the COVID-19 pandemic in students' educational experience, the basic configurations underlying their motivation profiles remained stable. Noteworthy, our participants were all first-year undergraduate students at the start of the study, which added another potential source of instability as new students are known to progressively adapt to the new reality of university life (Dyson & Renk, 2006). Our results thus clearly indicate that the impact of the lockdown measures imposed during the COVID-19 pandemic remained minimal in relation to the academic motivation profiles of university students. Our results thus add to those of previous research revealing that the nature and structure of academic motivation profiles tend to remain quite stable over time (Gillet et al., 2017; Xie et al., 2022).

Above this high within-sample stability, our results also revealed moderately high levels of within-person stability in profile membership, as only around 25 to 30% of our sample migrated to a different profile at T2. This moderately high level of within-person stability was the highest for the *Amotivated* profile (85.1%) while stability in profile membership ranged between 68.8% and 71.8% for the other profiles. Importantly, the stability of the *Self-Determined* profile (70.7%) was close to that observed in previous person-centered research conducted among university students (stability of 75.9% for the *Autonomous* profile in Gillet et al., 2017). Moreover, none of the students who initially belonged to this profile migrated to the *Amotivated* profile at T2, suggesting that the *Self-Determined* profile remained the most desirable from a transitional perspective. Beyond this specific observation, no other clear positive or negative transitional pattern emerged from our results. Indeed, while approximately 13% of our participants migrated to a less adaptative profile over time, approximately the same proportion experienced positive changes by "upgrading" to a more adaptative profile at T2.

These results globally suggests that the lockdown measures imposed during the COVID-19 pandemic did not result in any major change in the motivational landscape of most university students. Contrary to Hypothesis 2, it thus appears that university students' autonomous motivation did not follow a negative trend following the onset of the pandemic. However, it is important to point out that at each measurement occasion, only a small proportion (less than 20%) of our participants experienced a *Self-*

Determined motivation profile, while almost 60% of them experienced a profile dominated either by external regulation or amotivation. Moreover, some students did worse than others when facing the pandemic, either by maintaining their membership into an undesirable profile or by switching to a less adaptative profile. These results highlight the importance of examining factors that might have played a role in shaping these configurations before and during the pandemic.

The Role of Educational Climate and Trait Self-Control

In support of Hypothesis 3, we found that students who reported being exposed to high levels of need nurturing conditions, as well as those with a greater capacity for self-control, were more likely to belong to the *Self-Determined* profile relative to any other profile. These students were also more likely to belong to the *Moderately Motivated* or *Extrinsically Motivated* profiles relative to the *Amotivated* one. In other words, a good need nurturing educational climate and high levels of trait self-control seemed to be particularly important to the prediction of membership into profiles characterized by high levels of self-determined forms of motivation (*Self-Determined* and *Moderately Motivated* profiles) and low levels of amotivation (*Extrinsically Motivated* profile). These results are particularly robust, as they are equivalent over time and obtained while controlling for sex and age[2].

These findings have many implications for research and practice. First, they match Gilbert et al.'s (2021, 2022) propositions in demonstrating the importance of supporting university students' psychological needs at a more general level (i.e., study program) to foster positive forms of functioning. In the present situation, supporting students' psychological needs seems to have helped them develop or maintain more optimal motivation profiles in the context of the COVID-19 pandemic (T2), but also in a more normative context (T1). It may thus be worthwhile for universities to invest in interventions designed to provide students with sufficient opportunities to fulfill their needs for autonomy, competence, and relatedness through their study programs (Gilbert et al., 2021, 2022; Ryan & Deci, 2020). Second, our findings add to an emerging literature arguing for the importance of trait self-control in determining the quality of students' academic motivation (Converse et al., 2019; Holding et al., 2019). In this regard, our results refine those obtained in these previous studies by illustrating that the benefits of trait self-control generalize to the consideration of motivation profiles. Interventions should thus also focus on accompanying students in developing their self-control abilities, which could be done by helping them master a variety of self-deployed strategies aiming at facilitating self-control (e.g., goal setting, planning, self-monitoring; see Duckworth et al., 2018).

Limitations and Future Directions

This study has limitations that should be addressed in future research. First, it relied entirely on self-report measures, which are known to be prone to social desirability and self-evaluation biases. Although these measures were useful to capture students' perceptions of the educational climate, this study lacked more objective information on the characteristics which generated these perceptions. Future studies could include other sources of information regarding the evaluation of the educational climate, such as an external and objective evaluation of study program components. Second, our sample includes a majority of women (roughly 80%) who were on the average slightly older than expected for first-year university students (roughly 22 years old). In addition, an important proportion of T1 participants did not complete the T2 questionnaire, meaning that latent transitions could only be estimated based on the subset of participants who completed both time points. These limitations impair the generalizability of our results to the whole population of university students and should therefore be considered when interpreting the present findings. Third, this study assessed motivation profiles stability across two-time points separated by a 12-month interval. Future longitudinal research should include at least three time points to examine the consistency and stability of motivation profiles more thoroughly across time. Lastly, we only considered a limited number of variables in the prediction of profile membership. We thus cannot rule out that other individual or contextual factors might have played a role in shaping students' motivational experiences.

Conclusion

[2] Although sex and age were only included as controlled variables, some results associated with these variables are worth mentioning. First, older students were more likely to belong to the *Self-Determined* profile, which is aligned with previous research revealing a positive relation between age and autonomous motivation (Gillet et al., 2017; Stynen et al., 2014). Second, men were less likely than women to correspond to the *Extrinsically Motivated* profile relative to the *Moderately motivated* and *Amotivated* profiles. This result suggests that, relative to women, men lacking a purely self-determined profile seemed less likely to engage in their studies for purely externally-driven reasons and more likely to experience amotivation (Vallerand et al.,1989; 1992).

Relying on a person-centered perspective, this study suggests that the closure of campuses and the hasty shift to distance learning that followed the COVID-19 outbreak did not profoundly alter university students' motivational landscape. Indeed, most students maintained the same motivational profile over time and some students even developed a more adaptative configuration of motivation despite exposure to these unfavorable learning conditions. A need-nurturing educational climate and high levels of trait self-control seemed to protect students against endorsing controlled forms of motivations and amotivation both before and during the pandemic, suggesting that these factors should be targeted for intervention purposes.

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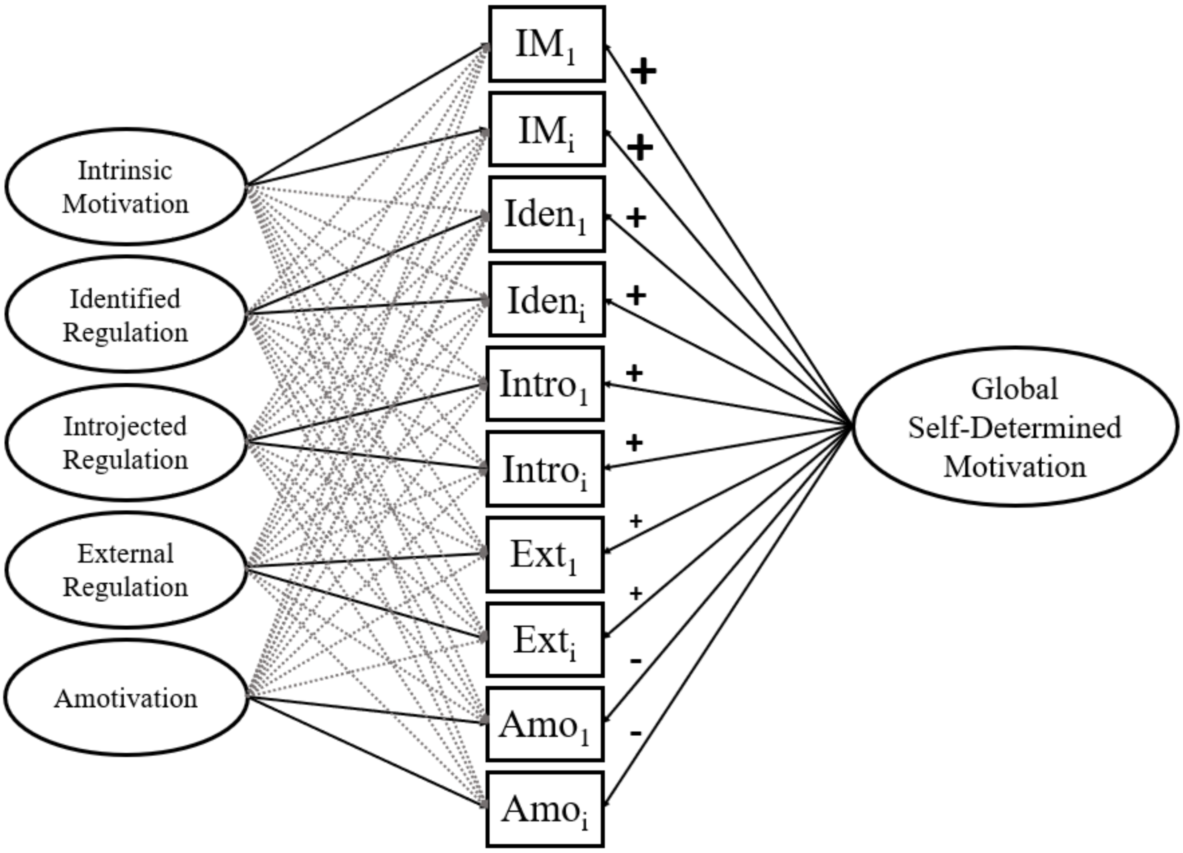
Figure 1

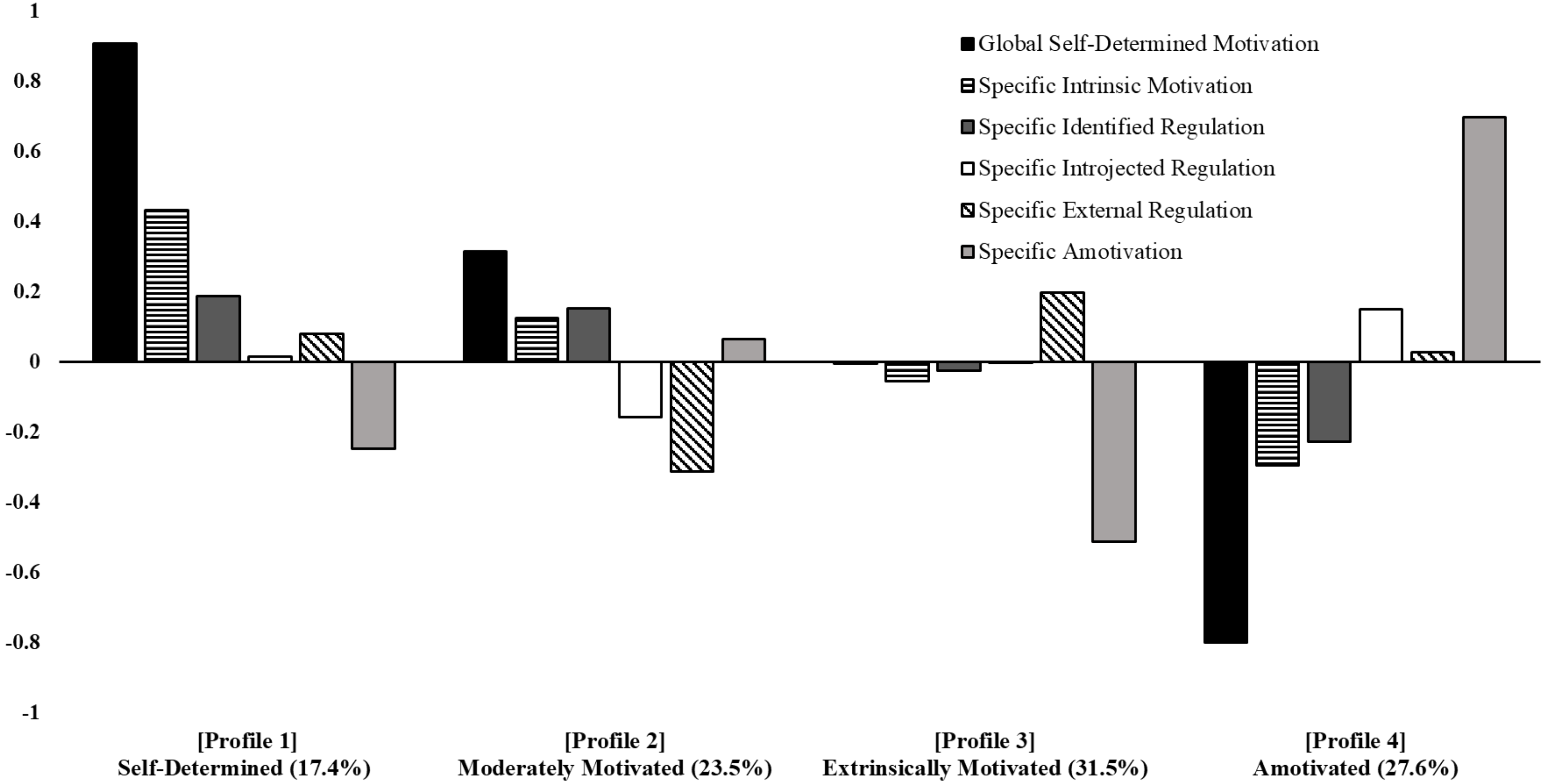
Bifactor Representation of the Specific and Global Dimensions of Academic Motivation



Note. Ovals represent latent factors while rectangles represent items. The + and - signs represent the direction of the loadings of the items on the global self-determined motivation factor while the size of these signs represent the strength of these loadings. IM = Intrinsic motivation; Iden = Identified regulation; Intro = Introjected regulation; Ext = Extrinsic regulation; Amo = Amotivation. i = Items 2 to 4.

Figure 2

Final 4-Profile Solution Selected at Both Time Points (Distributional Similarity)



Note. The profile indicators are estimated from factor scores with mean of 0 and a standard deviation of 1.

Table 1
Correlations Between Study Variables

Measure	1	2	3	4	5	6	7	8	9
1. Sex									
2. Age	.025								
3. T1 Global Self-Determined Motivation	-.015	-.010							
4. T1 Specific Intrinsic Motivation	.109**	.102**	.260**						
5. T1 Specific Identified Regulation	-.049	.002	.064*	-.102**					
6. T1 Specific Introjected Regulation	-.013	-.048	.040	-.078**	-.046				
7. T1 Specific External Regulation	.017	-.102**	.028	-.061*	.025	.077**			
8. T1 Specific Amotivation	.044	-.089**	-.055*	.061*	-.054*	.039	.023		
9. T1 Need Nurturing Program Climate	.018	-.038	.374**	.202**	.056*	-.099**	-.110**	-.298**	
10. T1 Trait self-control	-.098**	.102**	.185**	.120**	-.062*	-.143**	-.114**	-.215**	.263**
11. T2 Global Self-Determined Motivation	-.093	.065	.814**	.078	-.153**	-.023	-.154**	-.037	.262**
12. T2 Specific Intrinsic Motivation	.098	.113*	.240**	.615**	-.374**	.042	.092	-.016	.135**
13. T2 Specific Identified Regulation	-.113*	-.066	-.016	-.109*	.305**	-.027	-.002	.179**	-.001
14. T2 Specific Introjected Regulation	.068	.052	.042	-.044	-.225**	.713**	.123*	.064	-.152**
15. T2 Specific External Regulation	-.029	-.112*	.007	.015	-.200**	.139**	.816**	-.058	-.136**
16. T2 Specific Amotivation	.102	-.053	-.098	.155**	-.111*	.005	-.017	.691**	-.283**
17. T2 Need Nurturing Program Climate	-.002	-.032	.347**	.169**	.070**	-.136**	-.119**	-.277**	.843**
18. T2 Trait self-control	-.113*	.117*	.241**	.061	.012	-.101	-.088	-.124*	.170**
Mean	-	21.56	31.37	5.68	5.78	3.76	4.25	1.76	4.83
SD	-	4.99	6.49	1.21	1.05	1.75	1.61	1.17	1.00

Note. All variables used in our main analyses are factor scores estimated in standardized units with a M = 0 and a SD = 1. The means and SDs in this table were computed from the items and are only provided for descriptive purposes. For the indicator of global self-determined motivation, a weighted composite score was computed using a sum of the products of item score and item loading. T1 = Time; T2 = Time 2.
* p < .05. ** p < .01

Table 1 (continued)

Measure	10	11	12	13	14	15	16	17	18
11. T2 Global Self-Determined Motivation	.280**								
12. T2 Specific Intrinsic Motivation	.160**	.287**							
13. T2 Specific Identified Regulation	.041	.125**	-.073*						
14. T2 Specific Introjected Regulation	-.044	.066*	-.003	-.034					
15. T2 Specific External Regulation	-.067	.046	-.068*	.083*	.052				
16. T2 Specific Amotivation	-.297**	-.100**	.045	-.031	.010	.015			
17. T2 Need Nurturing Program Climate	.290**	.314**	.136**	.040	-.164**	-.148**	-.330**		
18. T2 Trait self-control	.713**	.199**	.185**	.026	-.127**	-.089*	-.236**	.221**	
Mean	3.29	31.71	5.75	5.82	3.85	4.27	1.82	4.69	3.19
SD	.67	6.68	1.20	1.06	1.80	1.55	1.20	1.05	.70

Note. All variables used in our main analyses are factor scores estimated in standardized units with a M = 0 and a SD = 1. The means and SDs in this table were computed from the items and are only provided for descriptive purposes. For the indicator of global self-determined motivation, a weighted composite score was computed using a sum of the products of item score and item loading. T1 = Time; T2 = Time 2.

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

Table 2

Results from the Longitudinal Latent Profile Analyses and Latent Transition Analyses

3-Profile Solution	LL	#fp	SC	AIC	CAIC	BIC	ABIC	Entropy
Longitudinal latent profile analyses								
Configural similarity	-14886.846	102	1.133	29977.692	30647.878	30545.878	30221.821	.477
Structural similarity	-14921.257	78	1.213	29998.513	30511.008	30433.008	30185.200	.442
Dispersion similarity	-14931.898	54	1.409	29971.796	30326.600	30272.600	30101.041	.441
Distributional similarity	-14933.711	51	1.418	29969.423	30304.515	30253.515	30091.487	.441
Predictive similarity								
Profile-specific free relations with predictors	-17691.355	83	2.492	35548.709	36113.394	36030.394	35766.684	.493
Free relations with predictors	-17638.481	131	1.651	35538.962	36430.212	36299.212	35882.994	.556
Equal relations with predictors	-17701.072	71	2.709	35544.144	36027.188	35956.188	35730.604	.491

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

Table 3

Latent Transition Probabilities

	Probability of Transition at Time 2 to…			
Time 1 Profile Membership	Profile 1 (Self-Determined)	Profile 2 (Moderately Motivated)	Profile 3 (Extrinsically Motivated)	Profile 4 (Amotivated)
Profile 1 (Self-Determined)	.707	.155	.138	.000
Profile 2 (Moderately Motivated)	.065	.718	.172	.046
Profile 3 (Extrinsically motivated)	.138	.091	.688	.083
Profile 4 (Amotivated)	.006	.105	.039	.851

Table 4

Results for the Effects of the Predictors on Profile Membership (Predictive Similarity)

	Self-determined (1) Vs. Moderately motivated (2)		Self-determined (1) Vs. Extrinsically motivated (3)		Self-determined (1) Vs. Amotivated (4)	
	Coefficient (SE)	OR	Coefficient (SE)	OR	Coefficient (SE)	OR
Need Nurturing Educational Climate	.854 (.152)**	2.348	.666 (.118)**	1.946	1. 690 (.138)**	5.419
Trait Self-Control	.640 (.161)**	1.896	.511 (.130)**	1.667	1.205 (.156)**	3.337
Sex	-.370 (.223)	.691	.179 (.202)	1.196	-.224 (.219)	.799
Age	.047 (.019)*	1.049	.034 (.016)*	1.034	.051 (.019)*	1.052
	Moderately motivated (2) Vs. Extrinsically motivated (3)		Moderately motivated (2) Vs. Amotivated (4)		Extrinsically motivated (3) Vs. Amotivated (4)	
	Coefficient (SE)	OR	Coefficient (SE)	OR	Coefficient (SE)	OR
Need Nurturing Educational Climate	-.188 (.101)	.829	.836 (.107)**	2.308	1.024 (.091)**	2.786
Trait Self-Control	-.129 (.131)	.879	.565 (.140)**	1.760	.694 (.121)**	2.002
Sex	.549 (.191)*	1.732	.145 (.185)	1.156	-.404 (.183)*	.668
Age	-.014 (.019)	.986	.003 (.020)	1.003	.017 (.017)	1.017

Note. SE = Standard error; OR = Odds ratio. The coefficients and ORs reflect the effects of the predictors on the likelihood of membership into the first listed profile relative to the second-listed profile. * $p < .05$. ** $p < .01$

Online Supplements for:

Undergraduate Students' Motivational Profiles Before and During the COVID-19 Pandemic:

The Role of Educational Climate and Trait Self-Control

Section 1

Preliminary Measurement Models

To verify the psychometric properties of our measures, we estimated a series of preliminary measurement models using the MLR estimator in Mplus 8.8 (Muthén & Muthén, 2017). We relied on the bifactor-exploratory structural equation modeling framework (B-ESEM; Morin et al., 2016) to evaluate the structure of the Academic Motivation Scale (AMS; Vallerand et al., 1992) and of the College Need Support/Thwarting Questionnaire (CNSTQ; Gilbert et al., 2021). This choice was based on recent studies showing that multidimensional measures of motivation (Howard et al., 2018, 2020; Litalien et al., 2017) and need-support/thwarting (Gilbert et al., 2021; Tóth-Király et al., 2020) based on SDT are best represented via B-ESEM. This framework allows the estimation of a global (G-) factor, defined by all items, along with specific (S-) factors reflecting the variance in each dimension of a measure left unexplained by the G-factor. For motivation, the G-factor reflects students' global levels of academic self-determined motivation (i.e., their position on the self-determination continuum), while each S-factor reflects the unique quality of each type of motivation (i.e., intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation). For need support/thwarting, the G-factor reflects the overall need-nurturing level of the programs, while each S-factor reflects the support or thwarting of one of the three basic psychological needs (autonomy, competence, relatedness). While the G-factor encompasses the commonalities (i.e., the common core) present among the items of a measure, the ESEM component allows conceptually relevant cross-loadings between the S-factors. For multidimension scales, this combination (i.e., B-ESEM) promotes more accurate model parameters than traditional approaches such as confirmatory factor analysis (Asparouhov et al., 2015; Morin et al., 2019). To evaluate the structure of the unidimensional Brief Self-control Scale (BSCS; Brevers et al., 2017), we relied on a confirmatory factor analytic (CFA) specification.

Next, we conducted tests of longitudinal measurement invariance on our models to ensure that the meaning of each factor, as well as the underlying measurement structure, did not change over time. This was crucial given that we estimated motivation profiles, and predicted membership to these profiles, at two time points separated by a 12-month interval. The longitudinal measurement invariance of our models was tested in the following sequence (Millsap, 2011): (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).

The goodness-of fit of all models was evaluated using recommended goodness of fit indices (Hu & Bentler, 1999; Marsh et al., 2005): The comparative fit index (CFI), the Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA). Adequate and excellent model fit are respectively indicated by CFI and TLI >.90 and .95, and by RMSEA values < .08 and .06. We relied on changes in goodness-of-fit indices to assess the invariance of these models. Decreases in CFI and TLI of ≤.01 or increases in RMSEA of ≤.015 between a model and a more restricted one (i.e., a more invariant model) support the more restricted model and thus reflect measurement invariance (Chen, 2007; Cheung & Rensvold, 2002).

Results

The fit indices of our models, as well as the tests of longitudinal invariance for these models, are reported in Table S1. These models demonstrated acceptable to excellent fit indices at Time 1 and Time 2. The results also supported their longitudinal invariance as the sequential changes in fit indices (CFI, TLI, RMSEA) were generally within the acceptable range. However, the strict invariance of the motivation measure was not supported by the data, as shown by a substantial decrease in model fit. The modification indices associated with this failed model of strict invariance suggested that this lack of invariance was mainly due to three item uniquenesses which tended to be slightly higher at Time 2. Invariance constraints were thus relaxed for these three uniquenesses, leading to a model of partial strict invariance which was supported by the data. From that model, the invariance of the latent variance-covariance and latent means was supported.

For the motivation measure, the longitudinally invariant factors were all well-defined as shown by appropriate McDonald's (1970) omega coefficients and items loadings (G-factor: $\omega = .88$, $M_\lambda = .370$; Intrinsic motivation: $\omega = .83$, $M_\lambda = .508$; Identified regulation: $\omega = .43$, $M_\lambda = .317$; Introjected regulation:

ω = .86, M_{λ} = .743; External regulation: ω = .81, M_{λ} = .682; Amotivation: ω = .90, M_{λ} = .776). Importantly, the loadings on the G-factor at each time point matched the self-determination continuum from intrinsic (λ = .542 to .785, M_{λ} = .694), identified (λ = 498. to .610, M_{λ} = .543), introjected (λ = .063 to .286, M_{λ} = .195), external (λ = -.035 to .180, M_{λ} = .139) to amotivation (λ = -229 to -.367, M_{λ} = -.281). For the educational context measure, our results also revealed a well-defined G-factor (□□□□□94, M_{λ} = .573). Items reflecting need support loaded positively on this G-factor (Autonomy: λ = .617 to .692, M_{λ} = .650; Competence: λ = .596 to .793, M_{λ} = .689; Relatedness: λ = .424 to .555, M_{λ} = .477) while items of need thwarting loaded negatively (Autonomy: λ = -.494 to -.625, M_{λ} = -.557; Competence: λ = -.500 to -.645, M_{λ} = -.573; Relatedness: λ = -.410 to -.549, M_{λ} = -.490), meaning that this factor represents the overall need nurturing characteristics of the program educational climate. After controlling for these general levels, most of the six S-factors maintained adequate levels of specificity (□□□□from □34 to .87, M_{λ} = from .240 to .678). However, our goal was to rely solely on the need nurturing G-factor in our main analyses as this indicator provides the most parsimonious synthesis of the educational climate. Lastly, for the trait self-control measure, the results revealed a well-defined factor (□□□□□84, λ = .381 to .625; M_{λ} = .536). Factor scores (with a mean of 0 and a standard deviation of 1) were therefore saved from the most invariant longitudinal solutions for our main analyses.

Section 2

Selecting the Optimal Number of Profiles

In addition to considering the theoretical meaningfulness, heuristic value, and statistically adequacy of each solution, statistical indices were also used to guide the selection of the optimal number of profiles at Time 1 and Time 2 (Morin & Litalien, 2019): the Akaïke Information Criterion (AIC), the Consistent AIC (CAIC), the Bayesian Information Criterion (BIC), the sample-size Adjusted BIC (ABIC), the adjusted Lo-Mendel-Rubin likelihood ratio test (aLMR; Lo et al., 2001) and the bootstrap likelihood ratio test (BLRT). Lower values on the AIC, CAIC, BIC, and ABIC are indicative of a better-fitting model while a significant *p*-value on the aLMR or BLRT indicates that the *k*-profile solution should be retained over the *k* – 1-profile solution. Importantly, simulation studies have demonstrated that some statistical indices (i.e., CAIC, BIC, ABIC, BLRT) are particularly effective and should therefore be prioritized in selecting the optimal number of profiles (Diallo et al., 2016, 2017; Peugh & Fan, 2013). Conversely, the AIC and aLMR should not be used in the selecting phase given their tendency to respectively over- and under-extract an incorrect number of profiles. With this in mind, we did not use these two statistical indices to inform the selection of our finale solution, and only report them to ensure transparency. Finally, the entropy reflects the precision with which participants are classified into the various profiles of a specific solution. Entropy value ranges between 0 and 1, with higher values reflecting a more precise classification. This indicator is descriptive only and should not be used to inform the selection of the optimal number of profiles (Lubke & Muthén, 2007).

Results

Fit indices for time-specific LPA solutions are presented in Table S2 and illustrated (in the form of elbow plots) in Figure S1. The results revealed that the CAIC, BIC, and ABIC kept on decreasing as the number of profiles increased. Similarly, all BLRTs were statistically significant, suggesting that adding profile always resulted in superior models. The examination of the elbow plots reported in Figure S1 shows that decreases in CAIC, BIC, and ABIC become negligible between the 4- and 6-profile solutions. After careful inspection of these three solutions, we observed that increasing the number of profiles to five or six did not result in more theoretically meaningful, distinct, and interpretable profiles compared to the 4-profile solution. Therefore, we retained the 4-profile solution for further analyses.

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Figure S1

Elbow Plot of the Information Criteria for the Latent Profile Analyses at Time 1 (Left) and Time 2 (Right)

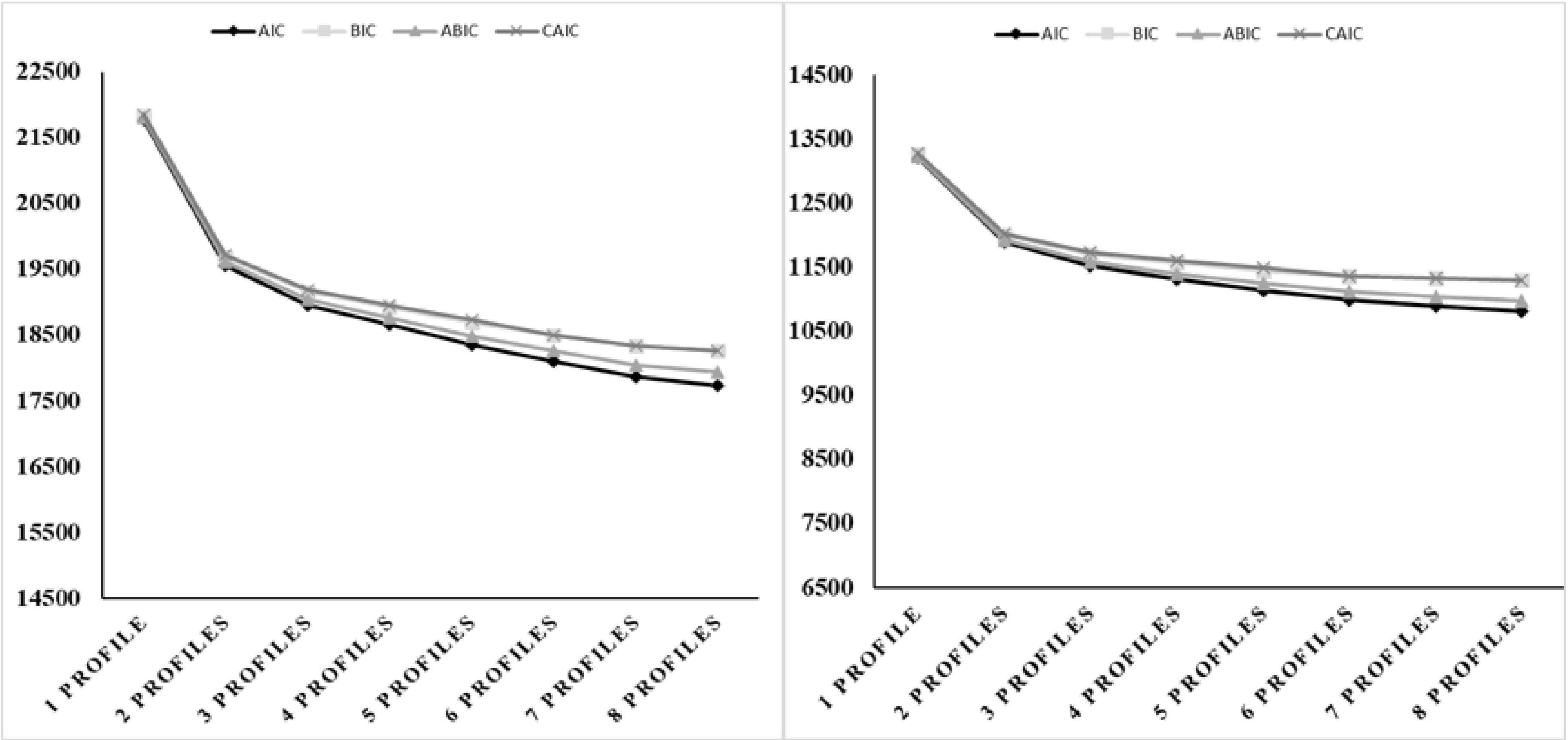

Table S1

Goodness-of-Fit Statistics for the Estimated Measurement Models

Description	χ^2	*df*	CFI	TLI	RMSEA	$\Delta\chi^2$ (Δdf)	ΔCFI	ΔTLI	ΔRMSEA
AMS									
Time 1	263.906*	85	.984	.963	.039	-	-	-	-
Time 2	194.063*	85	.984	.965	.039	-	-	-	-
Longitudinal: Configural Invariance	957.590*	514	.979	.968	.021	-	-	-	-
Longitudinal: Weak Invariance	981.938*	598	.982	.976	.018	67.648(84)	.003	.008	-.003
Longitudinal: Strong Invariance	1010.765*	608	.981	.976	.018	33.494(10)*	-.001	.000	.000
Longitudinal: Strict Invariance	1917.928*	628	.939	.924	.033	369.740(20)*	-.042	-.052	.015
Longitudinal: Strict Invariance (partial)	1034.823*	628	.981	.976	.018	29.501(20)	.000	.000	.000
Longitudinal: Latent variance/covariance Invariance	1042.927*	649	.981	.978	.018	15.380(21)	.000	.002	.000
Longitudinal: Latent mean Invariance	1050.275*	655	.981	.978	.018	6.938(6)	.000	.000	.000
Predictors (CNSTQ, BSCS)									
Time 1	1426.998*	498	.942	.922	.039	-	-	-	-
Time 2	1234.959*	498	.931	.908	.043	-	-	-	-
Longitudinal: Configural Invariance	4607.716*	2266	.921	.906	.024	-	-	-	-
Longitudinal: Weak Invariance	4756.297*	2397	.920	.910	.024	168.073(131)*	-.001	.004	.000
Longitudinal: Strong Invariance	4962.200*	2426	.914	.905	.025	235.369(29)*	-.006	-.005	.001
Longitudinal: Strict Invariance	5019.820*	2463	.914	.905	.024	61.119(37)*	.000	.000	-.001
Longitudinal: Latent variance/covariance Invariance	5081.884*	2499	.913	.906	.024	63.176(36)*	-.001	.001	.000
Longitudinal: Latent mean Invariance	5120.108*	2507	.912	.905	.025	33.577(8)*	-.001	-.001	.001

Note. χ^2 = 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; Δ = Change in fit indices; * $p < .05$.

Table S2

Goodness-of-Fit Results for the Time-Specific Latent Profile Analyses

Solution	LL	#FP	SC	AIC	CAIC	BIC	ABIC	aLMR	BLRT	Entropy
Time 1										
1 Profile	-10874.858	12	1.510	21773.716	21848.859	21836.859	21798.739			
2 Profiles	-9756.759	25	1.135	19563.517	19714.066	19695.066	19615.649	< .001	< .001	.752
3 Profiles	-9442.895	38	1.106	18961.789	19187.742	19161.742	19041.030	< .001	< .001	.795
4 Profiles	-9276.774	51	1.131	18655.547	18956.905	18923.905	18761.896	< .001	< .001	.804
5 Profiles	-9114.691	64	1.176	18357.382	18734.145	18694.145	18490.839	< .001	< .001	.831
6 Profiles	-8971.655	77	1.131	18097.311	18502.479	18502.479	18257.877	< .001	< .001	.806
7 Profiles	-8841.732	90	1.176	17863.463	18337.037	18337.037	18051.138	< .001	< .001	.795
8 Profiles	-8761.676	103	1.232	17729.352	18271.330	18271.330	17944.135	.289	< .001	.804
Time 2										
1 Profile	-6595.580	12	1.491	13215.160	13284.546	13272.546	13234.437			
2 Profiles	-5919.514	25	1.376	11889.028	12027.583	12008.583	11929.188	< .001	< .001	.763
3 Profiles	-5722.435	38	1.161	11520.87	11728.594	11702.594	11581.914	< .001	< .001	.769
4 Profiles	-5610.073	51	1.135	11322.145	11599.037	11566.037	11404.072	.001	< .001	.756
5 Profiles	-5506.442	64	1.138	11140.884	11486.944	11446.944	11243.693	.001	< .001	.780
6 Profiles	5423.627	77	1.270	11001.254	11369.483	11369.483	11124.947	.052	< .001	.800
7 Profiles	-5360.964	90	1.181	10901.928	11332.325	11332.325	11046.504	.005	< .001	.799
8 Profiles	-5301.579	103	1.232	10809.159	11301.725	11301.725	10974.618	.306	< .001	.821

Note. LL = Model LogLikelihood; #fp = Number of free parameters; SC = Scaling factor associated with MLR loglikelihood estimates; AIC = Akaïke Information Criteria; CAIC = Constant AIC; BIC = Bayesian Information Criteria; ABIC = Sample-Size adjusted BIC; aLMR: *p*-value for adjusted Lo-Mendel-Rubin likelihood ratio test; BLRT: *p*-value for bootstrap likelihood ratio test.

Table S3

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

	Global	Intrinsic	Identified	Introjected	External	Amotivation
Profile	Mean [CI]	Mean [CI]	Mean [CI]	Mean [CI]	Mean [CI]	Mean [CI]
Self-Determined	.909 [.871; .947]	.432 [.393; .471]	.188 [.131; .246]	.016 [-.189; .221]	.080 [-.210; .369]	-.248 [.294; -.201]
Moderately Motivated	.316 [.161; .472]	.125 [.033; .217]	.153 [.078; .229]	-.158 [-.430; .114]	-.311 [-.599; -.022]	.065 [-.150; .280]
Extrinsically Motivated	-.004 [-.106; .098]	-.054 [-.131; .022]	-.025 [-.080; .030]	-.003 [-.190; .185]	.199 [-.104; .502]	-.511 [-.561; -.461]
Amotivated	-.799 [-.937; -.662]	-.295 [-.404; -.187]	-.227 [-.323; -.131]	.151 [.067; .235]	.029 [-.072; .130]	.697 [.524; .870]
	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]
Self-Determined	.029 [.020; .039]	.044 [.026; .061]	.057 [.040; .073]	1.050 [.938; 1.162]	.835 [.525; 1.146]	.015 [.009; .022]
Moderately Motivated	.257 [.188; .325]	.307 [.233; .381]	.216 [.159; .274]	.838 [.761; .915]	1.018 [.898; 1.138]	.155 [.078; .232]
Extrinsically Motivated	.299 [.257; .341]	.403 [.303; .502]	.321 [.220; .422]	.829 [.758; .900]	.514 [.098; .930]	.027 [.018; .035]
Amotivated	1.052 [.911; 1.193]	1.248 [1.056; 1.439]	1.173 [.990; 1.355]	.750 [.674; .826]	.860 [.747; .973]	2.175 [1.825; 2.526]

Note. The profile indicators are estimated from factor scores with a mean of 0 and a standard deviation of 1. CI = 95% Confidence Interval.