Chronic and Temporary Exposure to Student Violence Predicts Emotional Exhaustion in High School Teachers

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Abstract

Introduction. This study investigates the nexus between teacher exposure to student aggression, their level of emotional exhaustion, and the role of belongingness and perceived school safety as mediators.
Method. Random-Intercept Cross-Lag Panel Models were conducted among a sample of 2,072 secondary teachers (57.14% female) from grades 7 to 11 in 77 schools.
Results. Chronic levels of exposure to globally high levels of student aggression and specific high levels of direct victimization were associated with increased levels of emotional exhaustion. These associations were fully mediated by teacher perceptions of school belongingness and safety. Temporary fluctuations in witnessing student-to-student aggression led to increased emotional exhaustion via decreased perceptions of safety. Specific levels of witnessing student-to-teacher aggression were not linked with exhaustion over time beyond global levels of exposure to student aggression.
Discussion. The chronicity of exposure to different forms of student aggression is a risk factor for emotional exhaustion among teachers.

Keywords: student aggression; school violence; teacher emotional exhaustion; perceived school safety

As many as 80% of North American teachers are regular victims of workplace aggression (McMahon et al., 2014; Wilson et al., 2011). Witnessing or being a direct victim of aggression predicts stress, emotional exhaustion and burnout, mental health problems, job satisfaction, work commitment, and turnover intentions (e.g., Bass et al., 2016; Bernotaite & Malinauskiene, 2017; Hershcovis & Barling, 2009). Despite the well-documented nature of these outcomes, the mechanisms that link them to teacher exposure to student aggression remain under-documented. In the school context, teacher belongingness and perceptions of safety represent two critical mechanisms underpinning their well-being. These mechanisms are relevant to understanding the effects of aggression in secondary school (Janosz et al., 2017). In the present study, we consider these two mechanisms as potential mediators of the associations between teacher exposure to student aggression and their level of emotional exhaustion. Recent research has highlighted the importance of properly defining the fluctuating nature (state) or chronicity (trait) of emotional exhaustion (Basinska & Gruszynska, 2020). Consequently, the present study examines these associations at the trait (stable or chronic levels observed across multiple years) and state (yearly fluctuations) levels.

Teacher Exposure to Student Aggression

Teachers, especially in secondary schools, are at high risk of exposure to student aggression. This exposure varies depending on the role (witness or victim) and nature of the aggression (verbal or physical; Espelage et al., 2013). The present study considers three types of exposure to student aggression: (1) witnessing student-to-student aggression; (2) witnessing student-to-teacher aggression; and (3) being a direct victim of verbal and physical student aggression. Some teachers may experience a globally high level of aggression across all three types of exposure, whereas some others may experience less or more of a specific form of aggression. Furthermore, some teachers may experience aggression on a chronic basis, year after year, whereas others may be exposed in a way that fluctuates widely from year to year. For this reason, it appears important to differentiate between teacher (1) global levels of exposure to all three types of student aggression relative to their specific level of exposure to aggression as a witness of student-to-student or student-to-teacher aggression or as a victim; and (2) stable (trait) versus temporary (state) levels of exposure to aggression (Hershcovis & Reich, 2013; Kauppi & Pörhölä, 2012).

A Job-Demand-Resources Perspective on the Link between Aggression and Exhaustion

Emotional exhaustion at work, defined as a "feeling of being emotionally overextended and exhausted by one's work" (Maslach & Jackson, 1981, p.101), is one of the defining components of burnout (e.g., Schaufeli et al., 2002). Exhausted teachers typically report lacking energy and being easily irritated (Fernet et al., 2012). The Job-Demand-Resources (JDR) model differentiates between two types of characteristics involved in the development of emotional exhaustion and ultimately, burnout (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001). Demands refer to job characteristics requiring employees to expend psychological or physical effort and often take a toll because of diminished resources (Schaufeli & Bakker, 2004). Resources refer to job or personal characteristics that help support employees, reduce the cognitive load from job demands, and stimulate personal growth (Schaufeli & Bakker, 2004).

According to the JDR model, emotional exhaustion results from chronic exposure to overwhelming stressors, or job demands, that exceed employee resources to cope with such demands (Bakker & Demerouti, 2007; Bakker et al., 2004). The JDR model also emphasizes that exposure to a time-limited stressor (temporary or circumscribed to a specific period) may not necessarily lead to emotional exhaustion, pending the availability of sufficient resources to cope with this stressor (Demerouti et al., 2010). In contrast, chronic exposure to stressors is more likely to deplete employees' resources making them at higher risk of exhaustion (Demerouti et al., 2010). Indeed, a recent study (Basinska & Gruszynska, 2020) reinforces the importance of differentiating repeated or chronic exposure to stressors (a stable trait-like characteristic) and temporary exposure to situation-specific stressors (a time-limited state-like characteristic). Whereas the former is more likely to lead to emotional exhaustion, the latter may be more easily managed by employees.

For teachers, exposure to student aggressive behaviors is among stressors that can, if repeated or chronic, easily become overwhelming. Still, even situation-specific exposure to student aggression is likely to dynamically influence teacher psychological functioning at the time of exposure, in a way that can either become crystallized into a new normative way of functioning when exposure becomes chronic or go back to previous normative levels when incidents are non-recurring. When exposed to student aggression, either as witnesses or as victims, teachers are likely to feel unsettled and concerned, requiring them to expand their own psychological resources to cope with the incident, thus resulting in a temporary depletion of these resources pending recovery (e.g., Sonnentag & Fritz, 2015). Although this temporary resource expenditure helps teachers to cope with isolated incidents, it may still lead them to experience some form of time-limited emotional exhaustion that fades out as resources are recovered, and life returns to normal. In contrast, repeated or chronic exposure to student aggression is likely to create an ever-increasing drain in teacher psychological resources, thus leading to more chronic states of exhaustion.

Student Aggression and Teacher Emotional Exhaustion

Empirical evidence generally supports the JDR assumption that exposure to workplace aggression leads to emotional exhaustion, although most studies involving teachers have been cross-sectional. Overall, these studies indicate that teachers who report being a direct victim of aggression perpetrated by a student tend to be exhausted (Bass et al., 2016; Berg & Cornell, 2016; Bernotaite & Malinauskiene, 2017; Fox & Stallworth, 2010; Hershcovis & Barling, 2009; Moon et al., 2015). Likewise, teachers who regularly witness aggression also present a higher risk of emotional exhaustion (Bernotaite & Malinauskiene, 2017; Galand et al., 2007), although these might be less pronounced than those of victimization (Gullander et al., 2014). Moreover, exposure to a globally high level of several types of aggression (combining witnessing and victimization) might impact teachers more severely than exposure to any specific type of aggression. However, research is lacking regarding the differentiated impact of exposure to various types of aggression.

Another shortcoming of existing research is the lack of longitudinal studies of teachers. Among other types of employees, there is sufficient evidence showing that being a direct victim leads, over time, to emotional exhaustion (Hogh et al., 2016; Laschinger & Fida, 2014; Naseer & Raja. 2019). However, such evidence is lacking among teachers, who are likely to differ from other employees on many levels, including their risk of exposure to various forms of aggression at work. Likewise, students usually change every year, which means that teachers are exposed to completely different students each year. Thus, it increases the likelihood of distinguishing the effects of chronic exposure to student aggression (spanning several years, likely to reflect a problematic school context) from that of a more temporary exposure (circumscribed to a specific year, likely to reflect a classroom effect).

Psychological Mechanisms Underpinning the Link between Aggression and Exhaustion

The JDR model acknowledges that resources are equally likely to emerge from the environment as from the employees themselves (Demerouti et al., 2001; Nielsen et al., 2017). Likewise, others have reinforced the need to consider psychological resources as the key mechanisms underpinning the effects of work characteristics on employees. Importantly, Self-Determination Theory (Ryan & Deci, 2017; Van den Broeck et al., 2008) positions the satisfaction of employees' basic psychological needs as one of the core mechanisms reinforcing the action of work characteristics, as well as a key individual resource to help employees cope with workplace demands (Ryan & Deci, 2017). In the present study, we focus more specifically on the satisfaction of teacher needs for belongingness and safety as two core psychological mechanisms likely to mediate the link between exposure to student aggression and emotional exhaustion.

School Belongingness

The need to belong is a fundamental human need (Baumeister & Leary, 1995; Ryan & Deci, 2017). This desire to form quality relationships and to feel connected with others is arguably a core component of emotional adjustment and well-being (Baumeister & Leary, 1995). For teachers, feelings of belongingness include being proud to work in their school, feeling part of the school, and believing that the school is important (Janosz et al., 2007). Teachers with a strong sense of belongingness are more likely to feel that their school offers a positive and supportive social context providing them with the resources needed to cope with school-related stressors (e.g., Ryan & Deci, 2017).

As a form of destructive interpersonal behavior, exposure to student aggression might impact teachers' sense of school belonging (Trépanier et al., 2013). More precisely, teachers exposed to a continuously harsh, threatening, or aggressive interpersonal work environment characterized by chronic exposure to student aggression should be less prone to develop a strong sense of school belonging, which, in turn, may hinder their emotional adjustment. In contrast, exposure to punctual incidents of student aggression, followed by longer periods of harmonious interpersonal interactions, might result in short-term decreases in teacher levels of school belonging, followed by a return to normative levels.

Empirically, a few cross-sectional studies suggest that teacher frequent victimization negatively influences belongingness (Gardner et al., 2013; Trépanier et al., 2013). However, studies are more equivocal regarding the secondary links between belongingness and emotional exhaustion. Thus, whereas some studies have shown that teacher belongingness, social affiliation, and high-quality relationships lead to lower levels of emotional exhaustion (Pas et al., 2012; Skaalvik & Skaalvik, 2011; Van Droogenbroeck et al., 2014), others have failed to find such an association (Cockshaw et al., 2014; Fernet et al., 2013). Moreover, one cross-sectional study has specifically assessed the intermediate role of belongingness in the association between exposure to verbal and physical threats and nurses' levels of emotional exhaustion, and failed to support the mediational role of belongingness (Trépanier et al., 2013). Yet, teachers may differ from nurses as they work a whole year with the same students and thus have more time to develop a strong sense of belongingness to their classroom and school, but also be distressed if they do not feel close to their students (Spilt et al., 2011). More importantly, none of the aforementioned studies have relied on longitudinal research designs allowing to achieve a complete picture of the directionality of these associations as they occur at the trait (chronic, stable) and state (time-related fluctuations) levels.

Perception of School Safety

The need to feel safe has long been recognized as a fundamental need for all human beings (Maslow, 1943) and intimately relates to the extent to which one feels secure at work. More precisely, teacher perceptions of school safety reflect a general feeling of security, order, and tranquility, accompanied by a lack of perceived threats, risks, and fear of aggression (e.g., Bass et al., 2016; Janosz et al., 2007). Arguably, punctual exposure to student aggression is likely to negatively exert a short-term impact on teacher sense of psychological safety. However, in the absence of prolonged exposure, these feelings are unlikely to be long-lasting. Many have reinforced that ongoing exposure to work-related threats, altercations, and aggressions was required to create lasting effects of teacher sense of safety, leading in turn to a higher risk of emotional exhaustion (e.g., LeBlanc & Kelloway, 2002; Portoghese et al., 2017).

Empirical evidence regarding the proposed intermediate role of school safety in the association between exposure to student aggression and emotional exhaustion has led to generally consensual results. Thus, witnessing or being a direct victim of aggression have been found to increase the fear of being involved in future altercations, leading in turn to diminished well-being, including elevated levels of emotional exhaustion (Akbolat et al., 2019; Leather et al., 2007; Mueller & Tschan, 2011; Portoghese et al., 2017; Rose et al., 2013). However, a single study has been conducted in a school setting. In this study, Bass et al. (2016) found that school employees who have been victims of verbal and physical aggression by students felt more unsafe in their work environment, which, in turn, was associated with higher levels of emotional exhaustion. However, despite this convergence in results, longitudinal studies relying on a proper state-trait disaggregation are still lacking.

Aims and Hypotheses

The present study aims investigates the association between exposure to student perpetrated aggression and teacher emotional exhaustion as mediated by feelings of belongingness and safety over a five-year period. The study also disentangles stable traits from changing states to properly investigate the assumptions from the JDR model that emotional exhaustion is more likely to emerge from a stable (chronic, trait) exposure to student aggression than from exposure to more circumscribed incidents. This study also assesses if, as expected, global exposure to various types of aggression have a stronger negative impact on emotional exhaustion than specific deviations in levels of exposure relative to this global level (witnessing student-to-student aggression and student-to-teacher aggression, and victimization by students).

Methods

Sample

The study relies on longitudinal data from the New Approaches, New Solutions project, collected in 2002 to 2008, among 77 secondary schools selected using a stratified random sampling procedure to represent schools in disadvantaged communities from all sizes and geographic locations throughout the province of Quebec, Canada (Janosz et al., 2010).

For this study, we rely on three time-points spreading across five school years: 2002-2003 (Y1), 2004-2005 (Y3), and 2006-2007 (Y5). The study includes 2,072 teachers (57.14% female) teaching in grades 7 to 11 (corresponding to the secondary school years in Quebec) across all subjects (Language

Arts, Mathematics, History, etc.), and who participated in at least two of the data collection points. Detailed information related to missing data and attrition, which was handled in all analyses using Full Information Maximum Likelihood (FIML, Enders, 2010) procedures, is provided in the online supplements. Participating teachers varied in age (20-30 years old: 24.3%; 31-40: 34.3%; 41-50: 23.3%; 51+: 10.0%) and tenure in their school (less than 1 year: 15.4%; 1-5: 33.8%; 6-10: 21.1%; 11+: 29.5%).

Procedure

In the spring of each year, teachers answered online questionnaires after providing informed consent. The research team informed teachers that their participation was voluntary, that answers were confidential, and that it was their right to refuse to participate. The ethics committee of the University approved this procedure.

Measures

Exposure to student aggression was measured with three sets of items: witnessing student-to-student (WSS) aggression, witnessing student-to-teacher (WST) aggression, and victimization by a student (VS) (Janosz et al., 2007). For the witnessing subscales, teachers rated the frequency at which they were exposed to different events since the beginning of the school year (0=never to 4=almost every day). WSS comprised four items: insults, threats (blackmail and verbal harassment, does not include rumors), fights, and beatings (Y1 α=.75; Y3 α=.76; Y5 α=.76). WST comprised three items: insults, threats, and physical attacks (Y1 α=.68; Y3 α=.68; Y5 α=.69). For the VS subscale, teachers evaluated how many times (0=never to 4=four times or more) they experienced insults, threats (blackmail and verbal harassment), and physical attacks from students since the beginning of the year (three items; Y1 α=.56; Y3 α=.56; Y5 α=.53). All items combined to form a global measure scale also has an adequate level of scale score reliability (Y1 α=.82; Y3 α=.81; Y5 α=.80).

The emotional exhaustion scale included five item adapted from the Maslach and Jackson (1981) scale, e.g., "I am so tired in the morning that I feel unable to go through another day of work." Teachers reported their answers on a four-point scale (1=completely disagree to 4=completely agree). The scale has a good scale score reliability at all three time-points (Y1: α=.82, Y3: α=.84, and Y5: α=.86).

The belongingness scale was measured with a five item scale reported by teachers and drawn from the Socio-educational Environment Questionnaire (Janosz et al., 2007), e.g., "I am proud to work in this school." Teachers reported their answers on a four-point scale (1=completely disagree to 4=completely agree). The scale has a good scale score reliability at Y1 (α=.92), Y3 (α=.91), and Y5 (α=.91).

The perceived school safety scale was measured with a six item scale also drawn from the Socio-educational Environment Questionnaire (Janosz et al., 2007), e.g., "Members of the school personnel do not feel safe in this school." and "Members of the school personnel are afraid to intervene when a violent situation occurs." Teachers reported their answers on a four-point scale (1=completely disagree to 4=completely agree). The scale has a good scale score reliability at Y1 (α=.86), Y3 (α=.86), and Y5 (α=.87).

Analyses

Model Estimation and Assessment

All analyses were conducted using the Maximum Likelihood Robust (MLR; which is robust to non-normality) estimator available in Mplus 8.2 (Muthén & Muthén, 2018), FIML (Enders, 2010) to handle missing data, and Mplus' "complex" survey design capability to account for the nesting of teachers within schools (Asparouhov, 2005).

To assess model adjustment, adequate and excellent model fit were respectively indicated by values above .90 and .95 on the Comparative Fit Index (CFI) and Tucker-Lewis Index, as well as values under .08 and .06 on the Root Mean Square Error Approximation (RMSEA) (Marsh et al., 2005).

Preliminary Analyses

Preliminary analyses were conducted to test the factor structure and longitudinal invariance of the measures (Millsap, 2011). Factor scores were saved from the most invariant models to ensure comparability over time and control for measurement errors and factor structure (Morin et al., 2020). A confirmatory factor analytic (CFA) model was used to represent exhaustion, belonging, and safety (i.e., three correlated factors were specified). A bifactor-CFA model was used for the aggression measure (Morin et al., 2020). This approach made it possible to obtain a direct estimate of teacher global exposure to student aggression across all dimensions (the global factor, or G-factor) together with a non-redundant (i.e., orthogonal) estimate of the degree to which teacher had been exposed to each specific type of aggression (WSS, WST, VS) beyond this global exposure (the specific factors, or S-factors). These preliminary analyses are reported in the online supplements (Tables S1 to S3).

Main Analyses

Our main analyses relied on Random-Intercepts Cross-Lag Panel Models (RI-CLPM; Hamacker et al. 2015). RI-CLPM make it possible to disaggregate observed scores into a time-invariant component reflecting aggregated levels across all time points (stable trait/chronic) and a time-variant component reflecting variations occurring around this stable component at specific points in time (changing state / temporary).

More precisely, the first series of latent variables (random intercepts) synthesize the average level of each variable experienced by a participant across all time points (stable trait level, aggregated across Y1, Y3, and Y5). Associations between these random-intercepts are interpreted as occurring at the trait level. The second series of latent variables are then used to represent intra-individual deviations (or fluctuations) from this stable trait occurring at each specific time-point. At this intra-individual level, autoregressive associations reflect the extent to which these time-specific deviations are correlated over time. Autoregressive associations thus represent carryover effects whereby time-specific deviations in relation to the trait-level occurring at one point in time can be expected to lead to further deviations from that same trait at a later time point (Basinska & Gruszynska, 2020). Strong autoregressions indicate that time-specific deviations are likely to have a lasting effect on the individual, whereas weak autoregressions suggest that these time-specific deviations tend to disappear (i.e., bounce back to normative levels) at later time points.

Cross-lagged associations included at the intra-individual level reflect the extent to which time-specific deviations on one variable (e.g., increases or decreases in exposure to aggression) influence time-specific deviations on a second variable occurring at a later point in time (e.g., increases or decreases in emotional exhaustion). These associations thus reflect lasting effects of time-specific influences. Finally, time-specific correlations reflect the extent to which time-specific fluctuations share cross-sectional associations.

We estimated a separate series of RI-CLPM for each exposure (global, specific WSS, specific WST, and specific VS)[1,2,3]. Because the four aggression factors are uncorrelated (bifactor models are orthogonal), their inclusion in separate models does not preclude a clear examination of their unique contribution. We first compared direct effects (M1a: direct links between aggression and the outcomes), full mediation (M1b: direct links between aggression and the mediators and between the mediators and the outcomes), and partial mediation (M1c: direct links between aggression and the mediators, between the mediators and the outcomes, and between aggression and the outcomes) models. In these models, all autoregressive, cross-lagged, and time-specific associations were constrained to be equal over time (i.e., predictive equilibrium; Cole & Maxwell, 2003) and the latent mean structure was specified as being entirely summarized as part of the random intercept factor (i.e., assuming equivalent means over time). Starting from the retained model, we estimated a series of four alternative models to verify whether the time-specific means of the repeated measures should be freely estimated (M2: Hamacker et al. 2015), the autoregressive associations should be allowed to vary over time (M3), the cross-lagged associations should be allowed to vary over time (M4), and the time-specific correlations should be allowed to vary over time (M5).

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[1] As part of preliminary analyses, we also estimated a preliminary set of models including covariates (teacher sex, years of teaching experience, and student indiscipline) with a known association with emotional exhaustion (Berg & Cornell, 2016; Fernet et al., 2012). As including these covariates did not result in any meaningful change in the observed relations among our main constructs and created some estimation difficulties, they were not included in the main analyses. This observation is aligned with the repeated observation that stable control variables are very seldom able to meaningfully change time-structured results obtained as part of longitudinal analyses, and thus should be excluded unless their inclusion is supported by a strong theoretical rationale (Bernerth & Aguinis, 2015; Carlson & Wu, 2012; Spector & Brannich, 2011).

[2] Attempts to include all four types of exposure in a single RI-CLPM resulted in non-converging models, suggesting overparameterization, forcing us to estimate separate models.

[3] Results from the models with the WST specific factor should be interpreted with caution as the composite reliability (see Table S2 of the online supplements) is low for this factor.

Results

Descriptive Statistics

The prevalence of teacher exposure to each type of aggression at Y1 is displayed in Figure S1 of the online supplements. Although 40.6% of teachers reported VS at least once, fewer reported more frequent incidents of victimization (6.8%). In contrast, almost all teachers reported WST once (73.3%), or more (21.6%), suggesting that few incidents might have many witnesses. Finally, the majority of teachers report having experienced WSS once (30.3%), twice (50.8%), or more (17.8%). Correlations among variables were generally all in the expected direction (see Table S4 of the online supplements).

RI-CLPM

For all aggression factors, these results supported the full mediation model (M1b), which systematically displayed a higher level of adjustment to the data than the direct effects model (M1a) and a comparable level of fit to the data than the less parsimonious partial mediation model (M1c; which was also consistent with a lack of direct effects beyond the mediated ones). Details about the fit of the alternative RI-CLPM solutions are reported in Table S5 of the online supplements. Models in which the time-specific means of the indicators were freely estimated also resulted in a systematic increase in model fit, leading to models displaying an excellent level of fit to the data for all aggression factors (M2 was retained). For most other models (i.e., global aggression, WSS, and VS), support was found for the equivalence of the remaining parameters (autoregressions, cross-lagged regressions, and time-specific correlations) over time (M3, M4, and M5 were rejected). However, M5 was supported for analyses involving WST, leading us to estimate a final model in which the Y1 time-specific correlations were allowed to differ from those estimated at Y3 and Y5. Parameter estimates obtained from all of these models are summarized in Figures 1 to 4, and reported in Tables S6 to S9 of the online supplements.

In all models, all autoregressive paths were significant, suggesting carryover effects over time via which state-like deviations in exposure to aggression, belongingness, perceived school safety, and emotional exhaustion had lasting effects on future time points. Likewise, the carryover effects of each specific form of exposure (WSS, WTS, VS) were stronger than that of the global aggression factor. In the following sections, we present the results related to the theoretical associations between each type of aggression, perceptions of school safety and belongingness, and emotional exhaustion occurring at the trait and state levels.

Global Exposure to Aggression. At the trait (stable, chronic) level, results indicate that global levels of exposure to aggression were associated with an increased risk for experiencing chronically high levels of emotional exhaustion indirectly via the effects of aggression on decreased levels of belongingness (indirect effect[4]=.152; 95% CI=.116 to .188) and perceived school safety (indirect effect=.174; 95% CI=.137 to .212), which in turn predicted reduced levels of emotional exhaustion. At the state level, prior global levels of exposure to aggression did not predict later levels of belongingness, which, in turn, did not predict later levels of emotional exhaustion. Surprisingly, prior global levels of exposure to aggression led to increased levels of perceived school safety, which themselves predicted lower levels of emotional exhaustion. Finally, time-specific correlations showed that all of these variables shared significant cross-sectional associations at all time points.

Witnessing Student-to-Student Aggression. At the trait level, results indicate that specific levels of WSS (reflecting stable deviations from global levels of exposure to aggression) were not associated with emotional exhaustion either directly (M1a or M1c) or indirectly, as these specific levels also were not found to predict trait levels of belongingness (indirect effect=-.014; 95% CI=- 3.134 to 3.106) and perceived safety (indirect effect=-.065; 95% CI =-3.520 to 3.390). At the state level, prior levels of WSS (reflecting time-specific deviations from global levels of exposure to aggression) were not associated with later levels of belongingness two years later, and prior levels of belongingness were not associated with later levels of exhaustion. However, prior levels of WSS were associated with decreased levels of school safety, which, in turn, were also associated with later levels of emotional exhaustion, suggesting a mediating role of decreased safety perceptions on the state level association between WSS and emotional exhaustion (indirect effect=.009; 95% CI=.003 to .014). Finally, time-specific correlations showed that all these variables shared significant cross-sectional associations at all

[4] The statistical significance of indirect effects is typically tested using bootstrapped confidence intervals (Cheung & Lau, 2008). This method has not yet been implemented for models including a correction for nesting. For this reason, we report symmetric confidence intervals, which should exclude 0.

time points.

Witnessing Student-to-Teacher Aggression. At the trait level, results indicate that specific levels of WST (reflecting stable deviations from global levels of exposure to aggression) were not associated with emotional exhaustion either directly (M1a or M1c) or indirectly, as these specific levels also were not found to predict trait levels of belongingness (indirect effect=-.021; 95% CI=-.072 to .067) and perceived safety (indirect effect=-.002; 95% CI=-.074 to .032). At the state level, prior levels of WST (reflecting time-specific deviations from global levels of exposure to aggression) were not associated with later levels of belongingness or perceived school safety. Although prior levels of belongingness were also not associated with later levels of exhaustion, prior levels of perceived school safety predicted decreases in emotional exhaustion over time. Finally, time-specific correlations showed that all of these variables shared significant cross-sectional associations at all time points, although these correlations were slightly higher at Y1.

Victim of Student Aggression. At the trait level, results indicate that chronic specific levels of VS (reflecting stable deviations from global levels of exposure to aggression) were associated with an increased risk of experiencing chronically high levels of emotional exhaustion indirectly via the effects of VS on decreased levels of belongingness (indirect effect=.370; 95% CI=.262 to .479) and perceived school safety (indirect effect=.151; 95% CI=.071 to .231). At the state level, prior levels of VS (reflecting time-specific deviations from global levels of exposure to aggression) were not associated with later levels of belongingness or perceived school safety. Although prior levels of belongingness were also not associated with later levels of exhaustion, prior levels of perceived school safety predicted decreases in emotional exhaustion over time. Finally, time-specific correlations showed that most variables shared significant cross-sectional associations. However, specific levels of VS did not share time-specific associations with belongingness and safety.

Discussion

Supporting previous studies (McMahon et al., 2014; Wilson et al., 2011), our results showed that teachers frequently reported being exposed to aggressive behaviors. They often report witnessing student altercations (98.9% at least once) or student aggression directed at a colleague (94.9% at least once). Less frequently, but still too often (47.4% at least once), teachers reported being direct victims of student aggression at least once in the school year.

Previous longitudinal studies tend to show a link between workplace aggression and emotional exhaustion (Hogh et al., 2016; Laschinger & Fida, 2014; Naseer & Raja, 2019). However, disentangling the effects of chronic levels of exposure form those of time-varying fluctuations revealed that student perpetrated aggression represents a risk for teacher emotional exhaustion that operates mainly chronically, rather than sporadically. In line with the JDR perspective (Demerouti et al., 2001), our results support that teacher risk of experiencing emotional exhaustion due to exposure to student aggression was mainly a function of their levels of chronic exposure to various types of aggression over time. Interestingly, these chronic effects seemed to operate by depleting teacher basic needs for belongingness and safety, also matching our expectations (e.g., LeBlanc & Kelloway, 2002; Van den Broeck et al., 2008). Chronically high levels of victimization, relative to teacher global levels of exposure to all forms of aggression, were also accompanied by a higher risk of emotional exhaustion. This effect was also mediated by the depletion of their needs for belongingness and safety.

In contrast, chronically high specific levels of exposure to any form of student aggression as a witness, beyond teacher global levels of exposure to all forms of aggression, did not carry additional risk in terms of emotional exhaustion. Such results suggest that, beyond teachers' global levels of exposure to student aggression, only the most threatening forms of exposure, namely direct victimization, seem to threaten teacher emotional well-being. Finally, time-specific fluctuations in levels of global and specific forms of aggression had generally fewer, and smaller, effects on later levels of emotional exhaustion.

Together, these results support the propositions from the JDR model (e.g., Basinska & Gruszynska, 2020; Demerouti et al., 2010) that teachers seem able to cope relatively well with temporary fluctuations in their degree of exposure to work-related stressors in a way that prevents them from experiencing lasting effects. However, chronic exposure to all types of student-perpetrated aggression, as well as to direct victimization, seems to drain teacher emotional resources. As demonstrated, their decreased perceived belongingness and safety (LeBlanc & Kelloway, 2002; Van den Broeck et al., 2008) over time crystallized in higher, and more chronic, levels of emotional exhaustion.

More specifically, the results obtained at the trait (chronic) level confirms that decreased perceptions of school safety may operate as mechanisms reflecting a fear of becoming involved in future altercations (Akbolat et al., 2019; Bass et al., 2016; Leather et al., 2007; Portoghese et al., 2017; Rose et al., 2013), leading in turn to a depletion of one's psychological resources and emotional exhaustion. Yet, this process may operate differently at the state-level. Indeed, and unexpectedly, teacher time-specific fluctuations in exposure to global levels of aggression led to increased perception of safety two years later (at the next time point). This suggests that teachers exposed to punctual aggressive events circumscribed to a specific school year may be able to tap into their resources in order to find solutions to prevent lasting effects on their emotional exhaustion (Nielsen et al., 2017). Nevertheless, as the opposite process was identified at the trait-level, this preventative mechanism seems to lack efficiency when applied continuously, possibly due to the costs involved in finding solutions to more chronic exposure to aggression (Sonnentag & Fritz, 2015).

Additionally, at the state level, time-specific increases in teacher specific levels of exposure to WSS (relative to their global level of exposure to student aggression) were associated with later decreases in perceptions of school safety. In turn, this led to increases in their levels of emotional exhaustion. Witnessing student-to-student aggression is the most frequent form of aggression to which teachers were exposed, as well as the only one (in this study at least), which does not involve teachers. As students change yearly, so do the dynamics between them. This changing nature of student interactions could explain why stronger results were found at the time-specific (state) level of this type of aggression (Patel & Cummins, 2019).

In relation to teacher feelings of school belongingness, the present study also sheds light on its proposed mediating role. Surprisingly, this theoretical mediating role (Ryan & Deci, 2017; Van den Broeck et al., 2008) had yet to be empirically supported (e.g., Trépanier et al., 2013) despite empirical support of associations between belongingness and emotional exhaustion (Pas et al., 2012; Skaalvik & Skaalvik, 2011; Van Droogenbroeck et al., 2014). Our results support that work-related stressors (exposure to student-perpetrated aggression) triggered this mechanism, but only at the trait level (chronic, stable). More precisely, teachers who were exposed to a chronically high global level of student aggression or who were often victimized reported a lower sense of belongingness over time, which in turn led to higher levels of emotional exhaustion over time.

Finally, it is important to keep in mind that, despite the presence, or lack thereof, of associations occurring at the trait or state level, teachers exposed to all global and specific forms of student aggression reported being more emotionally exhausted during the year in which these altercations happened. These results are consistent with cross-sectional studies that provide ample evidence that exposure to aggression in school is concomitantly associated with teacher emotional exhaustion (Bass et al., 2016; Berg & Cornell, 2016; Bernotaite & Malinauskiene, 2017; Fox & Stallworth, 2010; Moon et al., 2015). Our previous results suggest that, over time, teachers might be able to cope with temporary exposure to work-related stressors in a way that prevents them from experiencing lasting effects. However, the presence of cross-sectional time-specific correlations reinforces that exposure to aggression is not without short-term consequences for teachers.

Limitations

First, the participating schools were all located in disadvantaged areas, which may limit the generalizability of the results to other teacher populations. Moreover, data collection took place between 2002 and 2008. Although the forms of exposure to student aggression that were measured are still sources of concern today, teachers and school practitioners now also must deal with cybervictimization (INSPQ, 2019). This increased diversity in sources of exposure can complicate the required prevention strategies. Second, this study used teacher reports. Other measures, such as observations, would have provided an additional evaluation of the interpersonal climate within schools. There is also a potential limitation stemming from the fact that teachers retrospectively self-reported their experience of workplace aggression. To minimize recall bias, the questionnaire only focused on victimization during the past year (Nachreiner et al., 2007). Also, a few teachers may have dropped from the sample due to turnover, which may have been related to their level of emotional exhaustion. Although it is impossible to prevent such attrition, we applied a robust method to account for missing data. Finally, this study compared forms of student-perpetrated aggression. These forms are only a subset of all forms of aggression to which teachers can be exposed. Studying aggression perpetrated in person or online by students, colleagues, superiors, or parents would bring an additional perspective.

Implications for Research, Practice, and Policies

Overall, this study provides evidence that chronic, but also more sporadic, exposure to different forms of student aggression represents a risk factor for the development of work-related emotional exhaustion. At the trait (chronic) level, this risk operated through the mediating mechanism of decreased satisfaction of the basic needs for belongingness and safety. From a research perspective, it is critical to conduct more studies combining a longitudinal design comprising data collected over several years to better disentangle the trait (chronic, stable) and state (time-specific fluctuations) components of these associations. The JDR model postulates that emotional exhaustion is likely to result from exposure to chronic stressors, far more than from exposure to time-specific stressors. The present study is the first to clearly and unequivocally support this proposition. This study also demonstrates that time-specific exposure has a short-term impact on teacher emotional exhaustion, but rarely a lasting effect spanning several school years. Combining longitudinal designs, psychological mechanisms, and a fine-grained investigation of traits and states should allow researchers to achieve a better understanding of the processes involved in the development of emotional exhaustion.

Results can also bring insight to practitioners. Indeed, the present study suggests that most of the process (mediation) linking teacher exposure to student aggression operates chronically. As students change year after year, chronic exposure might reflect a problematic school context. As such, prevention and intervention strategies to reduce student aggression and its consequences should be implemented at the school level in a lasting manner in order to produce significant change (e.g., Spiel & Strohmeier, 2011). On the one hand, the lack of cross-lagged effects (i.e., exposure to aggression at a specific point in time rarely had an impact on emotional exhaustion at later time points) suggests that an intervention implemented within a single school year may not have effects beyond that year. On the other hand, the stable-trait (chronic) associations observed suggest that an intervention that aims to have long-term effects should be implemented over multiple consecutive years. Otherwise, it might not have a tangible impact on chronic student aggression and teacher exhaustion.

Finally, in the province where this study was conducted, teacher exhaustion is a national concern (Janosz et al., 2017). Pending replication of the present results, consistent findings can also guide policies aiming at reducing teacher exhaustion. If our results are replicated among other samples and school systems, leaders in education could strive to create long-term plans to reduce student-perpetrated aggression. Short-term plans are not likely to produce the desired effects on teacher well-being, as exhaustion is partly a chronic process. A global plan encompassing several school years is a more promising avenue to carry lasting benefits for teachers.

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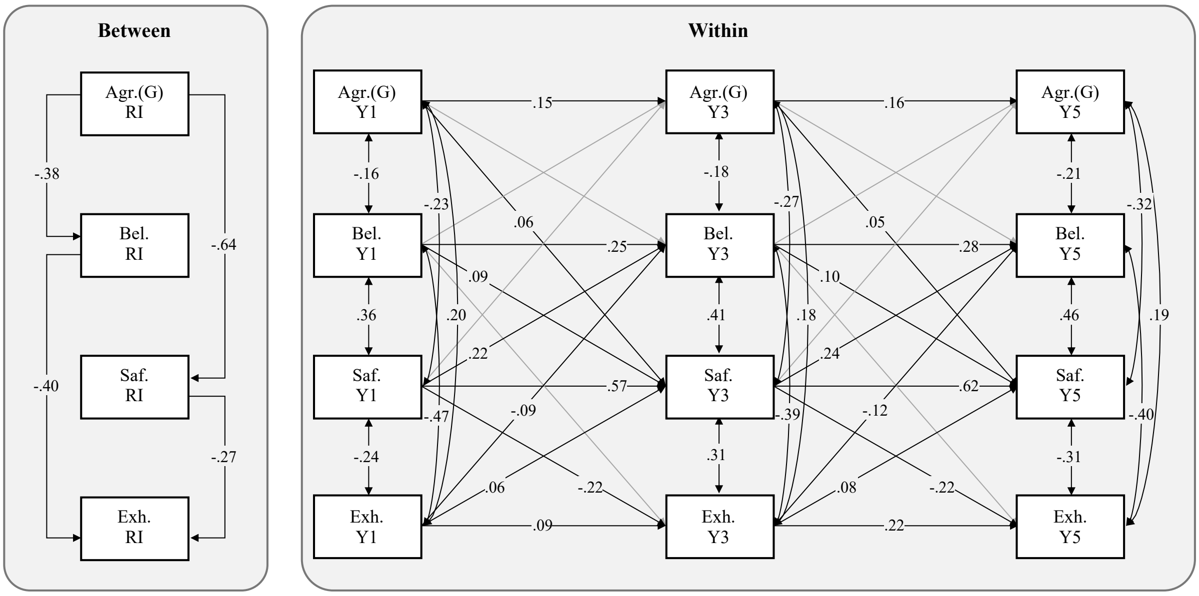

Figure 1. Results from the RI-CLPM (Model 2) with the Student-Perpetrated Aggression Global Factor.

Note. Model fit: χ^2 = 211.674 (df = 38), p < .05; RMSEA = .047; CFI =.989; TLI =.981. RI: Random intercept; Agr.(G): Global factor of exposure to aggression; Bel.: Feeling of belongingness; Saf.: Feeling of safety in school; Exh.: Emotional exhaustion. Non standardized betas are reported for paths significant at p < .05. Non-significant paths are displayed in grey. Slight variations in correlations are due to the standardization.

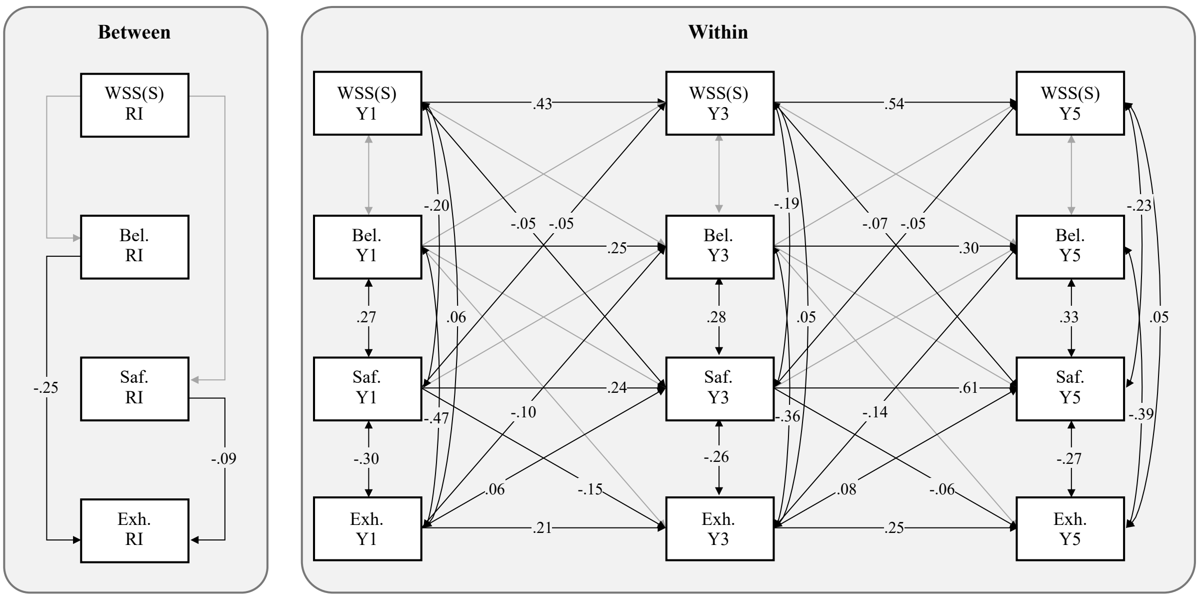

Figure 2. Results from the RI-CLPM (Model 2) with the Witnessing Student-to-Student Aggression Specific Factor.

Note. Model fit: χ^2 = 167.377 (df = 38), p < .05; RMSEA = .041; CFI =.988; TLI =.980. RI: Random intercept; WSS(S): Witnessing student-to-student aggression specific factor; Bel.: Feeling of belongingness; Saf.: Feeling of safety in school; Exh.: Emotional exhaustion. Non standardized betas are reported for paths significant at p < .05. Non-significant paths are displayed in grey. Slight variations in correlations are due to the standardization.

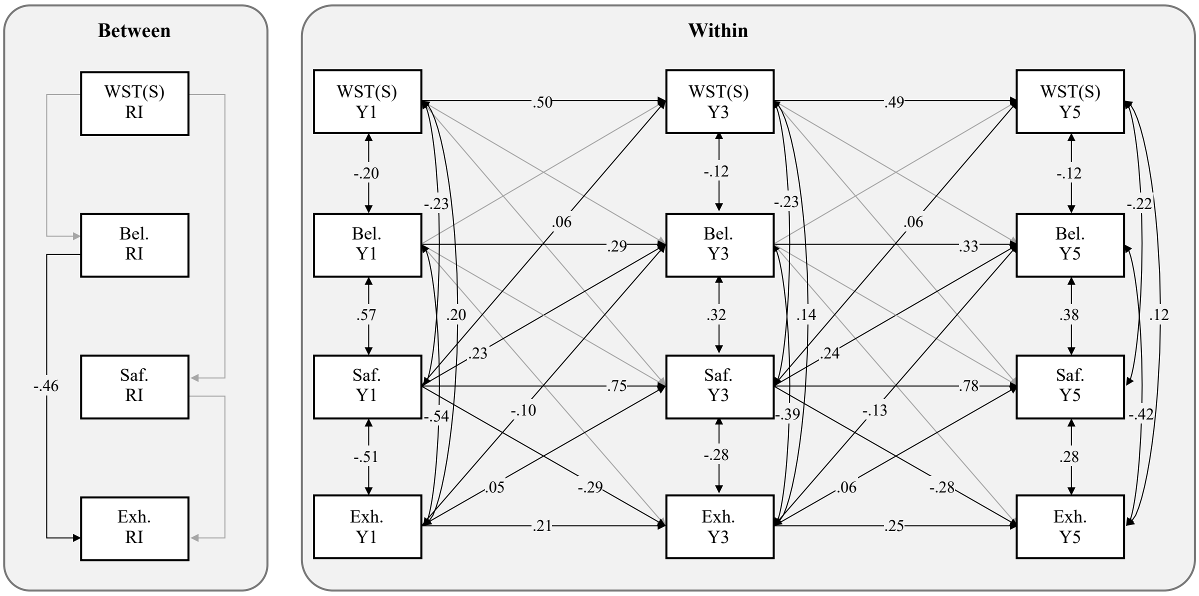

Figure 3. Results from the RI-CLPM (Model 5b) with the Witnessing Student-to-Teacher Aggression Specific Factor.

Note. Model fit: χ^2 = 129.862 (df = 32), p < .05; RMSEA = .038; CFI =.992; TLI =.984. RI: Random intercept; WST(S): Witnessing student-to-teacher aggression specific factor; Bel.: Feeling of belongingness; Saf.: Feeling of safety in school; Exh.: Emotional exhaustion. Non standardized betas are reported for paths significant at p < .05. Non-significant paths are displayed in grey. Slight variations in correlations are due to the standardization.

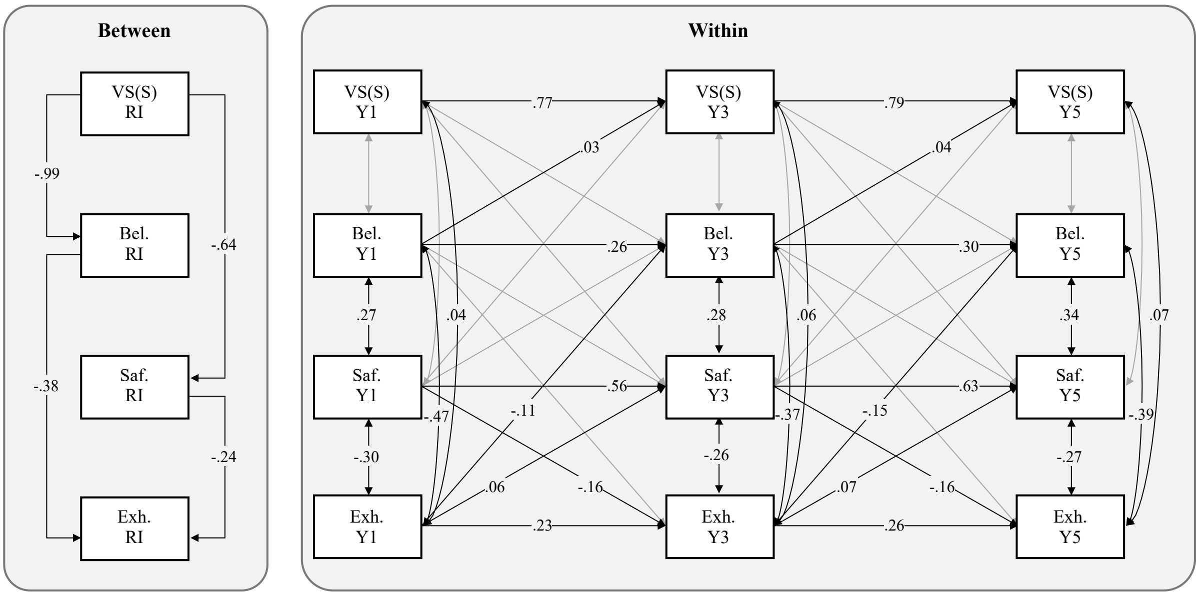

Figure 4. Results from the RI-CLPM (Model 2) with the Victim of Aggression Perpetrated by a Student Specific Factor.

Note. Model fit: χ^2 = 273.369 (df = 38), p < .05; RMSEA = .055; CFI = .981; TLI = .967. RI: Random intercept; VS(S): Being a victim of aggression perpetrated by a student specific factor; Bel.: Feeling of belongingness; Saf.: Feeling of safety in school; Exh.: Emotional exhaustion. Non standardized betas are reported for paths significant at p < .05. Non-significant paths are displayed in grey. Slight variations in correlations are due to the standardization.

Online Supplements for:
Chronic and Temporary Exposure to Student Violence Predicts Emotional Exhaustion in High School Teachers

Missing Data and Preliminary Measurement Models

Missing data

Our main analyses rely on a sample of 2,072 teachers who participated in at least two data collection points. Complete data over the three time-points was available for 745 teachers (1183 teachers had complete data for Y1 and Y3, 988 for Y1 and Y5, and 1251 for Y3 and Y5). Missing time points were mostly due to teachers not returning their questionnaires or being on temporary or permanent leave. Rates of incomplete data ranged from 14.14% to 27.70% across measures. More precisely, the aggression measure included 27.5% of missing data at Y1, 13.7% at Y3, and 24.4% at Y3, whereas the remaining measures included 27.4% of missing data at Y1, 13.6% at Y3, and 24.4% at Y3.

We conducted attrition analyses, comparing teachers with and without missing time points in relation to sociodemographic variables (sex, age, years of experience in their school) and all variables included in the models (aggression, belongingness, safety, and emotional exhaustion at Y1, Y3, and Y5). We found that females were slightly more likely than males to have missing data (66.47% vs 60.75%). There was no difference in relation to age and years of teaching experience. The only differences found on the variables included in the models were for perceived safety at Y1 (participants with missing data had a slightly higher mean score [+.124 s.d.] relative to those without missing data) and the global aggression factor at Y5 (participants with missing data had a slightly higher mean score [+.076 s.d.] relative to those without missing data). It is, however, important to reinforce that the procedure used to handle missing data (FIML), relies on the missing at random (MAR) assumptions. This means that it is robust to the presence of differences between participants related to attrition on all variables included in the model (Enders, 2010). The tenability of MAR is further enhanced in longitudinal designs to the extent that missingness on a specific variable is allowed to be a function of values on this same variable at another time point (e.g., Newman, 2014).

Preliminary Analyses

Due to the complexity of the longitudinal measurement models considered in the present study, we estimated two separate sets of models, one for the belongingness, safety, and eexhaustion measures (CFA), and one for the aggression measure (bifactor-CFA). For the aggression measure, before retaining the bifactor-CFA solution, we first contrasted it with a simpler CFA solution involving three correlated factors (one for each type of aggression, without the global factor. To select the optimal solution (CFA or bifactor-CFA), we relied on Morin et al.'s (2020) recommendations that a bifactor-CFA model should be retained over a CFA solution when: (i) it results in an equivalent or improved or level of fit the data, (ii) CFA factor correlations are high enough to support the need to incorporate a global factor (G-factor) to the model, (iii) it results in a well-defined G-factor, and (iv) at least some of the specific factors (S-factors) are also well-defined. All models were longitudinal, including separate sets of factors across time points, and a priori correlated uniquenesses among matching indicators of the constructs used repeatedly over time (Marsh, 2007).

The longitudinal measurement invariance of both models was then tested in the following sequence (Meredith, 1993): (1) configural invariance (same models with no constraint); (2) weak invariance (equal factor loadings); (3) strong invariance (equal item intercepts); (4) strict invariance (equal item uniquenesses). Following Hamacker's (2015) recommendation, we saved the factor scores from the most invariant (strict) models. For tests of measurement invariance, model comparison was based on the assessment of changes in goodness-of-fit indices, with decreases CFI and TLI ≤ .010 and increases in RMSEA ≤ .015 between each model and the previous one in the sequence considered as supportive of the added invariance constraint (Chen, 2007, Cheung & Rensvold, 2002; Marsh et al., 2005).

For all measures, we finally report the composite reliability of each factor using the omega (ω; McDonald, 1970), which takes into account the strength of the associations between items and all constructs and the item-specific measurement error. This metric is recommended to assess factor reliability in CFA and bifactor-CFA models (Morin et al., 2020). For CFA solutions, omega can be interpreted using the same interpretation guidelines as Cronbach's alpha. However, in bifactor solutions, Morin et al. (2020) warn against the application of similar interpretation guidelines given that a bifactor model involves the division of the reliable (true score) variance present at the item level into two distinct factors while the item uniqueness remains unitary and used in the calculation of the coefficients associated with both factors. For this reasons, a bifactor model typically results in slightly weaker S-factors. Current recommendations (Morin et al., 2020; Perreira et al., 2018) generally suggest that S-factors associated with an omega of roughly .500 or higher can be considered to retain enough specificity to be meaningful. In contrast, S-factors associated with lower omega values (closer to .400 or lower) can be considered to retain only limited specificity once the variance explained by the G-factor is taken into account, but retained them has been shown not to influence the rest of the model (Morin et al., 2020). Overall, this characteristic of bifactor models further reinforces the need to rely on analytical methods providing some degree of control for unreliability when adopting a bifactor approach (such as relying on factor scores) (Morin et al., 2020; Perreira et al., 2018).

Confirmatory Factor Analysis Results

Aggression. Model fit for the longitudinal CFA and bifactor-CFA models are reported on the top section of Table S1. As shown in this table, both models have an adequate level of fit to the data, although the fit of the bifactor-CFA solution was slightly higher than that of the CFA. However, although the CFA solution resulted in generally well-defined factors, it resulted in very high estimates of factor correlations (WSS with WTS $r = .763$; WTS with VS $r = .702$; WSS with VS $r = .478$), calling into question the true discriminant validity of the factors and reinforcing the usefulness of incorporating a G-factor to the model. Parameters estimates from the bifactor-CFA model are reported in Table S2, and reveal well-defined G-factors at all time points (ω = .838 at Y1, .827 at Y3, and .822 at Y5), as well as a adequately (but more weakly) defined WSS (ω = .578 at Y1, .598 at Y3, and .625 at Y5) and VS (ω = .577 at Y1, .535 at Y3, and .465 at Y5) S-factors at all time points. However, the WTS S-factors (ω = .341 at Y1, .349 at Y3, and .396 at Y5) was more weakly defined, suggesting that the items forming this S-factor mainly contributed to the definition of the G-factor, and retained only limited specificity once the variance explained by this G-factor was taken into account (Morin et al., 2020). Altogether, these results support the value of the bifactor-CFA solution, which was retained for tests of measurement invariance. The results from these tests, reported in the middle section of Table S1, support the configural, weak, strong, and strict invariance of this solution over time. It is important to note, however, that the lower reliability coefficients associated with the WSS, VS, and WTS S-factors reinforce the need to rely on factor scores, able to provide control for unreliability, in the main analyses – although results linked to the WTS S-factors would still have to be interpreted with caution.

Belongingness, Safety, and Exhaustion. Model fit results associated with the CFA model are reported in the bottom section of Table S1. These results reveal that the baseline model (configural) had a fully acceptable level of fit to the data. Furthermore, tests of measurement invariance supported the weak, strong, and strict invariance of this solution over time solution. The parameter estimates form this model are reported in Table S3, and reveal well-defined and reliable belongingness (ω = .920 at Y1, .919 at Y3, and .922 at Y5), safety (ω = .875 at Y1, .876 at Y3, and .877 at Y5), and exhaustion (ω = .802 at Y1, .820 at Y3, and .831 at Y5), factors across time points.

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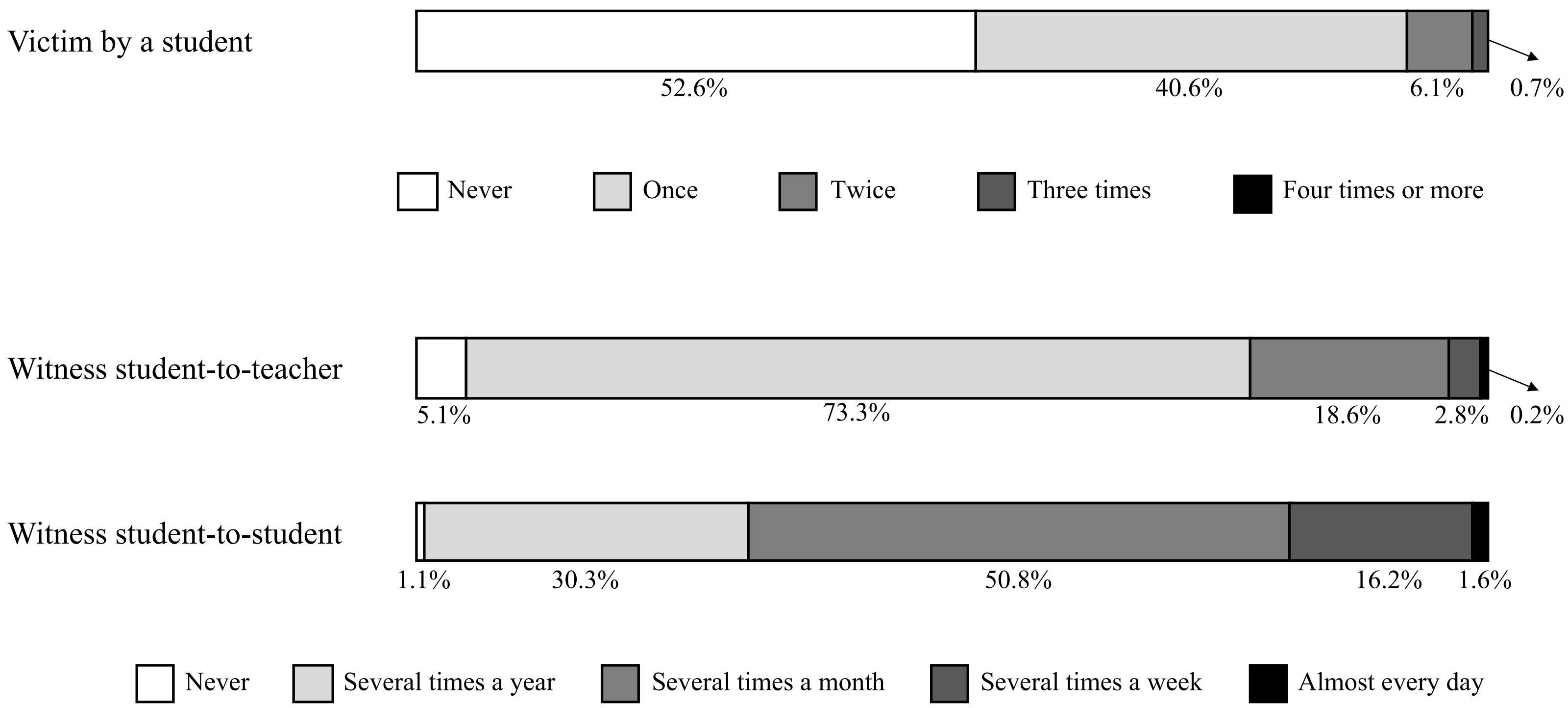

Figure S1.
Prevalence of each type of exposure to student-perpetrated aggression.

Table S1

Measurement models and longitudinal measurement invariance of the predictors and outcomes scales.

Model	χ^2	*df*	SCF	CFI	TLI	RMSEA	RMSEA 90% CI	$\Delta\chi^2$	Δdf	ΔCFI	ΔTLI	ΔRMSEA
Student-Perpetrated Aggression Scales												
Measurement Model Comparison												
CFA Model	951.245*	339	1.2842	.949	.934	.030	.027-.032	–	–	–	–	–
Bifactor-CFA Model	819.026*	297	1.1863	.956	.936	.029	.027-.032	–	–	–	–	–
Longitudinal (Y1-Y3-Y5) Measurement Invariance of the Bifactor-CFA Model												
1. Configural invariance	819.026*	297	1.1863	.956	.936	.029	.027-.032	–	–	–	–	–
2. Weak invariance	808.352*	329	1.2936	.960	.947	.027	.024-.029	32.354	32	+.004	+.011	-.002
3. Strong invariance	836.822*	341	1.2832	.958	.947	.026	.024-.029	28.180*	12	-.002	+.000	-.001
4. Strict invariance	694.117*	361	1.6356	.972	.966	.021	.019-.023	8.044	20	+.014	+.019	-.005
Teacher Perceived Belongingness, School Safety, and Emotional Exhaustion Scales												
Longitudinal (Y1-Y3-Y5) Measurement Invariance of the CFA Model												
1. Configural invariance	3491.834*	996	1.1658	.936	.927	.035	.034-.036	–	–	–	–	–
2. Weak invariance	3540.677*	1022	1.1719	.935	.928	.034	.033-.036	55.877*	26	-.001	+.001	-.001
3. Strong invariance	3694.791*	1048	1.1673	.932	.927	.035	.034-.036	165.149*	26	-.003	-.001	+.001
4. Strict invariance	3765.565*	1080	1.2096	.931	.928	.035	.033-.036	93.487*	32	-.001	+.001	+.000

Note. χ^2: Chi square test of model fit and associated degrees of freedom (*df*); CFI: Comparative Fit Index; SCF: Scaling Correction Factor; TLI: Tucker-Lewis Index; RMSEA: Root Mean Square Error of Approximation and 90% Confidence Interval (CI); Δ: Change according to the previous retained model; $\Delta\chi^2$: Chi square difference test calculated with the Satorra-Bentler correction.

$^*p < .01$.

Table S2

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Student-Perpetrated Aggression Scales Bifactor Confirmatory Factor Analytic Results.

	Agr.(G) λ Y1	WSS(S) λ Y1	WST(S) λ Y1	VS(S) λ Y1	Agr.(G) λ Y3	WSS(S) λ Y3	WST(S) λ Y3	VS(S) λ Y3	Agr.(G) λ Y5	WSS(S) λ Y5	WST(S) λ Y5	VS(S) λ Y5	δ Y1	δ Y3	δ Y5
Witnessing Student-Student Aggression															
Insults	.587	.241			.569	.254			.560	.270			.598	.611	.613
Threats	.580	.442			.559	.464			.545	.488			.468	.472	.465
Fights	.492	.562			.471	.584			.454	.609			.441	.437	.422
Physical attacks	.512	.434			.492	.454			.479	.477			.550	.552	.542
Witnessing Student-Teacher Aggression															
Insults	.781		.122		.768		.127		.761		.143		.375	.394	.401
Threats	.665		.460		.647		.475		.624		.518		.346	.356	.342
Physical attacks	.435		.285		.420		.292		.410		.322		.730	.739	.728
Victim of Aggression Perpetrated by a Student															
Insults	.518			.484	.514			.452	.523			.397	.497	.531	.569
Threats	.421			.742	.429			.713	.457			.655	.272	.308	.362
Physical attacks	.176			.278	.170			.253	.169			.217	.892	.907	.925
Composite reliability (ω)	.838	.578	.341	.577	.827	.598	.349	.535	.822	.625	.396	.465			

Note. ω: omega coefficient of composite reliability (McDonald, 1970).

All loadings and uniquenesses are constrained to equality over time (i.e., strict invariance). Slight variations reported in the table are due to the standardization process.

All results are statistically significant (p ≤ .05) are marked in italics.

Table S3

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Teacher Perceived Belongingness, School Safety, and Emotional Exhaustion Scales.

	Bel. λ Y1	Saf. λ Y1	Exh. λ Y1	Bel. λ Y3	Saf. λ Y3	Exh. λ Y3	Bel. λ Y5	Saf. λ Y5	Exh. λ Y5	δ Y1	δ Y3	δ Y5
Belongingness												
Proud of this school	.920			.919			.922			.153	.156	.150
Love my school	.922			.921			.924			.150	.152	.146
Feel I belong	.721			.717			.725			.481	.486	.474
Wish to work elsewhere (reverse)	.696			.693			.701			.515	.520	.508
This school is important to me	.893			.892			.896			.202	.205	.197
Perceived School Safety												
Staff fear for safety		.820			.822			.824		.328	.324	.322
Students often harassed		.574			.576			.579		.671	.668	.665
Students are fearful		.706			.709			.711		.501	.498	.495
Students do not feel safe		.712			.715			.717		.492	.489	.486
Staff fear to intervene		.624			.627			.630		.610	.606	.604
Staff do not feel safe		.826			.827			.829		.318	.315	.313
Emotional Exhaustion												
Tired			.723			.744			.756	.477	.447	.428
Not able to perform			.713			.734			.746	.492	.462	.443
Negative relationships			.625			.649			.663	.609	.579	.561
Irritated			.734			.754			.766	.461	.431	.413
Trouble sleeping			.540			.563			.578	.708	.682	.666
Composite reliability (ω)	.920	.875	.802	.919	.876	.820	.922	.877	.831			

Note. ω: omega coefficient of composite reliability (McDonald, 1970).
All loadings and uniquenesses are constrained to equality over time (i.e., strict invariance). Slight variations reported in the table are due to the standardization process.
All results are statistically significant ($p \leq .05$) are marked in italics.

Table S4

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Teacher Perceived Belongingness, School Safety, and Emotional Exhaustion Scales.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.
1. Agr.(G) Y1																					
2. WSS(S) Y1	.126**																				
3. WST(S) Y1	.066**	-.024																			
4. VS(S) Y1	.121**	-.101**	.180**																		
5. Bel. Y1	-.267**	-.018	-.100**	-.134**																	
6. Saf. Y1	-.455**	-.161**	-.153**	-.071**	.474**																
7. Exh. Y1	.256**	.000	.074**	.120**	-.477**	-.394**															
8. Agr.(G) Y3	.840**	-.013	-.005	.108**	-.244**	-.399**	.248**														
9. WSS(S) Y3	.235**	.370**	-.023	.073**	-.030	-.111**	.056*	.199**													
10. WST(S) Y3	-.019	-.041	.762**	.141**	-.042	-.104**	.041	.129**	-.030												
11. VS(S) Y3	.055*	-.150**	.185**	.805**	-.119**	-.051*	.114**	.104**	-.065**	.093**											
12. Bel. Y3	-.220**	.044*	-.075**	-.113**	.613**	.391**	-.406**	-.269**	-.008	-.071**	-.148**										
13. Saf. Y3	-.410**	-.098**	-.125**	-.040	.389**	.788**	-.335**	-.465**	-.153**	-.179**	-.040	-.433**									
14. Exh. Y3	.234**	-.027	.042	.131**	-.352**	-.336**	.746**	.295**	.044*	.064**	.172**	-.498**	-.376**								
15. Agr.(G) Y5	.827**	-.087**	-.004	.176**	-.224**	-.366**	.234**	.851**	.188**	.032	.151**	-.219**	-.406**	.257**							
16. WSS(S) Y5	.167**	.360**	.066**	-.118**	.009	-.073**	.029	.047*	.577**	.047*	-.061**	.035	-.093**	.022	.156**						
17. WST(S) Y5	.067**	-.063**	.607**	.135**	-.045*	-.113**	.036	.058**	-.005	.718**	.046*	-.048*	-.147**	.024	.206**	-.081**					
18. VS(S) Y5	-.096**	.000	.391**	.750**	-.096**	-.032	.078**	-.017	.026	.192**	.797**	-.096**	-.022	.112**	.081**	-.117**	.080**				
19. Bel. Y5	-.227**	.030	-.082**	-.106**	.548**	.369**	-.348**	-.255**	-.016	-.085**	-.121**	.673**	.387**	-.411**	-.283**	-.017	-.129**	-.092**			
20. Saf. Y5	-.400**	-.091**	-.119**	-.057**	.322**	.658**	-.298**	-.413**	-.158**	-.157**	-.050*	.330**	.783**	-.280**	-.457**	-.190**	-.209**	-.029	.463**		
21. Exh. Y5	.243**	.003	.031	.082**	-.295**	-.327**	.654**	.266**	.051*	.030	.110**	-.317**	-.374**	.682**	.305**	.065**	.078**	.077**	-.464**	-.433**	
Descriptive statistics																					
Mean	.000	.000	.000	.000	.000	.000	.000	-.198	.177	.384	.065	-.023	.140	.135	-.176	.284	.328	-.050	-.045	.180	.179
S.D.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	.841	.745	.692	.731	.925	.925	.939	.806	.770	.707	.575	.909	.893	.938

Note. Variables are factors scores from a longitudinal model of strict invariance in which they were set to have mean of 0 and a variance of 1 at time 1; bifactor correlations are not exactly zero as these involve factor scores; G: Global factor from a bifactor solution; S: Specific factor from a bifactor solution; Ext: Externalizing behaviors; H/I: Hyperactivity/Inattention; O/D: Oppositional/Defiant; Int: Internalizing behaviors; Anx: Anxiety; Dep: Depressive symptoms; Eng: Engagement; BE: Behavioral engagement; EE: Emotional engagement; CE: Cognitive engagement.

* $p \leq .05$; ** $p \leq .01$.

Table S5

RI-CLPM Comparison Results.

Model	χ^2	*df*	SCF	CFI	TLI	RMSEA	RMSEA 90% CI	$\Delta\chi^2$	Δdf	ΔCFI	ΔTLI	ΔRMSEA
Model with Exposure to Aggression Global Factor												
M1a – Direct model	1209.774*	55	1.4860	.927	.913	.101	.096-.106					
M1b – Full mediation	705.467*	46	1.4591	.959	.940	.083	.078-.089					
M1c – Partial mediation	689.386*	43	1.4833	.959	.938	.085	.080-.091					
M2 – Free mean structure	211.674*	38	1.3419	.989	.981	.047	.041-.053	369.730*	8	.030	.041	-.036
M3 – Free autoregressive paths	196.672*	34	1.2753	.990	.980	.048	.042-.055	17.416*	4	.001	-.001	.001
M4 – Free cross-lag paths	172.392*	28	1.3840	.991	.979	.050	.043-.057	37.136*	10	.002	-.002	.003
M5 – Free correlations Y1-Y3-Y5	107.097*	26	1.2468	.995	.987	.039	.031-.047	97.236*	12	.006	.006	-.008
Model with Witnessing Student-to-Student Aggression Specific Factor												
M1a – Direct model	856.453*	55	1.4525	.927	.912	.084	.079-.089					
M1b – Full mediation	418.343*	46	1.5132	.966	.951	.063	.057-.068					
M1c – Partial mediation	463.465*	43	1.4611	.962	.941	.069	.063-.074					
M2 – Free mean structure	167.377*	38	1.3885	.988	.980	.041	.034-.047	190.277*	8	.022	.029	-.022
M3 – Free autoregressive paths	291.559*	34	.9977	.977	.954	.060	.054-.067	12.417	4	-.011	-.026	.019
M4 – Free cross-lag paths	133.795*	28	1.4213	.990	.977	.043	.036-.050	32.576*	10	.002	-.003	.002
M5 – Free correlations Y1-Y3-Y5	159.848*	26	1.0954	.988	.969	.050	.043-.057	28.319*	12	.000	-.011	.009
Model with Witnessing Student-to-Teacher Aggression Specific Factor												
M1a – Direct model	1330.232*	55	1.4621	.896	.876	.106	.010-.111					
M1b – Full mediation	1227.369*	46	1.2465	.904	.862	.111	.106-.117					
M1c – Partial mediation	1891.981*	43	.8105	.850	.769	.144	.139-.150					
M2 – Free mean structure	268.130*	38	1.1981	.981	.968	.054	.048-.060	818.660*	8	.077	.106	-.057
M3 – Free autoregressive paths	250.742*	34	1.1222	.982	.966	.055	.049-.062	21.627*	4	.001	-.002	.001
M4 – Free cross-lag paths	221.286*	28	1.2023	.984	.963	.058	.051-.065	46.525*	10	.003	-.005	.004
M5 – Free correlations Y1-Y3-Y5	108.327*	26	1.1460	.993	.983	.039	.032-.047	150.348*	12	.012	.015	-.015
M5b – Free correlations Y1	129.862*	32	1.2042	.992	.984	.038	.032-.045	141.448*	6	.011	.016	-.016
Model with Victim of Student Aggression Specific Factor												
M1a – Direct model	946.418*	55	1.4371	.929	.914	.088	.084-.093					
M1b – Full mediation	969.683*	46	.9495	.926	.894	.098	.093-.104					
M1c – Partial mediation	906.774*	43	1.0019	.931	.894	.098	.093-.104					
M2 – Free mean structure	273.369*	38	1.4754	.981	.967	.055	.049-.061	334.115*	8	.055	.073	-.043
M3 – Free autoregressive paths	254.710*	34	1.1945	.982	.966	.056	.050-.063	25.647*	4	.001	-.001	.001
M4 – Free cross-lag paths	799.868*	28	.5905	.938	.854	.115	.109-.122	17.453	10	-.043	-.113	.060
M5 – Free correlations Y1-Y3-Y5	264.552*	26	1.2522	.981	.951	.067	.059-.074	36.782*	12	.000	-.016	.012

Note. χ^2: Chi square test of model fit and associated degrees of freedom (*df*); CFI: Comparative Fit Index; SCF: Scaling Correction Factor; TLI: Tucker-Lewis Index; RMSEA: Root Mean Square Error of Approximation and 90% Confidence Interval (CI); Δ: Change according to the previous retained model; $\Delta\chi^2$: Chi square difference test calculated with the Satorra-Bentler correction. Models in bold are those retained for the following steps. Models are compared (Δ) in reference to the last retained model. $^*p < .01$.

Table S6.

Detailed results from the RI-CLPM (Model 2) with the Global Aggression Factor.

Predictor	Outcome	*b*(s.e.)	*β*	Predictor	Outcome	*b*(s.e.)	*β*
Autoregressive paths							
Agr.(G) Y1	Agr.(G) Y3	.144(.069)*	.153	Agr.(G) Y3	Agr.(G) Y5	.144(.069)*	.158
Bel. Y1	Bel. Y3	.271(.072)**	.245	Bel. Y3	Bel. Y5	.271(.072)**	.279
Saf. Y1	Saf. Y3	.627(.026)**	.573	Saf. Y3	Saf. Y5	.627(.026)**	.624
Exh. Y1	Exh. Y3	.238(.048)**	.186	Exh. Y3	Exh. Y5	.238(.048)**	.224
Cross-lag paths							
Agr.(G) Y1	Bel. Y3	.044(.055)	.023	Agr.(G) Y3	Bel. Y5	.044(.055)	.023
Agr.(G) Y1	Saf. Y3	.100(.043)*	.056	Agr.(G) Y3	Saf. Y5	.100(.043)*	.053
Bel. Y1	Agr.(G) Y3	-.007(.019)	-.013	Bel. Y3	Agr.(G) Y5	-.007(.019)	-.016
Bel. Y1	Saf. Y3	.094(.025)**	.090	Bel. Y3	Saf. Y5	.094(.025)**	.099
Bel. Y1	Exh. Y3	.032(.028)	.035	Bel. Y3	Exh. Y5	.032(.028)	.037
Saf. Y1	Agr.(G) Y3	-.023(.025)	-.040	Saf. Y3	Agr.(G) Y5	-.023(.025)	-.048
Saf. Y1	Bel. Y3	.253(.050)**	.217	Saf. Y3	Bel. Y5	.253(.050)**	.244
Saf. Y1	Exh. Y3	-.203(.031)**	-.216	Saf. Y3	Exh. Y5	-.203(.031)**	-.221
Exh. Y1	Bel. Y3	-.138(.050)**	-.087	Exh. Y3	Bel. Y5	-.138(.050)**	-.115
Exh. Y1	Saf. Y3	.094(.026)**	.063	Exh. Y3	Saf. Y5	.094(.026)**	.081
Trait-level associations							
Agr.(G) RI	Bel. RI	-.272(.040)**	-.377	Bel. RI	Exh. RI	-.512(.052)**	-.403
Agr.(G) RI	Saf. RI	-.479(.042)**	-.638	Saf. RI	Exh. RI	-.333(.048)**	-.274

Note. * $p \leq .05$; ** $p \leq .01$; *b* = Unstandardized regression coefficient; s.e. = Standard error of the coefficient; *β* = Standardized coefficient

Table S7.

Detailed results from the RI-CLPM (Model 2) with the Witnessing Student-to-Student Aggression Specific Factor.

Predictor	Outcome	*b*(s.e.)	*β*	Predictor	Outcome	*b*(s.e.)	*β*
Autoregressive paths							
WSS(S) Y1	WSS(S) Y3	.521(.018)**	.430	WSS(S) Y3	WSS(S) Y5	.521(.018)**	.536
Bel. Y1	Bel. Y3	.276(.063)**	.253	Bel. Y3	Bel. Y5	.276(.063)**	.297
Saf. Y1	Saf. Y3	.601(.030)**	.539	Saf. Y3	Saf. Y5	.601(.030)**	.613
Exh. Y1	Exh. Y3	.265(.048)**	.205	Exh. Y3	Exh. Y5	.265(.048)**	.250
Cross-lag paths							
WSS(S) Y1	Bel. Y3	.012(.022)	.011	WSS(S) Y3	Bel. Y5	.012(.022)	.014
WSS(S) Y1	Saf. Y3	-.054(.015)**	-.053	WSS(S) Y3	Saf. Y5	-.054(.015)**	-.065
Bel. Y1	WSS(S) Y3	.022(.025)	.018	Bel. Y3	WSS(S) Y5	.022(.025)	.020
Bel. Y1	Saf. Y3	-.022(.025)	-.021	Bel. Y3	Saf. Y5	-.022(.025)	-.024
Bel. Y1	Exh. Y3	.035(.028)	.038	Bel. Y3	Exh. Y5	.035(.028)	.039
Saf. Y1	WSS(S) Y3	-.063(.028)*	-.047	Saf. Y3	WSS(S) Y5	-.063(.028)*	-.054
Saf. Y1	Bel. Y3	.041(.043)	.035	Saf. Y3	Bel. Y5	.041(.043)	.042
Saf. Y1	Exh. Y3	-.154(.033)**	-.154	Saf. Y3	Exh. Y5	-.154(.033)**	-.162
Exh. Y1	Bel. Y3	-.154(.051)**	-.101	Exh. Y3	Bel. Y5	-.154(.051)**	-.101
Exh. Y1	Saf. Y3	.088(.030)**	.061	Exh. Y3	Saf. Y5	.088(.030)**	.080
Trait-level associations							
WSS(S) RI	Bel. RI	.251(6.559)	.171	Bel. RI	Exh. RI	-.434(.062)**	-.381
WSS(S) RI	Saf. RI	.087(6.811)	.062	Saf. RI	Exh. RI	-.256(.066)**	-.227

Note. * $p \leq .05$; ** $p \leq .01$; *b* = Unstandardized regression coefficient; s.e. = Standard error of the coefficient; *β* = Standardized coefficient

Table S8.
Detailed results from the RI-CLPM (Model 5b) with the Witnessing Student-to-Teacher Aggression Specific Factor.

Predictor	Outcome	*b*(s.e.)	*β*	Predictor	Outcome	*b*(s.e.)	*β*
Autoregressive paths							
WST(S) Y1	WST(S) Y3	.544(.056)**	.500	WST(S) Y3	WST(S) Y5	.544(.056)**	.493
Bel. Y1	Bel. Y3	.315(.062)**	.288	Bel. Y3	Bel. Y5	.315(.062)**	.330
Saf. Y1	Saf. Y3	.778(.040)**	.754	Saf. Y3	Saf. Y5	.778(.040)**	.783
Exh. Y1	Exh. Y3	.267(.044)**	.205	Exh. Y3	Exh. Y5	.267(.044)**	.252
Cross-lag paths							
WST(S) Y1	Bel. Y3	-.052(.042)	-.030	WST(S) Y3	Bel. Y5	-.052(.042)	-.034
WST(S) Y1	Saf. Y3	-.034(.026)	-.018	WST(S) Y3	Saf. Y5	-.034(.026)	-.019
Bel. Y1	WST(S) Y3	.010(.019)	.015	Bel. Y3	WST(S) Y5	.010(.019)	.015
Bel. Y1	Saf. Y3	.044(.025)	.036	Bel. Y3	Saf. Y5	.044(.025)	.040
Bel. Y1	Exh. Y3	.027(.026)	.031	Bel. Y3	Exh. Y5	.027(.026)	.033
Saf. Y1	WST(S) Y3	-.035(.017)*	-.060	Saf. Y3	WST(S) Y5	-.035(.017)*	-.057
Saf. Y1	Bel. Y3	.209(.031)**	.225	Saf. Y3	Bel. Y5	.209(.031)**	.243
Saf. Y1	Exh. Y3	-.215(.028)**	-.291	Saf. Y3	Exh. Y5	-.215(.028)**	-.284
Exh. Y1	Bel. Y3	-.158(.054)**	-.097	Exh. Y3	Bel. Y5	-.158(.054)**	-.131
Exh. Y1	Saf. Y3	.087(.033)**	.048	Exh. Y3	Saf. Y5	.087(.033)**	.063
Trait-level associations							
WST(S) RI	Bel. RI	.048(.072)	.046	Bel. RI	Exh. RI	-.643(.093)**	-.461
WST(S) RI	Saf. RI	.002(.028)	.004	Saf. RI	Exh. RI	-2.063(4.717)	-.600

Note. * $p \leq .05$; ** $p \leq .01$; *b* = Unstandardized regression coefficient; s.e. = Standard error of the coefficient; *β* = Standardized coefficient

Table S9.
Detailed results from the RI-CLPM (Model 2) with the Victim of Aggression Perpetrated by a Student Specific Factor.

Predictor	Outcome	*b*(s.e.)	*β*	Predictor	Outcome	*b*(s.e.)	*β*
Autoregressive paths							
VS(S) Y1	VS(S) Y3	.672(.016)**	.767	VS(S) Y3	VS(S) Y5	.672(.016)**	.791
Bel. Y1	Bel. Y3	.281(.063)**	.255	Bel. Y3	Bel. Y5	.281(.063)**	.301
Saf. Y1	Saf. Y3	.622(.031)**	.562	Saf. Y3	Saf. Y5	.622(.031)**	.634
Exh. Y1	Exh. Y3	.274(.049)**	.231	Exh. Y3	Exh. Y5	.274(.049)**	.257
Cross-lag paths							
VS(S) Y1	Bel. Y3	.034(.023)	.037	VS(S) Y3	Bel. Y5	.034(.023)	.035
VS(S) Y1	Saf. Y3	.021(.016)	.024	VS(S) Y3	Saf. Y5	.021(.016)	.022
Bel. Y1	VS(S) Y3	.035(.012)**	.033	Bel. Y3	VS(S) Y5	.035(.012)**	.043
Bel. Y1	Saf. Y3	-.021(.025)	-.020	Bel. Y3	Saf. Y5	-.021(.025)	-.022
Bel. Y1	Exh. Y3	.034(.027)	.036	Bel. Y3	Exh. Y5	.034(.027)	.037
Saf. Y1	VS(S) Y3	.018(.011)	.016	Saf. Y3	VS(S) Y5	.018(.011)	.021
Saf. Y1	Bel. Y3	.051(.046)	.044	Saf. Y3	Bel. Y5	.051(.046)	.052
Saf. Y1	Exh. Y3	-.155(.034)**	-.157	Saf. Y3	Exh. Y5	-.155(.034)**	-.163
Exh. Y1	Bel. Y3	-.163(.051)**	-.107	Exh. Y3	Bel. Y5	-.163(.051)**	-.148
Exh. Y1	Saf. Y3	.081(.032)*	.056	Exh. Y3	Saf. Y5	.081(.032)*	.074
Trait-level associations							
VS(S) RI	Bel. RI	-5.560(1.595)**	-.987	Bel. RI	Exh. RI	-.430(.064)**	-.375
VS(S) RI	Saf. RI	-3.640(1.094)**	-.640	Saf. RI	Exh. RI	-.268(.068)**	-.236

Note. * $p \leq .05$; ** $p \leq .01$; *b* = Unstandardized regression coefficient; s.e. = Standard error of the coefficient; *β* = Standardized coefficient