Stability and change in academic motivation patterns among adolescents with different SES background before and during Covid-19 pandemic

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Abstract

This study aimed to identify achievement goal orientations patterns and their dynamics among adolescents from different SES backgrounds before and during the Covid-19 pandemic. A sample of 1268 adolescents (51.7% females; *M*=14.87; *SD*=0.39) took part in one pre-pandemic (start of 9th grade) and three subsequent assessments during Covid-19 pandemic, spaced out with equal half-year intervals. Latent transition analyses revealed unique, mostly unfavorable dynamics of academic motivation during the pandemic, especially for highly motivated adolescents. It also revealed a huge motivational disadvantage among low SES students, which was particularly pronounced before the pandemic, but remained salient throughout the study.

Keywords: achievement goal orientations, Covid-19, SES, person-oriented approach, latent transition analysis

Introduction

Learning at school is among the most affected areas of adolescent lives during the Covid-19 pandemic (Branje & Morris, 2021). At the onset of the pandemic, most schools were abruptly closed in many European countries, and all learning was suddenly moved to an online environment in spring 2020, with subsequent school activity constraints of varying scope and duration depending on local policies (UNESCO, 2020). This unprecedented situation with large abrupt changes in the schooling process has raised questions on how students adjusted to the changes and managed to sustain their academic motivation to continue learning.

Some researchers have voiced concerns over potential negative tendencies in student motivation due to the pandemic (Branje & Morris, 2021). Indeed, there are indications of unfavorable dynamics in school motivation among children and adolescents, including decreased school bonding (Maiya et al. , 2021), lower levels of academic motivation on online school days compared with physical school days (Klootwijk et al., 2021), as well as a slight to steeper decrease in academic wellbeing for most students, but also an increase in wellbeing for a substantial share of adolescents (Salmela-Aro et al., 2021). Therefore, it remains essential to identify who does better and who does worse during the pandemic in terms of academic motivation and the factors behind potential heterogeneity. Our study analyzed stability and change in academic motivation profiles among high school students before and during the Covid-19 pandemic to address these questions. We also examined the role of student socioeconomic background (SES) in these dynamics.

Achievement goal orientations and their profiles in adolescence

Academic motivation, viewed as an aspect of a broader concept of competence motivation (Elliot et al., 2017), can be defined as how students energize and direct their academic behaviors.

Through the perspective of achievement goals theory (Elliot & Murayama, 2008), academic motivation is described as a tendency to prefer particular academic outcomes (i.e., mastery or performance) and treat these outcomes with a certain valence (approach or avoid them). The difference between mastery-performance and approach-avoidance determines four achievement goal orientations (AGOs): mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance (Elliot & Murayama, 2008). Mastery-approach goals reflect the learners' intentions to improve their competence, master the tasks and the content of learning materials, and make progress in learning. Mastery-avoidance reflects the desire to avoid learning failure and loss of competence (Elliot & Murayama, 2008). Performance-approach goals reflect the desire to outperform other students, demonstrate competence, gain public recognition for demonstrating higher skills and abilities than others. Performance-avoidance goals reflect students' intention to avoid falling behind others and preventing the disclosure of competence deficiencies (Elliot & Murayama, 2008). AGOs are expected to shape academic processes and emotional, cognitive, and behavioral outcomes.

A multiple goals perspective (Pintrich, 2000) suggests that mastery and performance goals together could form different patterns of motivation related to particular academic processes and outcomes. This approach considers multiple AGOs together by identifying their most common patterns, usually implemented applying a person-oriented methodology (Niemivirta et al., 2019). This approach emphasizes the heterogeneity of motivational functioning and the possibility of multiple pathways to favorable and unfavorable outcomes among the students (Pintrich, 2000). Certain AGO combinations are most common among the students (Niemivirta et al., 2019). Specifically, these are mastery-oriented (high mastery, low performance), performance-oriented (low mastery, high performance) profiles, as well as profiles with similar levels across multiple-goal dimensions: success-oriented (high mastery and performance), moderate (moderate mastery and performance), and low motivation (low mastery and performance). The profiles differ in covariance with a range of adolescent educational outcomes, with some of the most favorable academic outcomes linked to success-oriented and mastery profiles (Niemivirta et al., 2019).

Developmental dynamics of achievement goals orientations and their patterns in adolescence

Longitudinal findings suggest moderate to high stability in student AGOs (Sherrer & Preckel, 2019) and their profiles (Niemivirta et al., 2019). At the same time, change is observed within a school year, across school years, and during the school transitions (Scherrer et al., 2020; Scherrer & Preckel, 2019; Niemivirta et al., 2019). A slight overall decline in AGOs occurs during school transitions and throughout the secondary school years (Scherrer et al., 2020), which is attributed to a low fit between the school context and developmental needs of adolescents such as autonomy, personal identity, and peer-group belonging (Eccles & Roeser, 2009). According to stage-environment fit theory (Eccles & Roeser, 2009), the students are most motivated to learn when their learning environment matches their developmental needs.

Longitudinal person-oriented studies show that around one-third of the students change their motivational profiles over time. Notably, the change that occurs in profile membership is not qualitatively large. The majority tend to move to a fairly similar profile (e.g., from mastery- to success-oriented), but not a substantially different profile (e.g., from mastery- to low motivation-oriented) (Niemivirta et al., 2020). In fact, previous studies report lower instances of extreme changes in AGO profiles than would be expected by chance (e.g., Tuominen-Soini et al., 2011).

The pandemic-related changes in adolescent academic motivation

As both mean-level and profile stability and change in academic motivation result from student intra-psychic development and the learning environment, abrupt and unexpected changes in the schooling process brought by the Covid 19 pandemic may provide insights into the development of adolescent AGOs. Initial research studies indicate some unfavorable tendencies in the academic functioning of children and adolescents during the pandemic. Specifically, children and adolescents in the US schools reported decreased school bonding at the onset of the pandemic (i.e., feeling less close to and less a part of the school community and being less happy at school) (Maiya, et al., 2021). Adolescents from Dutch schools reported lower levels of academic motivation on online school days than physical school days during the pandemic (Klootwijk et al., 2021). The majority of adolescents in a Finnish sample showed a slight normative decline in academic wellbeing, but some smaller subgroups experienced a relatively steep decrease (15%) or increase (17%) in their academic wellbeing (Salmela-Aro et al., 2021). Overall, polarisation of academic functioning was observed during the pandemic – students demonstrated either well-being or ill-being during this period, while functioning was more diverse before the pandemic (Salmela-Aro et al., 2021).

Adolescents from disadvantaged backgrounds might be more likely to be affected by the pandemic (Branje & Morris, 2021). Adolescents from low-SES contexts not only tend to have lower academic motivation in general (Chmielevski, 2019) but might also be facing more challenges during the pandemic. They might lack facilities such as a personal laptop or a quiet room to follow homeschooling, and their academic motivation might be more negatively affected by lockdowns and online education. To address the heterogeneity in the student responses to the pandemic-related changes in schooling, we applied a person-oriented approach to identify AGO profiles and observed their stability and change among adolescents from different SES backgrounds before and during pandemic-related school closures.

This study

This study was carried out in Lithuania, where, similarly as in other countries, most schools were abruptly closed, and all learning was moved online in spring 2020. While during subsequent pandemic waves, national policies on school closures varied considerably, many countries, including Lithuania, transferred most of the learning to online environments again in a prolonged lockdown from late autumn 2020 till late spring 2021 (UNESCO, 2020). These changes frequently occurred with schools and teachers unprepared for the new online or hybrid teaching forms. Besides academic activities, communication and relationships among students, teachers, and other school personnel were affected. Based on a stage-environment fit approach, the learning environment during the pandemic may have been even less responsive to the developmental needs of adolescent students than the usual school environment.

Based on these observations and previous findings, overall unfavorable tendencies in students' academic motivation could be expected with the onset of the pandemic. While there are no yet published findings on AGOs in the context of the pandemic, it may be expected that they will follow a trend of decrease in adaptive motivation during the pandemic, particularly, for students from low SES backgrounds. Since reduced stability of motivational profiles was previously observed during school transitions (Niemivirta et al., 2019), we expect less stability in the profile membership during the pandemic.

Methods

Participants and procedures

Data for this investigation come from a four-wave longitudinal study "Goals' Lab," which focuses on the development of adolescent goals in the context of socioeconomic inequalities. The initial sample included 1,268 adolescents (51.7% females; $M = 14.87$; $SD = 0.39$) attending 36 gymnasiums (25% in non-urban locations) in Lithuania. The sample was diverse in terms of family socioeconomic backgrounds and family composition. Regarding socioeconomic status, 12.9% received free nutrition at school (compared to 13.7% in the overall population of school children in Lithuania in 2019; Ministry of Social Security and Labour, 2020) and 15.1% had at least one unemployed parent. Around 67% lived with two parents, while others had different family compositions. The sample was homogeneous in ethnic background (98% self-identified as Lithuanian).

The first assessment (T1) took place in November 2019 before the onset of the pandemic. The second assessment (T2) took place five months later, in the spring of 2020 (end of April-early May), during the first pandemic wave. The third assessment (T3) took place in October 2020 at the onset of the second wave of the pandemic. The fourth (T4) took place in the spring of 2021 (March-April) during the decline of the second wave of the pandemic. All four assessments were similarly spaced out with a median difference of 23-24 weeks.

Overall, participant retention rates were 95% ($n = 1204$), 96.1% ($n = 1218$), and 92.8% ($n = 1177$) at T2, T3, and T4. Little's MCAR test suggested that overall missing data were likely missing completely at random ($\chi^2 = 309.697$; $df = 267$; $p = .080$). SOM provides the details on handling missing data in the analyses.

Measures

AGOs were measured using a scale developed by Elliot and Murayama (2008). It consists of four three-item subscales: *mastery-approach* (e.g., "My aim is to completely master the material presented in this class"), *mastery-avoidance* (e.g., "My aim is to avoid learning less than I possibly could"), *performance-approach* (e.g., "My goal is to perform better than the other students"), and *performance-avoidance* (e.g., "My aim is to avoid doing worse than other students"). To each item, participants responded on a scale of 1 (strongly disagree) to 5 (strongly agree), and the items were averaged to form the indexes of each achievement goal orientation at each assessment wave. Measurement invariance and composite reliability analyses, reported in SOM, supported the validity of the instrument in our study.

SES background was assessed through family material conditions and measured only at the first assessment wave. Five indirect indicators included the availability of a personal bedroom at home, the number of cars and computers owned by the family, the number of family holiday trips outside of the country, and eligibility for free meals at school. The composite reliability was sufficient: $\rho = .60$. SOM provides more details on this measure.

Data analysis

First, we conducted latent profile analysis (LPA) of the four AGOs separately for each assessment wave data. Models containing from one to eight latent profiles were tested and compared against each other in terms of fit with data, and then the same analysis was repeated for each wave. In every case, the best-fitting model was chosen by investigating a set of criteria suggested by Masin (2013). More details on the criteria used are provided in SOM.

Second, we built a latent transition analysis (LTA) model and analyzed the longitudinal similarity of latent profiles. Specifically, using a stepwise approach and guidelines provided by

Morin and colleagues (2016), we investigated configural (same number of profiles), structural (within-profile mean), dispersion (within-profile variability), and distributional (profile proportion) similarity of the profiles uncovered in each wave. Lastly, we investigated whether the profile transition rates changed across different assessment waves. To estimate if the included model constraints worsen model-data fit, we examined the criteria provided by Masin (2013). The same criteria were used to evaluate the similarity of latent transition patterns (see SOM for more details). All analyses were conducted with *Mplus 8.7* software.

Results

The SOM presents the means, standard deviations, and correlations between study variables.

Latent profile analysis results

The results of the LPA analysis conducted for each assessment wave were relatively similar and favored either a four- or a five-class solution. Considering the indicators of classification quality (see SOM for more details), we decided that a more parsimonious four-profile solution best represented the latent profiles at each assessment wave.

Latent transition analysis

Evidence advocating the four-profile model across the four waves suggested that longitudinal configural latent profile similarity held. Considering these findings, we built an LTA model and proceeded to structural, dispersion, distributional, and transition similarity analysis. The inclusion of between-wave equality constraints for the within-profile means did not worsen model fit, and the entropy levels remained stable, suggesting that the included constraints only made these models more parsimonious. However, the inclusion of distribution equality constraints resulted in an increase of model-fit indices and a decrease in entropy, indicating that the proportion of participants assigned to the four profiles differed across the four occasions. We then removed the distribution similarity constraints and tested for the transition similarity by including constraints on transition probabilities. The resulting model also increased model-fit indices values and decreased entropy, indicating that transition patterns at different transitional periods were distinct.

Since the within-profile means and variances were the same across the T1-T4, the interpretation of the profiles was identical for each assessment wave. Figure 1 presents the four profiles' mean levels, and Figure 2 provides profile prevalence rates (probability that a random participant will be assigned to a specific profile) and transition rates for each assessment wave. SOM Table 4 provides exact prevalence and transition rates.

The profile labeled *moderately motivated* was characterized by slightly elevated scores on all four AGOs and had the highest prevalence rate among the four profiles (45% at T1 and T3 and ~50% at T2 and T4). This profile was also characterized by the highest stability, which was around 75% at the first (T1→T2) and second (T2→T3) transition and around 80% at the last (T3→T4) transition. During the first and third transition, those who moved out of this profile moved either to *unmotivated* or to *success-oriented* profiles, while during the second transition, those who moved out of this profile moved either to *mastery* or *success-oriented* profiles.

The *success-oriented* profile was characterized by high scores on all four AGOs and was the second most common profile in all four assessments. (~40% at T1, 35% at T2 and T3, 31% at T4). This profile was also characterized by high stability (~70% during the first and third transition, ~80% during the second transition). During the first and third transition, most of those who moved out of this profile moved to the *moderately motivated* profile. During the first and second transition, some of those who moved out of this profile also moved to the *mastery-oriented* profile.

The *mastery-oriented* profile was characterized by high scores on mastery goals and low on performance goals. The prevalence rate at T1 was below 10% but was somewhat higher on subsequent occasions. This profile was also characterized by moderate stability at the first and third transitions and high stability (close to 80%) during the second transition. At all three transitions, those who moved out of this profile moved either *moderately motivated* or *success-oriented* profiles.

Lastly, the *unmotivated* profile was characterized by low scores on all four achievement goal orientations. On all four occasions, the estimated prevalence for this profile was lowest among the four (5% at T1, slightly increased at later occasions). The profile was also characterized by the lowest levels of stability (around 50%), which was slightly lower at the second transition and slightly higher at the third. Those who moved out of this profile moved to the moderately motivated profile at all three transitions.

The overall profile stability (calculated as the sum of profile prevalence rates multiplied by a transition to the same profile rate) was lowest during the transition to the first pandemic-related school closure, i.e., when students first moved from school-based learning to online learning. During this transition (T1→T2), 67% of the total sample remained in the same profile, compared to 75% for the second (T2→T3) and 74% for the final (T3→T4) transition.

Lastly, we estimated a series of LTA models with a time-invariant continuous covariate (SES background) to investigate if student SES predicted the four T1 profiles and transitions from profile to profile between the assessments. Findings indicated that SES background was associated with T1 profiles but did not directly affect the between-occasion transition probabilities; SES was linked with the motivation profiles at subsequent occasions only indirectly via the initial ones. Estimated conditional profile prevalence rates for low and high

SES condition ("low" - score value two standard deviations below the sample mean and "high" - score value two standard deviations above the mean) indicated that at the first occasion, unmotivated and moderately motivated profiles were more characteristic to low SES condition. In contrast, the success-oriented profile was more prominent in the high SES condition (presented in Figure 3). More so, profile prevalence rates at the four measurement occasions were relatively stable for the low SES adolescents; that is, the distribution of profiles was somewhat similar across all four occasions. In contrast, profile prevalence rates for the adolescents characterized by high SES were quite distinct between assessment waves. The decrease in the proportion of adolescents assigned to the success-oriented profile and an increase in the three remaining profiles was most evident for those from more advantaged backgrounds. SOM provides a detailed report of these analyses.

Discussion

This study focused on distinct motivational patterns and their dynamics among adolescents before and during the Covid-19 pandemic. While the results indicate high overall stability in motivational patterns across the assessment waves, normative, seasonal, and, potentially, pandemic-related change is also reflected in our findings. Moreover, the prevalence of motivational patterns is linked to student SES background, especially before and during the early stages of the pandemic. We discuss these results below in more detail.

Similarly to previous studies conducted during regular school functioning periods (see Niemivirta et al., 2019), we identified pronounced qualitative differences in how students approach their academic goals. Three motivational patterns differed in their scores across multiple goal dimensions (success-oriented, moderately motivated, and unmotivated), and one pattern had a prevailing goal orientation type (mastery-oriented). These profile patterns and their prevalence rates are similar to previous findings with adolescent samples (e.g., (Niemivirta et al., 2019; Tuominen-Soini et al., 2011; Tuominen-Soini et al., 2020).

However, the exact proportion of participants assigned to the four profiles differed across the four assessment waves. The largest change was observed in the share of those with success orientation (high mastery and high performance) – their share decreased by 10% throughout the study. A decrease in the success-oriented students over time was observed previously in other European countries. A 3% to 8% yearly/ half-yearly decrease among adolescents in Finland was reported (Tuominen-Soini et al., 2011; Tuominen-Soini et al., 2020), and a one and a half-year decrease of 11% and 6 % was observed for similar subject-specific AGO patterns among Dutch early adolescents (Jansen in de Wal et al., 2016). Considering that the reported period in our study covers two academic years, the overall decrease in the share of students in success-oriented profile could reflect a normative decline in academic motivation, described by stage-environment fit theory (Eccles & Roeser, 2009).

The overall stability in AGO profile transitions identified in our study (67% to 75% across different waves) is also similar to the stability rates in most of the previous studies with secondary school students. The stability rates during regular schooling periods in secondary school samples varied from 57 % to 76% (Lo et al., 2017; Tuominen-Soini et al., 2011; Tuominen-Soini et al., 2020). Thus, the expectation that the pandemic circumstances would bring less stability in the motivational profiles of adolescents compared to regular school functioning periods was not supported by our findings. Moreover, most changes observed in our study follow the pattern reported in previous person-oriented longitudinal studies (Niemivirta et al., 2020): of those who do change their motivation pattern over two academic years, the majority move to a neighboring group, the one that is qualitatively most similar to the initial motivational profile.

Nevertheless, our findings also revealed some unique patterns of change that were not characteristic of previous studies and coincided with a transition to pandemic-related online learning periods. Specifically, we observed some unfavorable transitions identified as atypical (i.e., occurring less frequently than expected by chance) by previous person-oriented longitudinal studies in the field. One such transition concerns the change from a success-oriented to a moderately motivated profile. This transition was atypical among Taiwanese adolescents (Lo et al., 2017). However, in our study, around one-fourth of adolescents in a success-oriented profile made this transition during both academic periods covered in our study (i.e., the first and the last transition). Another unfavorable transition, which was not characteristic of adolescents in previous studies, concerns the transition from mastery-oriented to moderately motivated. This transition was atypical among Finnish adolescents (Tuominen-Soini et al., 2011). In our study, around one-fifth of adolescents in a mastery-oriented profile made this transition during both academic periods covered in our study. As the timing of these unfavorable changes in adolescent motivation in our study coincided with pandemic-related online learning periods, these atypical transitions could be at least partly explained by a pandemic shock (the first transition with an abrupt move to online learning) or pandemic fatigue (the last transition with an extended period of online learning experiences).

When we look at the prevalence of those unfavorable transitions, which were found atypical in previous studies, we see around 13% of such students in the first pandemic-related online learning period and around 11% in the second period of extended online learning (for comparison, there were only 4% of such students over a summer break). The prevalence of these substantive unfavorable motivational transitions in our sample seems much larger compared to 1-3% reported in previous studies during regular school functioning periods (Tuominen-Soini et al., 2011), but in line with the results of a recent Finnish study during the pandemic (Salmela-Aro et al., 2021). This study reported a steeper than normatively expected decrease in school wellbeing (academic engagement and school burnout) for 15% of adolescent study participants. Notably, the students with initially very high motivation levels prevail among those who lost their motivation during the pandemic both in our and the Finnish study.

However, some atypical favorable changes were also observed in our study. Specifically, this concerns a move from moderately motivated to success-oriented or mastery-oriented profiles. This transition was atypical among Finnish adolescents (Tuominen-Soini et al., 2011). In our study, around one-fifth of adolescents in a moderately-oriented profile made this transition during a summer break. This pattern was somewhat weaker during the academic periods. It may be assumed that the summer break during the pandemic was a period of rebound for some highly motivated students, who lost a substantial part of their motivation over pandemic online learning periods.

To summarize, while the overall motivational profile membership stability during the pandemic is high and similar to regular schooling times, the motivational transitions that occur during the pandemic show a different pattern compared to previous studies. While the changes in academic motivation during the pandemic are not more frequent, they are more substantive, marked by more pronounced qualitative changes than would be observed in regular school functioning periods. Unfortunately, most of these substantive changes are unfavorable and of considerable size. While substantive favorable transitions were also observed in our study, they were smaller than motivational losses and were most pronounced during the summer. Overall, summer break is marked by elevated motivational gains both for highly motivated and unmotivated students and a more pronounced motivational stability among highly motivated students.

Finally, we aimed to assess the role of student SES for academic motivation patterns and their dynamics. Our findings showed a substantial effect of student SES on the initial distribution of AGO profiles in the pre-pandemic period, which revealed a substantial motivational advantage among the high SES students. These results align with previous findings on the effects of SES in the Lithuanian educational settings, which revealed sizeable SES-related achievement gaps among students, classes, and schools (NEC, 2018; OECD, 2019).

However, contrary to our expectations, no direct SES effect on longitudinal transitions in academic motivation patterns was observed. More students from high SES backgrounds lost their high motivation during the pandemic because there were more of them in highly motivated profiles already before the pandemic. On the one hand, this somewhat counter-intuitive finding demonstrates the persistent, chronic effects of socioeconomic disadvantage, which holds even in the absence of other external (e.g., pandemic) challenges. For disadvantaged students, substantive motivational damage occurred long before the start of the pandemic, in fact, their pre-pandemic level of academic motivation was similar to that demonstrated by high-SES students after a long experience of the pandemic challenges. On the other hand, certain educational policy measures taken during the later waves of the pandemic could have contributed to the stability of the motivational functioning of students from low SES backgrounds. In Lithuania, during the second pandemic wave, students from vulnerable backgrounds could take their online classes using their school premises, equipment, learning assistance from school personnel (Ministry of Education, Science, and Sports, 2021). Our findings provide some optimism concerning these educational policy interventions during the pandemic.

The limitations of this study should be considered. First of all, no national data for direct comparison of motivational patterns and their dynamics among adolescents in Lithuania or other countries with similar socioeconomic and educational trends are available. Thus, the observed differences from previous findings could be at least partly related to cross-national differences in educational systems or broader socioeconomic contexts. Also, a relatively narrow conceptualization and operationalization of student SES background were used in our study. The studies assessing not only material but also cultural and family stress aspects of SES are necessary to better understand the role of SES in adolescents' academic functioning during the pandemic. Finally, SES measures included at each assessment wave could help better understand the motivational transitions that occurred during the pandemic. Nevertheless, the findings of this study provide evidence on unique, mostly unfavorable dynamics of academic motivation during the pandemic, especially for highly motivated adolescents. It also revealed a huge motivational disadvantage among low SES students, which was particularly pronounced before the pandemic, but remained salient throughout the study.

Data availability statement: The data that support the findings of this study are available from the corresponding author, RE, upon reasonable request.

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Table 1.

Results of Latent Transition Analysis (N = 1267)

Model fit indices	*Configural similarity*	*Structural similarity*	*Dispersion similarity*	*Distribution similarity*	*Transition similarity*
Number of parameters	119	71	63	54	37
Log-likelihood	-21240	-21326	-21317	-21441	-21631
Scaling factor	1.59	1.58	1.56	1.72	1.89
CAIC	43450	43231	43147	43322	43562
BIC	43331	43160	43085	43268	43525
AWE	44538	43880	43723	43816	43901
Entropy	.835	.839	.839	.820	.817

Notes.
CAIC – Consistent Akaike's Information Criterion; BIC – Bayesian Information Criterion; AWE - Approximate Weight of Evidence.

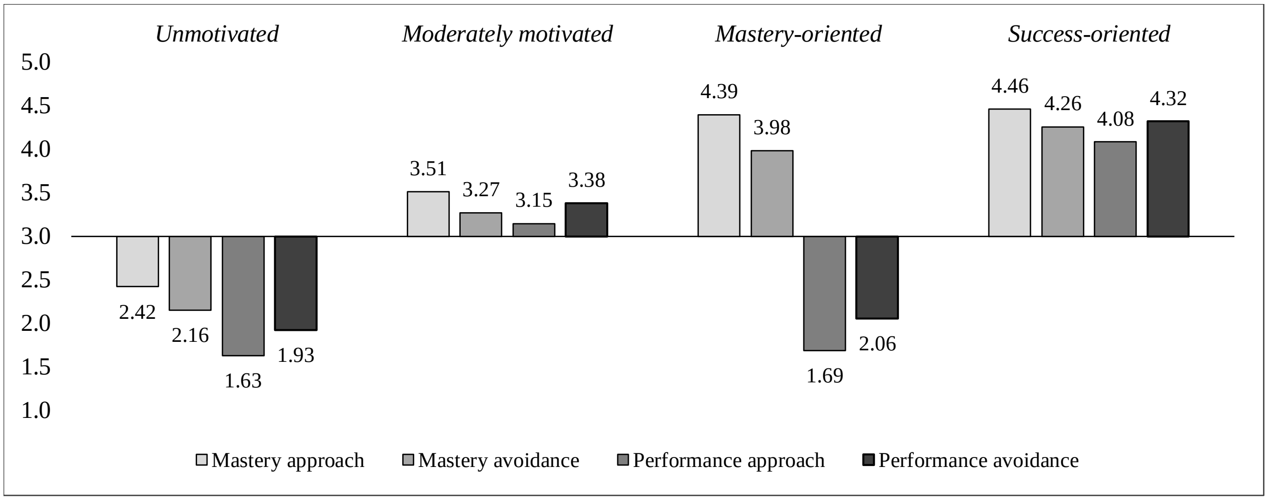

Figure 1. Mean levels of four achievement goal orientation scores across the four academic motivation profiles.

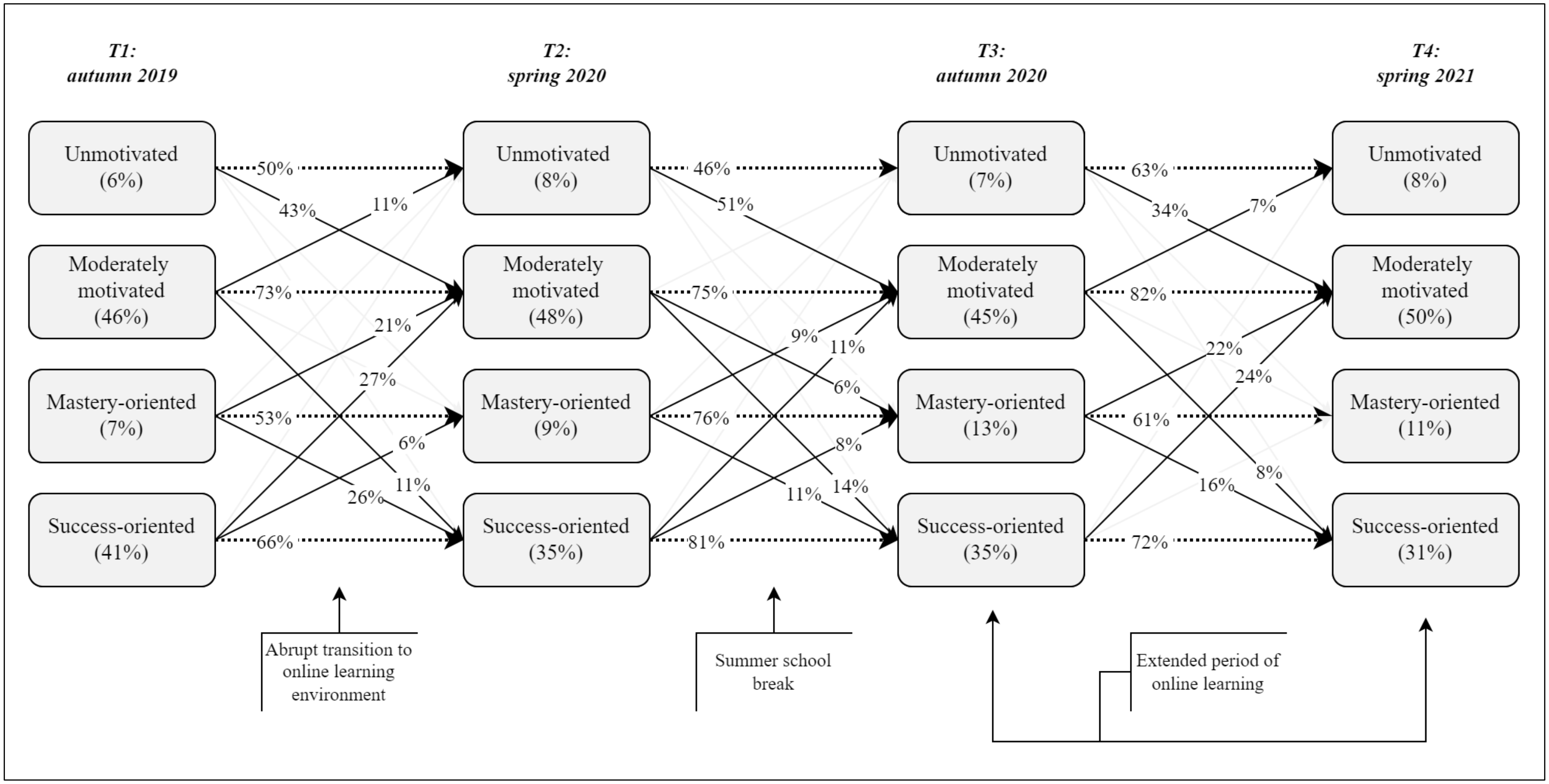

Figure 2. Academic motivation profile distributions and transitions probabilities during the four assessments (N = 1267). Percentages presented beside the profile names indicate profile prevalence rates at a particular measurement occasssion. Percentages placed on the arrows indicate transition rates (proportion of participants assigned to a certain profile transitioning to another profile). Transition rates equal to or lower than 5% are shaded.

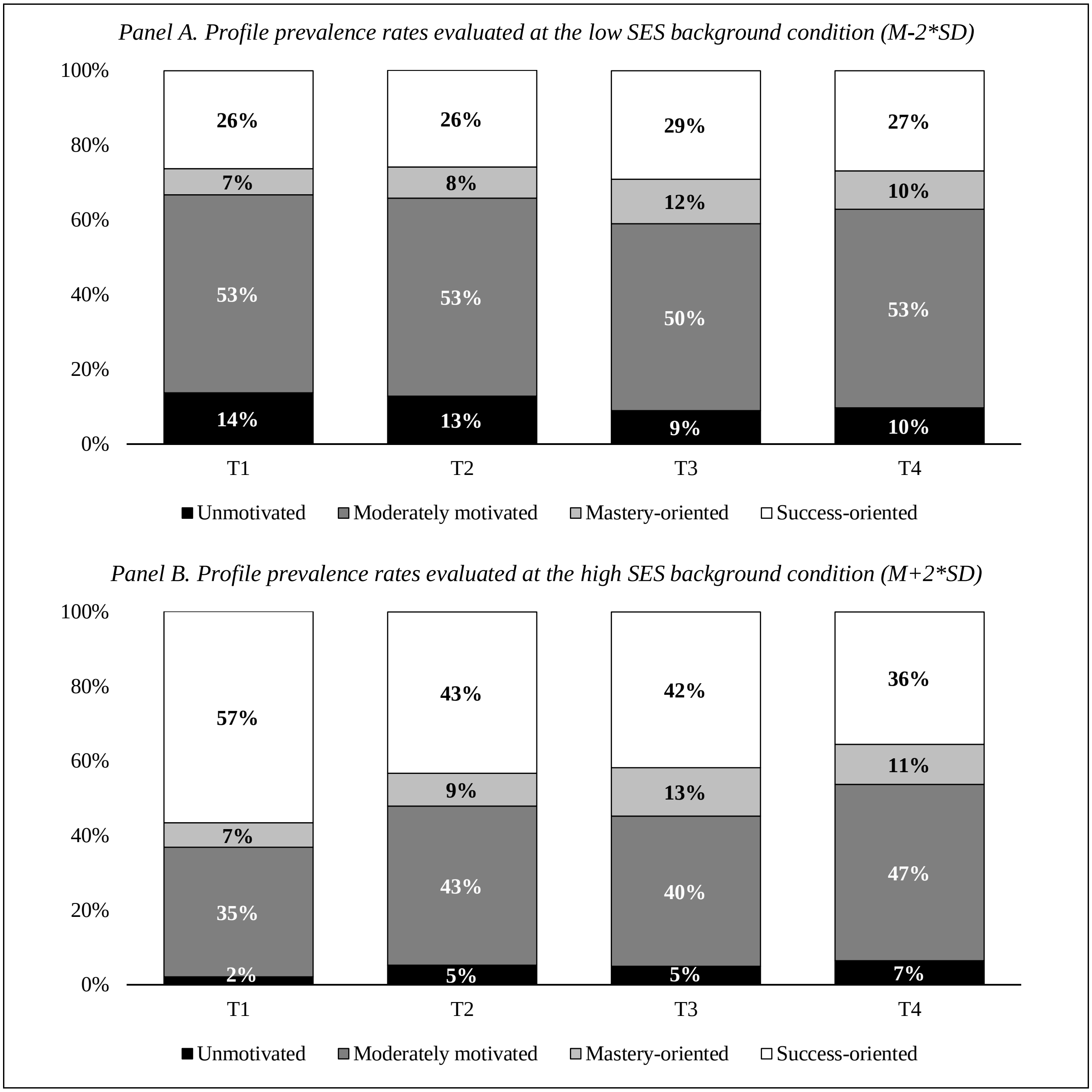

Figure 3. Academic motivation profile conditional prevalence rates (distributions) during the four assessments, evaluated at the poor (panel A) and good (panel B) family material conditional (N = 1267).

Supplementary Online Materials for

Stability and change in academic motivation patterns among adolescents with different SES background before and during Covid-19 pandemic

Contents

Participants and procedures

Data for this investigation come from a four-wave longitudinal study "Goals' Lab" that focuses on the development of adolescent goals in the context of socioeconomic inequalities. The initial sample included 1,268 adolescents (51.7% females; M = 14.87; SD = 0.39) attending 36 gymnasiums (25% in non-urban locations) in Lithuania. The sample was diverse in terms of family socioeconomic backgrounds and family composition. Concerning socioeconomic status, 12.9% received free nutrition at school (compared to 13.7% in the overall population of school children of all grades in Lithuania in 2019; Ministry of Social Security and Labour, 2020) and in 15.1% of cases at least one of the parents was unemployed. Around 67% of participants lived with two parents, while others had different family compositions. The sample was homogeneous in ethnic background, as over 98% of the participants self-identified as Lithuanian.

The first assessment (T1) took place in November 2019 before the onset of the pandemic. The second assessment (T2) took place five months later, in the spring of 2020 (end of April-early May), during the first pandemic wave. The third assessment (T3) took place in October 2020 at the onset of the second wave of the pandemic. The fourth (T4) took place in the spring of 2021 (March-April) during the decline of the second wave of the pandemic. All four assessments were similarly spaced out with a median difference of 24 weeks between T1 and T2 and a median difference of 23 weeks between T2 and T3 and between T3 and T4.

Overall, participant retention rates were 95% (n = 1204), 96.1% (n = 1218), and 92.8% (n = 1177) at T2, T3, and T4. Since some survey questions were possibly sensitive, participants were not required to answer all survey questions and were given the option to skip specific pages on the electronic survey. In consequence, additional missing data on the construct level (assessment of achievement goals) were present at each assessment wave, and the effective sample size for the T1, T2, T3, and T4 was n = 1264 (0.32% missing), n = 1182 (6.78% missing), n = 1067 (15.85% missing), and n = 1163 (8.28% missing), respectively. Little's MCAR test suggested that overall missing data were likely missing completely at random (χ^2 = 309.697; df = 267; p = .080). In latent profile analysis, we used listwise deletion to handle missing data, i.e., participants who did not respond to the items of achievement goal measure or did not participate in an assessment (dropouts) were not included in the LPA analysis. In latent transition analysis, we used Full Information Maximum Likelihood estimation to deal with missing data (Enders, 2010), i.e., we included all participants who, during the four assessments, at least once (n = 1267) responded to the achievement goal measure.

Measurement of achievement goal orientations

Achievement goal orientations were measured using a scale developed by Elliot and Murayama (2008). It consists of four three-item subscales: *mastery-approach* (e.g., “My aim is to completely master the material presented in this class”), *mastery-avoidance* (e.g., “My aim is to avoid learning less than I possibly could”), *performance-approach* (e.g., “My goal is to perform better than the other students”), and *performance-avoidance* (e.g., “My aim is to avoid doing worse than other students”). To each item, participants responded on a scale of 1 (strongly disagree) to 5 (strongly agree), and the items were averaged to form the indexes of each achievement goal orientation at each assessment wave.

To test the assumption that achievement goal scores are comparable across time, we conducted the analysis measurement invariance (MI) for the achievement goal measure, i.e., we tested for configural, weak, strong, and strict longitudinal invariance, using Little’s (2013) guidelines. Results supported configural, weak, and strong MI, which are all required for longitudinal comparisons. Results did not support strict invariance, that is, while item loadings and intercepts were the same across assessment waves, residual variances were not. Based on the strong longitudinal MI model, we estimated composite reliability (CR) for each scale and assessment wave. CR at T1, T2, T3, and T4 were: .86, .87, .88, .86 for *mastery-approach*; .86, .85, .90, and .86 for *mastery-avoidance*; .85, .83, .89, .82 for *performance-approach*; .88, .89, .90, .88 for *performance-avoidance*.

Longitudinal measurement invariance analysis of achievement goal orientations measure

To test the assumption that achievement goal scores are comparable across time, we tested for configural, weak, strong, and strict longitudinal invariance, using Little's (2013) guidelines. In these analyses, latent variables were scaled using the "effects coding" method (Little, Slegers, & Card, 2006). Three model fit indices were used to assess the model's fit with data: The Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). CFIs > .90 and RMSEAs and SRMRs <.08 indicated acceptable fit, and CFIs > .95 and RMSEAs and SRMRs <.05 indicated good fit (Little, 2013). Statistically significant differences between nested models were tested using the Scaled χ^2 Difference test (Satorra & Bentler, 2001). Practically significant differences were assessed using model fit statistics: ΔCFI $\geqslant$ -.01 was considered a substantial decrease in model fit (Little, 2013).

The results of longitudinal MI analysis are summarized in SOM Table 3. An unconstrained (configural) model had a good fit with the data. The inclusion of equality constraints for factor loadings across time (weak invariance model) did not produce any statistically or practically significant change of model-data fit. Adding intercept constraints to test for strong measurement invariance did produce statistically significant change ($p < .001$) of model-data fit. However, ΔCFI indicated that this change was only trivial. However, adding residual error constraints did produce a statistically and practically significant change of model-data fit (ΔCFI > .01). Overall, MI analysis results supported weak and strong invariance but not strict invariance.

SOM Table 2.

Results of Longitudinal Measurement Invariance (N = 1267)

Model tested (model compared with)	Model fit statistics							Model comparison				
	χ^2	*df*	n_{par}	*p*	CFI	RMSEA [90% CI]	SRMR	$\Delta\chi^2$	Δdf	*p*	ΔCFI	ΔRMSEA
Configural	1509.271	924	300	<.001	.979	.022 [.020 .024]	.027	-	-	-	-	-
Weak (vs configural)	1542.225	948	276	<.001	.979	.022 [.020 .024]	.028	32.425	24	.117	.000	.000
Strong (vs weak)	1613.210	972	252	<.001	.977	.023 [.021 .025]	.029	74.815	24	<.001	-.002	.001
Strict (vs strong)	1965.697	1008	216	<.001	.965	.027 [.026 .029]	.035	249.012	30	<.001	-.012	.004

Note. CFI - Comparative Fit Index; RMSEA – Root Mean Square Error of Approximation; SRMR – Standardized Root Mean Square Residual; CI – Confidence Interval. n_{par} – number of free parameters in the model.

Measurement of student SES background

Student SES background was measured using six indirect indicators. However, one of these indicators created for this study was not used in the analysis due to the lack of variability in some response categories. In particular, the discarded item asked participants to indicate the kind of accommodation the participant's family was living in ("What kind of accommodation do you live in?"). The response options and frequencies of responses to this question were "family-owned accommodation" (88.1%), "rented apartment/home" (6.5%), "social housing" (2.3%), "other" (1.3%), and "I don't know" (1.8%). Considering that almost 90% of participants were living in a family-owned accommodation, we decided that this variable does not contain any valuable variance regarding SES background. One of the indicators (i.e., the eligibility for free nutrition at school) was created based on the information obtained from schools. The four remaining indicators were adopted from the Czech Family Affluence Scale (Hobza et al., 2017) and filled out by the participating adolescents. Before proceeding with the analysis of these items, some categories were merged to avoid using low-variability responses.

The original item "Do you have your own bedroom?", used in Hobza et al. (2017), had three response options ("I share my room with all family," "I share my room with brother/sisters", and "I have my own room"). However, very few participants in our study indicated that they share their room with all family members (3.5%). As such, this category was merged with "I share my room with brothers/sisters" to create a new category of "I share my room with someone." In addition, the original item "How many computers including laptops and tablets do your family own?" had four response options ("None," "One," "Two," "Three or more"). However, very few participants indicated that their family does not own any computers (1.4%). As such, this category was merged with "one" to create a new category - "One or none."

The remaining two items ("number of cars owned by the family" and the "number of family holiday trips outside of the country") were not modified. SOM Table 1 presents count and frequencies in the sample of the final categories.

The five items were subjected to a CFA for categorical indicators. Results supported a one-dimensional structure: WLSMV χ^2 (5) = 24.74; p = .0002; RMSEA = .056, CI90% = [.035, .079], CFI = .952. The reliability was sufficient: ρ = .60.

SOM Table 1.

Frequencies of student SES background indicators (N = 1268).

Indicator	**Response option**	**Count**	**% of the sample**
Receives free nutrition at school	*Yes*	163	12.9
	No	1105	87.1
The availability of a personal bedroom at home	*Sharing room with someone*	346	27.3
	Has a personal room	922	72.7
Number of cars owned by the family	*None*	124	9.8
	One	444	35.0
	Two	495	39.0
	Three or more	205	16.2
Number of computers, including laptops and tablets owned by the family	*One or none*	408	32.2
	Two	474	37.4
	Three or more	386	30.4
Number of family holiday trips outside of the country	*None*	456	36.0
	One	455	35.9
	Two	197	15.5
	Three or more	160	12.6

Latent profile analysis (LPA) results

In both LPA and LTA analysis, to ensure that the Log-likelihood value does not represent local maxima, all models were estimated using 500 random sets of start values with 200 iterations. Maximum Likelihood with Robust standard errors (MLR) estimator was used to estimate model parameters. Since participants were nested within classes, in all our analyses, we used the “type = complex” command.

We conducted LPA of the four achievement goal orientations separately for each assessment wave data. Models containing from one to eight latent profiles were tested and compared against each other. The best-fitting model was chosen by investigating a set of criteria suggested by Masyn (2013). First, we looked for smaller values in Bayesian Information (BIC) and Consistent Akaike’s Information (CAIC) Criterions, as well as the Approximate Weight of Evidence (AWE) index. We also inspected which solutions were characterized by higher entropy values. We also looked for significant *p*-values of the Lo-Mendell-Rubin likelihood-ratio test (LMR-LRT test), which would indicate that the model with k profiles fitted the data better than the model with k-1 profiles. Lastly, we looked at the percentage of participants assigned to the smallest latent class. Solutions with the profiles consisting of fewer than 5% of the individuals were considered less parsimonious.

The results are summarized in SOM Table 3. Results favored either a four- or a five-class solution on each occasion. Considering solutions for different assessment waves containing up to six latent profiles, entropy was consistently highest for the four-profile solution. At each wave, the most visible elbow for the BIC, CAIC, and AWE criteria was at the five-profile solution; however, the difference between the four- and five-profile solutions was relatively small compared to the difference between the three- and four-profile solutions. In three out of four assessment waves LMR-LRT test favored four-profile solutions, and in one – a five-profile solution. However, most five-profile solutions have profiles that consist of 5% or fewer participants. Lastly, in every case, the five-profile solution resulted in two theoretically similar profiles, i.e., those characterized by a similar configuration of mean levels that differed only in terms of a slight elevation of all four achievement goal orientations. Considering these results, we opted for a more parsimonious four-profile solution.

SOM Table 3.

Results of Latent Profile Analysis.

Model fit indices	*1 Profile*	*2 Profiles*	*3 Profiles*	*4 Profiles*	*5 Profiles*	*6 Profiles*	*7 Profiles*	*8 Profiles*
	T1 results (n = 1264)							
Number of parameters	8	13	18	23	28	33	38	43
Log-likelihood	-6918	-6389	-6164	-6027	-5930	-5868	-5808	-5767
CAIC	13901	12884	12474	12241	12087	12004	11925	11883
BIC	13893	12871	12456	12218	12059	11971	11887	11840
AWE	13974	13003	12639	12451	12343	12305	12272	12276
Entropy		.751	.780	.814	.790	.826	.821	.822
LMR-LRT test value		1028.95	438.41	266.85	188.88	120.69	116.64	79.85
LMR-LRT *p*-value		<.001	.002	<.001	.546	.327	.376	.250
	T2 results (n = 1182)							
Number of parameters	8	13	18	23	28	33	38	43
Log-likelihood	-6455	-5970	-5710	-5555	-5444	-5386	-5329	-5288
CAIC	12975	12044	11565	11296	11113	11039	10965	10923
BIC	12967	12031	11547	11273	11085	11006	10927	10880
AWE	13048	12162	11728	11505	11367	11338	11310	11313
Entropy		.725	.804	.824	.803	.799	.830	.850
LMR-LRT test value		944.67	505.56	300.58	217.05	111.84	110.70	80.42
LMR-LRT *p*-value		<.001	<.001	.004	.002	.123	.397	.259
	T3 results (n = 1067)							
Number of parameters	8	13	18	23	28	33	38	43
Log-likelihood	-5800	-5411	-5175	-4992	-4910	-4870	-4834	-4803
CAIC	11664	10926	10493	10167	10043	10003	9971	9948
BIC	11656	10913	10475	10144	10015	9970	9933	9905
AWE	11735	11042	10655	10373	10294	10299	10312	10334
Entropy		.767	.795	.821	.797	.748	.766	.791
LMR-LRT test value		756.11	459.36	355.69	159.08	77.50	70.43	60.42
LMR-LRT *p*-value		.002	<.001	.001	.001	.248	.612	.411
	T4 results (n = 1163)							
Number of parameters	8	13	18	23	28	33	38	43
Log-likelihood	-6389	-5901	-5546	-5376	-5223	-5118	-5041	-4975

CAIC	12842	11906	11238	10937	10671	10502	10388	10296
BIC	12834	11893	11220	10914	10643	10469	10350	10253
AWE	12914	12024	11401	11145	10924	10801	10732	10686
Entropy		.721	.852	.858	.838	.836	.851	.868
LMR-LRT test value		949.35	689.12	331.82	297.79	202.91	150.49	128.13
LMR-LRT *p*-value		<.001	<.001	.064	.002	.002	.019	.061

Notes.
CAIC – Consistent Akaike's Information Criterion; BIC – Bayesian Information Criterion; AWE - Approximate Weight of Evidence. LMR-LRT - Lo-Mendell-Rubin likelihood ratio.

Latent transition analysis (LTA) results

We conducted longitudinal latent profile similarity analysis once the best fitting model was selected for each assessment wave. Using a stepwise approach and guidelines provided by Morin and colleagues (2016), structural (within-profile means), dispersion (within-profile variability), distributional (proportion) similarity of the profiles uncovered in each wave. Configural similarity model is a model that estimates a set of profiles at each assessment wave and does not impose any longitudinal parameter constraints. The structural similarity model is the same as the configural similarity model but includes between wave equality constraints on within-profile means. The dispersion similarity model is the same as the structural similarity model but includes longitudinal equality constraints on within-profile variance estimates. Lastly, the distributional similarity model is the same as the dispersion similarity model but includes between wave equality constraints on class probabilities.

Evidence advocating the four-profile model across the four waves suggested that longitudinal configural latent profile similarity holds. The inclusion of between-wave equality constraints for the within-profile means did not worsen model fit, and the same results were obtained for within-profile variance parameters, i.e., CAIC, BIC, and AWE values decreased when these constraints were included in the LTA model. At the same time, the entropy levels remained stable, suggesting that the included constraints only made these models more parsimonious. However, the inclusion of distribution equality constraints resulted in an increase of all three model-fit indices and a decrease in entropy, indicating that the proportion of participants assigned to the four profiles differed across the four occasions. We then removed the distribution similarity constraints and tested for the transition similarity by including constraints on transition probabilities. The resulting model also increased CAIC, BIC, and AWE values and decreased entropy, indicating that transition rates between the profiles differed across the three transitions.

SOM Table 4.

Academic motivation profile distributions and transitions probabilities during the four assessments (N = 1267)

Prevalence rates of achievement goal profiles at the four assessments				
	T1 (autumn 2019)	*T2 (spring 2020)*	*T3 (autumn 2020)*	*T4 (spring 2021)*
Unmotivated	.06	.08	.07	.08
Moderately motivated	.46	.48	.45	.50
Mastery-oriented	.07	.09	.13	.11
Success-oriented	.41	.35	.35	.31
Transitions across profiles between T1 (autumn 2019) and T2 (spring 2020)				
	Unmotivated (T2)	*Moderately motivated (T2)*	*Mastery-oriented (T2)*	*Success-oriented (T2)*
Unmotivated (T1)	.50	.43	.02	.05
Moderately motivated (T1)	.11	.73	.05	.11
Mastery-oriented (T1)	.00	.21	.53	.26
Success-oriented (T1)	.01	.27	.06	.66
Transitions across profiles between T2 (spring 2020) and T3 (autumn 2020)				
	Unmotivated (T3)	*Moderately motivated (T3)*	*Mastery-oriented (T3)*	*Success-oriented (T3)*
Unmotivated (T2)	.46	.51	.03	.00
Moderately motivated (T2)	.05	.75	.06	.14
Mastery-oriented (T2)	.04	.09	.76	.11
Success-oriented (T2)	.00	.11	.08	.81
Transitions across profiles between T3 (autumn 2020) and T4 (spring 2021)				
	Unmotivated (T4)	*Moderately motivated (T4)*	*Mastery-oriented (T4)*	*Success-oriented (T4)*
Unmotivated (T3)	.63	.34	.04	.00
Moderately motivated (T3)	.07	.82	.03	.08
Mastery-oriented (T3)	.02	.22	.61	.16
Success-oriented (T3)	.01	.24	.04	.72

Covariate effects on latent profile membership and between-profile transitions

As the last step of our analysis, we investigated if student SES background predicted the four profiles at the first assessment and the transitions from profile to profile between the four assessment waves. To do so, we estimated a series of LTA models with a time-invariant continuous covariate (SES background), following the guidelines provided by Collins & Lanza (2010), Morin and colleagues (2021), Muthén (2021), and Newsom (2015). Each of these models was compared to the baseline model (M1) to assess if the inclusion of specific covariate effects improved model fit. Improvement of model fit was evaluated using the scaled log-likelihood difference test and by investigating the change in the Bayesian Information Criterion (BIC), where the decrease of BIC would indicate improvement of fit.

The initial model (M0) was the final LTA model that included structural and dispersion similarity constraints but did not include the covariate. The covariate (SES background) was included in the baseline model (M1) as the predictor of the achievement goal orientation profiles estimated at the first measurement occasion. The inclusion of the covariate improved model-data fit, as indicated by the significant model log-likelihood difference test and the decrease of BIC (see SOM Table 5).

In the following three models, referred to as "main effect" models (see Muthén, 2021), we investigated if the covariate predicts transition probabilities. Specific to the "main effect" models was that the covariate effect did not depend on the previous profile (the effect does not vary between the profiles at the previuos occasion). That is, in model 2 (M2), by regressing the T2 profiles on the covariate, we allowed the covariate to predict T1-T2 transition probabilities. In model 3 (M3), by regressing the T3 profiles on the covariate, we allowed the covariate to predict T2-T3 transitions. Finally, in model 4 (M4), by regressing the T4 profiles on the covariate, we let the covariate predict T3-T4 transition probabilities. The inclusion of these effects did not improve model-data fit, as neither of these models had a better fit with data than the baseline (M1) model.

In the last three models, referred to as "interaction effect" models (see Muthén, 2021), we investigated if the covariate predicts transition probabilities. Specific to the "interaction effect" models was that the covariate effect depended (varied) on the profiles at the previuos occasion. That is, in model 5 (M5), by regressing the T2 profiles on the covariate, we allowed the covariate to predict T1-T2 transition probabilities; however, we allowed this effect to be specific to the four profiles estimated at T1. In model 6 (M6), by regressing the T3 profiles on the covariate, we allowed the covariate to predict T2-T3 transition probabilities; however, we allowed this effect to be specific to the four profiles estimated at T2. Finally, in the very last model 7 (M7), by regressing the T4 profiles on the covariate, we let the covariate predict T3-T4 transition probabilities, and we allowed this effect to be specific to the four profiles estimated at T3. The inclusion of the covariate effects for M5 and M6 did not improve model-data fit. However, the inclusion of the covariate effects for M7 significantly improved model-data fit, as indicated by the statistically significant log-likelihood difference test. However, an increase in the BIC index suggested that the model with all of these effects did not substantially improve the model. A closer inspection of the results for this model indicated that the effects of student SES background on transition probabilities were relatively small, marginally significant, and slightly more specific to the two smallest classes ("unmotivated" and "mastery-oriented").

Overall, this result suggested that student SES background was associated with the profile membership at the first measurement occasion, but it did not substantially alter the between-occasion transition probabilitiesm, at least not to the extent that our study could clearly detect. As for the first measurement occasion, results indicated that belonging to the "unmotivated" profile, compared to the "moderately motivated" profile, was associated with lower SES background (B = -0.37, p = .003; OR = 0.69, $95\%\ CI_{LB}$ = 0.55, $95\%\ CI_{UB}$ = 0.88). Results also showed that belonging to the "success-oriented" profile, compared to the "moderately motivated" profile, was also associated with higher SES background (B = 0.30, p = .001; OR = 1.35, $95\%\ CI_{LB}$ = 1.13, $95\%\ CI_{UB}$ = 1.61). Lastly, results also suggested that belonging to the "mastery-oriented" profile, compared to the "moderately motivated" profile, was not significantly predicted by student SES background (B = 0.08, p = .559; OR = 1.09, $95\%\ CI_{LB}$ = 0.83, $95\%\ CI_{UB}$ = 1.43).

SOM Table 5.

Results of Latent Transition Analysis: Model Fit and Model Comparison in Models with Different Covariate Effects on Profiles and Profile Transitions

Model		**Model fit**			**Model comparison: Log-likelihood difference test**			
No.	*Description*	*Log-likelihood*	*#par*	*BIC*	*Compared with*	χ^2	*df*	*p*
M0	No covariate	-21318	63	43086	-	-	-	-
	Baseline model: Covariate predicts T1 profiles only							
M1	M0 + covariate predicts T1 profiles	-21300	66	43072	M0	31.85	3	<.001
	Main effects models: Transition probabilities are predicted by covariate, but the covariate effect does not depend on the previous profile							
M2	M1 + covariate predicts T2 profiles	-21299	69	43091	M1	3.18	3	.365
M3	M2 + covariate predicts T3 profiles	-21296	72	43107	M1	7.71	6	.260
M4	M3 + covariate predicts T4 profiles	-21291	75	43118	M1	14.15	9	.117
	Interaction models: Transition probabilities are predicted by covariate, but the covariate effect is specific to the previous profile							
M5	M4 + covariate effect on T2 profiles varies	-21297	78	43150	M1	9.25	12	.681
M6	M5 + covariate effect on T3 profiles varies	-21286	90	43215	M1	30.53	24	.168
M7	M6 + covariate effect on T4 profiles varies	-21277	102	43283	M1	55.86	36	.018

Notes. #par – number of parameters; BIC – Bayesian Information Criterion; *df* – degrees of freedom; χ^2 – *Chi-square statistic*

Correlations between study variables

SOM Table 6.

Correlations Between Four Achievement Goal Orientations Measured at Four Occasions (N = 1267)

	Achievement goal orientation	Time	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	*Mastery-approach*	T1																
2	*Mastery-approach*	T2	***.53***															
3	*Mastery-approach*	T3	***.53***	***.59***														
4	*Mastery-approach*	T4	***.48***	***.59***	***.63***													
5	*Mastery-avoidance*	T1	.53	.31	.29	.27												
6	*Mastery-avoidance*	T2	.40	.65	.43	.41	***.39***											
7	*Mastery-avoidance*	T3	.45	.46	.68	.48	***.39***	***.46***										
8	*Mastery-avoidance*	T4	.42	.48	.51	.73	***.33***	***.44***	***.52***									
9	*Performance-approach*	T1	.38	.23	.22	.20	.39	.26	.27	.23								
10	*Performance-approach*	T2	.20	.34	.21	.21	.20	.40	.27	.21	***.45***							
11	*Performance-approach*	T3	.13	.17	.26	.17	.14	.18	.28	.16	***.42***	***.53***						
12	*Performance-approach*	T4	.17	.21	.21	.31	.17	.23	.25	.38	***.40***	***.51***	***.52***					
13	*Performance-avoidance*	T1	.36	.19	.22	.19	.49	.26	.28	.23	.75	.38	.35	.37				
14	*Performance-avoidance*	T2	.21	.37	.23	.21	.22	.47	.29	.24	.41	.77	.46	.47	***.40***			
15	*Performance-avoidance*	T3	.17	.19	.25	.18	.17	.22	.35	.21	.38	.51	.77	.48	***.38***	***.53***		
16	*Performance-avoidance*	T4	.19	.22	.24	.36	.21	.24	.29	.45	.39	.45	.50	.81	***.41***	***.49***	***.52***	
		M	3.24	3.09	3.01	3.00	3.77	4.06	4.31	4.07	4.66	4.32	4.54	4.21	3.65	3.49	3.33	3.36
		SD	1.04	1.05	1.05	1.05	.94	.88	.86	.89	.85	.89	.85	.89	.98	1.00	1.05	1.01

Notes.

All correlations are statistically significant at α = .001. Stability correlations are bolded and italicized. *M* – Mean, *SD* – Standard Deviation. All correlations are estimated using full-information maximum likelihood estimation.

SOM Table 7.

Correlations Between Family Material Capital and Four Achievement Goal Orientations Measured at Four Occasions (N = 1268)

	Time	*Achievement goal orientation*			
		Mastery-approach	Mastery-avoidance	Performance-approach	Performance-avoidance
Family material capital (T1)	T1	$.11^{***}$	$.11^{**}$	$.14^{***}$	$.13^{***}$
	T2	.07	.06	$.11^{**}$	$.10^{**}$
	T3	$.10^{**}$	$.13^{***}$	$.11^{**}$	$.10^{**}$
	T4	$.06^{*}$	$.07^{*}$	$.10^{***}$	$.11^{***}$

Notes.
* $p < .05$, ** $p < .01$, *** $p < .001$. All correlations are estimated using full-information maximum likelihood estimation.

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