The Interconnected Development of Depressive Symptoms and School Functioning from Mid-Adolescence to Early Adulthood: A Piecewise Growth Mixture Analysis

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Acknowledgements

The first author was supported by funding from the Canadian Institute for Military and Veteran Health Research (CIMVHR). Preparation of this paper was also supported by a grant from the Social Sciences and Humanities Research Council of Canada (435-2018-0368). The last author was supported by grants from the Academy of Finland 336138, 345117, and 308351.

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This is the prepublication version of the following manuscript:
Olivier, E.,* Morin, A.J.S.,* Leo, V., & Salmela-Aro, K. (In Press, 2022). The interconnected development of depressive symptoms and school functioning from mid-adolescence to early adulthood: A piecewise growth mixture analysis. *Journal of Educational Psychology*. https://doi.org/10.1037/edu0000761

Abstract

This study seeks to identify profiles of depressive symptoms trajectories among a sample of 2,696 Finnish students (56.8% female), followed from 13-14 to 18-19 years old. Piecewise growth mixture analyses identified five trajectories: Low Stabilizing (6.20%), Mild Increasing (47.90%), Moderate Stabilizing (36.82%), Low Increasing (3.62%), and High Stable (5.46%). Relative to boys, girls experienced more problematic depressive symptoms trajectories. The study also assesses whether achievement goals growth predict depression trajectories, and whether school burnout and engagement growth trajectories can be positioned as outcomes of depression trajectories. Adopting mastery-intrinsic and mastery-extrinsic goals was associated with a lower risk of feeling depressed, whereas adhering to performance-approach or performance-avoidance goals was associated with a higher risk of corresponding to a problematic trajectory-profile. School burnout and engagement trajectories closely matched youth depressive symptoms trajectory-profiles, except for youth corresponding to a High Stable profile who experienced an increase in their school engagement.

Keywords: Depression; Achievement Goals; School Engagement; School Burnout; Piecewise Growth Mixture Analyses.

Educational Impact and Implications Statement

This study identified five profiles of adolescents following distinct trajectories of depressive symptoms between the ages of 13-14 to 18-19 years old, while undergoing a school transition. Two of those trajectories seemed problematic (consistently high and stable; initially low and sharply increasing) in terms of achievement goals, engagement, and burnout. The study discusses the implications of these results for preventing depression and promoting positive school development during these critical years.

Depression is one of the most prevalent mental disorders worldwide (GBD 2017 Disease and Injury Incidence and Prevalence Collaborators, 2018), with over one in ten people suffering from at least one episode of depression throughout their lifetime (Lim et al., 2018). For many individuals, the first occurrence of depressive symptoms can be traced back to adolescence (Garber & Rao, 2014). These symptoms include negative thoughts and emotions, apathy, anhedonia, loneliness, worthlessness, guilt, hopelessness, lack of energy, concentration and sleep difficulties, and weight changes (APA, 2020). Even though they often first emerge in adolescence, depressive symptoms tend to follow trajectories that differ across individuals as they make their way from mid-adolescence to early adulthood (e.g., Vaillancourt & Haltigan, 2018). Indeed, depressive symptoms are often intimately tied to the social contexts in which individuals evolve. For adolescents and young adults, the school environment, and more specifically the motivational processes linked to youth's academic progression, are thus likely to play a key role in the emergence of depressive symptoms, in addition to being impacted by these symptoms (Eccles et al., 1993; Morin et al., 2009). However, apart from the known negative impact of depressive symptoms on academic achievement, research is still lacking to help clarify how depressive symptoms can be influenced by, and in turn influence, students' academic motivational processes (Garvik et al., 2014). To address this gap, this study seeks to identify the most commonly occurring profiles of depressive symptoms trajectories among youth followed from 13-14 to 18-19 years old. The study also considers how student achievement goals trajectories relate to these depression trajectory-profiles and, in turn, how these depression trajectory-profiles relate to students' trajectories of school engagement and burnout.

Heterogeneity in Youth's Trajectories of Depressive Symptoms

There is a consensus that youth follow heterogeneous trajectories of depressive symptoms from adolescence to early adulthood. In research assessing the evolution of depressive symptoms across the adolescent years into early adulthood, three to four distinct profiles of youth characterized by distinct trajectories of depressive symptoms (hereafter referred to as trajectory-profiles) have typically been identified (Barboza, 2020; Bulhoes et al., 2021; Kent & Bradshaw, 2021; Lee et al., 2017; Martinez & Armenta, 2020; Salmela-Aro et al., 2008a; Vaillancourt & Haltigan, 2018; Wang, Chan et al., 2018; Wickrama & Wickrama, 2010; Yaroslavsky et al., 2013). These trajectory-profiles generally describe youth presenting (a) consistently low, (b) moderate and slightly increasing or decreasing, (c) high and decreasing, and (d) consistently high trajectory of depressive symptoms.

These studies further indicate that girls (relative to boys) are more likely to follow trajectories characterized by higher levels of depressive symptoms (Barboza, 2020; Lee et al., 2017; Yaroslavsky et al., 2013). However, additional studies also suggest that boys might be more likely than girls to report initially low levels of depressive symptoms followed by a marked increase in these levels during the transition from adolescence into early adulthood (Martinez & Armenta, 2020). More generally, research suggests that girls are generally more at risk of experiencing depressive symptoms during adolescence (e.g., Lee et al., 2017) as they tend to report steeper increases in these symptoms when entering adolescence (Salk et al., 2017; Wang, Williams et al., 2018). Although these gender differences are notably due to biological factors (Costello et al., 2011), they also stem from girls' greater sensitivity to stressful life events (Oldehinkel & Bouma, 2011) and interpersonal stressors (Zimmer-Gembeck & Skinner, 2015). Such stressors are particularly prevalent in the lives of adolescent girls, who are also more likely to try and cope with them using rumination, a strategy that further increases their risk of feeling depressed (Nolen-Hoeksema et al., 1999). However, boys and girls seem equally at risk of experiencing an increase in depressive symptoms following school transitions occurring in the later adolescent years (Wang, Chan et al., 2018). Indeed, research indicates that most youth, irrespective of sex, will experience these transitions as stressful life events, leading to an increased risk of developing depressive symptoms (Guassi Moreira & Telzer, 2015; Marcotte et al., 2018).

Furthermore, depression trajectories might not be entirely linear, especially when considered over longer time frames (Barboza, 2020), possibly as a result of changes in youth life circumstances (Ge et al., 2006), such as school transitions (Ibrahim et al., 2013; Reed-Fitzke, 2020). Depending on their country and school system, school transitions occur at different ages. Of direct relevance to the present study, in Finland, students transition from basic comprehensive school to upper secondary school around 15 or 16 years old. The transition from one learning environment to another brings several social and academic changes that likely influence youth's risk for depression (e.g., Eccles et al., 1993). For instance, as students advance in their education, they progressively have to make more choices regarding the content of their course curriculum and educational program. The time they spend learning different subjects thus becomes progressively tailored to their interests and professional goals, which might result in feelings of personal accomplishment and better mental health (Yu et al., 2018). However, as students start to specialize in some subjects, the competitive climate of their educational institutions also tends to become more pronounced, which has been found to contribute to an increased risk of experiencing depression (Ibrahim et al., 2013). As such, when transitioning to higher levels of education (such as into the Finnish upper secondary school system), youth might move from an environment that did not exactly match their needs and interests to one that is more tailored to their goals and in which they feel better (Pittman & Richmond, 2008; Salmela-Aro et al., 2008b). In contrast, others might transition to an environment perceived as more competitive, stressful, and disconnected from their basic developmental needs, in which they receive less support (Posselt & Lipson, 2016). It is thus important to consider this school transition as a factor contributing to bending youth's trajectories of depressive symptoms upward or downward.

Youth's Achievement Goals as a Predictor of Depressive Symptoms

Motivation research has long acknowledged that individuals vary in the types of goals they pursue, and in their reasons for pursuing these goals (for reviews, see Monni et al., 2020; Senko & Tropiano, 2016). These goal orientations are closely tied to individuals' adjustment and mental health, and potentially contribute to increase or decrease (i.e., predict) their risk of experiencing depressive symptoms (Bendezú et al., 2021; Ellis et al., 2019; Masselink et al., 2018; Winch et al., 2015). Highly relevant to the educational area, the classical Achievement Goal Theory (Dweck, 1986) initially viewed students as pursuing academic goals centered on mastery or performance. This theory has since evolved to encompass a more refined and nuanced set of achievement goals (Elliot et al., 2011; Senko & Tropiano, 2016).

First, mastery-driven students are assumed to be motivated by a desire to master school subjects for their own personal growth. Some researchers (e.g., Niemivirta, 2002; Tuominen-Soini et al., 2008, 2011) have highlighted the importance of distinguishing two types of mastery goals. On the one hand, mastery-intrinsic goals are focused on learning for its own sake and for one's own personal growth (Heyman & Dweck, 1992; Niemivirta, 2002; Tuominen-Soini et al., 2008, 2011). On the other hand, mastery-extrinsic goals are focused on achievement as an external proof of mastery. More specifically, students pursuing these goals refer to external criteria (e.g., grades) to assess whether they have achieved their goal of mastering a subject (Heyman & Dweck, 1992; Tuominen-Soini et al., 2011). When seeking such external proof of mastery, students aim to obtain an external validation of their mastery (where the benchmark is their own expectations, their own previous level of mastery, or an external set of scoring criteria), rather than to demonstrate their success to others (where the benchmark is others' grades; which is captured by performance-approach goals, described below). Thus, whereas students pursuing mastery-intrinsic goals are characterized by a desire to develop their competence and acquire knowledge for its own sake with little concern for obtaining an external validation of their mastery, those pursuing mastery-extrinsic goals pursue similar learning objectives but seek to obtain an external validation of their success by getting good grades (Niemivirta, 2002; Tuominen-Soini et al., 2008, 2011). This conceptualization also echoes Elliot et al.'s (2011) 3 × 2 conceptualization of achievement goals, which differentiates between individuals driven by self-approach goals (i.e., doing better than before) from those driven by task-approach goals (i.e., doing the task correctly). Students pursuing these two types of goals also rely on external criteria to validate their success, respectively in relation to their prior level of performance and in relation to whether the task has been completed without errors or not. As such, both types of goals are reflected in mastery-extrinsic goals, although mastery-extrinsic goals do not specify the basis of comparison (one's achievement on the task itself or in relation to one's previous levels of achievement). Also contrasting with the 3 × 2 Model, mastery-intrinsic driven students are seen as being purely driven by knowledge acquisition, whereas self- and task-approach goals both refer to achievement or performance as external proofs of their mastery.

Second, performance-driven students are assumed to attribute significant value to other people's judgment about their performance, rather than to their own learning. More precisely, these students thus appear to be driven by a desire to demonstrate their ability (performance-approach), or to avoid demonstrating their lack of ability (performance-avoidance), to significant others (e.g., Dweck, 1986; Elliot & Thrash, 2002; Elliot et al., 2011). More precisely, students driven by performance-approach goals seek to do better than others and to demonstrate their competence to others. Recently, many conceptualizations of achievement goals (Elliot & Thrash, 2001; Hulleman et al., 2010; Senko & Dawson, 2017; Senko & Tropiano, 2016; Urdan & Mestas, 2006) have highlighted that performance-approach goals can be focused on both normative (i.e., achieving competitive success relative to others) or appearance (i.e., demonstrating one's competence to others) goals. Yet, although Niemivirta (2002; Tuominen-Soini et al., 2008, 2011) acknowledge the relevance of these two focal points, they still see them as falling under the generic umbrella of performance-approach goals. Finally, students driven by performance-avoidance goals are far more concerned with avoiding the demonstration of their incompetence (Elliot & Thrash, 2002). Anchored in Niemivirta's (2002; also see Tuominen-Soini et al., 2008, 2011) perspective, the present study thus relies on a conceptualization of achievement goals encompassing mastery-intrinsic, mastery-extrinsic, performance-approach, or performance-avoidance goals.

According to theoretical conceptualizations of goal orientations (see Monni et al., 2020), people develop different mindsets when seeking to attain their personal goals. Of particular interest to the present study, Dykman's (1998) goal-orientation model of depression anticipates that the adoption of a performance-oriented mindset might create a vulnerability to depression by pushing youth to position their personal growth as secondary to others' approval. Furthermore, mindsets involving attempts to *approach* one's goals are expected to support positive development and well-being, whereas a tendency to *avoid* reaching undesired goals is expected to predispose adolescents to develop feelings of depression (Dykman, 1998; McNaughton & Corr, 2004; Monni et al., 2020). This perspective thus suggests that pursuing performance-avoidance goals and, to a lesser extent, performance-approach goals (Hulleman et al., 2010; Senko & Dawson, 2017; Senko & Tropiano, 2016) might contribute to the emergence and development of depressive symptoms.

Furthermore, individuals pursuing mastery goals (intrinsic or extrinsic) should have more confidence in their ability to reach these goals, which in turn should help them attain more adaptive outcomes (Heyman & Dweck, 1992). Mastery-intrinsic goals might help limit the emergence and development of depressive symptoms (Dykman, 1998; 2005) as individuals pursuing these goals tend to be purely motivated by the learning process in a way that remains mainly disconnected from external contingencies. In contrast, mastery-extrinsic goals, even though they also seek learning, require reliance on external indicators to validate this learning. Thus, although these goals are also likely to result in positive adjustment and a lower risk of feeling depressed via their valorization of learning, this positive adjustment is likely to be conditioned on external criteria that do not entirely fall under one's control. By making one's sense of self-worth and success contingent on external criteria, mastery-external goals may thus make students' more vulnerable to depression in situations where these external criteria are inconsistent with their feelings of mastery (e.g., Kernis, 2003, 2005; Zeigler-Hill & Wallace, 2012). As a result, mastery-intrinsic goals are likely to lead to the lowest risk of feeling depressed, followed by mastery-extrinsic goals. The anticipation that pursuing mastery-intrinsic versus mastery-extrinsic goals might yield different adjustment outcomes is a clear advantage of this conceptualization of Achievement Goal Theory over more common ones such as Elliot et al.'s (2011) 3 × 2 conceptualization.

Empirical evidence generally supports the idea that, because performance-oriented students often tend to display lower levels of self-esteem (Vannucci & McCauley Ohannessian, 2018), they tend to be more likely to seek external sources of valorization by proving their value, competence, and performance to others (e.g., parents or teachers). In turn, and although they are often able to maintain adequate academic performance (Ellis et al., 2019), performance-oriented students may come to experience a higher risk of depressive symptoms whenever they fail to receive the expected external validation (Dykman, 1998). As a result, performance-oriented students seem to be more prone to develop depressive symptoms relative to their mastery-oriented peers (Bendezú et al., 2021; Tuominen et al., 2020). However, performance-avoidance goals seem to be even more damaging to youth's mental health than performance-approach goals (Ellis et al., 2019; Masselink et al., 2018; Miller & Markman, 2007; Rudolph et al., 2017; Sherratt & NacLeod, 2013; Sideridis, 2005; Winch et al., 2015). Likewise, students pursuing mastery goals in general tend to display a better adjustment and fewer depressive symptoms than their peers pursuing performance (approach or avoidance) goals (Madjar et al., 2021). Unfortunately, the distinction between mastery-intrinsic and mastery-extrinsic goals has not yet been investigated in relation to youth's depression trajectories. It is thus uncertain whether adolescents pursuing these two types of goals would evolve differently in their risk of feeling depressed.

Despite these reasonably well-documented associations between achievement goals and youth's depressive symptoms, knowledge is currently lacking regarding the longitudinal associations between youth achievement goals trajectories and their depressive symptoms trajectories. More precisely, although we know how achievement goals and depression are linked to one another at one specific point in time, we still do not know how trajectories of achievement goals might impact the heterogeneous development (i.e., trajectory-profiles) of depressive symptoms over time. The present study was designed to address this gap.

Spillover of Depressive Symptoms on School Engagement and Burnout (Outcomes)

Just like students' achievement goals trajectories might predict their trajectory-profiles of depressive symptoms, these trajectory-profiles of depressive symptoms are also likely to play a role in (or to spillover on) youth's school functioning. Often studied together, school engagement and school burnout (Fiorilli et al., 2017; Schaufeli et al., 2002; Salmela-Aro & Upadyaya, 2014a; Tuominen-Soini & Salmela-Aro, 2014; Virtanen et al., 2018) are two indicators of how much energy and effort youth dedicate to their studies, which might be influenced (i.e., as outcomes) by their depressive symptoms. School engagement is a state in which students experience vigor, dedication, and absorption in their school tasks, and more generally in the learning process (Salmela-Aro & Upadyaya, 2012; Schaufeli et al., 2002). Engaged students have energy and are willing to put efforts into their work (i.e., vigor), they feel driven, enthusiastic, and inspired (i.e., dedication), as well as entirely concentrated on work that they enjoy doing (i.e., absorption). Although originally conceptualized by distinct components (Fredricks et al., 2004), researchers now increasingly recognize that a global indicator of engagement including all components exists (Wang et al., 2016), but is also highly relevant when studying mental health (Olivier et al., 2020). In contrast to school engagement, school burnout occurs when students feel overwhelmed by the demands of their studies (Schaufeli et al., 2002). As a result, these students tend to feel exhausted and pressured by their studies, become cynical toward their schoolwork, and come to feel inadequate or unable to reach their goals (Salmela-Aro et al., 2009b).

In adolescence, youth engagement and burnout trajectories have been shown to present some level of malleability, consistent with the likely influence of many individual and contextual determinants, themselves likely to change during this critical developmental period (e.g., Archambault et al., 2009; Salmela-Aro & Upadyaya, 2014b). Although students might follow heterogeneous trajectories of school engagement during adolescence, a general trend throughout these years is that engagement tends to slightly decrease over time (Archambault et al., 2009; Engels et al., 2017; Wang & Eccles, 2011). Likewise, burnout levels also tend to slightly increase throughout adolescence as a result of students' exposure to developmental stressors (Parviainen et al., 2021; Salmela-Aro & Upadyaya, 2014b).

Garvik et al. (2014) noted that very few studies have considered how depressive symptoms might influence student school functioning beyond the aforementioned negative association with their levels of academic achievement. The cognitive processes associated with depressive symptoms are likely to affect youth's ability to be fully dedicated to their schoolwork. For instance, rumination and the inability to stop focusing on one's negative emotions tend to distract youth suffering from depressive symptoms when they are at school, making it harder for them to be fully engaged in their studies (Dorio et al., 2019). Research supports this assertion by revealing negative associations between depressive symptoms and school engagement (Fiorilli et al., 2017; Garber & Rao, 2014; Li & Lerner, 2011; Olivier et al., 2020; Salmela-Aro & Upadyaya, 2012; Wang et al., 2015). Likewise, depressive symptoms and school burnout tend to be similarly associated with a variety of problematic cognitive styles (Bianchi & Schnfeld, 2016). Youth suffering from depressive symptoms also tend to display concomitantly higher levels of school burnout (Salmela-Aro et al., 2009a), depression potentially predisposing youth to school burnout (Parviainen et al., 2021).

Despite the general agreement that depression, school engagement, and school burnout are all likely to change over time, research is currently lacking to properly document the dynamic interplay between depression and adolescents' levels of school functioning, a limitation that the current study seeks to address. A single study has assessed how the heterogeneous development (i.e., trajectory-profiles) of depression might impact student engagement trajectories. In this study, Brière et al. (2015) found that youth's attitudes toward school partially corresponded to their trajectories of depressive symptoms between 12 and 16 years old. Likewise, another study conducted among a sample of early-career young adults demonstrated that depressive symptoms systematically increase the risk for professional burnout across four time-points spanning eight years (Tóth-Király et al., 2021). However, research remains too scarce to properly understand the role of depression trajectories (and trajectory-profiles) on school engagement and burnout trajectories, particularly among youth undergoing a school transition likely to impact their functioning across all life domains (Griep & Wingate, 2018; Salmela-Aro et al. 2008b; Widlund et al., 2021).

The Present Study

The present study pursues four objectives. Objective 1 seeks to identify the most commonly occurring depressive symptoms trajectory-profiles among a sample of Finnish youth followed from mid-adolescence to early adulthood and across the transition into upper secondary school. In line with studies assessing developmental trends in depressive symptoms, we expect to identify distinct trajectory-profiles of students characterized by consistently low, increasing, decreasing, and consistently high depressive symptoms over six years (e.g., Barboza, 2020). As this period encompasses a school transition (comprehensive school to upper secondary school in Finland), depressive symptoms trajectories should also reflect how the transition might bend these trajectories by including pre-transition and post-transition slopes. Consistent with the idea that the transition into upper secondary schools might potentially result in a learning environment better suited to the needs of a subset of students but less suited to the needs of other students, we expect some of the trajectory-profiles to be characterized by a decrease in depressive symptoms following this transition (i.e., post-transition slope), but other trajectory-profiles to be characterized by an increase in depressive symptoms during the same period (Ibrahim et al., 2013).

Our second objective is to determine whether the likelihood of membership into the depressive symptoms trajectory-profiles, as well as the shape of the within-profile depressive symptoms trajectory (initial level, pre-transition, and post-transition slopes), would differ between boys and girls. Following previous studies, we anticipate that girls (relative to boys) should be more at risk of membership into more problematic trajectories of depressive symptoms, and more likely to display higher levels of depressive symptoms within their own trajectory-profile (e.g., Lee et al., 2017).

Our third objective is to investigate whether and how mastery-intrinsic, mastery-extrinsic, performance-approach, and performance-avoidance goals trajectories will be associated with (as predictors) youth's likelihood of membership into the depressive symptoms trajectory-profiles, as well as with within-profile trajectories of depressive symptoms. Based on previous research (Bendezú et al., 2021; Ellis et al., 2019), we anticipate that students endorsing mastery-intrinsic goals will present the lowest risk of displaying problematic trajectories of depressive symptoms (i.e., membership into more desirable trajectory-profiles, and more desirable within-profile trajectories), followed by those endorsing mastery-extrinsic goals. In contrast, students endorsing performance-avoidance goals should present the highest risk of displaying problematic trajectories of depressive symptoms (i.e., membership into less desirable trajectory-profiles, and less desirable within-profile trajectories), followed by those endorsing to performance-approach goals.

Our fourth objective is to investigate whether and how youth's depressive symptoms trajectory-profiles will be associated with their trajectories of school engagement and school burnout (i.e., as outcomes) over time. Following previous studies (Fiorilli et al., 2017; Salmela-Aro et al., 2009a), we expect that students characterized by more problematic depressive symptoms trajectory-profiles will display the lowest levels of school engagement and the higher levels of school burnout.

Methods

Participants and Procedures

The present study relies on data from the Millennial Cohort of the Bridging the Gaps and Mind-the-Gap ongoing longitudinal study involving the annual participation of public schools located in the city of Helsinki, Finland (Mind the Gap and Bridging Gap, 2014). More precisely, this convenience sample has been followed since 2014, when students were enrolled in their seventh grade of comprehensive schooling. At this initial data collection point, efforts were made to contact comprehensive schools located in all geographical areas within the city of Helsinki, leading to 20 schools that agreed to participate. Participants were followed annually for three years until the end of their comprehensive schooling (T1: Grade 7, 13-14 y.o.; T2: Grade 8, 14-15 y.o.; T3: Grade 9, 15-16 y.o.), and then again after having transitioned into upper secondary school (T4: Second year, 17-18 y.o.; T5: Third year, 18-19 y.o.). The total sample used in this study includes 2,696 participants (56.8% female) who were recruited from 20 schools during comprehensive schooling and 26 schools during secondary schooling. Of those, 91.3% had Finnish as a mother tongue, 79.4% reported that their family's financial situation was better than average, and 7.5% identified as ethnic or cultural minorities. Moreover, 1,316 participated at T1, 1,183 at T2, 871 at T3, 1,271 at T4, and 667 at T5. For all participants, questionnaires were administered during school hours, and completion took approximately an hour. Participation was voluntary and both parents and youth provided active consent. Ethical approval was obtained from the University of Helsinki Ethical Review Board in the Humanities and Social and Behavioural Sciences.

Transparency and Openness

We report how we determined the sample size (convenience sampling procedures), all manipulations, and all measures in the study, and we follow JARS (Kazak, 2018). All data, analysis code, and research materials are available upon request by contacting the first or second authors. Data were analyzed using Mplus, version 8.4 (Muthén & Muthén, 2020). This study's design and its analyses were not preregistered.

Measures

Depressive symptoms. Youth self-reported their depressive symptoms using the Depression Scale (DEPS; Salokangas et al., 1995). This scale includes 10 items (e.g., "In the last month, I have felt hopeless about the future") rated on a four-point response scale (0-*not at all* to 3-*extremely*). The scale score reliability across all time-points ranged between α=.918 and .940.

Achievement Goals. Achievement goal orientations were assessed using four subscales validated by Niemivirta (2002). Each subscale includes 3 items rated on a seven-point response scale (1-*not true* to 7-*very true*): (a) mastery-intrinsic orientation (α=.870 to .906; e.g., "I study in order to learn new things" and "An important goal for me is to acquire new knowledge"); (b) mastery-extrinsic orientation (α=.879 to .907; e.g., "An important goal for me is to succeed in school" and "It is important for me that I get good grades"); (c) performance-approach orientation (α=.737 to .791; e.g., "It is important for me that others consider me capable and competent" and "I feel like I've achieved my goal when I get better scores than many other students"); (d) performance-avoidance orientation (α=.860 to .898; e.g., "I try to avoid situations in which I may appear dumb or incompetent" and "It is important for me not to fail in front of other students").

School Engagement. School engagement was measured with the Schoolwork Engagement Inventory (Salmela-Aro & Upadyaya, 2012). This scale includes 9 items (α=.943 and .956) tapping into energy (or vigor; e.g., "At school, I am bursting with energy"), dedication (e.g., "I find the schoolwork full of meaning and purpose"), and absorption (e.g., "Time flies when I'm studying") rated on a seven-point scale (1-*never* to 7-*daily*). This measure was not administered at Time 4.

School Burnout. The 10 items from the School Burnout Inventory (Salmela-Aro et al., 2009b) were used to assess youth's levels of school burnout (α=.895 and .939). This scale includes items tapping into feelings of emotional exhaustion (e.g., "I feel overwhelmed by my schoolwork"), cynicism (e.g., "I feel that I am losing interest in my schoolwork"), and inadequacy (e.g., "I often have feelings of inadequacy at school"). All items were rated using a six-point response scale (1- *completely disagree* to 6-*completely agree*).

Analyses

Preliminary Analyses

The indicators of the growth mixture trajectories (i.e., depressive symptoms), the predictors (i.e., achievement goals), and the outcomes (i.e., school engagement and school burnout) used in this study are factor scores saved from preliminary measurement models. To ensure the comparability of the measures over time, these factor scores were saved from longitudinally invariant measurement models (Millsap, 2011). Factor scores have the advantage of partially controlling for measurement error and preserving the nature of the underlying measurement structure (DiStefano et al., 2009). These preliminary measurement models and their invariance are reported in Tables S1 to S6 of the online supplements. Missing data was handled using multiple imputation procedures as part of these preliminary analyses (see page S2 of the online supplements for details).

Growth Mixture Analyses (GMA)

Objective 1 was assessed using GMA. The analyses were conducted using Mplus 8.4's (Muthén & Muthén, 2020) robust maximum likelihood estimator (MLR). To avoid converging on a local maximum, analyses were conducted with 6000 random sets of start values, 1000 iterations, and 100 final stage optimizations (Hipp & Bauer, 2006). GMA are built from latent curve models and aim to identify subpopulations of participants following distinct longitudinal trajectories (e.g., Grimm et al., 2016; Morin et al., 2011). In the present study, we rely on a piecewise linear GMA specification. Piecewise linear GMA summarize a series of repeated measures by estimating profile-specific (1) random intercepts, which represents the initial level of the growth trajectories (the loadings of the time-specific measures on this factor are all fixed to 1), (2) a first random slope factor reflecting the rate of change over time in the pre-transition trajectories (i.e., comprehensive schooling: T1 to T3), and (3) a second random slope factor reflecting the rate of change over time in the post-transition trajectories (i.e., upper secondary schooling: T4 to T5). The loadings of the time-specific measures on the slope factor are fixed to reflect the passage of time before (Slope 1: 0, 1, 2, 2, 2) or after (Slope 2: 0, 0, 0, 2, 3) the transition. In GMA, the latent profiles are defined based on these latent intercepts and slope factors to obtain subgroup-specific latent trajectories. The mean of these latent factors reflects the average level (intercept) and rate of change before and after the transition (slopes) in each profile. The variances of these factors reflect the level of within-profile inter-individual variability of the intercept and slopes.

Current statistical recommendations are that GMA should ideally be estimated with all model parameters (intercept and slope means, intercept and slope variances and covariances, and time-specific residuals) to be freely estimated across all profiles (Diallo et al., 2016; Morin et al., 2011). This recommendation comes with the caveat that estimating models in which all parameters are free to vary across profiles might be impossible due to the tendency of such complex models to converge on improper solutions, or not to converge at all (Diallo et al., 2016) when they are overparameterized (e.g., Bauer & Curran, 2003; Chen et al., 2001), in which case simpler models should be considered. As it was also the case in the present study, we relied on a more parsimonious operationalization according to which the intercept and slope means, variances, and covariances were freely estimated across profiles, while also allowing the time-specific residuals to be freely estimated in each profile but specified to be equal over time (homoscedastic) within each time period (before, and after, the transition (Diallo et al., 2016). This specification of the residuals still allows an estimation of the profiles providing an equally efficient representation of the repeated measures within each developmental period, while allowing that explanatory power to differ across profiles and period.

Models including one to eight latent profiles of depressive symptoms trajectories (M1 to M8) were estimated and contrasted. To determine the optimal number of latent trajectory-profiles, we considered the substantive meaning (i.e., all profiles make sense and each additional profile is qualitatively distinct from the profiles identified in the solution including one fewer profile), theoretical conformity (the profiles make sense in relation to theoretical expectations and present a differentiated pattern of associations with predictors and outcomes), and statistical adequacy (statistical indicators support the retained solution, which results in proper parameter estimates) of each solution (Bauer & Curran, 2003; Marsh et al., 2009; Muthén, 2003). The following statistical indicators were used to guide this selection: the Akaïke Information Criterion (AIC), the Consitent AIC (CAIC), the Bayesian Information Criterion (BIC), the sample-size Adjusted BIC (ABIC), the Lo et al.'s (2001) Adjusted Likelihood Ratio (ALMR) test, and the Bootstrap Likelihood Ratio Test (BLRT). A lower value on the AIC, CAIC, BIC, and ABIC suggests a better-fitting model, while a statistically significant ALMR or BLRT supports the addition of a profile relative to the previous solution. Simulation studies indicate that five of these indicators (CAIC, BIC, ABIC, ICL-BIC, and BLRT) are particularly effective (e.g., Diallo et al., 2016, 2017; Nylund et al., 2007; Peugh & Fan, 2013; Tein et al., 2013; Tofighi & Enders, 2008), while the AIC and ALMR should not be used (we thus only report them to ensure complete disclosure). As these tests are influenced by sample size (Marsh et al., 2009) and often keep on decreasing without reaching a minimum, it is recommended to rely on an "elbow plot," which illustrates the gains for each additional profile (Petras & Masyn, 2010). In these plots, the point after which the slope flattens suggests the optimal number of profiles.

Predictors and Outcomes

Once the optimal solution was selected, we assessed the relations between the resulting depression trajectory-profiles and predictors (Objective 2: youth sex, and Objective 3: achievement goals) and outcomes (Objective 4: school engagement and school burnout). Relying on a strategy proposed by Morin et al. (2011), we saved factor scores from piecewise linear latent curve models reflecting trajectories of the achievement goals, and from linear latent curve models reflecting trajectories of engagement and burnout (Bollen & Curran, 2006). (Given that the school engagement measure was not administered at T4, it was impossible to model a piecewise latent curve with this variable. For burnout, as noted in the online supplements, the linear model was found to provide a more accurate representation of the trajectories.) Results from these models are reported in Table S7 of the online supplements, and the correlations between these covariates and the depressive symptoms are reported in Table S8 of the online supplements. To ensure stability (i.e., that the nature of the profiles remained unchanged) following the incorporation of the predictors and outcomes, these covariates were included in a model defined using the fixed parameter estimates from the retained unconditional GMA (Diallo et al., 2017; Morin et al., 2016).

Following recommendations by Diallo et al. (2017), we compared a series of models in which the predictors were incorporated. In a first series of models, to assess the effect of participants' sex (Objective 2) and of the intercepts of the predictors' trajectories (i.e., achievement goals; Objective 3), we estimated a null effects model (M9) in which the effects of the predictors on the probability of membership in all depressive symptoms trajectory-profiles, as well as on the within-profile intercept and pre- and post-transition slope factors of the depressive symptoms trajectories, were constrained to be zero. A first alternative model was tested in which the predictors (i.e., achievement goal intercepts and participants' sex) were allowed to predict trajectory-profiles membership through a multinomial logistic regression link function (M10). Additional models were then estimated in which the intercepts of the predictors' trajectories were progressively allowed to influence within-profile variation in the intercepts, pre-transition slope, and post-transition slope equally across all profiles (M11, M12, M13), or differently across profiles (M14, M15, M16). As recommended by Diallo et al. (2017, also see Morin et al., 2016), the fit of the alternative models was contrasted using the information criteria described above, with a lower value indicating a better fitting model.

In a second series of models, starting from the model retained in the previous step, the same sequence of tests was repeated to test the effects of the pre-transition slopes of the predictors' trajectories on youth's depressive symptoms trajectory-profiles and within-profile trajectories. We contrasted models in which the pre-transition slopes of the predictors were allowed to influence trajectory-profiles membership (M17) and the pre- and post-transition depressive symptoms slopes in a manner assumed to be identical (M18, M19, M22, M23) or different (M20, M21, M24, M25) across trajectory-profiles.

In a third series of models, starting from the model retained in the previous step, we applied the same sequence to test the effects of the post-transition slopes of the predictors' trajectories on the trajectory-profiles and within-profile trajectories. We contrasted models in which the post-transition achievement goal slopes were allowed to predict trajectory-profiles membership (M26) and the post-transition depressive symptoms slopes in a manner assumed to be identical (M27, M29) or different across trajectory-profiles (M28, M30).

Finally, outcomes (i.e., the intercepts and slopes of the school engagement and burnout trajectories) were contrasted across trajectory-profiles using a model-based approach proposed by Lanza et al. (2013) and implemented through the Auxiliary (DCON) function (Asparouhov & Muthén, 2014). This allowed comparing the probabilities-based profiles on the outcomes without allowing these outcomes to change the nature of the trajectory-profiles.

Results

Unconditional Models: Identifying Trajectory-Profiles of Depressive Symptoms

Results from the alternative unconditional GMA (Objective 1) are reported in the top section of Table 1. The CAIC reached its lowest value at 4 profiles, the BIC at 5 profiles, and the ABIC at 6 profiles. The BLRT also suggested a 6-profile solution. In contrast, the elbow plot (see Figure S1 of the online supplements) suggested a flattening out in the decrease of the information criteria value around 3 profiles. Solutions including 3 to 6 profiles were thus more thoroughly examined. The 3-profile solution resulted in the identification of two profiles respectively characterized by low or moderate initial levels of depressive symptoms both followed by increasing pre- and post-transition slopes, as well as of an additional profile characterized by moderate initial levels of depressive symptoms followed by an increasing pre-transition slope and a stable post-transition slope. In the 4-profile solution, the additional profile was characterized by high initial levels of depressive symptoms followed by stable pre- and post-transition slopes. Then, in the 5-profile solution, the additional profile was characterized by an initially low level of depressive symptoms followed by an increasing pre-transition slope and a stable post-transition slope. These two profiles (identified in the 4- and 5-profile solutions) were considered to represent a substantively meaningful addition to the previous three profiles (as discussed in the following sections, and further highlighting the theoretical adequacy of this solution, the fifth profile also proved relevant through its unique associations with predictors and outcomes). In contrast, the 6-profile solution resulted in the addition of an empty profile (i.e., no youth corresponded to this profile) and was thus deemed inappropriate. The 5-profile solution, illustrated in Figure 1, was thus retained for interpretation. This solution resulted in the identification of five qualitatively distinct profiles, qualified as: (a) High Stable (representing 5.46% of the sample); (b) Low Stabilizing (6.20%); (c) Moderate Stabilizing (36.82%); (d) Mild Increasing (47.90%); (e) Low Increasing (3.62%). The parameter estimates from this solution are reported in Table 2. When interpreting these results, it is important to keep in mind that all depression scores were in standardized units. Further information is also provided on page S9 and Table S9 of the online supplements to help interpret the levels of depression observed in each trajectory-profiles to cut-off scores used to identify clinical levels of depression (Poutanen et al., 2010; Salokangas et al., 1995).

Predictors: Student Sex and Achievement Goal Trajectories

The model fit results from the solutions including the predictors are reported in the middle and bottom sections of Table 1. Assessing Objectives 2 and 3, the first series of models estimated the effects of participants' sex and of the intercepts of the achievement goals trajectories (M9 to M16). The information criteria were systematically the lowest for M13. This model, in which the predictors had an effect on trajectory-profiles membership, as well as on the within-profile intercept and slopes of the depressive symptoms trajectories in a profile-invariant manner, was thus retained. Starting from this model, the second series of models (M17 to M25) supported M19, consistent with a profile-invariant effect of the predictors' pre-transition slopes on the pre- and post-transition slopes of youth's depressive symptoms. Finally, the last series of models (M26 to M30) revealed that adding the predictors of post-transition slopes did not further improve the fit of M19, which was retained for interpretation. Parameter estimates from this model are reported in Table 3.

These results reveal that girls were respectively 5.85, 2.28, and 4.55 times more likely than boys to correspond to the High Stable depressive symptoms profile relative to the Low Stabilizing, Moderate Stabilizing, and Mild Increasing profiles. They were also 2.56 times more likely than boys to correspond to the Moderate Stabilizing profile than in the Low Stabilizing profile, and 3.59 times more likely than boys to correspond to the Low Increasing profile than to the Low Stabilizing profile. However, boys were also respectively 2.00 and 2.79 times more likely than girls to correspond to the Mild Increasing profile relative to the Low Increasing and Moderate Stabilizing profiles. Finally, within profiles, girls tended to report higher levels of initial depressive symptoms and steeper increases in depressive symptoms after the school transition, whereas boys tended to report steeper pre-transition increases in depressive symptoms.

Higher initial levels of mastery-intrinsic goals were not associated with youth's likelihood of trajectory-profiles membership but were associated with less pronounced within-profiles increases in depressive symptoms after the transition. Likewise, pre-transition increases in mastery-intrinsic goals were associated with less pronounced within-profiles increases in depressive symptoms after the transition. Youth with higher initial levels of mastery-extrinsic goals were more likely to correspond to the Low Stabilizing profile relative to the High Stable, Moderate Stabilizing, and Low Increasing ones. They were also more likely to correspond to the Mild Increasing profile relative to the Moderate Stabilizing one. In addition, higher initial levels of mastery-extrinsic goals were associated with lower within-profile levels of depressive symptoms, but with steeper within-profile increases in depressive symptoms after the school transition. Youth with higher initial level of performance-approach goals were more likely to correspond to the High Stable profile relative to any other profile. They were also more likely to correspond to the Moderate Stabilizing profile relative to the Mild Increasing one. Youth endorsing higher initial levels of performance-avoidance goals were also more likely to correspond to the High Stable profile relative to any other profile. Within profiles, initial levels of performance-avoidance goals were associated with higher initial levels of depressive symptoms, but with less pronounced increases in depressive symptoms after the transition. Finally, steeper pre-transition increases in performance-avoidance goals were associated with steeper pre-transition within-profiles increases in depressive symptoms.

Outcomes: Student Engagement and Burnout Trajectories

Results from the comparison of the profiles in relation to the outcome trajectories (Objective 4) are reported in Table 4 and displayed in Figures 2 and 3. In terms of youth's initial levels of engagement, the results indicate that youth with a High Stable depressive symptoms trajectory-profile tended to report the lowest initial level of engagement, whereas those with a Low Stabilizing trajectory-profile tended to report the highest initial levels of engagement. Moreover, youth with a Mild Increasing trajectory-profile reported a significantly higher initial level of engagement than those with a Moderate Stabilizing or Low Increasing trajectory-profile, but the initial levels of engagement observed in both of those profiles did not differ from each other. In terms of growth in youth's levels of school engagement over time, youth with a Low Increasing trajectory-profile reported the most stable levels of engagement relative to all other trajectory-profile, thus further supporting the relevance of retaining this trajectory-profile (i.e., which was the fifth to emerge as part of the class enumeration process leading us to retain a five-profile solution). Levels of engagement of youth corresponding to a Low Increasing trajectory-profile were then followed by those of youth in the Low Stabilizing, Mind Increasing, Moderate Stabilizing, and finally youth from the High Stable trajectory-profile who reported the steepest increase in engagement.

Second, all depressive symptoms trajectory-profiles displayed significantly different initial levels of school burnout. More precisely, youth with High Stable trajectory-profile reported the highest levels of burnout, followed by those with Moderate Stabilizing trajectory-profile, then by those with Mild Increasing trajectory-profile, followed by those with Low Increasing trajectory-profile, and finally by those with Low Stabilizing trajectory-profile. Likewise, most profiles were characterized by distinct burnout trajectories over time. More precisely, youth with Low Increasing trajectory-profile reported the steepest increase in burnout over time (reaching levels as high as those observed in the High Stable profile by the end of the study), followed by those with Mild Increasing trajectory-profile then by those with Moderate Stabilizing trajectory-profile, and finally by those with Low Stabilizing and High Stable trajectory-profile. These results overall suggest that school burnout and depressive symptoms follow similar developmental trends.

Discussion

Although they also occur during childhood, depressive symptoms often emerge in adolescence and are typically marked by an increase in severity as youth undergo various life transitions (Garber & Rao, 2014; Reed-Fitzke, 2020), such as the entry into upper secondary school in Finland. The present study sought to identify the various trajectory-profiles of depressive symptoms manifested by adolescents and their association with several indicators of school functioning, including achievement goals, school engagement, and school burnout. As such, this study adds to our understanding of the heterogeneous development of depressive symptoms during the critical years encompassing adolescence and early adulthood by providing replication evidence among a Finnish sample to the previous studies of depression trajectory-profiles covering this critically important developmental period (e.g., Bulhoes et al., 2021; Lee et al., 2017; Yaroslavsky et al., 2013). Replication evidence is particularly important for research seeking to identify developmental profiles, as it makes it possible to differentiate between idiosyncratic profiles that only emerge occasionally as a result random sampling variations from the more relevant profiles that systematically emerge across contexts and within specific developmental periods (Morin et al., 2020). The present study is, however, the first to document the dynamic nature of the longitudinal associations between youth's developmental trajectories (or trajectory-profiles) of depressive symptoms and their achievement goals, engagement, and burnout. In doing so, this study thus addresses previous calls for increased scientific attention to be allocated to our understanding of the interrelations between adolescent depression and motivation (e.g., Garvik et al., 2014).

Our results support that this developmental period is a source of some psychological distress for many adolescents (85% of the sample) who reported mild to moderate levels of depression over the course of the study. In contrast, only a small proportion (6%) of the sample displayed depressive trajectories that remained low over the course of the study. The remaining 9% displayed more problematic trajectories characterized either by persistently high symptoms, or by initially low but drastically increasing symptoms. Taken together these results highlight the need to consider developmental heterogeneity when seeking to understand the development of depressive symptoms and indicate that many depressed young adults start to experience depressive symptoms in adolescence or even earlier (Fernandez Castelao et al., 2013; Lewis et al., 2020).

In addition, our results generally supported our expectations, revealing that girls were more likely to display undesirable trajectories of depressive symptoms, both in terms of membership into trajectory-profiles characterized by more severe levels of depressive symptoms, but also in terms of displaying more problematic within-profile variations in the initial and post-transition shape of their depressive symptoms trajectories. Our results were also generally consistent with our expectations, anchored in Dykman's (1998) goal-orientation model of depression, suggesting that mastery goals (intrinsic or extrinsic) should be associated with a lower risk of feeling depressed, whereas performance goals (approach or avoidance) should increase youth's risk of experiencing problematic depressive symptoms trajectory-profiles. Finally, youth's levels of school burnout followed developmental trends similar to those observed for depressive symptoms (i.e., youth with problematic depression trajectories also tended to report more problematic burnout trajectories), whereas school engagement trajectories seemed to follow an opposite developmental trend (i.e., youth with problematic depression trajectories tended to report less favorable engagement trajectories). However, and contrasting with our expectations, youth following High Stable depressive symptoms trajectory-profiles significantly increased their levels of school engagement over time. In the following pages, we discuss each of these key results.

Depressive Symptoms Trajectories and Turning Points

Considering the evolution of depressive symptoms from mid-adolescence to early adulthood, a period that also encompassed a major school transition, allowed us to uncover four key findings. First, almost half of the sample followed a Mild Increasing trajectory-profile (47.90%), whereas slightly over a third followed a Moderate Stabilizing trajectory-profile (36.82%). By the end of the study, the levels of depressive symptoms observed in these two trajectory-profiles were almost identical and suggested the presence of subclinical levels of depression (see page S19 of the Online Supplements for further information). In contrast, very few students (6.20%) followed a persistently low trajectory-profile of depressive symptoms. These results suggest that it is normative to experience mild to moderate, yet subclinical, levels of emotional distress during adolescence, confirming previous claims that adolescence might be an unsettling period for many youth (Guassi Moreira & Telzer, 2015; Marcotte et al., 2018).

Second, two trajectory-profiles appeared to be far more problematic. On the one hand, close to 5.5% of the sample displayed persistently high levels of depressive symptoms, corresponding to clinical levels of depression. On the other hand, close to 4% of the students displayed initially very low levels of depressive symptoms that increased very steeply over time, reaching the clinical level of depression observed in the High Stable trajectory-profile by the end of the study. Together, these two trajectory-profiles correspond to 9% of the sample, matching international statistics regarding the prevalence of depressive disorders (Lim et al., 2018). These two trajectory-profiles appear to be worth considering for targeted preventive interventions seeking to limit the consequence of chronically high levels of depressive symptoms (High Stable trajectory-profile), but also to prevent the dramatic increase in depressive symptoms observed among the Low Increasing trajectory-profile.

Third, relying on existing findings (Barboza, 2020; Martinez & Armenta, 2020; Wickrama & Wickrama, 2010), we expected to identify trajectory-profiles characterized by low stable, high stable, increasing, and decreasing levels of depressive symptoms. Although our results identified trajectory-profiles corresponding to most of these patterns (i.e., low stable, high stable, and increasing), no profile in which youth displayed a trajectory characterized by decreasing levels of depressive symptoms was identified in this study. This observation is particularly worrisome and highlights the need for more potent school-based intervention to counteract the upward evolution of depressive symptoms. A closer examination of the results obtained in previous studies supported that such a decreasing trajectory was also not systematically identified when participants were followed across the transition from adolescence into early adulthood (Bulhoes et al., 2021). In some studies, the tendency for youth to report declining symptoms of depression seems to correspond to far more restricted developmental periods. For instance, Lee et al. (2017) and Wang, Chan et al. (2018) suggest that youth might experience a slight decrease in their levels of depressive symptoms around the *beginning* of adolescence (12-13 y.o.). Among slightly older youth, Kent and Bradshaw (2021) and Yaroslavsky et al. (2013) found that decreases in depressive symptoms sometimes occurred *after* the transition into early adulthood (in the mid 20'), thus after the end of the present study. Our results, combined to those studies, suggest decreases in depressive symptoms might not occur during adolescence, but rather at the start of this critical developmental period, or much later. Clearly, investigations are still needed to properly understand if and why youth might report decreasing symptoms of depression during the transition to early adulthood, as well as on how to best help youth navigate away from the problematic trajectory-profiles identified in this study.

Fourth, we hypothesized that the school transition would prove challenging for some students but stimulating for others. Indeed, whereas some students enter a new environment that they see as more demanding and less supportive, others might perceive the transition as an opportunity to pursue career orientations and interests better aligned with their goals and better suited to nurturing their feeling of personal accomplishment (Ibrahim et al., 2013; Posselt & Lipson, 2016; Reed-Fitzke, 2020). We thus expected the transition to result in increases in depressive symptoms for some youth and in decreases for others. Rather, our results suggest that, although some followed increasing trajectories throughout the transition, others experienced a stabilization of their depressive symptoms after this transition. However, none reported a decrease. These findings reinforce that, at least for a few students, the school transition, and more generally the transition to adulthood, is a stressful and distressing period (Ibrahim et al., 2013). It also suggests that a more desirable transition might help to stop further increases in depressive symptoms from occurring, but that it might not be sufficient (in the absence of other types of interventions) to lead to a decrease in these symptoms.

Sex Differences in Depressive Symptoms Trajectories

Overall, and consistent with previous results (Barboza, 2020; Lee et al., 2017; Yaroslavsky et al., 2013), our results revealed that girls tended to present a higher risk of corresponding to the more problematic trajectory-profiles (High Stable and Low Increasing). Such findings are consistent with the idea that girls might be exposed to more interpersonal stressors during this critical developmental period and may rely on rumination coping strategies to a greater extent than boys to handle these stressors (Nolen-Hoeksema et al., 1999; Oldehinkel & Bouma, 2011; Zimmer-Gembeck et al., 2015), along with their biological predisposition to being more depressed than boys (Costello et al., 2011). Interestingly, girls were more likely to correspond to the Moderate Stabilizing trajectory-profile, whereas boys were more likely to correspond to the Mild Increasing trajectory-profile, which are the two profiles considered to be normative (i.e., more frequent) in our sample. Martinez and Armenta (2020) similarly noted that boys might be more at risk of experiencing increasing trajectories of depressive symptoms during the transition into early adulthood, whereas Matud et al. (2020) and Salk et al. (2017) suggested that sex differences in the prevalence of depressive symptoms tend to fade out during emerging adulthood. Our results might help to reconcile these diverging perspectives, suggesting that across all trajectory-profiles, girls tended to report higher initial levels of depressive symptoms and steeper increases in their levels of depressive symptoms *after* the school transition, whereas boys tended to report steeper increases *before* the school transition. This finding is particularly informative in that it differs from previous findings suggesting that boys and girls report a similar increase in depressive symptoms when going through this school transition (Wang, Chan et al., 2018), a difference that warrants further investigation. These results clearly call for replications of sex differences in depression trajectories, and for a better understanding of the mechanisms underpinning these differences.

The Role of Achievement Goals in Depressive Symptoms Trajectories

Our results were consistent with the assumptions of the goal-orientation model of depression (Dykman, 1998) in showing that performance-approach and performance-avoidance goals generally tended to be associated with poorer mental health than mastery-intrinsic and mastery-extrinsic goals. Our results first evidenced that the benefits of mastery-intrinsic goals extended to all trajectory-profiles of depressive symptoms, whereas those of mastery-extrinsic goals were specific to some trajectory-profiles. More specifically, mastery-intrinsic goals were not associated with the likelihood of membership into any of the trajectory-profiles. However, within all profiles, initial levels of mastery-intrinsic goals, and increases over time in these levels prior to the school transition were both found to be associated with lower levels of depressive symptoms after the transition. This result thus suggests that nurturing the endorsement of mastery-intrinsic goals might be one way to curb the post-transition increases in depressive levels observed among a subset of students. In contrast, students endorsing mastery-extrinsic goals were less likely to correspond to the most problematic trajectory-profiles. Besides, within all trajectory-profiles, youth endorsing mastery-extrinsic goals tended to display initially lower levels of depressive symptoms, but report a slightly steeper increase after the transition. Such results are consistent with the idea that the new school environment might be more competitive and thus more stressful for externally driven youth (Posselt & Lipson, 2016). These results also raise questions that could be informed through the lens of Self-Determination Theory. Indeed, even if Achievement Goal Theory and Self-Determination Theory conceptualize intrinsically and extrinsically driven individuals in a slightly different manner, the latter framework anticipates better developmental outcomes for intrinsically driven youth relative to their extrinsically driven peers (Vansteenkiste & Ryan, 2013). Thus, although youth driven by mastery-intrinsic and mastery-extrinsic goals tend to experience more positive school-related development, those endorsing extrinsic goals may also come to experience higher levels of depressive symptoms over time (Bendezú et al., 2021; Howard et al., 2021). This suggests that whereas it might be desirable to nurture mastery-extrinsic goals early in adolescence, it might be equally important to ensure that goals become intrinsically driven as students get older.

Turning our attention to performance goals, it was interesting to note that initial levels (13-14 years old) of performance-approach and performance-avoidance goals showed surprisingly similar patterns of associations with youth's depressive symptoms trajectory-profiles. More precisely, students endorsing higher levels of both types of goals were more likely to follow a High Stable trajectory-profile relative to all other types of trajectories. These findings are first aligned with Dykman's (1998) theoretical suggestion that pursuing performance goals, which are contingent on others' perceptions, represents a risk factor for depressive symptoms. Even performance-approach goals, which contrary to performance-avoidance goals are usually found to benefit youth's school functioning (e.g., Ellis et al., 2019), seem to come at a cost for their mental health. In addition, pursuing performance-approach goals also seem to increase students' likelihood of membership into the Moderate Stabilizing trajectory-profile relative to the Mild Increasing one, consistent with the limited effect of these goals on increasing the likelihood of membership into trajectory-profiles characterized by higher initial levels of depressive symptoms. Indeed, beyond these two noteworthy exceptions, performance-approach goals did not seem to share any other type of associations with depressive symptoms trajectory-profiles, consistent with the idea that this type of orientation might have undesirable implications for youth mental health, but that these implications do not seem to be dynamic (evolving) in nature. In contrast, initial levels of performance-avoidance goals were associated with higher initial levels of depressive symptoms, and pre-transition increases in the endorsement of performance-avoidance goals also seemed to be associated with pre-transition increases in depressive symptoms. As a result, performance-avoidance goals seem to act as a more dynamic predictor of undesirable trajectory-profiles of depressive symptoms. Beyond these undesirable effects, initial levels of performance-avoidance goals also predicted a slight post-transition decrease in depressive symptoms. However, this effect was so small as to be negligible, suggesting that further research is needed to assess its robustness to replication, and the possible mechanisms involved in this unexpected association. For the moment, our results mainly reinforce previous results highlighting the generally undesirable nature of performance goals on mental health (Bendezú et al., 2021; Tuominen et al., 2020).

Engagement and Burnout: Depressive Symptoms Interfere with School Investment

Youth corresponding to all five longitudinal trajectory-profiles of depressive symptoms were characterized by well-differentiated trajectories of school engagement and school burnout, indicating that depressive symptoms are closely related to youth's levels of school functioning. In fact, the trajectories of school engagement and school burnout observed in each of the depression trajectory-profiles generally mimic the trajectories of depressive symptoms observed in these profiles from mid-adolescence to early adulthood.

First, school burnout trajectories corresponded almost perfectly to youth's depressive symptoms trajectories, thus supporting the convergent validity of our trajectory-profiles of depression. However, this correspondence could also raise the question of whether depression and burnout are conceptually and empirically distinct from one another. Conceptually, whereas depression tends to affect several or all aspects of one's life (APA, 2020), burnout is typically defined as being restricted to a specific environment (i.e., school or work; Salmela-Aro et al., 2009b; Schaufeli et al., 2002). Empirically, Koutsimani et al.'s (2019) meta-analysis demonstrated that, despite some overlap, depression and burnout are not equivalent to one another. Likewise, a recent longitudinal study also confirms this conceptual and empirical distinction, further showing that burnout and depression can fuel each other in a downward spiral (Tóth-Király et al., 2021). Yet, despite reflecting distinct types of symptoms, burnout and depression tend to follow similar developmental trends (Salmela-Aro et al., 2009a). This could possibly be explained by the negative cognitive styles associated with both types of mental health difficulties (Bianchi & Schnfeld, 2016), and by the negative world view typical of depression which may have a spillover effect on school burnout. Understanding risk factors of school burnout, such as depression, is especially relevant among adolescents, who tend to be exposed to increased levels of strain, stress, and demands as they progress through their schooling (Ibrahim et al., 2013; Posselt & Lipson, 2016).

Second, across all trajectory-profiles of depressive symptoms, youth displayed slight to moderate increasing trajectories of school engagement. This result is surprising given that levels of school engagement have been reported to decrease during the secondary school years (i.e., corresponding to the comprehensive school years in Finland; Archambault et al., 2009; Engels et al., 2017; Wang & Eccles, 2011). However, when reaching post-secondary education (i.e., corresponding to upper secondary school in Finland), these trajectories of engagement have been found to stabilize or to increase for several youth in a way that is consistent with our results (Griep & Wingate, 2018; Widlund et al., 2021).

When specifically considering the school engagement trajectories observed in each depressive symptoms trajectory-profile, youth corresponding to the Low Stabilizing profile displayed the most positive school engagement trajectories, characterized by the highest initial levels that kept increasing over time. Interestingly, youth corresponding to one of the two most problematic depression trajectory-profile (High Stable) reported the steepest increase in school engagement over time, although they initially displayed the lowest level of school engagement. In contrast, youth corresponding to the other problematic trajectory-profile (Low Increasing) displayed initially average levels of school engagement, comparable to those associated with the Moderate Stabilizing trajectory-profile, but did not experience any increase in school engagement over time. In fact, their level of school engagement at the end of the study was even lower than those observed in the High Stable trajectory-profile.

Contrasting youth corresponding to the two problematic depressive symptoms trajectory-profiles (i.e., High Stable and Low Increasing), who both reported equally problematic burnout trajectories, suggests that youth who consistently report high levels of depressive symptoms over time might have learned to live with their symptoms better, allowing them to engage more efficiently in, and enjoy their learning tasks. Grob et al. (2020) conducted a qualitative study highlighting the complex and multifaceted development of depressive symptoms, emphasizing the fact that adolescence and early adulthood is a period during which youth have to learn different coping strategies to better manage their symptoms in order to maintain an efficient level of functioning. Alternatively, youth with a High Stable trajectory-profile might be prone to overcommitment or compensatory behaviors. Overcommitment is reflected in excessive work and effort dedicated to a task, in this case schoolwork, often associated with a high need to gain others' approval (Siegrist et al., 2004). Compensatory behaviors aim at balancing out the negative impacts of having one's basic needs not fulfilled, usually by trying to gain external satisfaction (Vansteenkiste & Ryan, 2013). Both behaviors could be reflected in the increasing levels of engagement observed in the High Stable trajectory-profile. Likewise, their need for approval and search for external satisfaction might be illustrated by their tendency to pursue performance over mastery goals, a question that could be addressed in future studies incorporating analyses of mediation.

In comparison, youth with a Low Increasing trajectory-profile experienced a drastic increase in their depressive symptoms, which might have hampered their ability to maintain an efficient level of functioning in the various spheres of their lives, as illustrated by their more problematic school engagement trajectories. Another unexpected finding was that youth characterized by a Low Increasing trajectory-profile displayed lower initial levels of engagement than those corresponding to a Mild Increasing trajectory-profile, despite their higher levels of depressive symptoms at the start of the study. Although these results clearly warrant further investigation and replication, there are potential explanations. For instance, youth with a Low Increasing trajectory-profile, despite their apparently good initial levels of mental health, might have presented a vulnerability to depression, which might have been latent, or not yet triggered by stressful events, at the start of the study (Guassi Moreira & Telzer, 2015; Marcotte et al., 2018). This vulnerability, however, might have been reflected in other areas of functioning, such as school engagement. Also, youth corresponding to this trajectory-profile only represented a small proportion of the sample (< 4%), which could suggest an unusual pattern of functioning not typically found in studies not focused on the identification of distinct profiles of adolescents.

For practitioners, these results are a clear indication that even though youth with high stable trajectories of depressive symptoms need support, those characterized by steeply increasing trajectories should not be neglected. Students corresponding to Low Increasing profiles might easily go unnoticed by school professionals as they initially display very low depression symptoms. However, the sharp increase in their symptoms, as well as their risk in terms of engagement and burnout, warrants careful attention by these professionals.

Limitations

The results of this study ought to be interpreted in light of its limitations. No data was available during the first year following the transition into upper secondary school. Although all models allowed estimating longitudinal trajectories across this transition, it remains possible that this lack of information might have impeded our ability to detect possible more marked modifications occurring right after this transition. Similarly, the school engagement measure was not administered during the second year of upper secondary school, making it even more likely that we might have missed specificities of the early upper secondary school years. Likewise, our measure of performance-approach goals did not allow us to investigate the possibly differential role played by normative and appearance focuses (e.g., Senko & Dawson, 2017; Senko & Tropiano, 2016). This distinction has been found to be highly relevant in relation to student school functioning (e.g., normative goals tend to be associated with higher levels of achievement, whereas appearance goals tend to be associated with lower levels of achievement; Hulleman et al., 2010; Senko & Dawson, 2017; Senko & Tropiano, 2016). Whether this distinction is also relevant to our understanding of youth's depression and mental health problems more generally, thus remains to be investigated. In addition, some of the correlations found between the various types of achievement goals were unexpected. For instance, mastery-extrinsic goals were more strongly related to mastery-intrinsic goals within time points than to themselves over time. Similarly, mastery-extrinsic goals and performance-approach goals shared strong correlations within time points. Although the stability coefficients observed (i.e., same goal over time) are not concerning, the correlations between the goals might suggest some level of conceptual overlap. In addition, this result might also support the idea that mastery-extrinsic goals share some similarities with mastery-intrinsic goals and performance-approach goals and could even suggest the presence of a goal continuum. However, these possibilities warrant further investigation and replication.

Moreover, the study included students enlisted in academic tracks, but not in vocational tracks. As students' school experience, engagement, and burnout are affected by their tracks (Salmela-Aro et al., 2008b; Salmela-Aro & Upadyaya, 2012), this limits the generalizability of our results to students enlisted in academic education. Results also indicate that students with missing data might have been slightly more at risk of presenting higher levels of depressive symptoms and school burnout, as well as lower levels of school engagement. Although this might limit the generalizability of our results, all missing data were treated following best practice recommendations (Enders, 2010). Furthermore, students attended different schools, a nesting structure that changed over time and thus could not be controlled in the present study. Controlling for this nesting structure might have resulted in a slightly more accurate estimate of standard errors in our predictive analyses, and thus in possibly additional statistically significant results. More generally, the present study relied on a convenience sample of students, which cannot be considered to be fully representative of the Finnish, or Helsinki, population. For all of these reasons, replication efforts seem to be particularly important to consider. Finally, person-centered evidence, such as that obtained with the piecewise GMA approach used in the present study, is cumulative in nature so multiple studies are needed to better separate the trajectory-profiles that systematically emerge all the time from those that only emerge in specific contexts (Morin et al., 2020). As a result, future research will be needed to replicate the present study using a more consistent set of measurements, and possibly within more diversified samples exposed to different school systems and cultures.

Conclusion

Our results showcased that depressive symptoms tend to follow complex and heterogeneous developmental trajectories from adolescence to early adulthood, which were intimately related to their school engagement and school burnout trajectories. These trajectories also shared noteworthy associations with youth's achievement goals trajectories, suggesting that, whereas it might be initially desirable to favor the development of mastery-extrinsic goals in early adolescence, it is even more important to nurture the emergence of a more intrinsically-driven goal orientation as students age. In contrast, performance-approach and -avoidance goals, despite their persistent presence in education systems worldwide, seem to carry short and long terms risks for the development of depressive symptoms. Our results thus provide preliminary responses to Garvik et al.'s (2014) call for more studies investigating how the development of youth depressive symptoms is embedded within their motivational and school functioning. From a practical standpoint, a few studies reached promising results by showing that teachers and school practitioners can support their students' motivation. For instance, by showing interest in the various subjects and promoting mastery goals, teachers are usually able to elicit intrinsic motivation in their students (Schiefele, 2017; Schiefele & Schaffner, 2015). Combining these results with those of the present study suggests that teachers could help prevent depression in their adolescent students by nurturing mastery goals, a hypothesis that warrants further investigation.

In addition, our results reinforce the need for practitioners to pay particular attention to youth whose depressive symptoms trajectories follow a sharp increase during this developmental period of transition into postsecondary education, without neglecting those presenting chronically high levels of depressive symptoms. Indeed, these youth, even more than those with persistently high levels of depressive symptoms, experienced the least positive school engagement trajectories, suggesting that they may need additional adult support to facilitate their transition into postsecondary education. To prevent depression, practitioners typically promote the development of individual skills, such as coping strategies (Rohde et al., 2014). However, it seems that depression might also be influenced by the school contexts in which youth evolve. Practitioners could thus also target the environment, for instance, by preparing youth for the school transition and challenges they might face, as well as improving their experience in the new school environment, notably through institutional responsiveness and policy reflexivity (see Abbott-Chapman, 2011).

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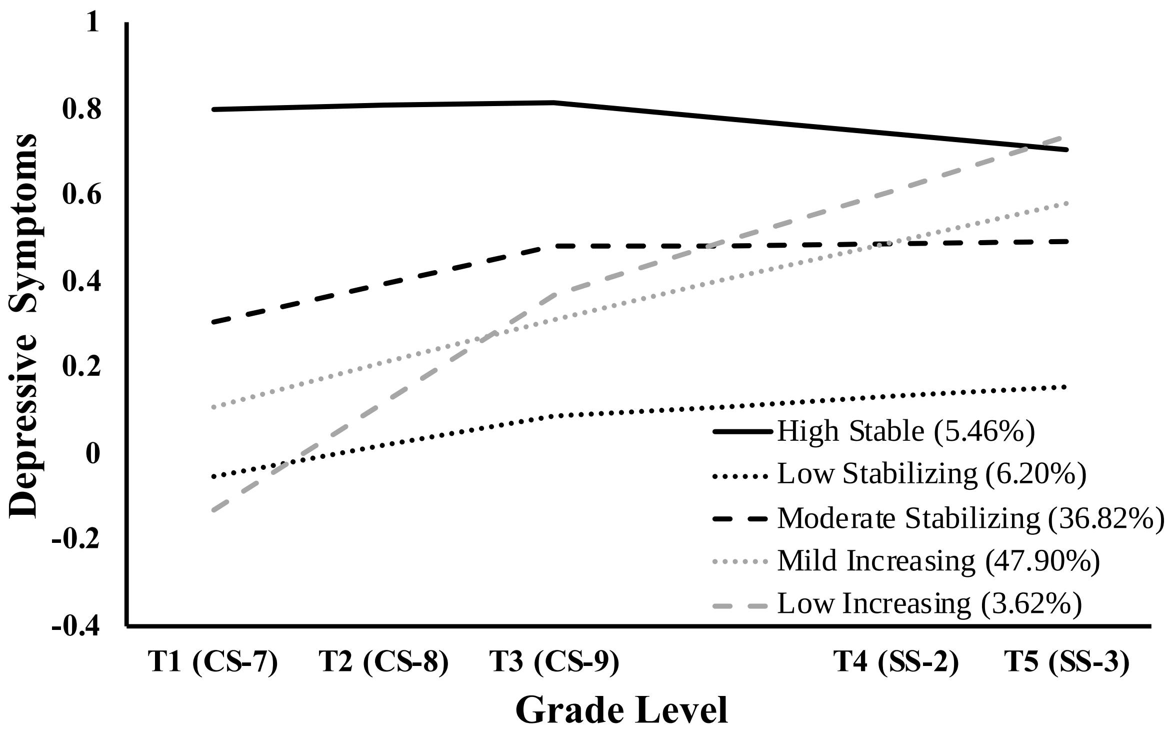

Figure 1

Estimated Growth Trajectory-Profiles of Depressive Symptoms

Note. Depression scores are standardized factor scores with a mean of 0 and a SD of 1.

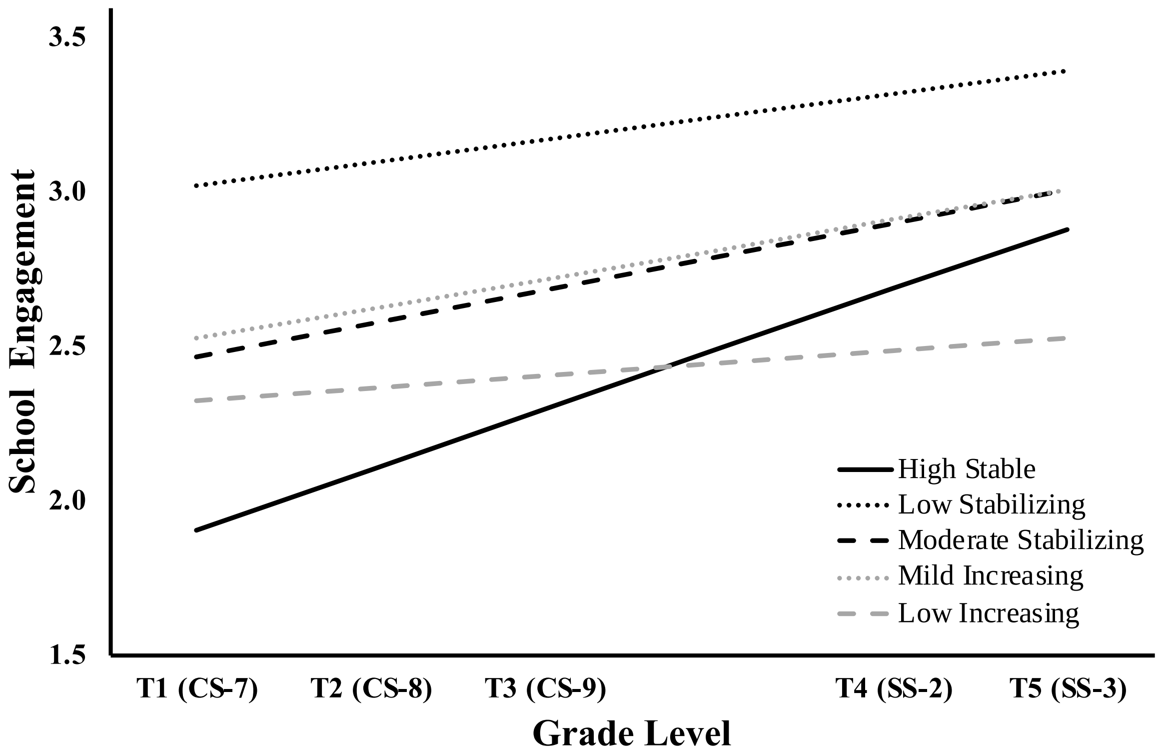

Figure 2
School Engagement Trajectories Corresponding to each Depressive Symptoms Trajectory-Profile

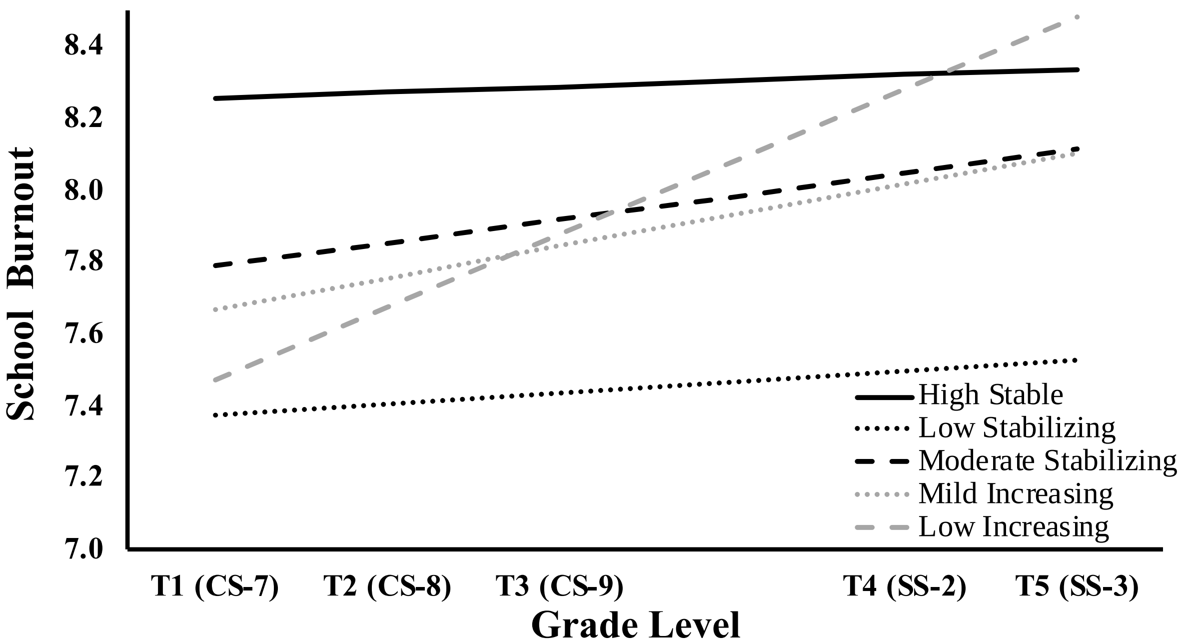

Figure 3
School Burnout Trajectories Corresponding to each Depressive Symptoms Trajectory-Profile

Table 1

Results from the Growth Mixture Analyses

Model		LL	#fp	SCF	AIC	BIC	CAIC	ABIC	Entropy	aLMR (*p*)	BLRT (*p*)
Unconditional Models											
M1	1 profile	-4451.659	11	1.439	8925.319	8990.213	9001.213	8955.263	NA	NA	NA
M2	2 profile	-3214.641	23	1.355	6475.283	6610.972	6633.972	6537.894	.685	.000	.000
M3	3 profile	-2621.315	35	1.075	5312.631	5519.114	5554.114	5407.908	.690	.000	.000
M4	4 profile	-2532.981	47	1.053	5159.962	5437.240	5484.240	5287.906	.741	.000	.000
M5	5 profile	-2509.839	59	1.032	5137.678	5485.750	5544.750	5298.288	.775	.000	.000
M6	6 profile	-2465.518	71	1.052	5073.035	5491.901	5562.901	5266.312	.788	.000	.000
M7	7 profile	-2460.591	83	.764	5087.183	5576.853	5659.853	5313.127	.752	1.000	1.000
M8	8 profile	-2449.608	95	.660	5089.216	5649.671	5744.671	5347.826	.734	.000	.000
Models with the Intercepts of the Predictors' Trajectories from M5											
M9	Null Effect	-2523.231	4	1.000	5054.461	5078.059	5082.059	5065.350	.766	NA	NA
M10	Effects on C	-2327.632	24	1.2098	4703.264	4844.853	4868.853	4768.597	.779	NA	NA
M11	Effects on C, I (inv.)	-2270.737	29	1.1671	4599.474	4770.560	4799.560	4678.418	.781	NA	NA
M12	Effects on C, I, S1 (inv.)	-2223.937	34	1.1993	4515.874	4716.458	4750.458	4608.430	.784	NA	NA
M13	Effects on C, I, S1, S2 (inv.)	-2196.210	39	1.2025	4470.420	4700.501	4739.501	4576.586	.785	NA	NA
M14	Effects on C, I (free)	-2233.137	49	1.0784	4564.273	4853.350	4902.350	4697.662	.772	NA	NA
M15	Effects on C, I, S1 (free)	-2162.377	74	1.1215	4472.754	4909.318	4983.318	4674.197	.774	NA	NA
M16	Effects on C, I, S1, S2 (free)	-2107.547	99	1.0879	4413.094	4997.146	5096.146	4682.593	.779	NA	NA
Models with the Pre-transition Slopes of the Predictors' Trajectories from M13											
M17	Effects on C	-2149.037	55	1.3322	4408.074	4732.548	4787.548	4557.796	.793	NA	NA
M18	Effects on S1 (inv.)	-2166.595	43	1.2073	4419.190	4672.869	4715.869	4536.245	.786	NA	NA
M19	Effects on S1, S2 (inv.)	-2158.305	47	1.2002	4410.609	4487.887	4534.887	4538.553	.786	NA	NA
M20	Effects on S1 (free)	-2139.597	59	1.1189	4397.195	4745.266	4804.266	4557.805	.778	NA	NA
M21	Effects on S1, S2 (free)	-2109.400	79	1.0549	4376.799	4842.862	4921.862	4591.854	.782	NA	NA
M22	Effects on C, S1 (inv.)	-2127.160	59	1.2967	4372.320	4720.391	4779.391	4532.930	.794	NA	NA
M23	Effects on C, S1, S2 (inv.)	-2119.318	63	1.2714	4364.636	4736.306	4799.306	4536.135	.794	NA	NA
M24	Effects on C, S1 (free)	-2109.577	75	1.2452	4369.154	4811.618	4886.618	4573.319	.788	NA	NA
M25	Effects on C, S1, S2 (free)	-2087.551	95	1.1964	4365.102	4925.556	5020.556	4623.712	.789	NA	NA
Models with the Post-transition Slopes of the Predictors' Trajectories from M18											
M26	Effects on C	-2119.258	63	1.3434	4364.516	4536.186	4599.186	4536.015	.792	NA	NA
M27	Effects on S2 (inv.)	-2095.069	51	1.2381	4292.137	4593.013	4644.013	4430.970	.788	NA	NA
M28	Effects on S2 (free)	-2067.566	67	1.2188	4269.132	4664.400	4731.400	4451.520	.784	NA	NA
M29	Effects on C, S2 (inv.)	-2062.873	67	1.2864	4259.747	4655.015	4722.015	4442.135	.798	NA	NA
M30	Effects on C, S2 (free)	-2038,756	83	1.2594	4243.512	4733.173	4816.173	4469.456	.794	NA	NA

Note. LL = Model LogLikelihood; #fp = Number of free parameters; SCF = Scaling correction factor; AIC = Akaïke Information Criteria; CAIC = Constant AIC; BIC = Bayesian Information Criteria; ABIC = Sample-size adjusted BIC; aLMR = Lo-Mendell-Rubin adjusted likelihood ratio test; BLRT = Bootstrap likelihood ratio test; NA = Not applicable

Table 2

Parameters Estimates from the Final Unconditional Growth Mixture Analysis (M5)

	Profile 1 High Stable Estimate (t)	Profile 2 Low Stabilizing Estimate (t)	Profile 3 Moderate Stabilizing Estimate (t)	Profile 4 Mild Increasing Estimate (t)	Profile 5 Low Increasing Estimate (t)
Intercept Mean	.802(14.653)**	-.049(-.982)	.307(57.892)**	.112(7.321)**	-.131(-2.150)*
Pre-transit. Slope Mean	.007(.154)	.068(2.886)**	.087(25.209)**	.101(13.199)**	.250(5.329)**
Post-transit. Slope Mean	-.036(-1.810)	.023(1.078)	.004(.878)	.089(26.883)**	.122(4.491)**
Intercept Variability (SD = $\sqrt{\sigma}$)	.071(.155)	.063(.299)**	.077(5.563)**	.283(9.247)**	.138(.473)
Pre-transit. Slope Variability (SD = $\sqrt{\sigma}$)	.190(1.959)*	.000(100.000)**	.000(100.000)**	.089(3.372)**	.000(100.000)**
Post-transit. Slope Variability (SD = $\sqrt{\sigma}$)	.000(100.000)**	.000(100.000)**	.063(4.081)**	.032(1.838)	.134(1.997)*
Intercept–Pre-transit. Slope Correlation	-.033(-1.501)	.011(1.893)**	-.001(-1.495)	-.023(-5.577)**	.003(.147)
Intercept–Post-transit. Slope Correlation	.031(3.186)**	-.013(-2.516)**	.005(7.437)**	-.009(-6.767)**	.042(2.647)**
Pre-transit. Slope–Post-transit. Slope Correlation	-.013(-2.394)*	.000(.054)	.000(-.052)	.002(2.7680)**	-.012(-1.277)
Time-Specific Residual SD(*εyi*): Pre-Transition	.329(12.010)	.116(12.513)	.017(23.535)	.108(25.580)	.124(6.218)
Time-Specific Residual SD(*εyi*): Post-Transition	.046(6.045)	.122(8.217)	.125(20.446)	.011(16.865)	.146(3.683)

Note. * $p \leq .05$; ** $p \leq .01$. t = Estimate / standard error of the estimate (t value are computed from original variance estimate); SD(εyi) = Standard deviations of the time-specific residuals; We present the square roots of the estimates of variability (trajectory factors, time-specific residuals) so that these results can be interpreted in the same units as the constructs (here, standardized factor scores with a mean of 0 and a SD of 1).

Table 3

Results from the Predictive Analyses (M19)

	Profile HS vs LS		Profile HS vs MS		Profile HS vs MI		Profile HS vs LI		Profile MI vs LI	
Predictors	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Sex (0 = boys)	-1.767(.408)**	.171	-.825(.316)**	.438	-1.516(.334)**	.220	-.488(.572)	.614	1.027(.460)*	2.794
Mastery Intrinsic (I)	.890(.564)	2.435	.771(.400)	2.162	.746(.451)	2.108	1.480(.949)	4.395	.735(.834)	2.085
Mastery Extrinsic (I)	1.853(.504)**	6.380	.255(.398)	1.291	.509(.437)	1.663	.035(.666)	1.036	-.473(.505)	.623
Perfo. Approach (I)	-1.101(.388)**	.333	-.900(.311)**	.407	-1.226(.343)**	.293	-1.787(.605)**	.167	-.561(.484)	.571
Perfo. Avoidance (I)	-1.756(.382)**	.173	-1.405(.240)**	.245	-1.516(.268)**	.220	-1.470(.499)**	.230	.046(.435)	1.047
	Profile LS vs MS		Profile LS vs MI		Profile LS vs LI		Profile MS vs MI		Profile MS vs LI	
Predictors	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Sex (0 = boys)	.941(.259)**	2.564	.251(.261)	1.285	1.278(.557)*	3.590	-.691(.112)**	.501	.337(.464)	1.400
Mastery Intrinsic (I)	-.119(.374)	.888	-.144(.397)	.866	.591(1.047)	1.805	-.025(.143)	.975	.709(.832)	2.033
Mastery Extrinsic (I)	-1.598(.296)**	.202	-1.345(.310)	.261	-1.818(.610)**	.162	.253(.117)*	1.288	-.220(.499)	.803
Perfo. Approach (I)	.201(.197)	1.222	-.125(.212)	.882	-.686(.557)	.503	-.326(.095)**	.722	-.887(.485)	.412
Perfo. Avoidance (I)	.351(.271)	1.420	.240(.280)	1.271	.286(.619)	1.331	-.111(.089)	.895	-.065(.434)	.937
	Intercept factor	S1 factor	S2 factor				S1 factor	S2 factor		
Predictors	Coef. (SE)	Coef. (SE)	Coef. (SE)		Predictors		Coef. (SE)	Coef. (SE)		
Sex (0 = boys)	.087(.010)**	-.047(.006)**	.015(.004)**							
Mastery Intrinsic (I)	.013(.019)	-.007(.011)	-.013(.006)*		Mastery Intrinsic (S1)		-.037(.044)	-.096(.040)*		
Mastery Extrinsic (I)	-.071(.016)**	.019(.011)	.017(.008)*		Mastery Extrinsic (S1)		.063(.055)	.005(.045)		
Perfo. Approach (I)	.002(.013)	-.009(.010)	.002(.006)		Perfo. Approach (S1)		.012(.033)	-.010(.028)		
Perfo. Avoidance (I)	.074(.011)**	.000(.007)	-.017(.004)**		Perfo. Avoidance (S1)		.092(.019)**	-.027(.016)		

Note. * $p < .05$; ** $p < .01$; SE: standard error of the coefficient; OR: odds ratio; the coefficients and OR reflects the effects of the predictors on the likelihood of membership into the second listed profile relative to the first listed profile; HS: High Stable; LS: Low Stabilizing; MS: Moderate Stabilizing; MI: Mild Increasing; LI; Low Increasing.

Table 4

Associations Between Profile Membership and the Outcomes

	1: HS Profile *M*[C.I.]	2: LS Profile *M*[C.I.]	3: MS Profile *M*[C.I.]	4: MI Profile *M*[C.I.]	5: LI Profile *M*[C.I.]	Summary of significant differences
Engagement (I)	1.909 [1.782; 2.036]	3.025 [2.921; 3.129]	2.466 [2.425; 2.507]	2.529 [2.492; 2.566]	2.326 [2.175; 2.477]	2 > 4 > 3 = 5 > 1
Engagement (S)	.195 [.175; .215]	.075 [.057; .093]	.109 [.101; .117]	.096 [-.092; .284]	.041 [.017; .065]	1 > 3 > 4 > 2 > 5
Burnout (I)	8.257[8.198; 8.316]	7.374[7.327; 7.421]	7.789[7.773; 7.805]	7.670[7.654; 7.686]	7.471[7.408; 7.534]	1 > 3 > 4 > 5 > 2
Burnout (S)	.016[.002; .030]	.031[.019; .043]	.065[.059; .071]	.087[.083; .091]	.202[.182; .222]	5 > 4 > 3 > 2 = 1

Note. M: Mean; C.I.: 95% Confidence Interval. HS: High Stable; LS: Low Stabilizing; MS: Moderate Stabilizing; MI: Mild Increasing; LI; Low Increasing.

Online Supplemental Materials for:

The Interconnected Development of Depressive Symptoms and School Functioning from Mid-Adolescence to Early Adulthood: A Piecewise Growth Mixture Analysis

Preliminary Measurement and Latent Curve Models

Preliminary Measurement Models: Estimation

Preliminary measurement models were estimated using Mplus 8.4 (Muthén & Muthén, 2019) and the robust Weighted Least Square estimator with Mean and Variance adjusted statistics (WLSMV). This estimator outperforms Maximum Likelihood estimation (robust to nonnormality or not) with ordinal rating scales following asymmetric response thresholds such as those used in this study (Finney & Di Stephano, 2013). Due to the complexity of the models underlying all constructs assessed in this study, preliminary analyses were conducted separately for the depressive symptoms, achievement goals, school engagement, and school burnout measures.

As noted in the main manuscript, out of the 2,696 participants included in this study, 1,316 participated at T1, 1,183 at T2, 871 at T3, 1,271 at T4, and 667 at T5. Furthermore, having missing data on three or more time points (74.0% of the sample) was only weakly correlated (> r = .200) with students levels of depressive symptoms (at T1, T2, T3, T5), as well as with their levels of engagement (lower intercept and higher slope), burnout (higher intercept and lower slope), initial levels of mastery-intrinsic and mastery-extrinsic goals (lower intercept), and changes over time in mastery-extrinsic goals (higher pre- and post-transition slopes). Missing data was not associated with performance-approach and performance-avoidance goals. As a result, it was important to rely on a missing data strategy allowing missing responses to be conditioned on all variables included in the model (i.e., Missing at Random assumptions; Enders, 2010; Graham, 2009). Because Full Information Maximum Likelihood (FIML) estimation is not available with WLMSV estimation (Asparouhov & Muthen, 2010), all measurement and latent curve models were estimated using Multiple imputation (10 imputed data sets) to handle attrition and missing responses (Enders, 2010; Graham, 2009). This method has been found to be adequate even in the presence of large amounts of missing data (e.g., reaching over 70%; Kontopantelis et al., 2017; Madley-Dowd et al., 2019). Across imputations, the results were aggregated using the Rubin (1987) strategy (automatically implemented in Mplus) to obtain unbiased parameter estimates and standard errors.

For the depressive symptoms measure, a one-factor confirmatory factor analytic (CFA) solution was estimated separately at each time point. Likewise, a CFA solution including four correlated factors was estimated separately at what time points for the achievement goals measure. For the burnout measure, as our objective was to rely on a global indicator of burnout estimated while accounting for the specificity of each burnout subscale, we relied on a bifactor-CFA operationalization advocated in previous studies of burnout (e.g., Barcza-Renner et al., 2016; Doherty et al., 2019; Hawrot & Koniewski, 2018; Isoard-Gautheur et al., 2018; Mészáros et al., 2014; Szigeti et al., 2017). More precisely, at each time point, this solution included one burnout G-factor defined by all items, and three orthogonal S-factors (emotional exhaustion, cynicism, and inadequacy) reflecting subscale specificity left unexplained by the G-factor. A similar bifactor operationalization was also retained for school engagement (e.g., Dierendonck et al., 2020; Olivier et al., 2020; Stefansson et al., 2016; Wang et al., 2016), including one engagement G-factor and three orthogonal S-factors (energy, dedication, and absorption). In all of these models, a priori correlated uniquenesses were included between the matching indicators of each construct used over time to avoid converging on inflated estimates of stability (Marsh, 2007).

We then verified whether these models operated in the same manner over time through tests of measurement invariance (Millsap, 2011). More precisely, we assessed: (1) configural invariance; (2) weak invariance (loadings); (3) strong invariance (loadings and thresholds); (4) strict invariance (loadings, thresholds, and uniquenesses); (5) invariance of the latent variances and covariances (loadings, thresholds, uniquenesses, and latent variances and covariances); and (6) latent means invariance (loadings, thresholds, uniquenesses, latent variances and covariances, and latent means).

Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications (e.g., Marsh et al., 2005), we relied on sample-size independent goodness-of-fit indices to describe the fit of the alternative models (Hu & Bentler, 1999; Yu, 2002): The comparative fit index (CFI), the Tucker-Lewis index (TLI), as well as the root mean square error of approximation (RMSEA) and its 90% confidence interval. Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA respectively support acceptable and excellent model fit. Like the chi-square, chi-square difference tests present a known sensitivity to sample size and minor model misspecifications so that recent studies suggest complementing this information with changes in CFIs and RMSEAs (Chen, 2007; Cheung & Rensvold, 2002) in the context of tests of measurement invariance. A ΔCFI of .010 or less, a ΔTLI of .010 or less, and a ΔRMSEA of .015 or less between a more restricted model and the previous one support the invariance hypothesis. For all models, we also report composite reliability indices (ω; McDonald, 1970).

Preliminary Measurement Models: Results

Depressive Symptoms. We first tested the longitudinal invariance of scores obtained on the depressive symptoms measure across the five time points. The fit of the alternative models are reported in Table S1 of these online supplements. The models supported the invariance of the loadings (MD2), thresholds (MD3), uniquenesses (MD4), and latent variances and covariances (MD5). The latent mean invariance was not supported (MD6). However, a model of partial latent mean invariance (MD7), in which the latent means of depressive symptoms were constrained to be equal between the two first time points (CS-7 and CS-8) and between the three last time points (CS-9, SS-2, and SS-3) was supported. These results indicate that the latent means of the depressive symptoms factor was 0.499 SD lower in CS-7 and CS-8 relative to CS-9, SS-2, and SS-3. Detailed parameter estimates from the model of strict invariance (MD4), which was retained for further analyses, is reported in Table S2 of these online supplements. Across all time points, the factor loadings were acceptable and ranged between roughly 0.450 and 0.850. The composite reliability was also acceptable across all time points with omega values greater than 0.900.

Achievement goals. The results from the models used to test the longitudinal invariance of scores obtained on the achievement goals measure are reported in Table S1 of these online supplements. These results supported the measurement invariance of these scores up to the model of latent variance and covariance invariance (MG5). The model of latent mean invariance (MG6) was not supported by the data, due to a lack of invariance of the latent means of the mastery-extrinsic goals factor. However, a model of partial latent mean invariance (MG7), in which the latent means of the mastery-extrinsic goals factors were fixed to equality between the two first time points (CS-7 and CS-8) and between the three last time points (CS-9, SS-2, and SS-3) was supported by the data. These results indicate that the latent means of the mastery-extrinsic goals factor were 0.277 SD lower in CS-9, SS-2, and SS-3 relative to CS-7 and CS-8. Detailed parameter estimates from the model of strict invariance (MG4) are reported in Table S3 of these online supplements. Across all time points, the factor loadings on all four factors were acceptable and ranged between 0.600 and 0.900. The composite reliability was also acceptable, with omega values ranging between 0.725 and 0.888. Correlations between all four factors across time points are reported in Table S4 of these supplements.

School Engagement. The results from the models used to test the longitudinal invariance of scores obtained on the school engagement measure are reported in Table S1 of these online supplements. These results supported the measurement invariance of these scores up to the model of latent variance and covariance invariance (ME5). The model of latent mean invariance (ME6) was not supported by the data. However, a model of partial latent mean invariance (ME7), in which the latent means of one specific factor (dedication) was freed at time SS-3. Importantly, the latent means of the global factor, which is the factor retained for the main analyses, were equivalent across all time points. Detailed parameter estimates from the model of strict invariance (ME4) are reported in Table S5 of these online supplements. As the specific factors are not retained for further analyses, we focus on the global factor. Across all time points, the loadings on this global factor are acceptable, ranging from 0.650 and 0.870. The composite reliability of the global factor was also satisfactory, with omega values above 0.925.

School Burnout. The results from the models used to test the longitudinal invariance of scores obtained on the school burnout measure are reported in Table S1 of these online supplements. These results supported the measurement invariance of these scores up to the model of latent variance and covariance invariance (MB5). The model of latent mean invariance (MB6) was not supported by the data. However, a model of partial latent mean invariance (MB7), in which the means of the global burnout factor and of one specific factor (cynicism) were constrained to equality between the first three time points (CS-7, CS-8, and CS-9) and between the two last time points (SS-2, and SS-3) was supported. More specifically, for the global factor (which is the one retained for the main analyses), these results indicated that the mean of the school burnout factor was 0.461 SD higher in SS-2 and SS-3 relative to CS-7 to CS-9. Detailed parameter estimates from the strict invariance model are reported in Table S6 of these online supplements. As the specific factors are not retained for further analyses, we focus on the global factor. Across all time points, the loadings on this global factor are acceptable, ranging from 0.400 and 0.900. The composite reliability of the global factor was also satisfactory, with omega values above 0.910.

For all measures, factor scores were saved from the model of strict invariance for use in the main analyses. To facilitate the interpretation of our main results, the depressive symptoms factor scores were saved in standardized units (M = 0 and SD = 1) at Time 1, meaning that the factors scores obtained at later time points were directly expressed as deviation from Time 1. However, to preserve the natural measurement units of the predictors and outcomes, the scale of these repeated measures (i.e., the factors) was set with the referent indicator approach, allowing us to freely estimate the means and variance of each factor across all time points prior to estimating the latent curve models. For all models, 10 set of factor scores (one for each imputed data set) were saved, and then combined into a single dataset for the main analyses.

Preliminary Latent Curve Models for the Predictors and Outcomes

To account for the shape of the intra-individual trajectories of the predictors and outcomes when testing their associations with the depressive symptoms trajectories, we relied on a method initially proposed by Morin et al. (2011; see also Guay et al., 2021). More precisely, latent curve models were estimated for each predictor and outcome variable to depict the longitudinal intra-individual trajectories of each of these variables observed in the sample (Bollen & Curran, 2006). As noted in the main manuscript piecewise linear latent curve models were used for the achievement goals (with time codes identical to those used in the main study for the depressive symptoms growth mixture analyses), and from linear latent curve models for the engagement and burnout measures, using time codes directly reflecting the passage of time (0-1-2-4-5). Indeed, the school engagement measure was not administered at T4, making it impossible to model a piecewise latent curve with this variable. For burnout, the decision to retain a linear model is related to the fact that the initial estimation of a piecewise model did not add any value in terms of parameter estimates (consistent with the presence of a continuous slope over the course of the study). In addition, the model fit (as shown at the bottom of Table S7 in these online supplements) information suggested that the linear model had a better adjustment to the data than the piecewise linear model.

Across models, time specific residuals were set up to be freely estimated across all time points.

The results from these analyses are reported in Table S8 of these online supplements. These results are first consistent with the presence of between-person heterogeneity in the shape of all of these trajectories. For mastery-intrinsic goals, the results reveal average trajectories characterized by a slight decreasing tendency prior to the transition, and a slight increasing tendency after the transition. For mastery-extrinsic goals, the results reveal average trajectories characterized by a more pronounced decreasing tendency prior to the transition which stabilizes after the transition. For performance-approach goals, the results revealed generally stable trajectories on the average. For performance-avoidance goals, the trajectories remained stable, on the average, before the transition and displayed a slight increase over time after the transition. Finally, both burnout and engagement displayed trajectories that, on the average, tended to slightly increase over time. Factor scores, reflecting the initial level and the linear slopes (pre- and post- transition for the predictors), were saved from these models and used in the main analyses.

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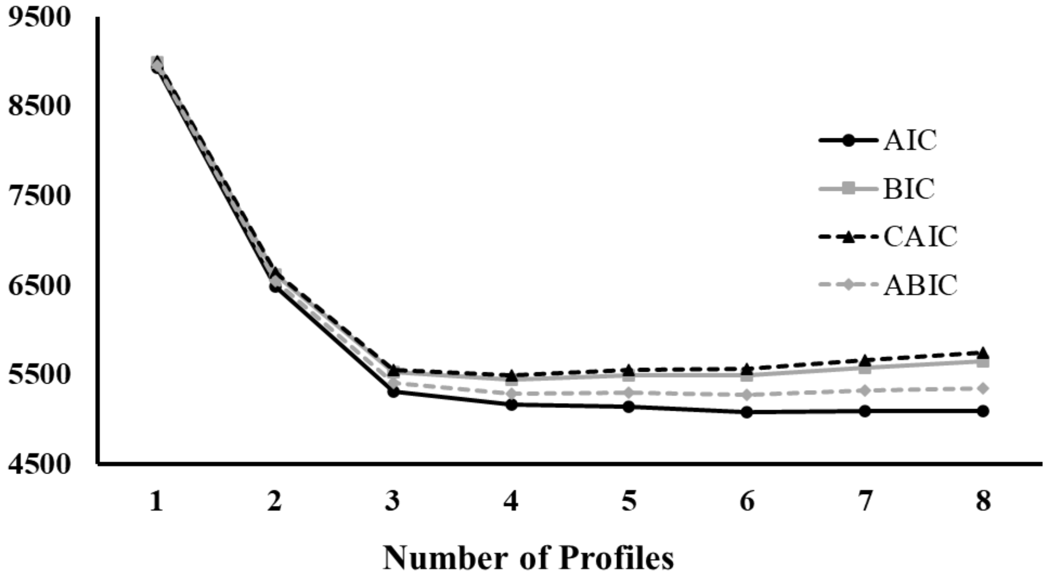

Figure S1
Elbow Plot of the Value of the Information Criteria for 1- to 8-profile Solutions

Table S1

Measurement Model Fit and Longitudinal Measurement Invariance

	χ^2	df	CFI	TLI	RMSEA	ΔCFI	ΔTLI	ΔRMSEA
Depressive Symptoms (CFA Model)								
MD1. Configural Invariance	5701.523	1065	.953	.946	.040			
MD2. Weak Invariance	6077.509	1101	.950	.944	.041	-.003	-.002	+.001
MD3. Strong Invariance	6434.013	1177	.947	.945	.041	-.003	+.001	+.000
MD4. Strict Invariance	7049.737	1217	.941	.941	.042	-.006	-.004	+.001
MD5. Latent Var.-Covar. Invariance	6765.392	1221	.944	.944	.041	+.003	+.003	-.001
MD6. Latent Means Invariance	10414.221	1225	.908	.908	.053	-.036	-.036	+.012
MD7. Partial Latent Means Invariance	7230.757	1224	.940	.940	.043	-.004	-.004	+.002
Achievement Goals (CFA Model)								
MG1. Configural Invariance	9460.559	1400	.934	.917	.046			
MG2. Weak Invariance	9505.492	1432	.934	.919	.046	+.000	+.002	+.000
MG3. Strong Invariance	10737.327	1656	.926	.921	.045	-.008	+.002	-.001
MG4. Strict Invariance	11430.547	1704	.921	.918	.046	-.005	-.003	+.001
MG5. Latent Var.-Covar. Invariance	11155.482	1743	.923	.922	.045	+.002	+.004	-.001
MG6. Latent Means Invariance	12902.747	1759	.909	.909	.048	-.014	-.013	+.003
MG7. Partial Latent Means Invariance	12168.559	1758	.915	.915	.047	-.008	-.007	+.002
School Engagement (Bifactor-CFA Model)								
ME1. Configural Invariance	4604.586	408	.962	.941	.062			
ME2. Weak Invariance	4425.721	450	.964	.949	.057	+.002	+.008	-.005
ME3. Strong Invariance	5704.946	573	.953	.948	.058	-.011	-.001	+.001
ME4. Strict Invariance	5680.147	600	.953	.951	.056	+.000	+.003	-.002
ME5. Latent Var.-Covar. Invariance	5163.643	612	.958	.957	.052	+.005	+.006	-.004
ME6. Latent Means Invariance	7042.225	624	.941	.941	.062	-.017	-.016	+.010
ME7. Partial Latent Means Invariance	6137.176	623	.949	.949	.057	-.009	-.008	+.005
School Burnout (Bifactor-CFA Model)								
MB1. Configural Invariance	5476.921	865	.949	.927	.044			
MB2. Weak Invariance	5850.238	929	.944	.927	.044	-.005	+.000	+.000
MB3. Strong Invariance	6965.505	1073	.934	.924	.045	-.010	-.003	+.001
MB4. Strict Invariance	7623.534	1113	.927	.920	.047	-.007	-.004	+.002
MB5. Latent Var.-Covar. Invariance	8331.953	1129	.920	.913	.049	-.007	-.007	+.002
MB6. Latent Means Invariance	11994.121	1145	.879	.871	.059	-.041	-.042	+.010
MB7. Partial Latent Means Invariance	8922.323	1143	.913	.907	.050	-.007	-.006	+.001

Note. $*p < .05$; χ^2: robust weighted least square with mean and variance adjusted statistics (WLSMV) chi-square test of exact fit; df: degrees of freedom; CFI: comparative fit index; TLI: Tucker-Lewis index; RMSEA: root mean square error of approximation; 90% CI: 90% confidence interval for the RMSEA; Δ: change in model fit relative to the previous model; *p*-values associated with the chi-square are not available with multiple imputation; with WLSMV estimation, chi-square difference tests have to be calculated using the DIFFTEST function (Asparouhov & Muthén, 2006), a function that is not available with multiple imputation.

Table S2

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Depressive Symptoms Measurement Model (Strict Longitudinal Invariance)

	Time 1		Time 2		Time 3		Time 4		Time 5	
	λ	δ	λ	δ	λ	δ	λ	δ	λ	δ
Item 1	.464	.785	.480	.769	.457	.791	.449	.798	.410	.832
Item 2	.767	.412	.781	.390	.762	.420	.754	.431	.716	.487
Item 3	.697	.514	.713	.492	.691	.523	.682	.534	.641	.589
Item 4	.704	.505	.719	.483	.697	.513	.689	.525	.648	.580
Item 5	.715	.489	.730	.467	.709	.498	.700	.509	.659	.565
Item 6	.751	.436	.765	.414	.745	.444	.738	.456	.698	.512
Item 7	.834	.304	.845	.286	.830	.311	.824	.321	.792	.372
Item 8	.840	.294	.851	.275	.836	.301	.830	.311	.799	.361
Item 9	.846	.284	.857	.266	.842	.291	.836	.301	.806	.350
Item10	.829	.313	.840	.294	.824	.321	.818	.331	.786	.383
ω	.927		.933		.925		.922		.906	

Note. ω: omega coefficient of composite reliability. All parameters are significant ($p < .05$).

Table S3

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Achievement Goals (Predictors) Measurement Model (Strict Longitudinal Invariance).

	Time 1		Time 2		Time 3		Time 4		Time 5	
	λ	δ	λ	δ	λ	δ	λ	δ	λ	δ
Mastery Intrinsic										
Item 1	.762	.419	.787	.380	.772	.404	.772	.404	.789	.378
Item 2	.849	.280	.867	.248	.856	.267	.856	.267	.868	.247
Item 3	.823	.323	.844	.288	.831	.309	.831	.309	.845	.286
ω	.853		.872		.861		.861		.873	
Mastery Extrinsic										
Item 1	.825	.319	.841	.292	.831	.310	.798	.363	.813	.338
Item 2	.855	.269	.869	.245	.860	.261	.831	.309	.845	.287
Item 3	.861	.259	.875	.235	.865	.251	.838	.298	.851	.276
ω	.884		.896		.888		.863		.875	
Performance Approach										
Item 1	.656	.569	.691	.523	.670	.551	.660	.564	.688	.527
Item 2	.624	.611	.659	.565	.637	.593	.628	.606	.656	.570
Item 3	.768	.410	.797	.365	.779	.393	.771	.405	.794	.370
ω	.725		.760		.739		.729		.757	
Performance Avoidance										
Item 1	.829	.313	.833	.307	.803	.356	.810	.344	.836	.302
Item 2	.843	.290	.846	.284	.818	.331	.825	.320	.849	.279
Item 3	.818	.331	.822	.324	.790	.375	.798	.363	.825	.320
ω	.869		.872		.846		.852		.875	

Note. ω: omega coefficient of composite reliability. All parameters are significant ($p < .05$).

Table S4

Correlations Between Achievement Goals from the Strict Longitudinal Invariant Measurement Model.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.
1. Mastery Intrinsic CS-7 (T1)																			
2. Mastery Intrinsic CS-8 (T2)	.361*																		
3. Mastery Intrinsic CS-9 (T3)	.334*	.353*																	
4. Mastery Intrinsic SS-2 (T4)	.132	.191*	.188*																
5. Mastery Intrinsic SS-3 (T5)	.139*	.192*	.182*	.478*															
6. Mastery Extrinsic CS-7 (T1)	.773*	.247*	.259*	.105	.109														
7. Mastery Extrinsic CS-8 (T2)	.289*	.700*	.200*	.154*	.104	.436*													
8. Mastery Extrinsic CS-9 (T3)	.261*	.210*	.613*	.086	.042	.363*	.349*												
9. Mastery Extrinsic SS-2 (T4)	.101*	.098	.103	.590*	.174*	.106*	.158*	.105											
10. Mastery Extrinsic SS-3 (T5)	.086	.136*	.141*	.179*	.432*	.102	.143	.138*	.494*										
11. Performance Approach CS-7 (T1)	.431*	.137*	.145*	.012	.058	.537*	.215*	.133*	-.005	.023									
12. Performance Approach CS-8 (T2)	.172*	.444*	.032	.011	.034	.244*	.588*	.173*	.062	.102	.546*								
13. Performance Approach CS-9 (T3)	.083	.074	.363*	-.025	-.043	.131*	.164*	.601*	.034	.076	.373*	.401*							
14. Performance Approach SS-2 (T4)	.046	.026	.023	.256*	.072	.042	.088*	.036	.604*	.374*	.162*	.270*	.126*						
15. Performance Approach SS-3 (T5)	.037	.066	.067	.066	.215*	.068	.098	.070	.274*	.603*	.122*	.262*	.168*	.609*					
16. Performance Avoidance CS-7 (T1)	.177*	.057	.015	-.048	.030	.242*	.119*	.035	.024	-.011	.596*	.309*	.140	.077	.014				
17. Performance Avoidance CS-8 (T2)	.036	.230*	.030	-.054	-.027	.095	.297*	.049	.021	.077	.286*	.621*	.184*	.135*	.104	.436*			
18. Performance Avoidance CS-9 (T3)	-.020	-.006	.183*	-.052	-.035	.019	.022	.214*	.030	.023	.188*	.188*	.592*	.086	.024	.335*	.417*		
19. Performance Avoidance SS-2 (T4)	-.021	-.031	.001	.051	.006	-.002	.012	-.020	.221*	.137*	.012	.065	.017	.490*	.218*	.127*	.223*	.218*	
20. Performance Avoidance SS-3 (T5)	-.054	.008	-.029	-.074	-.016	.026	.060	-.005	.024	.253*	.027	.058	.055	.217*	.483*	.085	.176*	.169*	.338*

Note. * $p \leq .05$. CS=comprehensive school; SS=upper secondary school.

Table S5

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the School Engagement (Outcome) Measurement Model (Strict Longitudinal Invariance).

	Time 1			Time 2			Time 3			Time 5		
	G-Factor λ	S-Factor λ	δ	G-Factor λ	S-Factor λ	δ	G-Factor λ	S-Factor λ	δ	G-Factor λ	S-Factor λ	δ
Energy												
Item 1	.711	.560	*.174*	.764	.470	.185	.673	.605	*.175*	.705	.504	*.240*
Item 4	.832	.074	.301	.844	.058	.285	.818	.083	.324	.786	.063	.378
Item 8	.772	-.117	.389	.787	-.090	.372	.754	-.130	.413	.718	-.098	.474
ω S-factor		.395			.312			.423			.288	
Dedication												
Item 2	.706	.306	.401	.734	.237	.398	.661	.397	.391	.653	.294	.481
Item 5	.860	*.032*	.258	.870	*.024*	.242	.847	*.047*	.278	.818	*.032*	.328
Item 7	.850	-*.242*	.206	.870	-*.186*	.198	.823	-.309	.216	.806	-*.252*	.265
ω S-factor		.280			.193			.390			.237	
Absorption												
Item 3	.765	-*.224*	.346	.790	-*.175*	.338	.750	-*.223*	.370	.729	-*.145*	.440
Item 6	.733	*.131*	.407	.754	*.115*	.389	.710	*.136*	.431	.668	*.129*	.484
Item 9	.760	*.309*	.304	.778	*.270*	.294	.745	*.311*	.324	.720	*.247*	.384
ω S-factor		.383			.315			.373			.238	
ω G-factor	.946			.950			.940			.926		

Note. ω: omega coefficient of composite reliability; G- and S-: global and specific factors from a bifactor measurement model; Non significantly significant parameters ($p > .05$) are marked in italic.

Table S6

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the School Burnout (Predictors) Measurement Mode (Strict Longitudinal Invariance)

	Time 1			Time 2			Time 3			Time 5			Time 5		
	G-Factor λ	S-Factor λ	δ	G-Factor λ	S-Factor λ	δ	G-Factor λ	S-Factor λ	δ	G-Factor λ	S-Factor λ	δ	G-Factor λ	S-Factor λ	δ
Exhaustion															
Item 1	.472	.302	.686	.520	.266	.659	.466	.286	.700	.427	.308	.723	.410	.342	.715
Item 4	.554	.482	.459	.612	.425	.444	.553	.462	.479	.507	.497	.495	.479	.542	.474
Item 8	.494	.648	.335	.558	.587	.341	.498	.627	.357	.448	.663	.358	.414	.707	.327
Item 10	.624	.350	.487	.675	.302	.453	.619	.334	.504	.575	.364	.535	.553	.404	.530
ω S-factor		.618			.568			.589			.614			.660	
Cynicism															
Item 2	.693	.413	.349	.757	.307	.331	.696	.381	.370	.647	.429	.395	.581	.566	.341
Item 5	.723	.354	.351	.780	.259	.323	.725	.324	.369	.681	.368	.401	.625	.498	.361
Item 6	.706	.322	.398	.760	.236	.366	.705	.294	.416	.661	.334	.451	.613	.456	.415
ω S-factor		.519			.387			.464			.506			.674	
Inadequacy															
Item 3	.748	.196	.395	.790	.150	.349	.741	.201	.405	.711	.176	.459	.695	.202	.471
Item 7	.850	-.445	*.073*	.899	-.347	*.065*	.835	-.464	*.077*	.837	-.439	*.091*	.812	-.486	*.092*
Item 9	.711	*.007*	.494	.750	*.005*	.437	.703	*.007*	.505	.665	*.007*	.557	.652	*.008*	.574
ω S-factor		.304			.228			.314			.259			.299	
ω G-factor	.915			.930			.911			.895			.888		

Note. ω: omega coefficient of composite reliability; G- and S-: global and specific factors from a bifactor measurement model; Non significantly significant parameters (*p* > .05) are marked in italic.

Table S7

Parameter Estimate the Latent Curve Models (Predictors and Outcomes)

	Predictors: Piecewise linear models[1]				Outcomes: Linear models[2]	
	Mastery-Intrinsic	Mastery-Extrinsic	Perfo.-Approach	Perfo.-Avoidance	Engagement	Burnout
Intercept Mean (s.e.)	3.303(.074)**	4.009(.085)**	1.490(.073)**	2.416(.052)**	2.498(.021)**	7.730(.010)**
Slope 1 Mean (s.e.)	-.112(.029)**	-.239(.032)**	.003(.027)	.001(.027)	.103(.005)**	.076(.003)**
Slope 2 Mean (s.e.)	.158(.017)**	-.032(.023)	-.027(.019)	.102(.028)**	NA	NA
Intercept Variance (s.e.)	.660(.176)**	1.085(.189)**	1.086(.199)**	1.275(.264)**	.747(.037)**	.182(.011)**
Slope 1 Variance (s.e.)	.052(.064)	.042(.084)	.133(.096)	.197(.105)	.027(.002)**	.012(.001)**
Slope 2 Variance (s.e.)	.115(.028)**	.141(.023)**	.139(.058)*	.143(.044)**	NA	NA
Intercept-Slope 1 Correl. (s.e.)	-.079(.100)	-.178(.115)	-.265(.106)*	-.294(.146)*	-.208(.031)**	-.034(.002)**
Intercept-Slope 2 Correl. (s.e.)	-.102(.050)*	-.198(.048)**	-.110(.042)**	-.161(.053)**	NA	NA
Slope 1-Slope 2 Correl. (s.e.)	.007(.033)	.045(.033)	.007(.049)	-.012(.050)	NA	NA
Time 1 Standardized Residual (s.e.)	.552(.107)**	.452(.094)**	.204(.127)	.432(.107)**	.804(.046)**	.535(.022)**
Time 2 Standardized Residual (s.e.)	.686(.026)**	.645(.031)**	.572(.039)**	.600(.031)**	.805(.044)**	.717(.017)**
Time 3 Standardized Residual (s.e.)	.646(.079)**	.737(.055)**	.634(.117)**	.509(.067)**	.622(.036)**	.672(.015)**
Time 4 Standardized Residual (s.e.)	.576(.029)**	.580(.038)**	.475(.051)**	.628(.029)**	NA	.633(.015)**
Time 5 Standardized Residual (s.e.)	.415(.057)**	.367(.073)**	.206(.115)	.535(.055)**	.386(.034)**	.282(.031)**

Notes. *$p < .05$; ** $p < .01$; NA = Not applicable.

[1]For the predictor models, Slope 1 is the linear pre-transition slope and Slope 2 is the linear post-transition slope.

[2]For the outcome models, Slope 1 is the linear slope encompassing all time points.

Fit indices:

Mastery intrinsic model: $\chi^2 = 1150.835$ (df = 132), $p < .001$; RMSEA = .053; CFI = .972; TLI = .978.

Mastery extrinsic model: $\chi^2 = 1476.392$ (df = 132), $p < .001$; RMSEA = .061; CFI = .969; TLI = .976.

Performance approach model: $\chi^2 = 1079.141$ (df = 132), $p < .001$; RMSEA = .051; CFI = .943; TLI = .955.

Performance avoidance model: $\chi^2 = 696.366$ (df = 132), $p < .001$; RMSEA = .040; CFI = .985; TLI = .988.

Engagement model: $\chi^2 = 66.009$ (df = 5), $p < .001$; RMSEA = .067; CFI =.950; TLI = .940.

Burnout model (Linear): $\chi^2 = 168.246$ (df = 10), $p < .001$; RMSEA = .077; CFI = .911; TLI = .911.

Burnout model (Piecewise): $\chi^2 = 125.196$ (df = 6), $p < .001$; RMSEA = .086; CFI = .933; TLI = .889.

Table S8

Correlations Among All Variables Used in the Present Study

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.
1. Depression CS-7																					
2. Depression CS-8	.429*																				
3. Depression CS-9	.300*	.395*																			
4. Depression SS-2	.168*	.251*	.196*																		
5. Depression SS-3	.200*	.232*	.228*	.565*																	
6. Mast.-Intrinsic (I)	-.105*	-.091*	-.144*	-.061*	-.112*																
7. Mast.-Intrinsic (S1)	.097*	.058*	.035	.010	-.014	-.475*															
8. Mast.-Intrinsic (S2)	.046*	.021	.025	.012	.005	-.367*	.685*														
9. Mast.-Extrin. (I)	-.107*	-.068*	-.159*	-.076*	-.082*	.684*	-.387*	-.302*													
10. Mast.-Extrin. (S1)	.103*	.071*	.144*	.063*	.063*	-.631*	.484*	.399*	-.944*												
11. Mast. Intrinsic (S2)	.054*	.062*	.083*	.021	.009	-.273*	.431*	.475*	-.462*	.719*											
12. Perfo. Appro. (I)	.102*	.047*	.028	-.045*	-.032	.289*	-.234*	-.180*	.397*	-.393*	-.211*										
13. Perfo. Appro. (S1)	-.108*	-.010	-.019	.089*	.042*	-.263*	.298*	.169*	-.330*	.402*	.339*	-.864*									
14. Perfo. Appro. (S2)	-.035	.047*	-.007	.121*	.104*	-.104*	.189*	.244*	-.140*	.296*	.539*	-.284*	.471*								
15. Perfo. Avoid. (I)	.299*	.227*	.172*	.141*	.074*	.100*	-.123*	-.116*	.198*	-.195*	-.104*	.453*	-.404*	-.192*							
16. Perfo. Avoid. (S1)	-.223*	-.047*	-.040*	.079*	.036	-.128*	.204*	.064*	-.173*	.213*	.183*	-.350*	.458*	.225*	-.625*						
17. Perfo. Avoid. (S2)	-.154*	-.083*	-.086*	.071*	.132*	-.115*	.070*	.116*	-.119*	.152*	.190*	-.317*	.311*	.431*	-.605*	.453*					
18. Engagement (I)	-.196*	-.156*	-.153*	-.109*	-.157*	.600*	-.278*	-.202*	.427*	-.397*	-.183*	.219*	-.188*	-.099*	.004	-.083*	-.040*				
19. Engagement (S)	.186*	.139*	.129*	.036	.033	-.555*	.361*	.324*	-.393*	.418*	.312*	-.194*	.188*	.167*	-.026	.066*	.032	-.196*			
20. Burnout (I)	.471*	.375*	.342*	.153*	.104*	-.301*	.142*	.101*	-.280	.244*	.090*	.142*	-.142*	-.032	.299*	-.175*	-.180*	-.388*	.386*		
21. Burnout (S)	-.231*	-.087*	-.107*	.250*	.355*	.163*	-.187*	-.202*	.193*	-.219*	-.193*	-.115*	.122*	.029	-.090*	.193*	.190*	.211*	-.354*	-.649*	
22. Sex (0=male)	.175*	.180*	.035	.140*	.116*	.064*	.075*	.054*	.171*	-.126*	-.004	-.112*	.097*	.009	.096*	-.004	.019	-.008	.026	.000	.161*

Note. * $p \leq .05$. CS=comprehensive school; SS=upper secondary school; I=intercept; S1=pre-transition slope; S2=post-transition slope; S=slope.

Comparing Trajectory-Profiles to Clinical Levels of Depression

Poutanen et al. (2010) proposed interpretation guidelines to determined clinical and subclinical levels of depression when using Salokangas et al.' (1995) Depression Scale (DEPS). More precisely, they noted that scores of 11 or 12 (out of 30) could be used to indicate clinical levels of depression, whereas scores of 9 or 10 could be used to indicate subclinical levels of depression (Poutanen et al., 2010). Although the factor scores used in the present study to reflect depression were estimated in standardized units, we also calculated manifest depression scores for all participants (by summing the items to obtain scores ranging from 0 to 30). Table S9 reports the mean level of depression observed in the total sample at each time point, as well as the mean level of depression observed among participants corresponding to each trajectory-profiles.[1] As can be seen in this table, participants corresponding to the High Stable trajectory-profile systematically reported depression levels above the threshold for clinical depression. Participants with a Low Stabilizing trajectory-profile reported depression levels that did not indicate the presence of clinical or subclinical depression at any of the time points. Participants corresponding to the Moderate Stabilizing and Mild Increasing trajectory-profiles initially reported low levels of depression, but these levels eventually reached the threshold for the presence of subclinical depression at Time 5. Finally, participants with a Low Increasing trajectory-profile initially reported low depression levels, which reached the threshold for subclinical depression at Time 3, and clinical depression at Times 4 and 5.

Table S9

Scale Score Depression Levels per Trajectory-Profiles.

	Time 1		Time 2		Time 3		Time 4		Time 5	
	M	SD	M	SD	M	SD	M	SD	M	SD
Total Sample	6.14	4.55	6.37	4.43	8.52	4.43	8.45	4.83	9.79	4.26
High Stable	14.53	8.48	15.09	8.33	16.55	7.73	12.33	4.97	12.55	4.57
Low Stabilizing	3.32	3.04	2.83	3.12	5.14	4.23	3.35	3.56	4.70	3.14
Moderate Stabilizing	6.60	1.97	7.11	2.07	8.90	2.20	8.16	3.18	9.91	5.16
Mild Increasing	5.39	4.73	5.40	4.26	7.78	4.40	8.60	2.06	9.74	2.25
Low Increasing	3.43	2.86	4.51	4.18	9.51	5.13	14.38	9.36	15.17	8.78

Note. M = mean. SD = standard deviation.

[1] These results should be interpreted with caution as it required saving profile membership of participants within the different profiles. Indeed, GMA provides a probabilistic classification (i.e., corrected for classification error) of each participant into the profiles rather than a definite classification.