Predictors and Outcomes of Teachers' Burnout Trajectories over a Seven-Year Period

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Abstract

This research examines burnout trajectories over seven years (Time 1 and four months, eight months, and seven years after Time 1) among a sample of 951 teachers. Our results revealed three profiles of teachers presenting a *Moderate* (moderate levels that slightly decreased), *Low* (low levels that slightly increased), and *High* (high levels that slightly decreased) burnout trajectories. These profiles were found to be associated with predictors (self-efficacy, students' inattention, and principal's negative leadership) and outcomes (intentions to leave, somatization, sedatives, sleeping pills, and physical activity). These results thus documented the implications of these profiles, and potential levers of intervention.

Keywords: Burnout trajectories; growth mixture analyses; teachers; self-efficacy; lifestyle habits; intentions to leave; bifactor models.

Burnout, as a chronic psychological state of resource depletion, is highly prevalent among teachers (Schaufeli & Enzmann, 1998). Whereas between 5 to 30 percent of teachers will eventually report burnout symptoms (García-Carmona et al., 2019; Hakanen et al., 2006), Canadian estimates suggest that these symptoms are experienced, at least once a week, by 20 percent of them (Vlasie, 2021). When compared to other professions (e.g., nurses, mental health professionals), teachers have been found to show more signs of ill-being (Johnson et al., 2005), including burnout (Schaufeli et al., 2009). Presumably, the relational nature of teaching puts them at higher risk for emotional drainage, which could explain their vulnerability to burnout. Burnout is known to hinder individual and organizational (e.g., somatization, turnover; Halbesleben & Buckley, 2004) functioning in a way interfere with the accomplishment of the school's educational mission (Chang, 2009). In line with these observations, increasing attrition rates have been reported among US teachers (Carver-Thomas & Darling-Hammond, 2017), making burnout an increasing concern for schools (von der Embse et al., 2016).

Burnout is a psychological syndrome encompassing emotional exhaustion (i.e., depletion of physical energy and fatigue), depersonalization (i.e., excessively detached or negative responses to others), and a reduced sense of personal accomplishment (i.e., feelings of reduced work productivity and achievement) (Maslach & Jackson, 1986). However, workers also tend to experience burnout holistically as a single global dimension (Schaufeli & Enzmann, 1998). This global representation is supported by high correlations among burnout dimensions (Maslach et al., 2001), and stronger relations with covariates when burnout is defined globally (Shirom & Melamed, 2006).

Although burnout is a dynamic process unfolding over time (Dunford et al., 2012), few investigations have adopted a longitudinal perspective to understand the burnout trajectories most typically observed in the work context (Mäkikangas & Kinnunen, 2016), particularly among teachers. The current research contributes to burnout research in two manners. First, we rely on person-centered analyses (growth mixture modeling, GMM) to identify the distinct shape taken by teachers' burnout trajectories over seven years. Second, we document the theoretical and practical underpinnings of these trajectories by examining their links with individual and work-related predictors and outcomes.

Thus, a major contribution of this study lies in the adoption of a longitudinal design, allowing us to clarify how teachers' burnout evolves over the course of a seven-year period, and to examine their predictors and outcomes. On the one hand, and matching the design used in many previous studies (see Mäkikangas & Kinnunen, 2016), data was collected three times during the first year of the study (with four-month intervals) to examine the short-term trajectories of teachers' burnout. However, to obtain a more accurate understanding of the longer-term development of burnout (Mäkikangas et al., 2020), we also capitalized from a research opportunity allowing us to follow up all participants seven years after the first data collection. This design allows us to achieve a greater level of precision through the simultaneous consideration of teachers' short- and long-term trajectories of burnout, and to achieve a more accurate understanding of long-term trajectories by allowing us to capitalize on a baseline assessment covering three measurement points collected at four-month intervals. Moreover, this approach also made it possible to consider short- (involving the initial measurement points) and long- (involving the whole trajectories) associations between these trajectories, their predictors, and their outcomes. Consequently, our results are likely to improve our understanding of the psychological mechanisms at play in burnout development, leading to more focused interventions specific to the teaching profession. For instance, based on the present findings, we might suggest interventions aiming to decrease teachers' burnout by nurturing teachers' self-efficacy, which in turn should contribute to reduce their intentions to leave the occupation and facilitate their well-being.

A Longitudinal Investigation

Numerous studies on burnout, including research specifically focused on teachers, have adopted cross-sectional designs or limited longitudinal designs (i.e., two measurement occasions; e.g., Fernet et al., 2014; Huyghebaert et al., 2018) precluding the analysis of burnout trajectories (Mäkikangas et al., 2020). To inform this issue, more intensive longitudinal investigations are necessary (i.e., three or more measurement occasions). This relative dearth of longitudinal research is critical when considering burnout, which represents a contextual, domain-specific, construct (Maslach et al., 2001). Furthermore, Mäkikangas et al.'s (2020) recently showed that burnout levels fluctuated over time and across among white-collar professionals.

Previous Longitudinal Evidence

To better grasp the longitudinal dynamics of burnout, estimates of rank-order stability provide a first source of evidence. For instance, Frögéli et al. (2019) obtained a moderately high level of rank-order stability (*r* = .72) over a three-year period (see Kinnunen et al., 2019 for similar estimates over one and two years). Madigan et al. (2015) also reported slightly higher estimates of rank-order stability (*r* = .78) over a three-month period, consistent with the idea that burnout is more stable over a short period of time (Maslach & Leiter, 2008). Importantly, observing moderately high estimates of rank-order stability is not inconsistent with the idea that burnout levels might be impacted by work conditions which are themselves known to be quite stable over time (Lesener et al., 2019).

A second source of evidence comes from studies examining longitudinal burnout trajectories, which also supported the stability of burnout levels over time (e.g., May et al., 2020; Wang et al., 2015). However, just like estimates of rank-order stability, these average trajectories may mask substantial inter-individual heterogeneity (Mäkikangas & Kinnunen, 2016). Prior studies have thus adopted a person-centered approach to better understand the presence of inter-individual heterogeneity in the shape of burnout trajectories. Generally, these studies have relied on a maximum of three measurement occasions separated by a typical time lag of one or two years (Mäkikangas & Kinnunen, 2016). These studies have also most typically considered early career employees among different occupational groups (e.g., managers: Mäkikangas et al., 2012). In terms of results, these studies have identified solutions including three to eight profiles (e.g., Hultell et al., 2013; Mäkikangas et al., 2020), many of which were characterized by stable low, moderate or high levels of burnout, although profiles characterized by linear (decreasing or increasing) and curvilinear (U-shaped or reverse U-shaped) trajectories were identified. By showcasing the presence of distinct profiles of employees characterized by qualitatively different burnout trajectories, these studies support the idea that the moderately high levels of stability typically related to burnout levels might hide the presence of significant developmental heterogeneity. However, these results also show that many of these heterogenous profiles themselves generally tended to display relatively stable burnout trajectories (e.g., 3/4 of the managers in Mäkikangas et al., 2012), although trajectories characterized by longitudinal trends (i.e., increasing, decreasing, or curvilinear) can also happen, especially in longer-term studies (Mäkikangas & Kinnunen, 2016).

Longitudinal Heterogeneity in Teachers' Burnout Trajectories

Despite their interest, these prior studies present some noteworthy limitations. First, very little research has focused on the burnout trajectories, their predictors, and their outcomes among samples of teachers. To our knowledge, a single study has specifically sought to uncover the distinct profiles taken by burnout trajectories among a sample of new teachers followed during their first three years of employment (Hultell et al., 2013). This study revealed that seven trajectories were required to achieve a comprehensive representation of teachers' burnout. However, the generalizability of these findings remains limited as these authors adopted a highly restrictive analytic parameterization, coupled with the reliance on an analytic model that essentially ignored the time-related dependencies present in the data (e.g., Bauer & Curran, 2003; Morin et al., 2011). In addition, this study remains unable to inform the nature of teachers' burnout trajectories beyond this initial three-year period.

Second, little research has specifically sought to document the role played by work characteristics on the time-structured evolution of employees' burnout trajectories. Furthermore, the few studies in which efforts were made in this direction (Lee & Eissenstat, 2018; Mäkikangas et al., 2020) remained limited by their consideration of very generic work characteristics. Thus, despite their interest, these studies are unable to inform the development of interventions accounting for the specific reality of unique occupational groups, such as teachers (Fernet et al., 2012).

Third, although we have theoretical reasons (Maslach et al., 2001) to expect burnout trajectories to play a role in teachers' intentions to leave their profession and lifestyle habits (e.g., amount of physical activity), empirical evidence is currently lacking in this regard. Once again, Hultell et al. (2013) provided evidence showing that burnout trajectories were significantly related to teachers' self-efficacy, intentions to leave, and self-rated health during their first three years of employment, thus leaving as an open question whether similar associations would be maintained over time among more experienced teachers.

These limitations are addressed in the present research by focusing on teachers who completed a series of measures over a total of four measurement waves spanning seven years. Furthermore, rather than relying on restrictive methodological approaches (Hultell et al., 2013) the current research relies on a person-centered extension of latent curve models (Bollen & Curran, 2006), GMM. This approach makes it possible to identify population heterogeneity via the identification of distinct profiles of participants, each characterized by inter-individual variability and following qualitatively distinct longitudinal trajectories. Due to the limited number of previous studies able to offer theoretical or empirical guidance, it is difficult to provide clear expectations concerning the expected number and nature of the burnout trajectories which will be observed over time. However, in line with the findings reported above, we formulate the following hypothesis:

Hypothesis 1. We expect to identify one Low trajectory characterized by stable levels of burnout over time, one High trajectory characterized by stable levels of burnout over time, one Low-Increasing trajectory characterized by initially low levels of burnout that increase over time, and one High-Decreasing trajectory characterized by initially high levels of burnout that decrease over time. However, other qualitatively and quantitatively distinct burnout trajectories are also likely.

The present study also addresses the aforementioned limitations by seeking to better document the role played by a series of demographic, individual, and work environment predictors of these burnout trajectories embedded in the teaching context (Kofler et al., 2008). Finally, this research aims to improve our understanding of the implications of these burnout trajectories in relation to a variety of work-related and personal outcomes.

Predictors of Teachers' Burnout Trajectories

Self-efficacy refers to one's confidence in having the abilities required to handle job-specific tasks and to cope with work-related challenges, stress, and their consequences (Klassen et al., 2011; Tschannen-Moran & Hoy, 2001). Teachers' self-efficacy is assumed to influence how job-specific resources and hindrances are perceived and acted upon, and thus to act as a potentially important predictor of more desirable burnout trajectories (Aloe et al., 2014a; Skaalvik & Skaalvik, 2017). More precisely, teachers confident in their abilities to successfully perform classroom management tasks should be more likely to experience a feeling of competence and mastery, which should decrease their risk of experiencing undesirable (high and/or increasing) burnout trajectories (Cherniss, 1993).

Because teacher efficacy is viewed as context- and task-specific (Tschannen-Moran & Hoy, 2001), we decided to focus on classroom discipline efficacy. This construct refers to teachers' ability to control classroom discipline and student behavior calmly and effectively (Friedman, 2003) and has been found to be important for preventing burnout (Aloe et al., 2014a). Although other aspects of teachers' efficacy (e.g., maintaining structure, demonstrating warmth, supporting learning) are also likely to be highly important for teachers, numerous studies have shown that classroom discipline represents a significant concern for educational systems and a critical aspect of an effective learning environment (Kaufmann, 2020; Lopes & Oliveira, 2022). Moreover, teachers simply cannot ignore classroom misbehavior and discipline, as doing so will automatically interfere with all other aspects of their classroom behaviors and might even trigger a domino effect by communicating to students that such behaviors are acceptable (Scherzinger & Wettstein 2019). As a non-ignorable component of their work, and one that is often seen that taking time away from the more meaningful learning activities, classroom discipline can be conceptualized as a job demand for teachers, and thus as a likely driver of burnout (e.g., Bottiani et al., 2019). For this reason, teachers' perceptions of their efficacy in this domain are likely to be important in helping teachers avoid the development of problematic levels of burnout (e.g., Aloe et al., 2014a; Friedman, 2003).

Students' misconduct and lack of attention in the classroom are frequently reported as one of the top daily challenges faced by teachers (Aloe et al., 2014b). In the current research, we consider students' inattention in the classroom given substantial evidence that inattentive behaviors impair teachers' ability to focus on relevant aspects of their environment (Kofler et al., 2008). Indeed, students' inattention in the classroom is a form of misconduct which can arguably be considered as a factor impacting teachers' self-efficacy in their role as educators whose role is to nurture and maintain students' interest for learning. In accordance with social cognitive theory (SCT; Bandura, 1997), students' lack of attention in class has been found to increase the risk of teacher burnout (Friedman, 1995).

Finally, school principals have a key role both in developing collaborative school cultures and supporting teachers (Assunção Flores & Day, 2006). Moreover, principals can play an important role in the prediction, and prevention, of teacher burnout (Benita et al., 2019; Leithwood et al., 1996). Of directed relevance to the present investigation, principals' negative leadership behaviors (e.g., controlling, depreciative, laissez-faire) have been shown to have a detrimental effect on teachers' burnout (Eyal & Roth, 2011; Slemp et al., 2020). In prior studies, these leadership behaviors have been found to be closely related, forming a unitary leadership construct (Fernet et al., 2008, 2012). These behaviors can be oppressive, vindictive, and capricious, making them a high source of strain for exposed teachers by interfering with teachers' sense of agency and self-efficacy (Bandura, 1997). Based on previous evidence, we thus propose:

Hypothesis 2. Teachers' self-efficacy (initial levels and increases over time in these levels) is associated with profiles characterized by lower initial levels of burnout, and by stable or decreasing levels of burnout over time.

Hypothesis 3. Teachers' perceptions of students' inattention and of principals' negative leadership behaviors efficacy (initial levels and increases over time in these levels) are associated with profiles characterized by higher initial levels of burnout, and by stable or increasing levels of burnout over time.

Outcomes of Burnout Trajectories

Finally, we focus on the associations between teachers' burnout trajectories and one key indicator of professional dissatisfaction (i.e., intentions to leave) as well as various indicators of overall functioning in life (i.e., somatization, sedatives and sleeping pills consumption, and involvement in physical activity), all known to be intimately associated with burnout. The decision to focus on teachers' intentions to leave is predicated on the recognition that these intentions often accompany burnout (Gillet et al., 2015) and act as a core driver of voluntary turnover in various organizational settings (Rubenstein et al., 2018). Our decision to focus on somatic manifestations and the often associated use of sedatives and sleeping pills was predicated on the frequent observation that burnout is accompanied by a variety of health-related difficulties (Goering et al., 2017; van der Doef et al., 2012). Interestingly, teachers suffering from burnout also tended to go to bed earlier and wake up later (Kawamata et al., 2020). Conversely, involvement in physical activity is known to share negative associations with burnout (Gerber et al., 2020). Following from these considerations, we propose:

Hypothesis 4. Profiles with higher initial levels of burnout and with stable or increasing burnout levels over time are associated with higher and increasing levels of somatization, intentions to leave, and sedatives and sleeping pills consumption over time, as well as with lower and decreasing levels of involvement in physical activity.

Hypothesis 5. Profiles with lower initial levels of burnout and with stable or decreasing burnout levels over time are associated with lower and decreasing levels of somatization, intentions to leave, and sedatives and sleeping pills consumption over time, as well as with higher and increasing levels of involvement in physical activity.

Method

Procedure and Sample

This investigation was conducted among a sample of 951 French-Canadian public school teachers (elementary: 59.6%, high school: 24.9%, adults: 5.2%, and vocational: 9.8% education) from the Canadian province of Quebec who were followed over a seven-year period. They had a mean age of 42.3 years (*SD* = 10.3) and 14.9 years (*SD* = 10.3) of experience in teaching. Most worked full-time (77.0%) in a permanent position (76.3%) and were mostly women (76.2%). Data was collected four times (T1, T2: Four months after T1; T3: Eight months after T1; and T4: Seven years after T1).

At the start of the school year (T1), all teachers from two school boards received a letter in their pigeonhole explaining the goal of the research, the voluntary nature of the study, and the confidentiality of their responses. This package also included a pre-addressed return envelope and the questionnaire. Participants were informed that this was a longitudinal study and that they would be contacted to complete the same questionnaire at the three other time points. Interested participants had to provide their coordinates for the follow-up contacts.

Measures

All measures in the questionnaire, which were either originally developed in French, or previously validated in French, were administered in French at each time point. Validity and reliability of the French–Canadian version of these measures are similar to those of the original version and have been supported in prior studies (Fernet et al., 2008, 2012, 2015, 2016).

Burnout. Emotional exhaustion (nine items; e.g., "I feel emotionally drained from my work"; α between .89 and .93) and depersonalization (five items; e.g., "I've become more callous toward people since I took this job"; α between .67 and .77), which form the core components of burnout across conceptualizations (Kalliath et al., 2000; Schaufeli & Salanova, 2007), were measured using the Maslach Burnout Inventory (Maslach & Jackson, 1986; French version by Dion & Tessier, 1994). Indeed, researchers have shown that a two-factor model including only emotional exhaustion and depersonalization was more appropriate, based on methodological and conceptual rationales (Kalliath et al., 2000; Sandrin et al., 2022). For instance, Sandrin et al. (2022) reported moderately high positive correlations between depersonalization and emotional exhaustion ($r = .51$), but an almost null correlation with reduced sense of accomplishment ($r = -.02$ to $-.03$), consistent with the idea that this third component of burnout is conceptually distinct (also see Hawrot et al., 2017; Lee & Ashforth, 1996; Szigeti et al., 2017). This is consistent with the original definition of burnout that only included the two core symptoms of emotional exhaustion and depersonalization (Hakanen & Schaufeli, 2012; Maslach, 1993), and the observation that accomplishment remains unaffected for many burned-out employees (Schaufeli et al., 2001). More generally, numerous studies have questioned the validity of reduced sense of accomplishment as a third burnout dimension because it could rather reflect a personal characteristic (Cordes & Dougherty, 1993) or an outcome of burnout (Kim & Burić, 2020). Excluding this last component from the present study was also deemed necessary to avoid conceptual overlap between our measure of burnout and one of its theoretical predictors (self-efficacy). Responses were provided on a 0 (never) to 6 (daily) scale.

Teacher self-efficacy. The discipline subscale of the Classroom and School Context Teacher Self-Efficacy Scale (Friedman, 2003; French version by Fernet et al., 2005) was used to measure teacher self-efficacy (three items; e.g., "I believe I easily overcome student interruptions in class"; α between .76 and .84 at T4). Responses were provided on a 1 (never) to 6 (always) scale.

Students' inattention. Teachers' ratings of students' inattention (eight items; e.g., "Students in my class are indifferent, and I have to work hard to get them interested"; α between .71 and .87) were assessed using the Pupil Behavior Patterns Scale (Friedman, 1995; French version by Fernet et al., 2012). Responses were provided on a 1 (never) to 4 (very often) scale.

Principal's negative leadership behaviors. Teachers reported their perceptions of their principal's leadership behaviors using three items adapted from the Supervisory Style Inventory (Blais et al., 1991; originally developed in French). The items used in this study focus on negative leadership behaviors (laissez-faire, depreciative, and controlling; e.g., "I am very closely monitored by my school principal" [controlling]; α between .66 and .71)[1]. Responses were provided on a 1 (do not agree at all) to 7 (agree very strongly) scale. This measure has been found to be valid and reliable in assessing teachers' perceptions of leadership across cultures (Fernet et al., 2008, 2012; Levesque et al. 2004).

Intentions to leave. Teachers' intentions to leave their current job were assessed using three items (O'Driscoll & Beehr, 1994; French version by Fernet et al., 2015; e.g., "I'm thinking about leaving my job"; α between .84 and .85) rated on 1 (strongly disagree) to 7 (strongly agree) scale.

Somatization. Somatization was assessed with six items (e.g. "Faintness or dizziness"; α between .75 and .79) from the somatization subscale of the Brief Symptom Inventory (Derogatis & Melisaratos, 1983; French version by Fortin & Coutu-Wakulczyk, 1985). Responses were provided on a 0 (not at all) to 4 (excessively) scale in reference to the past week (seven days).

Lifestyle habits. Teachers were asked to indicate the total number of sedative and sleeping pills taken in the past week (seven days), as well as the number of hours they spend physically exercising over the same period of time (one week).

Analyses

Preliminary Measurement Models

The burnout trajectories, as well as their associations with the predictors and outcomes, were estimated using factor scores (providing a partial correction for unreliability) obtained as part of preliminary measurement models (in which their measurement invariance was established; Millsap, 2011). For the burnout measure, these factor scores were: (a) taken from a bifactor measurement model to simultaneously assess respondents' global burnout levels (G-factor), while taking into account the specificity of each burnout subscale (e.g., Doherty et al., 2020); and (b) estimated in standardized units

[1] Although these values are within the lowest range of acceptability, it is important to mention that they are based on only three items each. Knowing that reliability is negatively impacted by the number of items forming a scale (e.g., Streiner, 2003), it is noteworthy that these coefficients would be higher if they were based on a larger number of items. This observation reinforces the importance of relying on an approach providing a way to achieve some level of correction for unreliability in the estimation of the GMM models, such as our reliance on factor scores (partially controlled for unreliability) in the present study.

(M = 0, SD = 1) to simplify interpretations. In contrast, for the predictor and outcome variables, factor scores were taken from more typical correlated factors models while retaining their natural measurement units (to ensure consistency with the single indicator outcome measures). Details on these preliminary analyses, their longitudinal invariance, factor correlations, and reliability estimates can be consulted in the online supplements.

Growth Mixture Models (GMM)

All analyses were conducted using Mplus 8.4 (Muthén & Muthén, 2019) using the robust maximum likelihood robust (MLR) estimator. Models were estimated using 6000 random start values, 1000 iterations, 500 second stage optimizations, and 100 final optimizations (Hipp & Bauer, 2006). Missing responses were handled using Full Information Maximum Likelihood (FIML; e.g., Enders, 2010): 951 teachers provided 2297 occasion-specific ratings (with an average of 2.42 occasion-specific ratings by participant), and 141 participants (14.83 %) completing all four time points, 389 (40.90 %) completing three time points, 146 (15.35 %) completing two time points, and 275 (28.92 %) completing a single time point. Missing responses were very rare among participants within each occasion of measurement (0% to 1.0% across items at T1 to T4). Attrition analyses revealed a small, but statistically significant correlations between age (r = .188), tenure (r = .205), and number of children at home (r = -.135) and the likelihood of being lost to attrition at the last time point (later analyses confirmed that none of these variables played a role in profile prediction). None of the other variables considered in the present study (including earlier burnout levels measured at T1-T3) were associated with the likelihood of attrition.

Linear[2] GMM including one to five (solutions stopped converging or converged on improper solutions after this point) global burnout trajectories were contrasted. In linear GMM, repeated measures are summarized via random intercepts and random slope factors. The random intercept factor reflects the initial level of the trajectories (the occasion-specific measures are linked to this factor by loadings of 1). The random slope factor reflects the rate of change of these trajectories as a function of time (the occasion-specific measures are linked to this factor by loadings reflecting the passage of time in yearly units). In the current investigation, loadings on the slope factor were fixed to a value of 0 (T1: Initial level), .3 (T2: Four months after T1), .6 (T3: Eight months after T1), and 7 (T4: Seven years after T1)[3].

Ideally, all parameters (intercepts and slope means, intercept and slope variance-covariance, and time-specific residuals) should be freely estimated across profiles (Diallo et al., 2016; Morin et al., 2011). However, this free estimation often results in improper solutions or fails to converge due to overparameterization (Diallo et al., 2016), which supports the need to rely on simpler models (e.g., Bauer & Curran, 2003). When this happens, as in the present study, equality constraints should be progressively implemented across profiles (Diallo et al., 2016). We were able to allow the means, variance, and covariance of the intercept and slope factors defining the trajectories, as well as the time-specific residuals of these trajectories, to vary across profiles. We had, however, to constrain the time-specific residuals to equality over time (homoscedasticity) based on the traditional multilevel operationalization of growth models (Li & Hser, 2011). The process used to select the optimal number of profiles is described in Section 1 of the online supplements.

Predictors and Outcomes. Predictors and outcomes were integrated to the final solution. In this study, predictors and outcomes were also specified as factor scores reflecting their longitudinal trajectories, saved from preliminary latent curve models (following a method proposed by Morin et al., 2011). These factor scores thus reflect the intercept (initial level at T1), linear slope (rate of change per year), and quadratic slope (reflecting curvilinear trends). An intercept-only model (reflecting stable trajectories) was retained for sleeping pills consumption and involvement in physical activity, a linear (intercept and linear slope) model was retained for teachers' self-efficacy, intentions to leave, and sedative consumption, and a quadratic model (intercept, linear slope, and quadratic slope) was retained for students' inattention, principals' negative leadership behaviors, and teachers' somatization. Details

[2] To verify whether burnout dynamics could differ over the short- and long-term, we considered alternative solutions relying on a quadratic (curvilinear) or latent basis (non-linear) parameterization. However, none of these alternative solutions resulted in profiles displaying evidence of curvilinearity or non-linearity.

[3] When participants differ on more than one time metric (such as occasion of measurement, tenure, or age), it remains adequate to rely on uniform time codes when (Mehta & West, 2000): (1) the regression of the slope on the other metric is equal to zero; and (2) the regression of the intercept on the other metric is equal to the slope. Both conditions were met for age and tenure.

on the preliminary analyses are described in Section 1 of the online supplements.

In a second step, a similar sequence of models was estimated to verify the role played by the linear slope of the predictors' trajectories, starting from the model retained in the first step. More precisely, we verified whether these linear slopes (reflecting changes over time in predictor levels) could predict profile membership and the slope of the burnout trajectories in a way that was identical, or differed, across profiles. Finally, a third set of models was estimated to verify whether the quadratic slopes of the predictor trajectories played a role in the prediction of burnout trajectories beyond the role already played by the intercept and linear slopes. More precisely, we verified whether these quadratic slopes could predict profile membership and the slope of the burnout trajectories in a way that was identical, or differed, across profiles. These alternative models were contrasted using the aforementioned information criteria (where a lower value indicates a better model fit; Diallo et al., 2017; Morin et al., 2016).

Outcomes levels were finally contrasted across profiles using then Mplus' Auxiliary (DCON) function (Asparouhov & Muthén, 2014; Lanza et al., 2013). This approach makes it possible to compare the profiles, defined in a probabilistic manner, in relation to a variety of outcomes.

Results

Unconditional Models

Hypothesis 1 stated that qualitatively and quantitatively distinct burnout trajectories would be identified in this study, and more specifically expected Low-Stable, Low-Increasing, High-Stable, and High-Decreasing trajectories. The results supported a three-profile solution (see Section 2 and Table S9 of the online supplements for details on this selection). This solution is illustrated in Figure 1, and had a moderate to high classification accuracy, ranging from 59.7% to 93.7% across profiles and matching the moderate entropy value (.641). Specific parameter estimates from this solution are reported in Tables S10 and S11 of the online supplements.

Profile 1 characterizes 46.06% of the teachers presenting initially moderate global levels of burnout following slightly decreasing trajectories over time (Moderate)[4]. Profile 2 represents 39.86% of the teachers characterized by initially low global levels of burnout following slightly increasing trajectories over time (Low). Finally, Profile 3 characterized a smaller proportion of teachers (14.08%) presenting initially high global levels of burnout following slightly decreasing trajectories over time (High). Although less obvious, another key difference between the profiles appears when considering the time-specific residuals, which reflect the extent to which individual scores tend to deviate from their model-estimated linear trajectories. These state-like deviations can be interpreted as the extent to which individual scores tend to follow smooth and stable linear trajectories over time (low time-specific residuals) or to follow more unstable trajectories characterized by multiple fluctuations around these linear trajectories (high time-specific residuals) (Morin et al., 2013, 2017). In this study, the size of these time-specific residuals increased as a function of profile-specific levels of burnout, so that the Low burnout profile is not only characterized by low burnout trajectories, but also by more stable trajectories, whereas the High burnout profile is characterized by more unstable burnout trajectories, with the Moderate burnout profile falling in between. These findings partially support Hypothesis 1.

Predictors

The results revealed a lack of effect of the demographic controls and supported a model in which the slopes of the predictors trajectories had an effect on the slopes of the burnout trajectories that did not differ across profiles (see Section 2 of the online supplements for additional details). Table 1 presents the results from the retained model. Hypothesis 2 stated that teachers' self-efficacy (initial levels and change) would be associated with profiles characterized by lower initial levels of burnout, and by stable or decreasing levels of burnout trajectories. Our results indicate that initial levels of self-efficacy predicted a higher probability of membership into the Low and Moderate burnout profiles relative to the High burnout one, and into the Moderate burnout profile relative to the Low burnout one. Initial levels of self-efficacy also predicted lower burnout levels at the beginning of the study beyond these effects on profile membership. Change in levels of self-efficacy, however, shared no associations with burnout

[4] In Figure 1, this decreasing tendency is only apparent after T3, even though all trajectories are linear. The appearance of non-linearity is related to the fact that time intervals were equally spaced in the drawing of the Figure to better capture the evolution of these trajectories across the first three time points (four months between T1 and T2; four months between T2 and T3), whereas the last time point (T4) was taken seven years after T1.

trajectories. These findings partially support Hypothesis 2.

Hypothesis 3 stated that teachers' perceptions of students' inattention and of principals' negative leadership behaviors (initial levels and change) would be associated with profiles characterized by higher initial levels of burnout, and by stable or increasing levels of burnout over time. Our results indicated that initial levels of students' inattention also predicted a lower probability of membership into the Low burnout profile relative to the High burnout one. Initial levels of students' inattention also predicted higher initial levels of burnout, and more pronounced decreases in burnout levels over time. Moreover, increases in students' inattention over time predicted more marked increases in burnout levels (slope factor). Finally, initial levels of principals' negative leadership behaviors (but not changes over time in these levels) predicted higher initial levels of burnout and more pronounced decreases in burnout over time. These findings partially support Hypothesis 3.

Outcomes

Hypothesis 4 stated that profiles characterized by higher initial levels of burnout and by stable or increasing burnout levels over time would be associated with higher and increasing levels of somatization, intentions to leave, and sedatives and sleeping pills consumption over time, as well as with lower and decreasing levels of involvement in physical activity. Likewise, Hypothesis 5 stated that profiles characterized by lower initial levels of burnout and by stable or decreasing burnout levels over time would be associated with lower and decreasing levels of somatization, intentions to leave, and sedatives and sleeping pills consumption over time, as well as with higher and increasing levels of involvement in physical activity. Our results reveal profiles clearly differentiated from one another on the outcomes in a way that slightly differs across outcomes (see Table 2). Initial levels of intentions to leave were the highest in the High burnout profile, then in the Moderate burnout profile, and finally in the Low burnout profile. Furthermore, whereas intentions to leave increased over time in the Low burnout profile, they decreased over time in the Moderate and High burnout profiles (more pronounced in the High burnout profile). As illustrated in Figure 2, the increasing and decreasing tendencies observed in the various profiles were not strong enough to counteract the differences observed initially, leaving the High burnout profile to experience the highest intentions to leave throughout the course of the study. The second highest levels of intentions to leave were then observed in the Moderate burnout profile, and the lowest were finally observed in the Low burnout profile.

Initial levels of somatization were the highest in the High burnout profile, then in the Moderate burnout profile, and finally in the Low burnout profile. Furthermore, whereas somatization levels increased over time in the Low and High burnout profiles, they decreased over time in the Moderate burnout profile. Somatization trajectories were also characterized by a slight quadratic (curvilinear) trend (mainly reflecting an acceleration of change after T3). This trend was more pronounced in the Moderate burnout profile, then in the Low burnout profile, and finally in the High burnout profile. As illustrated in Figure 2, the High burnout profile evidenced the highest levels of somatization, and these levels kept on increasing over time. In contrast, the Moderate burnout profile presented moderate somatization levels that decreased over time to reach a level lower than that of the Low burnout profile at the end of the study. Indeed, although the Low burnout profile presented initially low levels of somatization, these levels increased over time to reach a level higher than that of the Moderate burnout profile at the end of the study.

Initial levels of sedative consumption were the highest in the High burnout profile, and the lowest in the Low and Moderate burnout profiles. Although sedative consumption trajectories tended to display a slight increase over time, this increase did not differ across the three profiles. Levels of increases over time in sedative consumption did not differ across the three profiles. As illustrated in Figure 2, the level of sedative consumption of the High burnout profile remains higher than that of the other profiles over the course of the study.

Finally, levels of sleeping pills consumption were the highest in the High burnout profile, and the lowest in the Low and Moderate burnout profiles. In contrast, levels of involvement in physical activity over time were the highest in the Low burnout profile, and the lowest in the Moderate and High burnout profiles. Considered together, these findings generally support Hypotheses 4 and 5.

Discussion

The detrimental effects of burnout have been largely documented in past studies (Bakker & de Vries, 2020; Goering et al., 2017), especially among teachers (Capone & Petrillo, 2020). However, with few exceptions (Mäkikangas et al., 2020), past studies failed to consider the longitudinal dynamic nature of burnout among teachers, especially over extended periods spanning many years. It is an important concern given that burnout is viewed as a *chronic* psychological state of resource depletion likely to impact a large number of teachers at any given time in their career (Hakanen et al., 2006), along with substantial costs for teachers themselves (e.g., psychological distress, diminished well-being; Capone et al, 2019), and the organizations (e.g., absenteeism, turnover; Billingsley & Bettini, 2019), that can interfere with the school's educational mission (e.g., low student motivation and academic achievement; Madigan & Kim, 2020). Our study sought to address this limitation by identifying teachers' burnout trajectories over a period of seven years. We also considered the role of personal resources and job specific-stressors in relation to these trajectories. Finally, the associations between these burnout trajectories and a variety of work-related and personal outcomes were considered.

Longitudinal Trajectories of Burnout

While demonstrating the longitudinal dynamic nature of burnout, our empirical results suggested that only a limited number of profiles characterizes teachers' burnout trajectories over a seven-year period. Importantly, these three trajectories are aligned with those identified in prior research (e.g., Mäkikangas et al., 2020), and afford new insights into the developmental nature of burnout among teachers. For instance, in a sample of white-collar professionals, Mäkikangas et al. (2020) identified three longitudinal profiles representing burnout trajectories over a period of eight years. Interestingly, these profiles are very similar to those identified in the current research, displaying low and stable burnout levels (78% of the sample), high and increasing burnout levels (12%), and a last profile with more moderate burnout levels showing non-linear trajectories that differ across burnout components (10%). Indeed, the present study revealed three highly similar profiles of teachers presenting initially moderate levels of burnout following slightly decreasing trajectories (Moderate: 46.06%), initially low levels of burnout following slightly increasing trajectories (Low: 39.86%), and initially high levels of burnout following slightly decreasing trajectories (High: 14.08%).

It is noteworthy that the Low burnout profile was also the one displaying the most stable trajectory, whereas the High burnout profile displayed the most unstable trajectory, with the Moderate burnout profile falling in between. Lee and Lee (2018) also identified a well-adjusted trajectory presenting low and stable burnout levels among a sample of students. These results are interesting as they share a similarity with results obtained previously among adults (Mund & Neyer, 2016) and students (Morin et al., 2013, 2017) in the self-concept area, which have led to the development of the self-equilibrium hypothesis. According to this hypothesis, the ability to maintain high levels of self-esteem (notably affected in burnout; Ho, 2016) is conditioned on the presence of a strong core (i.e., stable) sense of identity, without which self-esteem levels are expected to become low and unstable over time. The present results suggest that a similar process might be involved in the ability to maintain low levels of burnout over time among teachers. Nevertheless, the fluctuations observed remained minimal, which is aligned with previous results showing that membership into burnout profiles generally remained stable over time (Kirves et al., 2014). Importantly, by failing to find evidence of non-linearity, our results clearly highlight similarities between the short- (four months) and long- (seven years) term dynamics of burnout. Clearly, our results reinforce the need to further investigate the mechanisms at play in these trajectories, as well as their generalizability to a broader range of cultures.

Predictors of Burnout Trajectories

Our results also demonstrated that burnout trajectories were independent from teachers' stable demographic characteristics (level of education, tenure, school level, work schedule, sex, marital status, and number of children at home), thus reinforcing the possible role of changing individual and work-related characteristics. In this regard, our results shed new light on some factors that seem to contribute to the development of teachers' burnout. More precisely, our findings confirmed the effects of job stressors (students' inattention and principal's negative leadership behaviors) and personal resources (teachers' self-efficacy) on teachers' burnout trajectories. First, initial self-efficacy levels predicted a higher probability of membership into the Low and Moderate burnout profiles relative to the High burnout profile. Initial self-efficacy levels also predicted lower initial burnout levels beyond these effects on profile membership. These results match previous cross-sectional results suggesting that teachers' self-efficacy acts as a protective individual resource against burnout (Aloe et al., 2014a; Shoji et al., 2016). Despite some previous tentative longitudinal evidence suggesting that teachers' self-efficacy might help alleviate feelings of burnout (e.g., Fernet et al., 2012), this is the first investigation to show a clear relation between teachers' self-efficacy and burnout trajectories. Thus, teachers who feel confident in having the skills necessary to successfully perform their tasks (Cherniss, 1993; Skaalvik & Skaalvik, 2017) are more likely to display low to moderate burnout trajectories over time.

However, initial levels of self-efficacy also surprisingly predicted a higher probability of membership into the Moderate burnout profile relative to the Low burnout one. Given that, from a theoretical standpoint, the degree of self-efficacy should decrease the probability of experiencing burnout (Markova, 2021), we propose a provisional explanation for this somewhat unexpected result. While self-efficacy is based on the exercise of agency, it is possible that teachers characterized by high self-efficacy may be more inclined to invest more energy in their work, especially when facing classroom management difficulties (Capone & Petrillo, 2020). The larger research on self-efficacy (e.g., Shoji et al., 2016) suggests that, when confronted with a challenging situation, individuals characterized by high self-efficacy are more proactive and innovative than others, and more likely to adopt bolder solutions to face these situations. This high involvement in a job that already requires strong commitment, such as teaching (Rickert & Skinner, 2021; Valdes et al., 2020), should contribute to reduce their emotional resources, in turn slightly increasing their burnout (Hobfoll, 2002).

Alternatively, from a developmental perspective, it is plausible that the benefits of self-efficacy might take longer to manifest, being largely influenced by experiences of mastery (Schiefele & Schaffner, 2015). Through mastery experiences, teachers would come to feel more self-efficacious and less exhausted over the course of their career, as suggested by the decreasing tendency observed among teachers belonging to the Moderate profile after T3 (i.e., seven years after T1). Additional investigations are required to clarify this question and attain a more precise understanding of the development of teachers' burnout and self-efficacy, including the possible moderating role of teachers' emotional investment in their work and exposure to stressful situations that pose a challenge to their sense of self-efficacy.

Second, initial levels of students' inattention predicted a higher probability of membership into the High burnout profile relative to the Low burnout one, as well as higher initial levels of burnout beyond these associations with profile membership. In addition, increases in students' inattention predicted more marked increases in teachers' burnout levels over time. These findings thereby accentuate that exposure to students' misbehaviors, such as inattention in the classroom, contribute to increase the risk of burnout among teachers (Aloe et al., 2014b). These effects may be explained by a decrease in teachers' self-efficacy emerging from the impression of being unable to nurture and maintain students' interest (Bandura, 1997; Friedman, 1995). Teachers' judgments about students' misbehaviors may also influence their experiences of distinct unpleasant emotions (e.g., frustration, anger), eventually increasing their risk of burnout (Chang, 2009).

Third, initial levels of principals' negative leadership behaviors predicted higher initial levels of teachers' burnout. These behaviors are known to elicit, among teachers, feelings of distrust and anxiety with regard to their exchanges with the direction (Chan & McAllister, 2014), variables themselves associated with higher burnout (Xu & Yang, 2018). While there is burgeoning evidence of the detrimental effect of principal's negative leadership behaviors (e.g., laissez-faire) on teachers' burnout (Eyal & Roth, 2011; Slemp et al., 2020), the current findings complement this focus on how these behaviors relate to burnout trajectories over the course of a career.

Finally, and unexpectedly, initial levels of students' inattention in the classroom and of exposure to principals' negative leadership behaviors predicted decreases over time in teachers' levels of burnout. Although unexpected, these results make sense from a professional identity perspective (Assunção Flores & Day, 2006), as well as according to SCT (Bandura, 1997). Indeed, when considering students' inattention, it should also be possible for teachers to learn and improve their teaching practices as a result of these early experiences of exposure to students' inattention in the classroom. Likewise, early experiences of exposure to principals' negative leadership behaviors might convey to teachers the impression that this is part of the job, leading them to become more resilient and better able to cope with such behaviors over time. Although these possibilities are supported by our results, it would be interesting to verify whether these findings would be replicated, and even would appear more pronounced, among samples of teachers entering the profession.

Outcomes of the Burnout Trajectories

The present results clearly demonstrate the associations between burnout trajectories and various work-related (intentions to leave) and personal (somatization, sedatives and sleeping pills consumption, and involvement in physical activity) outcomes. Thus, membership into the High burnout profile was linked to higher initial levels of intention to leave the profession, sedative use, sleeping pills consumption, and somatization, as well as more pronounced increases in teachers' somatization levels. In contrast, members of the Low burnout profile displayed the highest levels of involvement in physical activity. These results are generally aligned with previous research (Gerber et al., 2020; Goering et al., 2017) in relation to the detrimental effects of burnout on job and individual functioning. Such results are not surprising given that burnout entails feelings of mental distance from work and energy depletion (Maslach et al., 2001). Teachers experiencing high burnout are indeed described as disillusioned and worn-out, and are depicted as having lost the connection with their work (Maslach & Jackson, 1986), which can increase their probability of suffering from maladaptive individual and work-related consequences.

However, it should be acknowledged that teachers characterized by profiles with higher burnout levels also displayed more pronounced decreases over time in their levels of intentions to leave the occupation. This finding suggests that the positive association between burnout and intentions to leave could be limited to teachers' initial experiences of burnout, which over the long term might serve to transform the type of bond that they share with their occupation from an initially affective connection to a more instrumental one characterized by feelings of entrapment (Meyer & Allen, 1997; Meyer & Morin, 2016). Thus, it might become harder for teachers to think about leaving their occupation as instrumental benefits (i.e., side bets: Becker, 1960; Powell & Meyer, 2004) accumulate, leading to increases in the costs of leaving the occupation. This phenomenon is likely to be further reinforced by prolonged states of burnout, which are known to lead to a depletion of the psychological resources that teachers would need to successfully navigate a change of occupation (Stanley et al., 2013).

These results regarding somatization are particularly interesting as they provided further information about the shape of the longitudinal trajectories. More specifically, our results showed that the Moderate burnout profile presented moderate levels of somatization that declined over time to reach a level lower than that of the Low burnout profile at the end of the study, supporting the value of adopting a dynamic perspective. Although unexpected, this result can reflect to some extent the long-term adaptive nature of the Moderate burnout profile where decreases in burnout were complemented by corresponding decreases in somatization. This could reflect teachers who achieve an "optimal" adaptation to environment through a more challenging process, than those from the Low burnout profile, to become more effective at meeting the demands of a profession which slowly becomes part of their identity (Assunção Flores & Day, 2006). These results are encouraging as they suggest that, in this highly demanding occupation, challenging situations might strengthen psychological resilience and adaptability of teachers over the course of their career. It would be interesting to pursue this line of research by considering other positive and negative work-related (e.g., organizational commitment, presenteeism) and individual (e.g., life dissatisfaction, work-family conflict) outcomes.

Limitations and Future Directions

First, the present research relied on self-report measures, which come with an increased risk of social desirability and self-report biases. Future investigations could also consider adopting a broader multidimensional perspective for the measurement of teachers' self-efficacy, students' behaviors, and principals' leadership to widen the scope of the findings. This would make it possible, for instance, to investigate additional dimensions of teacher self-efficacy (e.g., instructional, organizational efficacy), while simultaneously considering positive (e.g., autonomy support) and negative types of leadership behaviors in the development of burnout trajectories. Future studies could also include objective indicators of teachers' behaviors (e.g., turnover), as well as multiple informants' ratings (e.g., students, peers). Second, this study involved a sample of Canadian teachers who were followed over a seven-year period. Other investigations will be needed to confirm the generalizability of the identified trajectories, and their associations with additional predictors and outcomes across different cultures and countries. Third, a strength of this study lies in the consideration of a seven-year period, the measurement sequence was more intensive at the start of the study (three time points during the first year) than later (more than six years between T3 and T4). Thus, although this allowed us to clearly establish baseline trajectories and long-term change, it made it impossible for us to specifically consider how this long-term change unfolded. It would be interesting for future studies to more intensively investigate long-term trajectories to enrich the current results.

Fourth, it is possible, given the long-term nature of the current research, that some of the teachers presenting high levels of burnout might have withdrawn from this study before the last data collection, although various verifications conducted as part of preliminary analyses suggest that this is not the case (i.e., attrition was slightly more prevalent in the Low burnout profile, and for older/more tenured employees). Unfortunately, the methods currently available to handle missing following a "not at random" process (Enders, 2011) proved to be too computationally complex to be used in combination with GMM. However, the nature of the trajectories observed within each of the profiles seems to be more consistent with a "regression to the mean" effect, where more extreme (high or low) levels of burnout seem to become less extreme over time than with losing the more highly burnout teachers through attrition. Indeed, this non missing at random data process would have resulted in a regression to the mean effect limited to the High burnout profile. Our results are thus more consistent with the idea that teachers might have developed a better balance at work: Having managed, over time, to find a greater equilibrium between their needs and the demands of their work, leading them to experience more normative levels of the negative emotions measured by burnout questionnaires over time. Future research should thus more attentively consider these various perspectives. Finally, although we considered individual and social predictors of teachers' burnout trajectories, upcoming investigations should incorporate other predictors from the larger school environment (e.g., parents, the community).

Practical Implications

Although additional research is needed to replicate our findings and shed greater clarity on the psychological mechanisms underpinning each of the burnout trajectories identified in this study, by uncovering these trajectories, as well as some of their predictors and outcomes, our findings provide insights on possible interventions to promote teachers' well-being. Importantly, all three trajectories identified in the present study, despite showcasing a slow tendency to become less extreme over time, remained quite stable over a relatively long period of time (7 years), thus suggesting that burnout is unlikely to resolve itself in the absence of intervention, and that even low levels of burnout could benefit from intervention to help them remain as low as possible. In particular, educational institutions and principals ought to focus on teachers characterized by high burnout levels as these levels are likely to persist over time and are accompanied by higher risks of impaired functioning (e.g., intentions to leave and somatization) that will prove costly for the teachers and their institutions over the long term.

Furthermore, our results also allowed us to uncover specific facets of teachers' work environment that may help nurture more desirable trajectories, or to prevent more problematic burnout trajectories and their consequences. The vision and actions of system leaders and school board members frequently determine whether principals can be effective in leading school improvement. Indeed, school board (or districts) can create the conditions that make it possible for principals to be more effective in leading school improvement. Yet, school boards may also fail to help create such favorable conditions. For instance, in some school boards, administrators try to own all the problems and enforce all solutions through top-down strategies. In others, administrators transfer all problems to the principal, offering little or no sense of direction or support, but still demanding results. Thus, in order to best manage any change initiative likely to help prevent burnout among teachers, school leaders and board members need to find the appropriate balance between central control and local autonomy (Leithwood & Janzi, 2008). Likewise, changes in the need-supportive conditions of the school board to foster more positive leadership behaviors and skills among principals may be useful to help teachers cope with job stressors and burnout (Slemp et al., 2018). More specifically, school board leaders may display a clear vision of what constitutes a good school and create a framework in which the principals have autonomy to work with the school staff and teachers on an improvement agenda while being able to capitalize on collaborative support from the school board. School board actions should also establish the conditions necessary for principals to create a different kind of school. For instance, they could expect and support the principal to become the school's instructional leader, and they could communicate the vision and strategic plan of the school to the public in a visible manner that provides a context to help principals' decisions to be supported by parents and the larger community.

Principals could also try to be less damaging through values statement, awareness campaigns, and leadership training programs (Hogan et al., 2011). More specifically, principals should create their own vision and goals of the school that are, in themselves, necessary to create a powerful learning experience for teachers and students. Under these conditions, principals should make decisions within the boundaries of a strategic framework and have control over the schedule and placement of personnel within the school. They should also be able to allocate resources for the improvement of their school, and to select professional development that is aligned with their school improvement plans.

Furthermore, the principal and teachers should also collaboratively design and implement solutions tailored to the unique needs of their own students and communities (e.g., relevant, rigorous, hands-on learning activities and programs to ensure that every student is connected with a goal and an adult who will serve as a mentor). To increase principals' awareness of their leadership behaviors, comprehensive assessments of their behaviors could be implemented. Then, principals with undesirable behaviors should be supported (e.g., training, mentoring, coaching) to become more autonomy-supportive or transformational, because these behaviors are likely to foster favorable perceptions of the workplace, including more resources and fewer demands, and to exert a lasting impact on teachers' burnout trajectories (Fernet et al., 2015; Sarmah et al., 2022).

More adaptive trajectories of burnout can also be promoted using strategies aimed at increasing self-efficacy, which can be implemented at the teacher, school, and even teacher education levels. These strategies can involve more effective cognitive emotion regulation strategies (e.g., perspective-taking, positive reappraisal; Burić et al., 2017). School leaders and professional learning facilitators have also a role in nurturing self-efficacy among teachers by helping them to develop pedagogical content knowledge (the integration of subject expertise and skilled teaching of that particular subject) as well as competence and confidence in the implementation of strategies to bring about desirable outcomes for students. In this regard, Bandura's (1997) four sources of SE, namely mastery experience, vicarious experience, social persuasion, and the interpretation of physiological and emotional states might prove particularly helpful (Dixon et al., 2020).

Finally, seeking to increase teachers' classroom management skills to deal more efficiently with challenging situations in the classroom may also be helpful for more adaptive burnout trajectories, as such training have been shown to result in a reduction of burnout (Dicke et al., 2015). For instance, teachers may make a habit of demonstrating behavior they want to see (e.g., being polite, let others speak uninterrupted), as many studies show that modelling effectively teaches students how to act in different situations (Diorio et al., 2020). Teachers may also encourage students to help build classroom expectations and rules by asking them what they believe should and should not fly in terms of appropriate behavior (e.g., acceptable noise levels). Then, they can print and distribute the list of rules that the class discussion generated and go through the list with their students. Doing so emphasizes that teachers respect students' ideas and intend to adhere to them (Ingemarson et al., 2020).

References

Aloe, A. M., Amo, L. C., & Shanahan, M. E. (2014a). Classroom management self-efficacy and burnout: A multivariate meta-analysis. *Educational Psychology Review, 26*, 101-126. https://doi.org/10.1007/s10648-013-9244-0

Aloe, A. M., Shisler, S. M., Norris, B. D., Nickerson, A. B., & Rinker, T. W. (2014b). A multivariate meta-analysis of student misbehavior and teacher burnout. *Educational Research Review, 12*, 30-44 https://doi.org/10.1016/j.edurev.2014.05.003

Asparouhov, T., & Muthén, B.O. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling, 21*, 329-341. https://doi.org/10.1080/10705511.2014.915181

Assunção Flores, M., & Day, C. (2006). Contexts which shape and reshape new teachers' identities: A multi-perspective study. *Teaching and Teacher Education, 22*, 219-232. https://doi.org/10.1016/j.tate.2005.09.002

Bakker, A. B., & de Vries, J. D. (2020). Job demands–resources theory and self-regulation: New explanations and remedies for job burnout. *Anxiety, Stress & Coping: An International Journal*. Advance online publication. https://doi.org/10.1080/10615806.2020.1797695

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.

Bauer, D. J., & Curran, P. J. (2003). Distributional assumptions of growth mixture models: Implications for overextraction of latent trajectory classes. *Psychological Methods, 8*, 338-363. https://doi.org/10.1037/1082-989X.8.3.338

Becker, H. S. (1960). Notes on the concept of commitment. *American Journal of Sociology, 66*, 32-40. https://doi.org/10.1086/222820

Benita, M., Butler, R., & Shibaz, L. (2019). Outcomes and antecedents of teacher depersonalization: The role of intrinsic orientation for teaching. *Journal of Educational Psychology, 111*, 1103-1118. https://doi.org/10.1037/edu0000328

Blais, M. R., Lachance, L., Brière, N. M., Dulude, D. M., & Richer, S. (1991). L'inventaire des perceptions du style de supervision au travail (IPSST) : Une mesure d'antécédents motivationnels [The Perceived Work Supervisors' Style Inventory (PWSSI): A measure of motivational antecedents]. Paper presented at the 14th Congrès annuel de la Société Québécoise pour la Recherche en Psychologie, Trois-Rivières, Canada.

Billingsley, B., & Bettini, E. (2019). Special education teacher attrition and retention: A review of the literature. *Review of Educational Research, 89*, 697-744. https://doi.org/10.3102/0034654319862495

Bollen, K. A., & Curran, P. J. (2006). *Latent curve models: A structural equation perspective*. Wiley.

Bottiani, J.H., Duran, C.A.K., Pas, E.T., & Bradshaw, C.P. (2019). Teacher stress and burnout in urban middle schools: Associations with job demands, resources, and effective classroom practices. *Journal of School Psychology*, *77*, 36-51. https://doi.org/10.1016/j.jsp.2019.10.002

Burić, I., Penezić, Z., & Sorić, I. (2017). Regulating emotions in the teacher's workplace: Development and initial validation of the Teacher Emotion-Regulation Scale. *International Journal of Stress Management*, *24*, 217-246. https://doi.org/10.1037/str0000035

Capone, V., & Petrillo, G. (2020). Mental health in teachers: Relationships with job satisfaction, efficacy beliefs, burnout and depression. *Current Psychology, 39*, 1757-1766. https://doi.org/10.1007/s12144-018-9878-7

Capone, V., Joshanloo, M., & Park, M. S. A. (2019). Burnout, depression, efficacy beliefs, and work-related variables among school teachers. *International Journal of Educational Research, 95*, 97-108. https://doi.org/10.1016/j.ijer.2019.02.001

Carver-Thomas, D., & Darling-Hammond, L. (2017). *Teacher turnover: Why it matters and what we can do about it*. Learning Policy Institute.

Chan, M. E., & McAllister, D. J. (2014). Abusive supervision through the lens of employee state paranoia. *The Academy of Management Review*, *39*, 44-66. https://doi.org/10.5465/amr.2011.0419

Chang, M.-L. (2009). An appraisal perspective of teacher burnout: Examining the emotional work of teachers. *Educational Psychology Review, 21*, 193-218. https://doi.org/10.1007/s10648-009-9106-y

Cherniss, C. (1993). Role of professional self-efficacy in the etiology and amelioration of burnout. In W. B. Schaufeli, C. Maslach, & T. Marek (Eds.), *Professional burnout: Recent developments in theory and research* (pp. 135-149). Taylor & Francis.

Cordes, C. L., & Dougherty, T. W. (1993). A review and an integration of research on job burnout. *The Academy of Management Review, 18*, 621-656. https://doi.org/10.2307/258593

Derogatis, L. R., & Melisaratos, N. (1983). The Brief Symptom Inventory: An introductory report. *Psychological Medicine*, *13*, 595-605. https://doi.org/10.1017/S0033291700048017

Diallo, T. M. O, Morin, A. J. S. & Lu, H. (2016). Impact of misspecifications of the latent variance-covariance and residual matrices on the class enumeration accuracy of growth mixture models. *Structural Equation Modeling, 23*, 507-531. https://doi.org/10.1080/10705511.2016.1169188

Diallo, T. M. O, Morin, A. J. S., & Lu, H. (2017). The impact of total and partial inclusion or exclusion of active and inactive time invariant covariates in growth mixture models. *Psychological Methods, 22*, 166-190. https://doi.org/10.1037/met0000084

Dicke, T., Elling, J., Schmeck, A., & Leutner, D. (2015). Reducing reality shock: The effects of classroom management skills training on beginning teachers. *Teaching and Teacher Education, 48*, 1-12. https://doi.org/10.1016/j.tate.2015.01.013

Dion, G., & Tessier, R. (1994). Validation de la traduction de l'Inventaire d'épuisement professionnel de Maslach et Jackson [Validation of a French translation of the Maslach Burnout Inventory (MBI)]. *Canadian Journal of Behavioural Science, 26*, 210-227. https://doi.org/10.1037/0008-400X.26.2.210

Diorio, R., Bray, M., Sanetti, L., & Kehle, T. (2019). Using video self-modeling to increase compliance to classroom requests in students with autism spectrum disorder. *International Journal of School & Educational Psychology, 7*, 145-157. https://doi.org/10.1080/21683603.2018.1443857

Dixon, H., Hawe, E., & Hamilton, R. (2020). The case for using exemplars to develop academic self-efficacy. *Assessment & Evaluation in Higher Education, 45*, 460-471. https://doi.org/10.1080/02602938.2019.1666084

Doherty, A., Mallett, J., Leiter, M., & McFadden, P. (2020). Measuring burnout in social work: Factorial validity of the Maslach Burnout Inventory-Human Services Survey. *European Journal of Psychological Assessment*. Advance online publication. https://doi.org/10.1027/1015-5759/a000568

Dunford, B. B., Shipp, A. J., Boss, R. W., Angermeier, I., & Boss, A. D. (2012). Is burnout static or dynamic? A career transition perspective of employee burnout trajectories. *Journal of Applied Psychology, 97*, 637-650. https://doi.org/10.1037/a0027060

Enders, C. K. (2010). *Applied missing data analysis*. Guilford.

Enders, C. K. (2011). Missing not at random models for latent growth curve analyses. *Psychological Methods, 16*, 1-16.

Eyal, R., & Roth, G. (2011). Principals' leadership and teachers' motivation: Self-determination theory analysis. *Journal of Educational Administration, 49*, 256-275. https://doi.org/10.1108/09578231111129055

Fernet, C., Senécal, C., & Guay, F. (2005). La perception d'efficacité des enseignants : validation canadienne-française du "Classroom and School Context Teacher Self-Efficacy Scale" [Teacher self-efficacy: The French Canadian validation of the "Classroom and School Context Teacher Self-Efficacy Scale"]. Paper presented at the 27th Congrès de la Société Québécoise pour la Recherche en Psychologie (SQRP), Québec, Canada.

Fernet, C., Guay, F., Senécal, C., & Austin, S. (2012). Predicting intraindividual changes in teacher burnout: The role of perceived school environment and motivational factors. *Teaching and Teacher Education, 28*, 514-525. https://doi.org/10.1016/j.tate.2011.11.013

Fernet, C., Lavigne, G. L., Vallerand, R. J., & Austin, S. (2014). Fired up with passion: Investigating how job autonomy and passion predict burnout at career start in teachers. *Work & Stress, 28*, 270-288. https://doi.org/10.1080/02678373.2014.935524

Fernet, C., Senécal, C., Guay, F., Marsh, H., & Dowson, M. (2008). The Work Tasks Motivation Scale for Teachers (WTMST). *Journal of Career Assessment, 16*, 256-279.

Fernet, C., Trépanier, S.-G., Austin, S., Gagné, M., & Forest, J. (2015). Transformational leadership and optimal functioning at work: On the mediating role of employees' perceived job characteristics and motivation. *Work & Stress, 29*, 11-31. https://doi.org/10.1080/02678373.2014.1003998

Fernet, C., Trépanier, S.-G., Austin, S., & Levesque-Côté, J. (2016). Committed, inspiring, and healthy teachers: How do school environment and motivational factors facilitate optimal functioning at career start? *Teaching and Teacher Education, 59*, 481-491. https://doi.org/10.1016/j.tate.2016.07.019

Fortin, M. F., & Coutu-Wakulczyk, G. (1985). *Validation et normalisation d'une mesure de santé mentale : le SCL-90-R*. Rapport présenté au Conseil Québécois de la Recherche Sociale (CQRS). Faculté des sciences infirmières, Université de Montréal.

Friedman, I. A. (1995). Student behavior patterns contributing to teacher burnout. *The Journal of Educational Research, 88*, 281-289. https://doi.org/10.1080/00220671.1995.9941312

Friedman, I. A. (2003). Self-efficacy and burnout in teaching: The importance of interpersonal-relations efficacy. *Social Psychology of Education: An International Journal, 6*, 191-215. https://doi.org/10.1023/A:1024723124467

Frögéli, E., Rudman, A., & Gustavsson, P. (2019). Preventing stress-related ill health among future nurses: Effects over 3 years. *International Journal of Stress Management, 26*, 272-286. https://doi.org/10.1037/str0000110

García-Carmona, M., Marín, M. D., & Aguayo, R. (2019). Burnout syndrome in secondary school teachers: A systematic review and meta-analysis. *Social Psychology of Education: An International Journal, 22*, 189-208. https://doi.org/10.1007/s11218-018-9471-9

Gerber, M., Schilling, R., Colledge, F., Ludyga, S., Pühse, U., & Brand, S. (2020). More than a simple pastime? The potential of physical activity to moderate the relationship between occupational stress and burnout symptoms. *International Journal of Stress Management, 27*, 53-64. https://doi.org/10.1037/str0000129

Gillet, N., Forest, J., Benabou, C., & Bentein, K. (2015). The effects of organizational factors, psychological need satisfaction and thwarting, and affective commitment on workers' well-being and turnover intentions. *Le Travail Humain, 78*, 119-140. https://doi.org/10.3917/th.782.0119

Goering, D. D., Shimazu, A., Zhou, F., Wada, T., & Sakai, R. (2017). Not if, but how they differ: A meta-analytic test of the nomological networks of burnout and engagement. *Burnout Research, 5*, 21-34. https://doi.org/10.1016/j.burn.2017.05.003

Hakanen, J. J., & Schaufeli, W. B. (2012). Do burnout and work engagement predict depressive symptoms and life satisfaction? A three-wave seven-year prospective study. *Journal of Affective*

Disorders, *141*, 415-424. https://doi.org/10.1016/j.jad.2012.02.043

Hakanen, J. J., Bakker, A. B., & Schaufeli, W. B. (2006). Burnout and work engagement among teachers. *Journal of School Psychology*, *43*, 495-513. https://doi.org/10.1016/j.jsp.2005.11.001

Halbesleben, J. R. B., & Buckley, M. R. (2004). Burnout in organizational life. *Journal of Management, 30*, 859-879. https://doi.org/10.1016/j.jm.2004.06.004

Hawrot, A., & Koniewski, M. (2017). Factor structure of the Maslach Burnout Inventory–Educators Survey in a Polish-speaking sample. *Journal of Career Assessment*, *26*, 515-530.

Hipp, J. R., & Bauer, D. J. (2006). Local solutions in the estimation of growth mixture models. *Psychological Methods, 11*, 36-53. https://doi.org/10.1037/1082-989X.11.1.36

Ho, S. K. (2016). Relationships among humour, self-esteem, and social support to burnout in school teachers. *Social Psychology of Education: An International Journal*, *19*, 41-59. https://doi.org/10.1007/s11218-015-9309-7

Hobfoll, S. E. (2002). Social and psychological resources and adaptation. *Review of General Psychology, 6*, 307-324. https://doi.org/10.1037/1089-2680.6.4.307

Hogan, J., Hogan, R., & Kaiser, R. B. (2011). Management derailment. In S. Zedeck (Ed.), *APA handbook of industrial and organizational psychology, Vol. 3. Maintaining, expanding, and contracting the organization* (pp. 555-575). American Psychological Association. https://doi.org/10.1037/12171-015

Hultell, D., Melin, B., & Gustavsson, J. P. (2013). Getting personal with teacher burnout: A longitudinal study on the development of burnout using a person-based approach. *Teaching and Teacher Education, 32*, 75-86. https://doi.org/10.1016/j.tate.2013.01.007

Huyghebaert, T., Gillet, N., Fernet, C., Lahiani, F.-J., & Fouquereau, E. (2018). Leveraging psychosocial safety climate to prevent ill-being: The mediating role of psychological need thwarting. *Journal of Vocational Behavior, 107*, 111-125. https://doi.org/10.1016/j.jvb.2018.03.010

Johnson, S., Cooper, C., Cartwright, S., Donald, I., Taylor, P., & Millet, C. (2005). The experience of work-related stress across occupations. *Journal of Managerial Psychology, 20*, 178-187. https://doi.org/10.1108/02683940510579803

Kalliath, T. J., O'Driscoll, M. P., Gillespie, D. F., & Bluedorn, A. C. (2000). A test of the Maslach Burnout Inventory in three samples of healthcare professionals. *Work & Stress, 14*, 35-50. https://doi.org/10.1080/026783700417212

Kaufmann, R. (2020). Negative instructor communication behaviours: Exploring associations between instructor misbehaviours and the classroom learning environment. *Learning Environments Research, 23*, 185-193. https://doi.org/10.1007/s10984-019-09297-8

Kawamata, M., Takeuchi, H., Kimura, N., Kawada, T., Milada, K., Taniwaki, N., & Harada, T. (2020). Relationship between burnout and circadian typology and sleep habits in Japanese nursery school and kindergarten teachers. *Biological Rhythm Research, 51*, 29-39. https://doi.org/10.1080/09291016.2018.1512300

Kim, L. E., & Burić, I. (2020). Teacher self-efficacy and burnout: Determining the directions of prediction through an autoregressive cross-lagged panel model. *Journal of Educational Psychology, 112*, 1661-1676. https://doi.org/10.1037/edu0000424

Kinnunen, U., Feldt, T., & de Bloom, J. (2019). Testing cross-lagged relationships between work-related rumination and well-being at work in a three-wave longitudinal study across 1 and 2 years. *Journal of Occupational and Organizational Psychology, 92*, 645-670. https://doi.org/10.1111/joop.12256

Kirves, K., Kinnunen, U., De Cuyper, N., & Mäkikangas, A. (2014). Trajectories of perceived employability and their associations with well-being at work: A three-wave study. *Journal of Personnel Psychology, 13*, 46-57. https://doi.org/10.1027/1866-5888/a000103

Klassen, R. M., Tze, V. M. C., Betts, S. M., & Gordon, K. A. (2011). Teacher efficacy research 1998-2009: Signs of progress or unfulfilled promise? *Educational Psychology Review, 23*, 21-43. https://doi.org/10.1007/s10648-010-9141-8

Kofler, M. J., Rapport, M. D., & Alderson, R. M. (2008). Quantifying ADHD classroom inattentiveness, its moderators, and variability: A meta-analytic review. *Journal of Child Psychology and Psychiatry, 49*, 59-69. https://doi.org/10.1111/j.1469-7610.2007.01809.x

Lanza, S. T., Tan, X., & Bray, B. C. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural Equation Modeling, 20,* 1-26. https://doi.org/10.1080/10705511.2013.742377

Lee, R. T., & Ashforth, B. E. (1996). A meta-analytic examination of the correlates of the three dimensions of job burnout. *Journal of Applied Psychology, 81*, 123-133. https://doi.org/10.1037/0021-9010.81.2.123

Lee, Y., & Eissenstat, S. J. (2018). A longitudinal examination of the causes and effects of burnout based on the job demands-resources model. *International Journal for Educational and Vocational Guidance, 18,* 337-354. https://doi.org/10.1007/s10775-018-9364-7

Leithwood, K., & Jantzi, D. (2008). Linking leadership to student learning: The contributions of leader efficacy. *Educational Administration Quarterly, 44*, 496-528. https://doi.org/10.1177/0013161X08321501

Leithwood, K., Menzies, T., Jantzi, D., & Leithwood, J. (1996). School restructuring, transformational leadership and the amelioration of teacher burnout. *Anxiety, Stress & Coping: An International Journal, 9*, 199-215. https://doi.org/10.1080/10615809608249402

Lesener, T., Gusy, B., & Wolter, C. (2019). The job demands-resources model: A meta-analytic review of longitudinal studies. *Work & Stress*, *33*, 76-103. https://doi.org/10.1080/02678373.2018.1529065

Levesque, M., Blais, M. R., & Hess, U. (2004). Dynamique motivationnelle de l'épuisement et du bien-être chez des enseignants africains. *Canadian Journal of Behavioural Science / Revue Canadienne des Sciences du Comportement, 36,* 190-201. https://doi.org/10.1037/h0087229

Li, L., & Hser, Y.-I. (2011). On inclusion of covariates for class enumeration of growth mixture models. *Multivariate Behavioral Research, 46,* 266-302. https://doi.org/10.1080/00273171.2011.556549

Lopes, J. A., & Oliveira, C. (2022). Teacher and school determinants of perceived classroom discipline: A multilevel analysis of TALIS 2013. *Learning Environments Research*, *25*, 41-58. https://doi.org/10.1007/s10984-021-09348-z

Madigan, D. J., & Kim, L. E. (2021). Does teacher burnout affect students? A systematic review of its association with academic achievement and student-reported outcomes. *International Journal of Educational Research, 105*, 101714. https://doi.org/10.1016/j.ijer.2020.101714

Madigan, D. J., Stoeber, J., & Passfield, L. (2015). Perfectionism and burnout in junior athletes: A three-month longitudinal study. *Journal of Sport & Exercise Psychology, 37*, 305-315. https://doi.org/10.1123/jsep.2014-0266

Mäkikangas, A., & Kinnunen, U. (2016). The person-oriented approach to burnout: A systematic review. *Burnout Research, 3,* 11-23. https://doi.org/10.1016/j.burn.2015.12.002

Mäkikangas, A., Feldt, T., Kinnunen, U., & Tolvanen, A. (2012). Do low burnout and high work engagement always go hand in hand? Investigation of the energy and identification dimensions in longitudinal data. *Anxiety, Stress & Coping: An International Journal*, *25*, 93-116. https://doi.org/10.1080/10615806.2011.565411

Mäkikangas, A., Leiter, M. P., Kinnunen, U., & Feldt, T. (2020). Profiling development of burnout over eight years: Relation with job demands and resources. *European Journal of Work and Organizational Psychology*. Advance online publication. https://doi.org/10.1080/1359432X.2020.1790651

Markova, Z. (2021). Towards a comprehensive conceptualisation of teachers' self-efficacy beliefs. *Cambridge Journal of Education, 51,* 653-671. https://doi.org/10.1080/0305764X.2021.1906844

Maslach, C. (1993). Burnout: A multidimensional perspective. In W. B. Schaufeli, C. Maslach, & T. Marek (Eds.), *Professional burnout: Recent developments in theory and research* (pp. 19-32). Taylor & Francis.

Maslach, C., & Jackson, S. E. (1986). *Maslach Burnout Inventory manual (2nd ed.)*. Consulting Psychologists Press.

Maslach, C., & Leiter, M. P. (2008). Early predictors of job burnout and engagement. *Journal of Applied Psychology, 93*, 498-512. https://doi.org/10.1037/0021-9010.93.3.498

Maslach, C., Schaufeli, W. B., & Leiter, M. P. (2001). Job burnout. *Annual Review of Psychology, 52,* 397-422. https://doi.org/10.1146/annurev.psych.52.1.397

May, R. W., Rivera, P. M., Rogge, R. D., & Fincham, F. D. (2020). School Burnout Inventory: Latent profile and item response theory analyses in undergraduate samples. *Frontiers in Psychology, 11,* Article 188. https://doi.org/10.3389/fpsyg.2020.00188

Mehta, P. D., & West, S. G. (2000). Putting the individual back into individual growth curves. *Psychological Methods, 5,* 23-43. https://doi.org/10.1037/1082-989X.5.1.23

Meyer, J. P., & Allen, N. J. (1997). *Advanced topics in organization behavior series. Commitment in the workplace: Theory, research, and application*. Sage Publications, Inc.

Meyer, J. P., & Morin, A. J. S. (2016). A person-centered approach to commitment research: Theory, research, and methodology. *Journal of Organizational Behavior, 37*, 584-612. https://doi.org/10.1002/job.2085

Millsap, R. (2011). *Statistical approaches to measurement invariance*. Taylor & Francis.

Morin, A. J. S., Maïano, C., Marsh, H. W., Nagengast, B., & Janosz, M. (2013). School life and adolescents' self-esteem trajectories. *Child Development, 84,* 1967-1988. https://doi.org/10.1111/cdev.12089

Morin, A. J. S., Maïano, C., Nagengast, B., Marsh, H. W., Morizot, J., & Janosz, M. (2011). General growth mixture analysis of adolescents' developmental trajectories of anxiety: The impact of untested invariance assumptions on substantive interpretations. *Structural Equation Modeling, 18,* 613-648. https://doi.org/10.1080/10705511.2011.607714

Morin, A. J. S., Maïano, C., Scalas, L. F., Janosz, M., & Litalien, D. (2017). Adolescents' body image trajectories: A further test of the self-equilibrium hypothesis. *Developmental Psychology*, *53*, 1501-1521. https://doi.org/10.1037/dev0000355

Morin, A. J. S., Meyer, J. P., Creusier, J., & Biétry, F. (2016). Multiple-group analysis of similarity in latent profile solutions. *Organizational Research Methods, 19,* 231-254. https://doi.org/10.1177/1094428115621148

Mund, M., & Neyer, F. J. (2016). Rising high or falling deep? Pathways of self-esteem in a representative German sample. *European Journal of Personality, 30*, 341-357. https://doi.org/10.1002/per.2063

Muthén, L. K., & Muthén, B. O. (2019). *Mplus user's guide*. Muthén & Muthén.

O'Driscoll, M. P., & Beehr, T. A. (1994). Supervisor behaviors, role stressors and uncertainty as predictors of personal outcomes for subordinates. *Journal of Organizational Behavior, 15*, 141-155. https://doi.org/10.1002/job.4030150204

Powell, D. M., & Meyer, J. P. (2004). Side-bet theory and the three-component model of organizational commitment. *Journal of Vocational Behavior, 65*, 157-177. https://doi.org/10.1016/S0001-8791(03)00050-2

Rickert, N. P., & Skinner, E. A. (2021). Parent and teacher warm involvement and student's academic engagement: The mediating role of self-system processes. *British Journal of Educational Psychology,* Article e12470. Advance online publication. https://doi.org/10.1111/bjep.12470

Rubenstein, A. L., Eberly, M. B., Lee, T. W., & Mitchell, T. R. (2018). Surveying the forest: A meta-analysis, moderator investigation, and future-oriented discussion of the antecedents of voluntary employee turnover. *Personnel Psychology*, *71*, 23-65. https://doi.org/10.1111/peps.12226

Sandrin, E., Morin, A. J. S., Fernet, C., & Gillet, N. (2022). Complementary variable- and person-centered approaches to the dimensionality of burnout among fire station workers. *Anxiety, Stress & Coping: An International Journal*, 35, 440-457. https://doi.org/10.1080/10615806.2021.1959917

Sarmah, P., Van den Broeck, A., Schreurs, B., Proost, K., & Germeys, F. (2022). Autonomy supportive and controlling leadership as antecedents of work design and employee well-being. *BRQ Business Research Quarterly, 25*, 44-61. https://doi.org/10.1177/23409444211054508

Schaufeli, W. B., & Enzmann, D. (1998). *The burnout companion to study and practice: A critical analysis*. Taylor & Francis.

Schaufeli, W. B., & Salanova, M. (2007). Efficacy or inefficacy, that's the question: Burnout and work engagement, and their relationships with efficacy beliefs. A*nxiety, Stress & Coping: An International Journal, 20*, 177-196. https://doi.org/10.1080/10615800701217878

Schaufeli, W. B., Bakker, A. B., Hoogduin, K., Schaap, C., & Kladler, A. (2001). On the clinical validity of the Maslach Burnout Inventory and the Burnout Measure. *Psychology & Health*, *16*, 565-582. https://doi.org/10.1080/08870440108405527

Schaufeli, W. B., Leiter, M., & Maslach, C. (2009). Burnout: 35 years of research and practice. *Career Development International, 14,* 204-220. https://doi.org/10.1108/13620430910966406

Scherzinger, M., & Wettstein, A. (2019). Classroom disruptions, the teacher–student relationship and classroom management from the perspective of teachers, students and external observers: A multimethod approach. *Learning Environments Research, 22*, 101-116. https://doi.org/10.1007/s10984-018-9269-x

Schiefele, U., & Schaffner, E. (2015). Teacher interests, mastery goals, and self-efficacy as predictors of instructional practices and student motivation. *Contemporary Educational Psychology*, *42*, 159-

171. https://doi.org/10.1016/j.cedpsych.2015.06.005
Shirom, A., & Melamed, S. (2006). A comparison of the construct validity of two burnout measures in two groups of professionals. *International Journal of Stress Management, 13*, 176-200. https://doi.org/10.1037/1072-5245.13.2.176
Shoji, K., Cieslak, R., Smoktunowicz, E., Rogala, A., Benight, C. C., & Luszczynska, A. (2016). Associations between job burnout and self-efficacy: A meta-analysis. *Anxiety, Stress & Coping: An International Journal, 29*, 367-386. https://doi.org/10.1080/10615806.2015.1058369
Skaalvik, E. M., & Skaalvik, S. (2017). Motivated for teaching? Associations with school goal structure, teacher self-efficacy, job satisfaction and emotional exhaustion. *Teaching and Teacher Education, 67*, 152-160. https://doi.org/10.1016/j.tate.2017.06.006
Slemp, G. R., Field, J. G., & Cho, A. S. H. (2020). A meta-analysis of autonomous and controlled forms of teacher motivation. *Journal of Vocational Behavior, 121*, Article 103459. https://doi.org/10.1016/j.jvb.2020.103459
Slemp, G. R., Kern, M. L., Patrick, K. J., & Ryan, R. M. (2018). Leader autonomy support in the workplace: A meta-analytic review. *Motivation and Emotion, 42*, 706-724. https://doi.org/10.1007/s11031-018-9698-y
Stanley, L., Vandenberghe, C., Vandenberg, R., & Bentein, K. (2013). Commitment profiles and employee turnover. *Journal of Vocational Behavior, 82*, 176-187. https://doi.org/10.1016/j.jvb.2013.01.011
Streiner, D. L. (2003). Starting at the beginning: An introduction to coefficient alpha and internal consistency. *Journal of Personality Assessment, 80*, 99-103. https://doi.org/10.1207/S15327752JPA8001_18
Szigeti, R., Balázs, N., Bikfalvi, R., & Urbán, R. (2017). Burnout and depressive symptoms in teachers: Factor structure and construct validity of the Maslach Burnout Inventory-Educators Survey among elementary and secondary school teachers in Hungary. *Stress & Health, 33*, 530-539. https://doi.org/10.1002/smi.2737
Tschannen-Moran, M., & Hoy, A. W. (2001). Teacher efficacy: Capturing an elusive construct. *Teaching and Teacher Education, 17*, 783-805. https://doi.org/10.1016/S0742-051X(01)00036-1
Valdes, O. M., Denner, J., Dickson, D. J., & Laursen, B. (2020). Teacher expectations and perceived teacher involvement anticipate changes in latino/a middle school students' expectations of math success. *Educational Psychology*. Advance online publication. https://doi.org/10.1080/01443410.2020.1837345
van der Doef, M., Mbazzi, F. B., & Verhoeven, C. (2012). Job conditions, job satisfaction, somatic complaints and burnout among East African nurses. *Journal of Clinical Nursing, 21*, 1763-1775. https://doi.org/10.1111/j.1365-2702.2011.03995.x
von der Embse, N. P., Pendergast, L. L., Segool, N., Saeki, E., & Ryan, S. (2016). The influence of test-based accountability policies on school climate and teacher stress across four states. *Teaching and Teacher Education, 59*, 492-502. https://doi.org/10.1016/J.TATE.2016.07.013
Vlasie, D. (2021). *Santé et bien-être du personnel enseignant : Portrait de la situation et pistes de solutions*. Études et recherches, Québec, Conseil supérieur de l'éducation.
Wang, M.-T., Chow, A., Hofkens, T., & Salmela-Aro, K. (2015). The trajectories of student emotional engagement and school burnout with academic and psychological development: Findings from Finnish adolescents. *Learning and Instruction, 36*, 57-65. https://doi.org/10.1016/j.learninstruc.2014.11.004
Xu, Z., & Yang, F. (2018). The impact of perceived organizational support on the relationship between job stress and burnout: A mediating or moderating role? *Current Psychology*. Advance online publication. https://doi.org/10.1007/s12144-018-9941-4

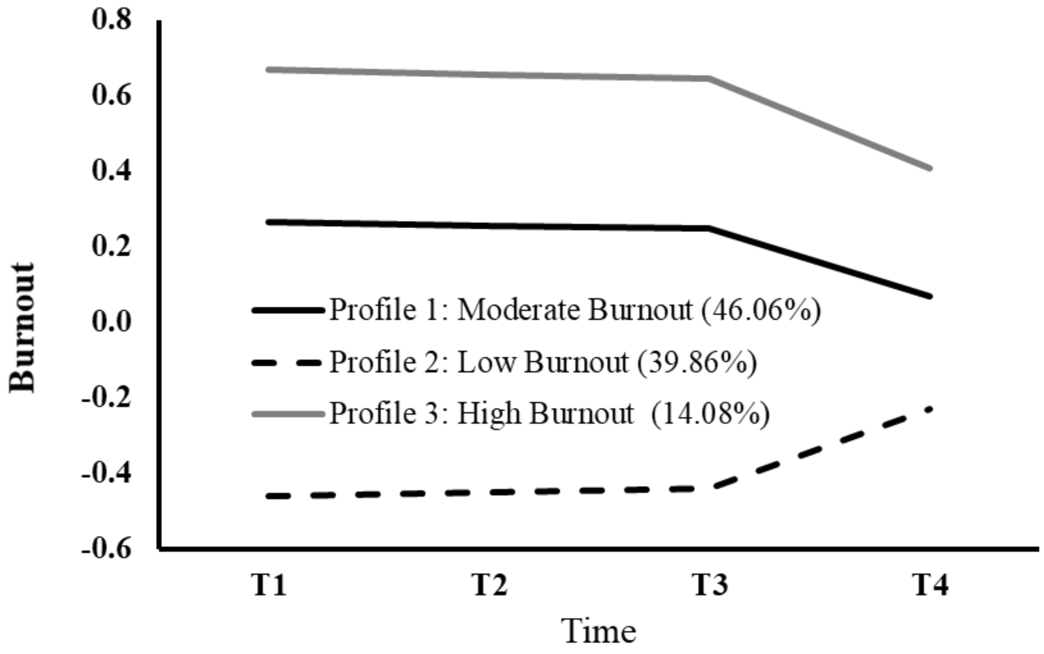

Figure 1
Burnout Growth Trajectories
Note. All trajectories are linear. The appearance of non-linearity is related to the fact that time intervals were equally spaced in the drawing of the Figure to better capture the evolution of these trajectories across the first three time points (interval between Time 1 and Time 2: Four months; between Time 2 and Time 3: Four months), whereas the last time point (Time 4) was taken seven years after Time 1.

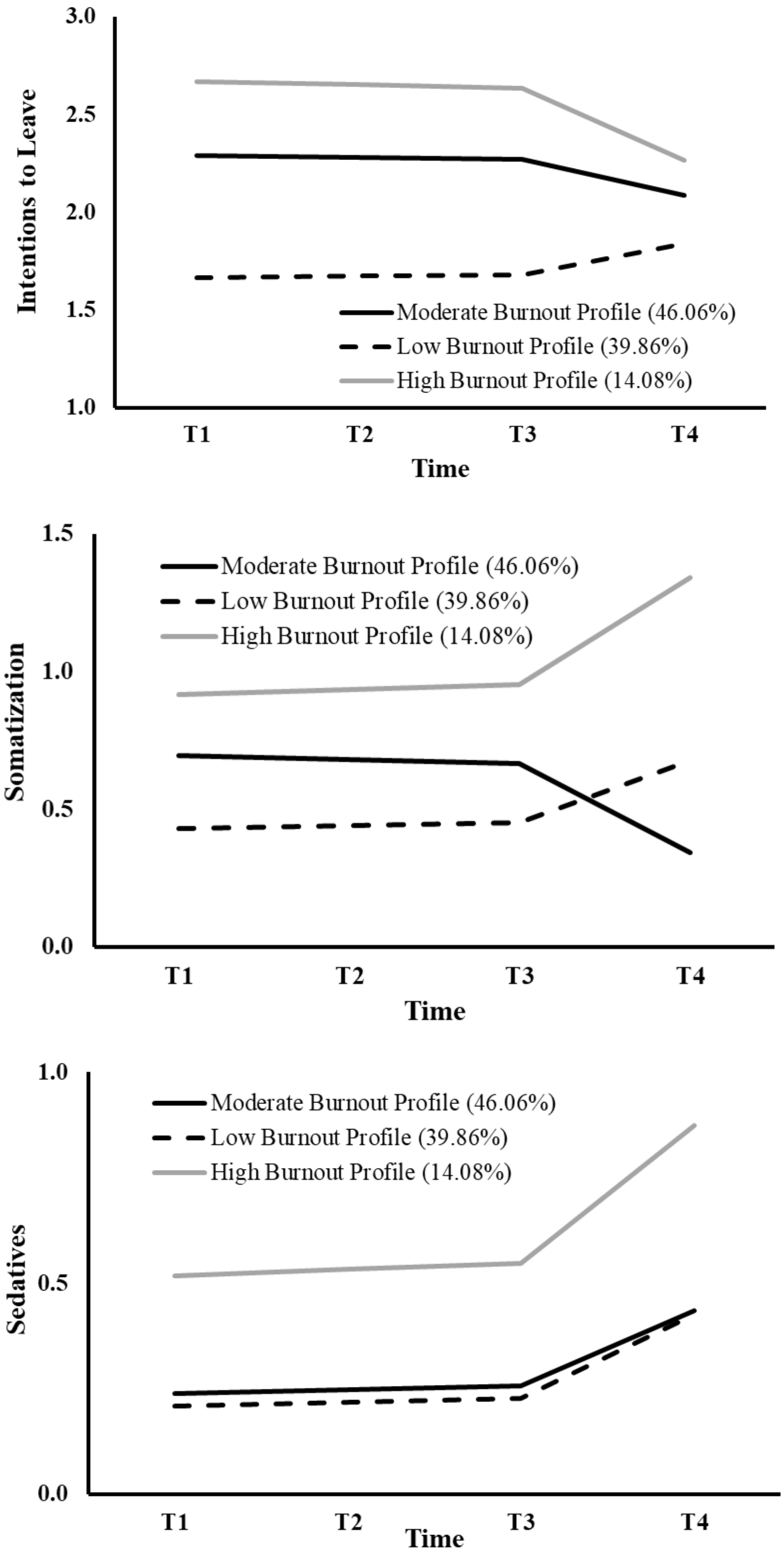

Figure 2
Profile-Specific Outcomes Trajectories
Note. Trajectories are linear for intentions to leave (upper left) and use of sedatives (bottom), but quadratic for somatization (upper right). The appearance of non-linearity for the intentions to leave and sedative trajectories is related to the fact that time intervals were equally spaced in the drawing of the Figure to better capture the evolution of these trajectories across the first three time points (interval between Time 1 and Time 2: Four months; between Time 2 and Time 3: Four months), whereas the last time point (Time 4) was taken seven years after Time 1.

Table 1

Results from the Predictive Analyses

	Profile 1 (Moderate) vs 3 (High)		Profile 2 (Low) vs 3 (High)		Profile 1 (Moderate) vs 2 (Low)	
Predictors	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Students' Inattention (Intercept)	-.765 (.780)	.465	-1.104 (.466)*	.331	.339 (.367)	1.403
Teachers' Self-Efficacy (Intercept)	.842 (.367)*	2.321	.923 (.308)**	2.517	.661 (.181)**	1.937
Principals' Negative Leadership Behaviors (Intercept)	.303 (.246)	1.353	-.359 (.227)	.699	-.081 (.197)	.922

	Intercept Factor		Slope Factor	
Predictors	*b* (SE)	β	*b* (SE)	β
Students' Inattention (Intercept)	.404 (.088)**	.154	-.032 (.008)**	-.242
Teachers' Self-Efficacy (Intercept)	-.240 (.047)**	-.186	.001 (.012)	.022
Principals' Negative Leadership Behaviors (Intercept)	.225 (.040)**	.213	-.017 (.004)**	-.323
Students' Inattention (Linear Slope)			.072 (.033)*	.132
Teachers' Self-Efficacy (Linear Slope)			-.003 (.007)	-.023
Principals' Negative Leadership Behaviors (Linear Slope)			-.214 (.185)	-.252

Note. * $p < .05$; ** $p < .01$; Coef.: Multinomial logistic regression coefficient; OR: Odds ratio; *b*: Unstandardized regression coefficient; β: Standardized regression coefficient; SE: Standard error of the coefficient; the coef. and OR reflect the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile.

Table 2

Associations between Profile Membership and the Outcomes

	Profile 1 (Moderate) *M* [CI]	Profile 2 (Low) *M* [CI]	Profile 3 (High) *M* [CI]	Significant Differences
Intentions to Leave (Intercept)	2.287 [2.179; 2.395]	1.664 [1.599; 1.729]	2.669 [2.444; 2.894]	3 > 1 > 2
Intentions to Leave (Linear)	-.029 [-.041; -.017]	.025 [.015; .035]	-.058 [-.082; -.034]	2 > 1 > 3
Somatization (Intercept)	.694 [.649; .739]	.431 [.400; .462]	.916 [.816; 1.016]	3 > 1 > 2
Somatization (Linear)	-.051 [-.075; -.027]	.035 [.013; .057]	.061 [.022; .100]	2 = 3 > 1
Somatization (Quadratic)	.029 [.025; .033]	.017 [.013; .021]	.006 [.000; .012]	1 > 2 > 3
Sedatives (Intercept)	.239 [.180; .298]	.208 [.155; .261]	.517 [.297; .737]	3 > 1 = 2
Sedatives (Linear)	.028 [.022; .034]	.031 [.023; .039]	.051 [.024; .078]	1 = 2 = 3
Sleeping Pills (Intercept)	.451 [.410; .492]	.418 [.391; .445]	.592 [.441; .743]	3 > 1 = 2
Physical Activity (Intercept)	3.743 [3.543; 3.943]	4.174 [3.911; 4.437]	3.431 [3.123; 3.739]	2 > 1 = 3

Note. M: Mean; CI: 95% confidence interval.

Online Supplemental Materials for:
Predictors and Outcomes of Teachers' Burnout Trajectories over a Seven-Year Period

Authors' note:

These online technical appendices are to be posted on the journal website and hot-linked to the manuscript. If the journal does not offer this possibility, these materials can alternatively be posted on one of our personal websites (we will adjust the in-text reference upon acceptance).
We would also be happy to have some of these materials brought back into the main manuscript, or included as published appendices if you deem it useful. We developed these materials to provide additional technical information and to keep the main manuscript from becoming needlessly long.

Section 1: Preliminary Measurement and Latent Curve Models

A Bifactor Operationalization of Burnout

As noted in the main manuscript, accumulating research evidence supports the idea that burnout ratings are best represented by a bifactor operationalization (e.g., Morin et al., 2016, 2020) making it possible to simultaneously assess respondents' global levels of burnout (G-factor; defined by all burnout items) while accounting for the specificity remaining at the levels of each burnout subscale (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).

Preliminary Measurement Models: Estimation

Preliminary measurement models were estimated using Mplus 8.4 (Muthén & Muthén, 2019) and the robust Maximum Likelihood (MLR) estimator, which provides parameter estimates, standard errors, and goodness-of-fit indices that are robust to the non-normality of the response scales used in the present study. These models were estimated using Full Information Maximum Likelihood (FIML; Enders, 2010) procedures to account for the limited amount of missing responses present at the item level (0% to 0.6% across items at Time 1; 0% to 0.9% across items at Time 2; 0% to 1.0% across items at Time 3; and 0% to 1.6% across items at Time 4). Due to the complexity of the models underlying all constructs assessed in this study, preliminary analyses were conducted separately for the burnout measure, for the multi-item predictors (students' inattention, teachers' self-efficacy, and principals' negative leadership behaviors), and for the multi-item outcomes (intentions to leave and somatization).

For the burnout measure, a bifactor-confirmatory factor analytic (CFA) model (e.g., Mészáros et al., 2014; Szigeti et al., 2017) including one burnout G-factor and two orthogonal S-factors (cynicism and emotional exhaustion) was estimated. We also contrasted this solution to a simpler correlated factors CFA solution in which items were only allowed to load on their a priori dimension. For the predictors, a CFA model including three correlated factors (i.e., students' inattention, teachers' self-efficacy, and principals' negative leadership behaviors) was estimated. Finally, for the outcomes, a CFA model including two correlated factors (i.e., intentions to leave and somatization) was estimated.

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

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

Preliminary Measurement Models: Results

The goodness-of-fit results from all burnout models are reported in Table S1. These results clearly support the adequacy of the a priori bifactor-CFA model underlying the burnout measure (with all CFI and TLI $\geq$ .90, and all RMSEA $\leq$ .08) and its superiority relative to the correlated factors CFA model which failed to achieve a satisfactory level of model fit at all time points. This solution was thus retained for tests of measurement invariance. The results from these tests, reported in the bottom section of Table S1, supported the configural, weak, strong, strict, latent variance-covariance, and latent means invariance of the model. These results thus show that the measurement model underlying burnout ratings is fully equivalent over time, leading to the estimation of similar constructs. The lack of latent mean difference indicates that average burnout levels remains stable over time. Factor scores were saved from this model of latent mean invariance for the main analyses, using the standardized factors approach to set the scale of the repeated measure, thus resulting in burnout scores that are easy to interpret in standardized units (with a mean of 0 and a SD of 1).

Parameter estimates from this final model of latent means invariance are reported in Table S2. When interpreting bifactor-CFA results, it is important to keep in mind that, because bifactor models rely on two factors to explain the covariance present at the item level for each specific item, factor loadings on G- and S-factors are typically lower than their first-order counterparts (e.g., Morin et al., 2016, 2020). As such, the critical question when interpreting a bifactor solution is whether the G-factor really taps into a meaningful amount of covariance shared among all items, and whether there remains sufficient specificity at the subscale level unexplained by the G-factor to result in the estimation of meaningful S-factors. The results from the bifactor-CFA solution revealed a well-defined G-factor over time (ω = .902) with strong positive loadings from the emotional exhaustion (λ = .516 to .832; M_λ =.668) items, and moderate positive loadings from the cynicism (λ = .249 to .541; M_λ = .357) items. Over and above this G-factor, items associated with the cynicism (λ =.227 to .685; M_λ = .427; ω = .583) and emotional exhaustion (λ = -.010 to .594; $M_{|\lambda|}$ = .360; ω = .758) S-factors both retained some specificity.

The goodness-of-fit results associated with all predictor models are reported in Table S3. These results clearly support the adequacy of the a priori CFA solution underlying the predictor measures (with all CFI and TLI ≥ .90, and all RMSEA ≤ .08), as well as its configural, weak, partial strong (equality constraints had to be relaxed on the intercepts of two of the students' inattention items which were slightly lower at Time 4), strict, and latent variance-covariance invariance. These results also revealed latent means differences over time, suggesting increased levels of students' inattention and teachers' self-efficacy at Time 4. The goodness-of-fit results from all outcome models are reported in the bottom section of Table S3. These results clearly support the adequacy of the a priori CFA model underlying the outcome measures (with all CFI and TLI ≥ .90, and all RMSEA ≤ .08), as well as its configural, weak, strong, strict, and latent variance-covariance invariance. These results revealed latent means differences over time, suggesting increased levels of somatization at Time 4.

Parameter estimates from the most invariant models are reported in Tables S4 (predictors) and S5 (outcomes). The results from these solutions revealed well-defined factors over time: Students' inattention (λ =.536 to .756; M_λ = .659; ω = .846 to .868), teachers' self-efficacy (λ = .612 to .884; M_λ = .759; ω = .782 to .821), intentions to leave (λ =.717 to .877; M_λ = .811; ω = .849 to .855), and somatization (λ =.476 to .661; M_λ = .586; ω = .733 to .779), and principals' negative leadership behaviors (λ =.581 to .739; M_λ = .652; ω = .666 to .717). Correlations obtained between all variables (i.e., factor scores and single-item measures) used in this study are reported in Table S6.

Preliminary Latent Curve Models for the Predictors and Outcomes

In order to be able to account for the shape of intra-individual trajectories characterizing individual scores on the predictors and outcomes when testing their associations with the burnout trajectories, we relied on a method initially proposed by Morin et al. (2011; see also Guay et al., 2020). More precisely, latent curve models were estimated for each predictor and outcome variable with the goal of identifying the optimal functional shape to depict the longitudinal trajectories taken by each of these variables in the sample (Bollen & Curran, 2006). For the single-indicators outcomes (i.e., sedatives, sleeping pills, and physical activity), these LCM were estimated using the raw scores obtained on these measures to retain their natural measurement scale. For the multiple-indicators outcomes, these LCM were estimated using factor scores saved from the models of strict invariance (the scale of the factors was set using the referent indicators approach) to preserve the natural measurement scale of these variables. Most variables were measured at all four time points, allowing us to contrast intercept-only (i.e. stable trajectories), linear (trajectories showing a linear increase or decrease), quadratic (U-shape, or inverted U-shape trajectories), and latent basis (non-linear trajectories) solutions (Grimm et al., 2016). However, sleeping pills consumption and involvement in physical activity were only measured at Times 1 to 3, making it impossible to estimate quadratic trajectories for these two outcomes. For all predictors and outcomes for which four time points were available, we needed to rely a homoscedastic specification of the time-specific residuals (i.e., constraining them to equality over time; e.g., Li & Hser, 2011; Tofighi & Enders, 2007) to achieve convergence. However, time-specific residuals were freely in the intercept-only, linear, and latent basis specifications.

The model fit results from these alternative solutions is reported in Table S7 of these online supplements. These results first support the superiority of a quadratic specification for students' inattention and principals' negative leadership behaviors (in terms of superior model fit and statistically significant estimates of the quadratic slope). Despite the fact that the latent basis specification appeared to fit better than the quadratic one for somatization, this latent basis specification essentially revealed trajectories matching a quadratic shape, without providing us with the ability to use this information in later analyses. For this reason, the quadratic model was also retained for somatization. In contrast, the linear parameterization appeared to provide an optimal representation of teachers' self-efficacy, intentions to leave, and sedative consumption (showing a level of fit that was higher, or equivalent, to that of the more complex quadratic or latent basis models who displayed no true evidence of non-linearity). Finally, sleeping pills consumption and involvement in physical activity displayed generally stable trajectories over time, leading us to retain an intercept-only model for these variables (although the linear and latent basis models provided a better fit the data for physical activity, they revealed no evidence of linearity or non-linearity). The parameter estimates from these models are reported in Table S8 of these online supplements. Factor scores, reflecting the initial level, linear slopes, and the quadratic slopes for these variables, were saved and used in the main analyses.

Section 2: Growth Mixture Models (GMM)

Selection of the Optimal Number of Profiles: Procedure

The optimal number of profiles was determined by considering the theoretical conformity, heuristic meaning, and statistical adequacy of each solution (Bauer & Curran, 2003; Muthén, 2003). This selection was also guided by statistical indices, including the Bayesian Information Criterion (BIC), its sample-size adjusted version (ABIC) and its Integrated Classification Likelihood version (ICL-BIC, which is corrected for the model entropy, an indicator classification accuracy), the Akaïke Information Criterion (AIC) and its consistent version (CAIC), and two types of likelihood ratio tests (LRT): (1) the Lo, Mendell, and Rubin's (2001) adjusted LRT (ALMR), and (2) the Bootstrap LRT (BLRT). When statistically significant, the ALMR or BLRT support the addition of a profile relative to the previous solution, whereas lower values on the BIC, ABOC, ICL-BIC, AIC, and CAIC suggest a superior model fit. According to statistical simulation studies, the BIC, ABIC, ICL-BIC, CAIC, and BLRT are effective (e.g., Nylund et al., 2007; Tein et al., 2013), whereas the AIC and ALMR seem to be problematic (we thus only report them to ensure complete disclosure). However, these indicators are all impacted by sample size (Marsh et al., 2009), and thus often fail to converge on a specific solution (i.e., they keep on suggesting the addition of profiles). When this happens, the information criteria should be presented graphically using "elbow plots" in which the point after which the slope flattens suggests the optimal number of profiles (Morin, 2016; Morin et al., 2011).

Selection of the Optimal Number of Profiles: Results

The top section of Table S9 includes the results from the unconditional GMM. All of the indicators failed to converge on a specific solution (kept on suggesting the addition of more profiles). The graphical representation of these indices (see Figure S1) reveals a plateau in the decrease of the values of the information criteria around two profiles for the BIC, ABIC and CAIC, but three profiles for the ICL-BIC. Examination of these two solutions, as well of the adjacent four-profile solution, reveals that moving from two to three profiles resulted in a meaningful addition to the solution, corresponding to a profile characterized by average levels of burnout. In contrast, the four-profile solution resulted in the estimation of two highly similar profiles (both presenting moderate, and similar, levels of burnout). The three-profile solution was thus selected.

Inclusion of Predictors: Procedure

Models including predictors were contrasted based on a strategy suggested by Diallo et al. (2017) and implemented in research by Morin et al. (2011, 2012, 2013). In a first step, we verified the role played by the intercepts of the predictors' trajectories by contrasting six alternative models: (a) A null effects model (the effects of the predictors on the probability of profile membership and the growth factors were fixed to be zero); (b) the predictors were allowed to predict profile membership; (c-d) the predictors were allowed to predict within-profile variations in the intercepts (c) and slopes (d) of the trajectories; and (e-f) in which these within-profile effects were allowed to differ across profiles. In a preliminary step, however, we realized preliminary analyses (using the same sequence) to verify the role played by control variables (sex, marital status, level of education, tenure, school level, work schedule, and number of children at home; age was not retained given its very high correlation with tenure) to assess whether these controls should be incorporated to the main models.

Inclusion of Predictors: Results

In relation to the demographic controls, the lowest values on all information criteria were associated with the null effects model (see Table S9), indicating a lack of effect of these variables. For this reason, these variables will not be retained as controls for the main analyses. Turning our attention to the models including the intercepts of the trajectories of our theoretical predictors, the results support a model including an effect of these intercepts on profile membership and on the intercept and slope of the burnout trajectories that did not differ across profiles (Model I5 resulted in the lowest BIC, ABIC, ICL-BIC, and CAIC). This model thus formed the baseline for the next analyses. These additional results supported a model in which the slopes of the predictors trajectories had an effect on the slopes of the burnout trajectories that did not differ across profiles (Model L3 resulted in the lowest BIC, ICL-BIC, and CAIC, and in a lower value on all information criteria relative to Model I5). Finally, results from analyses in which the quadratic slopes of the predictor trajectories were added to Model L3 supported a null effects model (Model Q1 resulted in the lowest values of the BIC, ICL-BIC, and CAIC), indicating a lack of effects of these quadratic slopes. It should be noted that, across all comparisons, the parameter estimates also supported our decision to retain Model L3.

References used in this supplement

Barcza-Renner, K., Eklund, R.C., Morin, A.J.S., & Habeeb, C.M. (2016). Controlling coaching behaviors and athlete burnout: Investigating the mediating roles of perfectionism and motivation. *Journal of Sport & Exercise Psychology, 38*, 30-44.

Bauer, D. J., & Curran, P. J. (2003). Distributional assumptions of growth mixture models: Implications for overextraction of latent trajectory classes. *Psychological Methods, 8*, 338-363.

Bollen, K.A., & Curran, P.J. (2006). *Latent curve models: A structural equation perspective*. Wiley.

Chen, F.F. (2007). Sensitivity of goodness of fit indexes to lack of measurement. *Structural Equation Modeling*, *14*, 464-504.

Cheung, G.W., & Rensvold, R.B. (2002). Evaluating goodness-of fit indexes for testing measurement invariance. *Structural Equation Modeling*, *9*, 233-255.

Doherty, A., Mallett, J., Leiter, M., & McFadden, P. (2020). Measuring burnout in social work: Factorial validity of the Maslach Burnout Inventory-Human Services Survey. *European Journal of Psychological Assessment*. Early view. doi: 10.1027/1015-5759/a000568

Enders, C.K. (2010). *Applied missing data analysis*. Guilford.

Grimm, K.J., Ram, N., & Estabrook, R. (2016). *Growth modeling*. Guilford.

Guay, F., Morin, A.J.S., Litalien, D., Howard, J.L. & Gilbert, W. (2020). Trajectories of self-determined motivation during the secondary school: A growth mixture analysis. *Journal of Educational Psychology*. Early view. doi: 10.1037/edu0000482

Hawrot, A., & Koniewski, M. (2018). Factor structure of the Maslach Burnout Inventory–Educators Survey in a Polish-speaking sample. *Journal of Career Assessment*, *26*, 515-530.

Hu, L.T., & Bentler, P.M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*, 1-55.

Isoard-Gautheur, S., Martinent, G., Guillet-Descas, E., Trouilloud, D., Cece, V., & Mette, A. (2018). Development and evaluation of the psychometric properties of a new measure of athlete burnout: The Athlete Burnout Scale. *International Journal of Stress Management, 25*, 108-123.

Li, L., & Hser, Y.-I. (2011). On inclusion of covariates for class enumeration of growth mixture models. *Multivariate Behavioral Research*, *46*, 266-302.

Lo, Y., Mendell, N., & Rubin, D. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*, 767-778.

Marsh, H.W., Hau, K., & Grayson, D. (2005). Goodness of fit evaluation in structural equation modeling. In A. Maydeu-Olivares & J. McArdle (Eds.), *Contemporary psychometrics*. Erlbaum.

Marsh, H.W., Lüdtke, O., Trautwein, U., & Morin, A.J.S. (2009). Latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to the internal/external frame of reference model. *Structural Equation Modeling*, *16*, 1-35.

Mészáros, V., Ádám, S., Szabó, M., Szigeti, R., & Urbán, R. (2014). The bifactor model of the Maslach Burnout Inventory–Human Services Survey (MBI-HSS)—An alternative measurement model of burnout. *Stress and Health*, *30*, 82-88.

Millsap, R. (2011). *Statistical approaches to measurement invariance*. Taylor & Francis.

Morin, A.J.S. (2016). Person-centered research strategies in commitment research. In J.P. Meyer (Ed.), *The handbook of employee commitment* (pp. 490-508). Edward Elgar.

Morin, A.J.S., Arens, A., & Marsh, H.W. (2016). A bifactor exploratory structural equation modeling framework for the identification of distinct sources of construct-relevant psychometric multidimensionality. *Structural Equation Modeling*, *23*, 116-139.

Morin, A.J.S., Maïano, C., Marsh, H.W., Nagengast, B., & Janosz, M. (2013). School life and adolescents' self-esteem trajectories. *Child Development*, *84*, 1967-1988.

Morin, A.J.S., Maïano, C., Nagengast, B., Marsh, H.W., Morizot, J., & Janosz, M. (2011). Growth mixture modeling of adolescents' trajectories of anxiety: The impact of untested invariance assumptions on substantive interpretations. *Structural Equation Modeling*, *18*, 613-648.

Morin, A.J.S., Myers, N.D., & Lee, S. (2020). Modern factor analytic techniques: Bifactor models, exploratory structural equation modeling (ESEM) and bifactor-ESEM. In G. Tenenbaum & R.C. Eklund (Eds.), *Handbook of sport psychology, 4th Edition, Vol. 2 (pp. 1044-1073)*. Wiley.

Morin, A.J.S., Rodriguez, D., Fallu, J.-S., Maïano, C., & Janosz, M. (2012). Academic achievement and smoking initiation in adolescence: A general growth mixture analysis. *Addiction*, *107*, 819-828.

Muthén, B.O. (2003). Statistical and substantive checking in growth mixture modeling: Comment on Bauer and Curran (2003). *Psychological Methods*, *8*, 369-377.

Muthén, L.K., & Muthén, B.O. (2019). *Mplus user's guide*. Muthén & Muthén.

Nylund, K.L., Asparouhov, T., & Muthén, B.O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, *14*, 535-569.

Szigeti, R., Balázs, N., Bikfalvi, R., & Urbán, R. (2017). Burnout and depressive symptoms in teachers: Factor structure and construct validity of the Maslach Burnout Inventory—Educators Survey among elementary and secondary school teachers in Hungary. *Stress and Health*, *33*, 530-539.

Tein, J.Y., Coxe, S., & Cham, H. (2013). Statistical power to detect the correct number of classes in latent profile analysis. *Structural Equation Modeling*, *20*, 640-657.

Tofighi, D., & Enders, C.K. (2007). Identifying the correct number of classes in growth mixture models. In G.R. Hancock & K.M. Samuelsen (Eds.), *Advances in latent variable mixture models* (pp. 317-341). Information Age.

Table S1

Preliminary Measurement Models: Fit Statistics (Burnout)

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Time 1 CFA	610.553 (76)*	.897	.877	.086	[.080; .093]				
Time 1 B-CFA	278.658 (63)*	.958	.940	.060	[.053; .068]				
Time 2 CFA	458.752 (76)*	.898	.878	.088	[.081; .096]				
Time 2 B-CFA	193.024 (63)*	.965	.950	.056	[.048; .066]				
Time 3 CFA	425.028 (76)*	.901	.882	.094	[.086; .103]				
Time 3 B-CFA	174.414 (63)*	.968	.954	.059	[.048; .069]				
Time 4 CFA	171.651 (76)*	.888	.866	.081	[.065; .098]				
Time 4 B-CFA	117.238 (63)*	.937	.909	.067	[.048; .086]				
Longitudinal B-CFA: Configural invariance	2027.286 (1290)*	.962	.955	.025	[.022; .027]	-	-	-	-
Longitudinal B-CFA: Weak invariance	2112.217 (1365)*	.962	.957	.024	[.022; .026]	89.349 (75)	.000	+.002	-.001
Longitudinal B-CFA: Strong invariance	2190.326 (1398)*	.960	.955	.024	[.022; .026]	78.303 (33)*	-.002	-.002	.000
Longitudinal B-CFA: Strict invariance	2309.897 (1440)*	.956	.952	.025	[.023; .027]	101.908 (42)*	-.004	-.003	+.001
Longitudinal B-CFA: Variance-Covariance invariance	2322.132 (1449)*	.955	.953	.025	[.023; .027]	12.210 (9)	-.001	+.001	.000
Longitudinal B-CFA: Latent means invariance	2377.344 (1458)*	.953	.950	.026	[.024; .028]	56.720 (9)*	-.002	-.003	+.001

Note. * $p < .01$; CFA: Confirmatory factor analysis; B-CFA: Bifactor-confirmatory factor analysis; χ^2: Robust 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; Δ: Change in fit relative to the comparison model.

Table S2

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Bifactor-CFA Solution (Burnout)

	G-Burnout	S-Cynicism	S-Emotional exhaustion	
Items	λ	λ	λ	δ
Cynicism				
Item 1	.359	.281		.792
Item 2	.356	.685		.404
Item 3	.451	.594		.444
Item 4	.249	.350		.815
Item 5	.369	.227		.812
Emotional exhaustion				
Item 1	.640		.497	.344
Item 2	.576		.594	.315
Item 3	.580		.492	.421
Item 4	.832		*-.010*	.307
Item 5	.700		.586	.165
Item 6	.662		.216	.515
Item 7	.516		.303	.642
Item 8	.801		*-.079*	.351
Item 9	.706		.464	.287
ω	.902	.583	.758	

Note. G = Global factor estimated as part of a bifactor model; S = Specific factor estimated as part of a bifactor model; λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of model-based composite reliability; non-significant parameters ($p \geq .05$) are marked in italics.

Table S3

Preliminary Measurement Models: Fit Statistics (Predictors and Outcomes)

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Predictors									
Time 1 CFA	250.215 (74)*	.948	.936	.050	[.043; .057]				
Time 2 CFA	251.925 (74)*	.934	.919	.061	[.053; .069]				
Time 3 CFA	211.011 (74)*	.942	.929	.060	[.050; .069]				
Time 4 CFA	98.390 (74)*	.965	.957	.041	[.013; .061]				
Longitudinal CFA: Configural invariance	2185.847 (1334)*	.940	.930	.026	[.024; .028]	-	-	-	-
Longitudinal CFA: Weak invariance	2221.148 (1367)*	.939	.932	.026	[.024; .028]	37.197 (33)	+.001	+.002	.000
Longitudinal CFA: Strong invariance	2464.508 (1400)*	.924	.917	.028	[.026; .030]	246.337 (33)*	-.015	-.015	+.002
Longitudinal CFA: Partial strong invariance	2353.234 (1398)*	.932	.925	.027	[.025; .029]	135.915 (31)*	-.007	-.007	+.001
Longitudinal CFA: Strict invariance	2511.699 (1440)*	.924	.919	.028	[.026; .030]	140.328 (42)*	-.008	-.006	+.001
Longitudinal CFA: Variance-Covariance invariance	2661.861 (1458)*	.915	.910	.029	[.028; .031]	144.303 (18)*	-.009	-.009	+.001
Longitudinal CFA: Latent means invariance	3211.107 (1467)*	.876	.870	.035	[.034; .037]	429.973 (9)*	-.039	-.040	+.006
Outcomes									
Time 1 CFA	82.538 (26)*	.963	.948	.048	[.036; .060]				
Time 2 CFA	70.317 (26)*	.960	.945	.051	[.037; .066]				
Time 3 CFA	27.273 (26)*	.998	.998	.010	[.000; .037]				
Time 4 CFA	32.287 (26)*	.983	.976	.032	[.000; .063]				
Longitudinal CFA: Configural invariance	728.141 (512)*	.969	.962	.021	[.017; .024]	-	-	-	-
Longitudinal CFA: Weak invariance	749.657 (533)*	.969	.964	.021	[.017; .024]	23.947 (21)	.001	+.002	.000
Longitudinal CFA: Strong invariance	830.608 (554)*	.961	.955	.023	[.020; .026]	83.440 (21)*	-.008	-.009	+.002
Longitudinal CFA: Strict invariance	853.025 (581)*	.961	.958	.022	[.019; .025]	31.250 (27)	.000	+.003	-.001
Longitudinal CFA: Variance-Covariance invariance	856.482 (589)*	.962	.959	.022	[.019; .025]	5.709 (8)	+.001	+.001	.000
Longitudinal CFA: Latent means invariance	1245.618 (595)*	.908	.902	.034	[.031; .037]	343.665 (6)*	-.054	-.057	+.012

Note. * $p < .01$; CFA: Confirmatory factor analysis; χ^2: Robust 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; Δ: Change in fit relative to the comparison model.

Table S4

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the CFA Solution (Predictors)

	INA T1	NB T1	SE T1		INA T2	NB T2	SE T2		INA T3	NB T3	SE T3		INA T4	NB T4	SE T4	
Items	λ	λ	λ	δ	λ	λ	λ	δ	λ	λ	λ	δ	λ	λ	λ	δ
Inattention																
Item 1	.581			.663	.589			.653	.616			.620	.590			.652
Item 2	.579			.665	.587			.656	.614			.622	.588			.654
Item 3	.629			.604	.637			.594	.664			.559	.638			.592
Item 4	.675			.544	.683			.534	.708			.498	.684			.533
Item 5	.725			.475	.732			.464	.756			.429	.733			.463
Item 6	.702			.507	.710			.496	.735			.460	.711			.495
Item 7	.670			.551	.678			.540	.704			.505	.679			.539
Item 8	.536			.713	.544			.704	.572			.673	.545			.703
NB																
Item 1		.581		.663		.587		.656		.614		.623		.628		.606
Item 2		.697		.514		.703		.506		.727		.471		.739		.453
Item 3		.615		.621		.621		.614		.648		.580		.661		.563
Self-efficacy																
Item 1			.764	.416			.778	.394			.768	.411			.736	.459
Item 2			.875	.235			.884	.219			.877	.231			.856	.267
Item 3			.645	.584			.662	.562			.649	.578			.612	.625
ω	.846	.666	.809		.852	.673	.821		.868	.703	.812		.852	.717	.782	

Note. INA: Inattention; NB: Principals' negative leadership behaviors; SE: Self-efficacy; T1: Time 1; T2: Time 2; T3: Time 3; T4: Time 4; λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of model-based composite reliability; all parameters are significant ($p < .05$).

Table S5

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the CFA Solution (Outcomes)

	INT T1	SOM T1		INT T2	SOM T2		INT T3	SOM T3		INT T4	SOM T4	
Items	λ	λ	δ	λ	λ	δ	λ	λ	δ	λ	λ	δ
Intentions to leave												
Item 1	.829		.313	.835		.302	.835		.303	.835		.303
Item 2	.872		.240	.877		.231	.877		.231	.877		.231
Item 3	.717		.485	.726		.473	.726		.474	.726		.473
Somatization												
Item 1		.655	.571		.628	.605		.661	.563		.613	.625
Item 2		.606	.633		.579	.665		.612	.625		.563	.683
Item 3		.628	.606		.601	.639		.634	.597		.585	.657
Item 4		.517	.732		.491	.759		.524	.725		.476	.774
Item 5		.567	.678		.540	.708		.574	.671		.525	.725
Item 6		.637	.595		.610	.628		.643	.586		.594	.647
ω	.849	.774		.855	.748		.855	.779		.855	.733	

Note. INT: Intentions to leave; SOM: Somatization; T1: Time 1; T2: Time 2; T3: Time 3; T4: Time 4; λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of model-based composite reliability; all parameters are significant ($p < .05$).

Table S6. *Correlations between Variables*

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Global Burnout (T1)	-.010	.939	-																
2. Global Burnout (T2)	.046	.890	.848**	-															
3. Global Burnout (T3)	.060	.875	.839**	.916**	-														
4. Global Burnout (T4)	-.007	.598	.678**	.780**	.779**	-													
5. Inattention (T1)	2.070	.354	.358**	.346**	.328**	.251**	-												
6. Negative behaviors (T1)	2.227	.767	.362**	.345**	.337**	.314**	.211**	-											
7. Self-efficacy (T1)	4.377	.711	-.387**	-.393**	-.378**	-.309**	-.557**	-.245**	-										
8. Intentions to leave (T1)	2.015	1.219	.490**	.426**	.414**	.337**	.237**	.302**	-.221**	-									
9. Somatization (T1)	.638	.527	.473**	.458**	.470**	.335**	.188**	.264**	-.187**	.413**	-								
10. Sedatives (T1)	.251	1.398	.156**	.157**	.149**	.136**	.041	.114**	-.023	.073*	.143**	-							
11. Sleeping pills (T1)	.582	6.124	.115**	.090**	.102**	.076*	-.056	.012	-.002	.020	.070*	.022	-						
12. Physical activity (T1)	3.859	3.437	-.087**	-.106**	-.104**	-.048	-.052	.044	.069*	-.030	-.082*	-.006	-.017	-					
13. Inattention (T2)	2.079	.340	.330**	.396**	.357**	.295**	.866**	.178**	-.530**	.214**	.196**	.055	-.029	-.057	-				
14. Negative behaviors (T2)	2.219	.743	.348**	.356**	.358**	.307**	.263**	.906**	-.257**	.294**	.268**	.090**	.005	.010	.267**	-			
15. Self-efficacy (T2)	4.400	.693	-.358**	-.458**	-.412**	-.364**	-.507**	-.308**	.823**	-.199**	-.213**	-.050	-.022	.045	-.608**	-.347**	-		
16. Intentions to leave (T2)	2.113	1.162	.462**	.509**	.465**	.382**	.231**	.316**	-.229**	.809**	.434**	.086**	.004	-.029	.261**	.317**	-.265**	-	
17. Somatization (T2)	.593	.457	.411**	.457**	.454**	.314**	.146**	.214**	-.144**	.360**	.870**	.147**	.087**	-.074*	.163**	.226**	-.192**	.468**	-
18. Sedatives (T2)	.270	1.610	.127**	.183**	.152**	.163**	.056	.138**	-.118**	.055	.212**	.337**	.066	-.031	.049	.126**	-.170**	.101**	.261**
19. Sleeping pills (T2)	.440	2.871	.086*	.085*	.088*	.068	-.021	-.001	.030	.090*	.157**	.039	.082*	-.072	-.039	.022	.015	.053	.245**
20. Physical activity (T2)	3.826	3.662	-.098*	-.103**	-.113**	-.058	-.037	-.004	.042	-.017	-.137**	.003	-.017	.539**	-.003	-.023	.020	.002	-.115**
21. Inattention (T3)	2.058	.360	.327**	.376**	.378**	.297**	.876**	.218**	-.543**	.217**	.184**	.045	-.022	-.043	.903**	.322**	-.581**	.236**	.154**
22. Negative behaviors (T3)	2.307	.775	.379**	.369**	.392**	.342**	.246**	.880**	-.330**	.309**	.289**	.089**	.012	.035	.236**	.921**	-.401**	.313**	.243**
23. Self-efficacy (T3)	4.426	.661	-.361**	-.403**	-.415**	-.341**	-.493**	-.313**	.876**	-.208**	-.200**	-.031	-.012	.059	-.514**	-.357**	.892**	-.232**	-.172**
24. Intentions to leave (T3)	2.094	1.128	.474**	.497**	.500**	.405**	.235**	.344**	-.229**	.801**	.493**	.098**	.020	-.025	.257**	.349**	-.262**	.897**	.478**
25. Somatization (T3)	.647	.484	.409**	.417**	.469**	.314**	.143**	.207**	-.144**	.379**	.841**	.131**	.063	-.086**	.156**	.218**	-.176**	.415**	.904**
26. Sedatives (T3)	.300	1.807	.100*	.154**	.197**	.155**	.040	.050	-.062	.060	.133**	.392**	.003	-.033	.049	.033	-.067	.142**	.167**
27. Sleeping pills (T3)	.450	2.259	.117**	.164**	.161**	.156**	-.021	.059	.019	.097*	.154**	.199**	.100*	.037	-.029	.055	-.003	.064	.127**
28. Physical activity (T3)	3.825	3.511	-.076	-.083	-.101*	-.003	-.025	.026	.054	-.005	-.101*	.042	-.044	.595**	-.018	.011	.043	-.032	-.133**
29. Inattention (T4)	2.885	.236	-.275**	-.311**	-.276**	-.341**	-.667**	-.301**	.390**	-.207**	-.154**	-.067*	.014	-.003	-.734**	-.217**	.375**	-.227**	-.115**
30. Negative behaviors (T4)	2.312	.564	.218**	.226**	.212**	.281**	.140**	.795**	-.062	.213**	.216**	.091**	-.004	-.004	.115**	.748**	-.124**	.230**	.168**
31. Self-efficacy (T4)	4.647	.423	-.268**	-.326**	-.306**	-.351**	-.360**	-.308**	.747**	-.145**	-.148**	-.042	-.016	.073*	-.396**	-.331**	.736**	-.174**	-.116**
32. Intentions to leave (T4)	2.013	.759	.321**	.322**	.281**	.382**	.191**	.263**	-.160**	.472**	.406**	.057	.004	-.011	.202**	.247**	-.177**	.560**	.191**
33. Somatization (T4)	1.642	.328	.436**	.438**	.436**	.440**	.198**	.283**	-.178**	.502**	.794**	.119**	.051	-.075*	.195**	.276**	-.205**	.526**	.703**
34. Sedatives (T4)	.390	1.654	.152**	.198**	.211**	.308**	.192**	.058	-.183*	.123	.065	-.003	.116	.119	.140	.041	-.169*	.160*	.082
35. Sleeping pills (T4)	3.837	3.809	-.036	-.004	.020	-.008	-.011	.030	-.082	-.048	-.090	.078	.045	.518**	-.041	.005	-.115	-.083	-.037
36. Physical activity (T4)	42.260	17.325	.044	.036	.034	.017	-.028	-.109	-.107	.055	.061	-.038	.032	.081	-.102	-.136	-.058	.023	.043
37. Level of education	.090	.287	-.082*	-.116**	-.096**	-.085*	-.032	.046	.059	.017	-.020	.004	-.016	.027	-.018	.032	.035	.002	-.052
38. Tenure	14.943	10.309	.147**	.126**	.124**	.146**	-.071*	.061	.078*	.057	.110**	.095**	.071*	.083*	-.074*	.033	.040	.034	.105**
39. School level dummy 1	.250	.434	-.026	-.039	-.065*	.009	.101**	.029	-.021	.036	-.014	.021	-.019	.092**	.155**	.032	-.038	.074*	-.012
40. School level dummy 2	.150	.357	-.042	-.089**	-.067*	-.039	-.168**	.178**	.061	-.023	.002	-.012	-.010	.075*	-.193**	.158**	.058	-.026	.004
41. Work schedule	.140	.342	-.020	-.008	-.010	.018	.028	.048	-.115**	-.004	-.030	-.040	.068*	.014	.037	.042	-.132**	.048	-.026
42. Sex	.230	.423	-.003	-.003	.014	.006	-.041	.002	-.004	-.026	-.018	.039	-.015	.266**	-.052	.001	-.009	-.034	-.021
43. Couple	.230	.424	-.041	-.029	-.013	-.023	-.046	-.067*	-.026	-.055	-.042	-.063	.003	-.057	-.050	-.056	-.017	-.057	-.040
44. Number of children	1.010	1.069	-.024	-.029	-.023	-.061	.011	.014	-.018	.028	-.014	-.054	-.039	-.028	.003	.003	.004	.006	-.010

Table S6. *Correlations between Variables (Continued)*

	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
18. Sedatives (T2)	-															
19. Sleeping pills (T2)	.075	-														
20. Physical activity (T2)	-.010	-.042	-													
21. Inattention (T3)	.044	.020	-.021	-												
22. Negative behaviors (T3)	.124**	.053	-.021	.284**	-											
23. Self-efficacy (T3)	-.135**	-.007	.045	-.572**	-.432**	-										
24. Intentions to leave (T3)	.103**	.063	-.025	.249**	.368**	-.250**	-									
25. Somatization (T3)	.222**	.245**	-.141**	.156**	.249**	-.180**	.484**	-								
26. Sedatives (T3)	.421**	.065	-.055	.047	.034	-.073	.164**	.186**	-							
27. Sleeping pills (T3)	.126**	.180**	-.035	.039	.038	-.002	.146**	.171**	.327**	-						
28. Physical activity (T3)	-.045	-.047	.616**	.022	-.002	.060	-.008	-.179**	-.038	.237**	-					
29. Inattention (T4)	.010	.012	-.006	-.734**	-.282**	.337**	-.234**	-.108**	-.029	-.008	-.027	-				
30. Negative behaviors (T4)	.113**	-.008	-.009	.107**	.673**	-.129**	.258**	.145**	.015	.032	.000	-.247**	-			
31. Self-efficacy (T4)	-.097*	.004	.061	-.477**	-.371**	.820**	-.182**	-.108**	-.031	-.009	.023	.482**	-.280**	-		
32. Intentions to leave (T4)	.045	-.060	.021	.171**	.253**	-.156**	.566**	.080*	.024	.038	.051	-.243**	.317**	-.190**	-	
33. Somatization (T4)	.201**	.142**	-.109**	.184**	.299**	-.200**	.568**	.709**	.105*	.131**	-.105*	-.199**	.316**	-.189**	.642**	-
34. Sedatives (T4)	-.027	-.049	.052	.152*	.101	-.183*	.142	.044	.230**	.278**	.163	-.123	.072	-.106	.224**	.239**
35. Sleeping pills (T4)	-.040	.038	.572**	.011	.074	-.097	-.052	-.057	-.006	.213*	.407**	-.072	.025	-.095	-.131	-.195*
36. Physical activity (T4)	.040	-.040	.118	-.095	-.030	-.117	.033	.097	.068	.084	.021	.054	-.125	-.059	-.076	-.092
37. Level of education	-.050	-.010	.066	-.008	.050	.039	.011	-.050	-.053	.014	-.002	-.003	.028	.057	.027	-.042
38. Tenure	.021	.082*	.066	-.072*	.061	.079*	.061	.093*	-.018	.124**	.147**	.013	.034	.049	.023	.067*
39. School level dummy 1	-.036	.030	.081*	.135**	.013	-.001	.055	-.037	-.060	.029	.133**	-.162**	.033	-.029	.080*	.014
40. School level dummy 2	-.006	.036	-.042	-.147**	.150**	.031	-.008	-.006	-.011	-.021	-.057	.108**	.145**	-.008	.034	.036
41. Work schedule	-.054	-.028	-.008	.036	.048	-.122**	.024	-.029	.027	-.045	.002	-.030	.018	-.123**	.026	-.018
42. Sex	.012	.011	.014	-.032	.010	-.012	-.027	-.028	.010	.013	.039	.042	-.007	-.032	-.003	-.056
43. Couple	.012	.011	.013	-.036	-.042	-.022	-.051	-.046	.010	.013	.037	.054	-.064*	-.036	-.022	-.072*
44. Number of children	.037	-.016	-.028	.020	.015	-.010	.024	.011	.028	.005	.005	-.014	-.034	.010	-.020	.018

Table S6. *Correlations between Variables (Continued)*

	34	35	36	37	38	39	40	41	42	43	44
34. Sedatives (T4)	-										
35. Sleeping pills (T4)	.075	-									
36. Physical activity (T4)	.069	.122	-								
37. Level of education	-.073	.189*	-.086	-							
38. Tenure	-.010	.030	.077	.096**	-						
39. School level dummy 1	.095	.048	.064	.049	-.015	-					
40. School level dummy 2	-.091	-.036	-.081	-.011	-.008	-.243**	-				
41. Work schedule	.041	.015	.019	-.086*	-.236**	.022	.067*	-			
42. Sex	.025	.071	-.066	.002	.153**	.229**	.195**	-.102**	-		
43. Couple	.025	.071	-.066	.011	-.038	-.026	-.045	.013	.844*	-	
44. Number of children	.023	-.068	.089	-.010	-.029	-.020	.005	-.082*	-.006	.028	-

Note. * $p < .05$; ** $p < .01$; all variables with the exception of sedatives, sleeping pills, physical activity, level of education (0: Undergraduate or 1: Master), tenure, school level dummy 1 (0: Primary or adult; 1: Secondary), school level dummy 2 (0: Primary and secondary; or 1: Adult), work schedule (0: Full time or 1: Part time), sex (0: Male or 1: Female), couple (0: Single or 1: In couple), and number of children at home are estimated from factor scores with a mean (M) of 0 and a standard deviation (SD) of 1.

Table S7

Model Fit Statistics for the Preliminary Latent Curve Models

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI
Inattention (Predictor)					
Intercept only	1800.146 (8)*	.000	.140	.485	[.466; .504]
Linear	220.259 (5)*	.862	.835	.213	[.189; .237]
Quadratic (Curvilinear)	40.704 (4)*	.977	.965	.098	[.072; .127]
Latent basis	209.014 (3)*	.868	.736	.268	[.238; .300]
Negative Behaviors- Principal (Predictor)					
Intercept only	375.361 (8)*	.761	.821	.220	[.201; .239]
Linear	56.248 (5)*	.967	.960	.104	[.080; .129]
Quadratic (Curvilinear)	28.786 (4)*	.984	.976	.081	[.055; .109]
Latent basis	64.618 (3)*	.960	.920	.147	[.117; .179]
Self-efficacy (Predictor)					
Intercept only	520.759 (8)*	.565	.674	.259	[.241; .278]
Linear	14.825 (5)*	.992	.990	.045	[.020; .073]
Quadratic (Curvilinear)	90.413 (4)*	.927	.890	.151	[.125; .178]
Latent basis	13.457 (3)*	.991	.982	.060	[.030; .095]
Intentions to Leave (Outcome)					
Intercept only	358.095 (8)*	.592	.694	.214	[.196; .234]
Linear	23.981 (5)*	.978	.973	.063	[.039; .089]
Quadratic (Curvilinear)	64.919 (4)*	.929	.894	.126	[.100; .154]
Latent Basis	16.914 (3)*	.984	.968	.070	[.040; .104]
Somatization (Outcome)					
Intercept only	1336.810 (8)*	.014	.261	.417	[.399; .437]
Linear	142.597 (5)*	.898	.878	.170	[.147; .195]
Quadratic (Curvilinear)	84.808 (4)*	.940	.910	.146	[.120; .173]
Latent basis	38.491 (3)*	.974	.947	.111	[.082; .144]
Habits: Sedatives (Outcome)					
Intercept only	7.878 (8)	1.000	1.005	.000	[.000; .038]
Linear	5.028 (5)	.998	.998	.002	[.000; .045]
Quadratic (Curvilinear)	.403 (4)	1.000	1.000	.000	[.000; .000]
Latent basis	.643 (3)	1.000	1.000	.000	[.000; .026]
Habits: Sleeping Pills (Outcome)					
Intercept only	.778 (4)	1.000	11.679	.000	[.000; .010]
Linear	.273 (1)	1.000	10.638	.000	[.000; .069]
Latent basis	.000 (0)	1.000	1.000	.000	[.000; .000]
Habits: Physical Activity (Outcome)					
Intercept only	5.456 (4)	.959	.969	.020	[.000; .056]
Linear	.004 (1)	1.000	1.084	.000	[.000; .009]
Latent basis	.000 (0)	1.000	1.000	.000	[.000; .000]

Note. * $p < .01$; χ^2: Robust 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.

Table S8

Parameter Estimates from the Preliminary Latent Curve Models

	Inattention	*NB*	*Self-efficacy*	*Intentions to Leave*
Intercept Mean	2.075 (.011)**	2.211 (.024)**	4.397 (.022)**	2.093 (.037)**
Intercept Variance	.107 (.006)**	.531 (.037)**	.436 (.023)**	1.237 (.087)**
Linear Slope Mean	-.031 (.010)**	.141 (.022)**	.036 (.002)**	-.012 (.005)*
Linear Slope Variance	.015 (.009)	.179 (.035)**	.003 (.000)**	.017 (.004)**
Quadratic Slope Mean	.021 (.002)**	-.018 (.003)**	NA	NA
Quadratic Slope Variance	.001 (.000)**	.004 (.001)**	NA	NA
Intercept-Linear Correlation	.101 (.111)	-.102 (.073)	-.820 (.023)**	-.751 (.075)**
Intercept-Quadratic Correlation	-.523 (.128)**	.014 (.071)	NA	NA
Linear-Quadratic Correlation	-.899 (.031)**	-.995 (.001)**	NA	NA
Time 1 Residual (standardized)	.113 (.009)**	.077 (.007)**	.179 (.013)**	.250 (.022)**
Time 2 Residual (standardized)	.110 (.008)**	.078 (.007)**	.160 (.015)**	.103 (.017)**
Time 3 Residual (standardized)	.107 (.008)**	.075 (.007)**	.053 (.009)**	.112 (.017)**
Time 4 Residual (standardized)	.244 (.021)**	.140 (.015)**	.056 (.004)**	.053 (.286)
	Somatization	*Habits: Sedatives*	*Habits: Sleeping Pills*	*Habits: PA*
Intercept Mean	.623 (.016)**	.266 (.042)**	.458 (.078)**	3.869 (.103)**
Intercept Variance	.238 (.017)**	.927 (.358)*	1.122 (.456)*	7.282 (.944)**
Linear Slope Mean	-.001 (.017)	.032 (.027)	NA	NA
Linear Slope Variance	.117 (.121)**	.049 (.023)*	NA	NA
Quadratic Slope Mean	.021 (.002)**	NA	NA	NA
Quadratic Slope Variance	.002 (.000)**	NA	NA	NA
Intercept-Linear Correlation	-.386 (.061)**	.000 (.773)	NA	NA
Intercept-Quadratic Correlation	.300 (.062)**	NA	NA	NA
Linear-Quadratic Correlation	-.995 (.001)**	NA	NA	NA
Time 1 Residual (standardized)	.092 (.008)**	.543 (.183)**	.970 (.027)**	.404 (.056)**
Time 2 Residual (standardized)	.103 (.008)**	.644 (.129)**	.863 (.112)**	.456 (.118)**
Time 3 Residual (standardized)	.107 (.009)**	.687 (.125)**	.779 (.134)**	.406 (.107)**
Time 4 Residual (standardized)	.225 (.022)**	.003 (.002)	NA	NA

Note. * $p < .05$; ** $p < .01$; NB: Principals' negative leadership behaviors; PA: Physical activity; NA: Not applicable.

Table S9

Results from the Growth Mixture Models

Model		LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	ICL-BIC	Entropy	aLMR	BLRT
Unconditional Models												
M1	1 Profile	-2745.571	6	2.0219	5503.141	5538.286	5532.286	5513.230	Na	Na	Na	Na
M2	2 Profiles	-2186.114	13	1.3200	4398.228	4474.375	4461.375	4420.088	5532.286	.735	< .001	< .001
M3	3 Profiles	-2116.813	20	1.0709	4273.626	4390.776	4370.776	4307.257	4461.375	.641	< .001	< .001
M4	4 Profiles	-2057.765	27	1.1970	4169.530	4327.683	4300.683	4214.932	4370.776	.711	.0348	< .001
M5	5 Profiles	-2015.667	34	1.1403	4099.333	4298.489	4264.489	4156.506	4300.683	.698	.0008	< .001
Models with Demographic Predictors												
D1	Null effects	-16475.604	61	1.2039	33073.208	33430.516	33369.516	33175.783	32619.364	.641	Na	Na
D2	Effects on C	-16534.209	77	5.1972	33222.419	33673.447	33596.447	33351.899	32885.996	.660	Na	Na
D3	Effects on C, I (invariant)	-16516.648	85	4.8285	33203.296	33701.184	33616.184	33346.228	32909.913	.662	Na	Na
D4	Effects on C, I (variant)	-16490.493	101	4.2438	33182.986	33774.595	33673.595	33352.824	33004.936	.680	Na	Na
D5	Effects on C, I, S (invariant)	-16505.146	93	4.4622	33196.292	33741.041	33648.041	33352.677	32941.770	.662	Na	Na
D6	Effects on C, I, S (variant)	-16480.743	125	3.5548	33211.485	33943.674	33818.674	33421.680	33160.462	.685	Na	Na
Models with the Intercepts of the Predictors' Trajectories (From D1)												
I1	Null effects	-2116.813	17	1.0388	4267.626	4367.203	4350.203	4296.212	3600.051	.641	Na	Na
I2	Effects on C	-2055.176	23	1.1898	4156.352	4291.074	4268.074	4195.028	3570.161	.666	Na	Na
I3	Effects on C, I (invariant)	-2021.857	26	1.2187	4095.714	4248.010	4222.010	4139.435	3503.201	.656	Na	Na
I4	Effects on C, I (variant)	-2006.095	32	1.1073	4076.190	4263.630	4231.630	4130.000	3506.552	.653	Na	Na
I5	Effects on C, I, S (invariant)	-1969.714	29	1.1130	3997.427	4167.295	4138.295	4046.193	3398.591	.646	Na	Na
I6	Effects on C, I, S (variant)	-1953.848	41	1.0950	3989.696	4229.854	4188.854	4058.640	3455.418	.649	Na	Na
Models with the Linear Slopes of the Predictors' Trajectories (From I5)												
L1	Null effects	-1969.714	29	1.1130	3997.427	4167.295	4138.295	4046.193	3398.591	.646	Na	Na
L2	Effects on C	-1962.249	35	1.3207	3994.497	4199.510	4164.510	4053.352	3433.164	.650	Na	Na
L3	Effects on S (invariant)	-1953.405	32	1.2594	3970.810	4158.250	4126.250	4024.620	3380.277	.643	Na	Na
L4	Effects on S (variant)	-1935.316	38	1.7017	3946.632	4169.218	4131.218	4010.531	3383.155	.642	Na	Na
L5	Effects on C, S (invariant)	-1948.562	38	1.3990	3973.124	4195.710	4157.710	4037.024	3422.185	.648	Na	Na
L6	Effects on C, S (variant)	-1927.682	44	1.5441	3943.364	4201.094	4157.094	4017.352	3413.210	.644	Na	Na
Models with the Quadratic Slopes of the Predictors' Trajectories (from L3)												
Q1	Null effects	-1635.272	68	1.1990	3406.544	3804.855	3736.855	3520.890	3101.629	.696	Na	Na
Q2	Effects on C	-1622.068	74	1.1809	3392.136	3825.592	3751.592	3516.571	3151.888	.713	Na	Na
Q3	Effects on S (invariant)	-1636.210	70	1.1293	3412.419	3822.445	3752.445	3530.128	3113.039	.694	Na	Na
Q4	Effects on S (variant)	-1620.474	76	1.4251	3392.947	3838.118	3762.118	3520.746	3118.533	.692	Na	Na
Q5	Effects on C, S (invariant)	-1610.167	76	1.1711	3372.333	3817.504	3741.504	3500.132	3156.427	.720	Na	Na
Q6	Effects on C, S (variant)	-1603.861	82	1.1409	3371.722	3852.038	3770.038	3509.610	3189.140	.722	Na	Na

Note. C: Profile membership; I: Intercept factor; S: Slope factor; LL: Model LogLikelihood; #fp: Number of free parameters; Scaling: Scaling factor associated with MLR loglikelihood estimates; AIC: Akaïke Information Criteria; CAIC: Constant AIC; BIC: Bayesian Information Criteria; ABIC: Sample-size Adjusted BIC; ICL-BIC: Integrated Classification Likelihood BIC; aLMR: Adjusted Lo-Mendel-Rubin likelihood ratio test; BLRT: Bootstrap Likelihood Ratio Test.

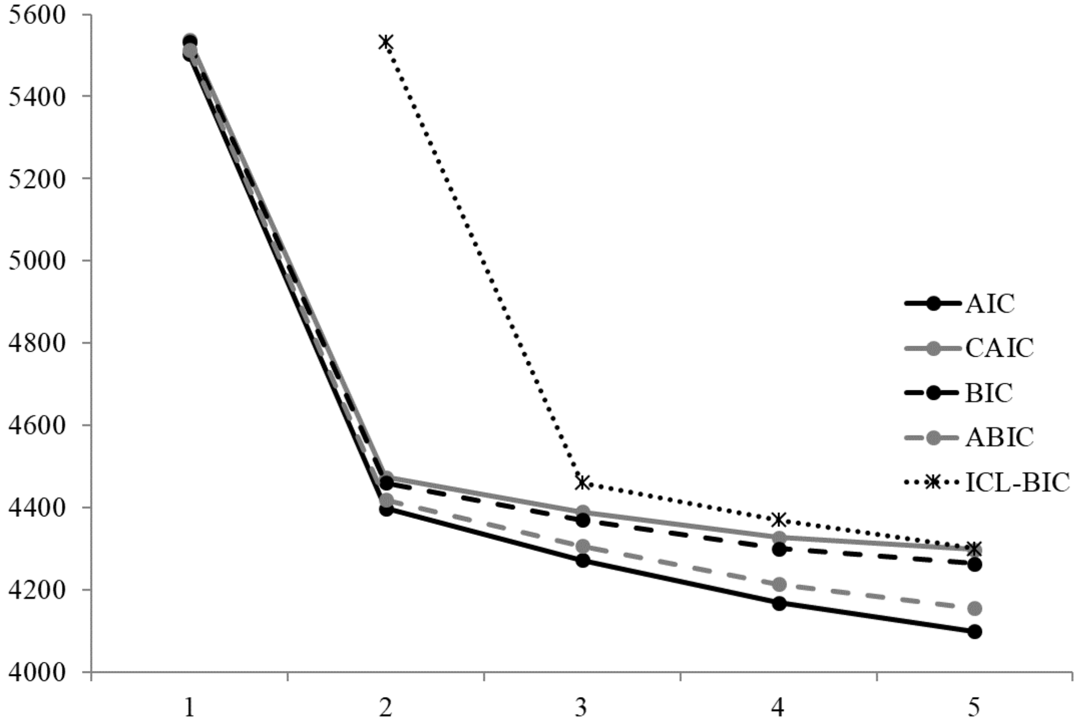

Figure S1
Elbow Plot of the Information Criteria for Solutions Including Different Numbers of Latent Profiles

Table S10

Parameters Estimates from the final Unconditional Growth Mixture Model

Parameter	Profile 1 (Moderate) Estimate (*t*)	Profile 2 (Low) Estimate (*t*)	Profile 3 (High) Estimate (*t*)
Intercept Mean	.265 (4.383)**	-.460 (-.8.529)**	.668 (5.172)**
Slope Mean	-.028 (-5.789)**	.033 (7.677)**	-.037 (-2.787)**
Intercept Variability (*SD* = √σ)	.861 (14.606)**	.589 (7.342)**	.722 (5.404)**
Slope Variability (*SD* = √σ)	.045 (3.452)**	.045 (7.216)**	.084 (1.977)*
Intercept-Slope Correlation	-.039 (-10.531)**	-.027 (-7.412)**	-.035 (-2.434)**
$SD(\varepsilon_{yi})$	.326 (9.113)**	.118 (13.652)**	.618 (6.948)**

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

Table S11

Classification Accuracy: Average Probability of Membership into Each Latent Profile (Column) as a Function of the Most Likely Profile Membership (Row)

	Profile 1 (Moderate)	Profile 2 (Low)	Profile 3 (High)
Profile 1 (Moderate)	.839	.126	.034
Profile 2 (Low)	.063	.937	0
Profile 3 (High)	.390	.013	.597