Students' Emotion Regulation and School-Related Wellbeing: Longitudinal Models Juxtaposing Between- and Within-Person Perspectives

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Abstract

There is a lack of research examining how students' emotion regulation is linked to their wellbeing at school. To address this gap in the current literature, we examined reciprocal relations between two important emotion regulation strategies (cognitive reappraisal and expressive suppression) and school-related wellbeing over 12 months across two school years. We collected data from 2,365 secondary and upper secondary students in England (aged 11-19 years) across three waves. Juxtaposing between-person and within-person perspectives, we used a tripartite (three-part) latent cross-lagged panel model (CLPM), and a tripartite latent random intercept-cross lagged panel model (RI-CLPM) to examine the directional ordering of the two strategies and wellbeing over time. Both the CLPM and RI-CLPM showed that reappraisal and school-related wellbeing were reciprocally related. Reappraisal positively predicted school-related wellbeing, and school-related wellbeing positively predicted reappraisal. Reappraisal also negatively predicted subsequent suppression, but not vice versa. Suppression and school-related wellbeing were not linked. Findings inform the design of intervention research in schools and colleges by highlighting the importance of cognitive reappraisal in the school-related wellbeing of adolescents.

Keywords: school wellbeing, emotion regulation, cognitive reappraisal, expressive suppression, adolescence

Educational Impact and Implications Statement

We show that cognitive reappraisal, an emotion regulation strategy, contributes to school wellbeing, and school wellbeing contributes to cognitive reappraisal. Cognitive reappraisal enhances students' wellbeing, and enhancing students' sense of wellbeing is beneficial for promoting the development of cognitive reappraisal. Our findings inform the development of interventions in schools and colleges to improve young people's wellbeing and emotion regulation.

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Young people undergo significant biological, cognitive, social, and psychological changes during their school years (Blakemore & Mills, 2014). In particular, adolescence is characterized by heightened emotional responses compared to those experienced in childhood (e.g., Stroud et al., 2009). In addition, emotionally challenging situations such as conflict with parents and sensitivity to peer interactions typically occur more often and with greater intensity during adolescence (Powers & Casey, 2015; Riediger & Klipker, 2014). This coincides with the substantial development of emotion regulation strategies (Zimmerman & Iwanski, 2014) which play a key role in managing emotions and determining socioemotional adjustment (for an overview, see Riediger and Klipker, 2014). As such, if young people can manage their emotions effectively through this developmental time, it can result in positive outcomes for their current and future mental health (Ahmed et al., 2015; Young et al., 2019).

Recent decades have seen a global increase in mental health problems and a decrease in the wellbeing of young people (Marquez & Long, 2021). Indeed, in England, where the present study was conducted, 12.6% of secondary school-aged students were identified as likely to be suffering from a mental disorder in 2017, rising to 17.6% in 2020 (Vizard et al., 2020). In addition, a recent review of 16 quantitative studies, with 40,076 participants, conducted from 2019-2021 in eight countries worldwide found that adolescents were suffering from higher rates of anxiety, stress, and depression. The COVID-19 pandemic exacerbated this situation (Jones et al., 2021). The inability to effectively regulate one's emotions is linked to developing and prolonging many of these mental health issues (Berking & Wupperman, 2012).

Effectively regulating emotions, therefore, is important for optimal mental health. In addition, managing and responding effectively to emotional experiences is also linked to important educational outcomes. For instance, regulating emotional experiences in the classroom to achieve one's goals is likely important for learning (Boekaerts, 2011). This may involve decreasing negative emotions which impede learning but also increasing positive emotions to enhance learning (Martin & Ochsner, 2016). Indeed, negative emotions such as anxiety, anger, and shame can negatively impact academic performance, and positive emotions such as enjoyment and pride can positively impact performance (e.g., Forsblom et al., 2022; Pekrun et al., 2017). In addition, students who use emotion regulation strategies to manage their classroom experiences successfully are more likely to feel capable of pursuing their academic goals and perceive the classroom environment as supportive and constructive (Bockaerts 2011; Boekaerts & Pekrun, 2016). These perceptions are likely to increase levels of subjective wellbeing.

However, few studies have considered examining the direct link between students' emotion regulation strategies and their subjective wellbeing at school. It is important to examine whether this direct link exists, which can lay the foundation for future studies to consider the mechanisms and processes which may explain how these constructs are related. As such, the first unique contribution of this study to the literature is to examine specifically how two well-researched emotion regulation strategies, cognitive reappraisal, and expressive suppression, relate to school wellbeing. Examining wellbeing using a domain-specific measure can provide insight into how the regulation of emotions is related to school wellbeing. Moreover, knowledge of how emotion regulation strategies could contribute to improving wellbeing and has potential downstream benefits for improving academic outcomes.

Examination of the bidirectional links between emotion regulation strategies and wellbeing in young people has been neglected in previous research. Awareness of these associations is important for school leaders and educators to consider when finding ways to promote students' wellbeing (e.g., through interventions to develop emotion regulation strategies). These associations are also important when considering how students' wellbeing, in turn, impact their emotion regulation capabilities, which have the potential to influence their psychological, emotional and social development, and their learning capacity. The present longitudinal study with secondary school students targets gaps in the literature by examining reciprocal relations between two well-researched emotion regulation strategies, cognitive reappraisal and expressive suppression, and school-related wellbeing.

The second unique contribution of this study is using two complementary strategies to examine the links between emotion regulation and wellbeing over time. We used the classic cross-lagged panel model (CLPM) as well as the random-intercept cross-lagged panel model (RI-CLPM; Hamaker et al., 2018) to investigate the directional ordering of these constructs. The CLPM uses a between-person perspective on the relations between variables, whereas the RI-CLPM provides an analysis of within-person relations. By juxtaposing CLPM and RI-CLPM using the same longitudinal design and measures, we investigate the robustness of the proposed links between emotion regulation and wellbeing across different analytic methodologies. This is especially important because the CLPM has been criticized for not being able to properly estimate directional relations, and because findings using between- and within-person perspectives can differ widely (Molenaar, 2004; Murayama et al., 2017). Moreover, we contribute to the literature by using a tripartite (three-part) latent modeling procedure including three constructs (reappraisal, suppression, and wellbeing) both for the CLPM and the RI-CLPM, thus positioning our study at the forefront of modeling the multivariate ordering of variables over time (see Hamaker et al., 2018; Marsh et al., 2022; Mulder & Hamaker, 2021; Pekrun et al., in press).

Emotion Regulation

We define emotion regulation as the active processes by which individuals influence the type of emotions they experience when they experience the emotions, and how the emotions are experienced and expressed (Gross, 1998). Gross's (1998) process model of emotion regulation postulates that emotion regulation strategies can be organized into two groups: 'antecedent-focused' strategies which are implemented prior to the onset, or just after activation, of the emotional response; and 'response-focused' strategies which are implemented after the emotional response has occurred (Gross, 1998, 2014). Similarly, in Pekrun's (2006, 2018, 2021) control-value theory of emotions, different strategies to regulate emotions are considered, with antecedent strategies including appraisal-oriented strategies (see Pekrun & Stephens, 2009).

Cognitive Reappraisal

An emotion regulation strategy that has been given much attention in the literature is cognitive reappraisal. This strategy involves changing the way one thinks about a situation to alter its emotional impact (Gross & John, 2003). Thus, when using reappraisal an individual will reframe their cognitions to prevent the activation or development of emotions (i.e., by restructuring beliefs about a situation which one may view as negative, the person regulates the emotional response to that situation). For example, students might view their exam as an opportunity to demonstrate their subject knowledge, rather than seeing it as something which they might fail, to reduce the arousal of negative emotions (e.g., anxiety). Reappraisal is well-known for its positive psychological, social, and cognitive outcomes, such as increased life satisfaction, closer relationships with friends, and greater self-esteem (e.g., Gross & John, 2003, Haga et al., 2009; Schwerdtfeger et al., 2019). It has also been linked to lower levels of psychopathology in children and adolescents (Aldao et al., 2010; Schäfer et al., 2017). This is due to reappraisal being an antecedent-focused strategy. By 'shutting down' the emotional response before it is activated or developed, reappraisal eliminates or reduces the physiological, expressive, and subjective consequences of negative emotions such as sadness and anger (Gross & John, 2003). It is considered an effective strategy for regulating emotions that can be applied relatively effortlessly (Gross & Thompson, 2007).

We focused on cognitive reappraisal out of the many emotion regulation strategies available as there is a wealth of research linking reappraisal to positive outcomes for mental health and wellbeing (e.g., Gross & John, 2003). However, adolescent studies are still largely lacking (Chervonsky & Hunt, 2019). In addition, reappraisal is a strategy that is modifiable by intervention (Denny et al., 2020); this would allow us to suggest practical applications for our findings (e.g., students could undergo interventions to enhance reappraisal to increase their school wellbeing). Finally, reappraisal may be important for improving academic outcomes as it may alleviate negative feelings, so students are able to focus their attention on educational material (Davis & Levine, 2013). For instance, using reappraisal to reduce sadness may improve memory for educational information (Davis & Levine, 2013), and using it to reduce anxiety may improve students' problem-solving abilities (Pizzie et al., 2020). Thus, it may be a particularly useful strategy for students to use at school to support their learning.

Expressive Suppression

An important response-focused strategy that has been given much attention is expressive suppression (hereafter referred to as suppression). Suppression is concerned with attempting to conceal the expression of emotion (Gross & Levenson, 1993). For instance, a young person may maintain a neutral facial expression in the classroom to hide their disappointment at receiving a low test score. Due to suppression being implemented after the emotional response has been activated, it is less effective at reducing the subjective experience of emotion (e.g., Webb et al., 2012). It has been linked to impaired memory (e.g., Richards, 2004), lower social support (e.g., Srivastava et al., 2009), and symptoms of psychopathology in adults (see Gross, 2013, for a review) and adolescents (Schäfer et al., 2017).

We chose to focus on suppression as much of the previous research concerning this emotion regulation strategy has been conducted with adults; research investigating how suppression is linked to adolescent wellbeing is lacking (Gross & Cassidy, 2019). Moreover, the motivation to suppress may increase during adolescence as young people become increasingly aware of the social consequences of displaying emotions (Gross & Cassidy, 2019; Zeman & Shipman, 1997). However, suppression may have negative consequences for academic outcomes. For instance, it may undermine learning as it can interfere with cognitive processes such as memory retrieval and problem-solving (Baumeister et al., 1998; Gross & Cassidy, 2019; Richards & Gross, 1999). In addition, students who frequently use suppression may experience more difficulties in monitoring task performance, organizing their environment, and completing tasks in a timely manner (Lantrip et al., 2016). This is likely due to individuals thinking about controlling their emotional responses and behaviour (Richards et al., 2003) which drains cognitive resources (Lantrip et al., 2016). Thus, suppression is likely to be an emotion regulation strategy which has particular relevance to students' education and school wellbeing.

Subjective and School-Related Wellbeing

We refer to subjective wellbeing as the assessment of the quality of one's life from his or her own point of view (Diener et al., 2018). We define school-related subjective wellbeing as "…an emotional experience characterized by the dominance of positive feelings towards school, persons in school, and the school context in comparison to negative feelings and cognitions towards school life" (Hascher, 2003, p. 129). Research has shown that subjective wellbeing is associated with positive educational outcomes for children and adolescents (e.g., Bücker et al., 2018; Steinmayr et al., 2018). However, domain-specific wellbeing (e.g., one's wellbeing at school) may not be influenced by the same factors as general wellbeing (Oishi & Diener, 2001). Specifically, reappraisal and suppression may influence school wellbeing more strongly than general wellbeing. There are fewer emotion regulation strategies students can use at school compared to when students are outside of school (for a discussion of situational constraints in using regulatory strategies, see Harley et al., 2019). For instance, they are less likely to be able to change a situation (e.g., walk out of a room) or distract themselves (e.g., by turning on the television). Thus, reappraisal and suppression may be important regulation strategies for influencing wellbeing at school due to the lack of access to other strategies.

In the relatively few studies that have examined the antecedents and outcomes of school-related wellbeing specifically, school wellbeing has been found to be negatively related to school and test anxiety (Hascher, 2007; Putwain et al., 2021) and risk of developing an emotion disorder (Putwain et al., 2021), and to be positively associated with adaptability, academic achievement, and lower levels of behavioral misconduct on school premises (Putwain et al., 2020). However, no studies to date have examined relations between emotion regulation strategies and school-related subjective wellbeing.

Cognitive Reappraisal and Wellbeing

We propose that reappraisal and wellbeing are likely to be related reciprocally, in that reappraisal predicts wellbeing, and wellbeing predicts the use of reappraisal (see Figure 1). According to Fredrickson's broaden-and-build theory (Fredrickson, 1998), positive emotions, as implied by wellbeing, broaden attention and cognition enabling individuals to derive positive meaning from events (Folkman & Moskowitz, 2000; Fredrickson, 2000; Fredrickson & Joiner, 2002). As such, persons experiencing a better balance of positive and negative emotions (i.e., those who experience greater levels of wellbeing) are more likely to have broadened cognition, enabling them to use reappraisal to reinterpret situations positively. Use of reappraisal, in turn, enhances wellbeing in terms of increasing positive emotions and reducing negative emotions.

Harley et al.'s (2019) emotion regulation in achievement situations model (ERAS) is a related theory that details how students interpret situations as having a positive meaning. In this model, which combines insight from Gross's (1998, 2015) process model of emotion regulation and Pekrun's (2006, 2018, 2021) control-value theory of emotions (CVT), control and value appraisals influence the generation and regulation of emotions at the cognitive change stage of Gross's model. For example, students could remind themselves that they can contribute meaningfully to a class discussion because they have prior knowledge of the topic (a control appraisal), which can increase enjoyment of the lesson. Students could also remind themselves that they need to pay attention to a boring lesson to memorize information for an upcoming important exam (a value appraisal), which can decrease their boredom. Thus, students use reappraisal (changing control and value appraisals) to regulate their emotional responses. Positive control and value appraisals (or reappraisals) can increase positive emotions (e.g., enjoyment of a discussion) and decrease negative emotions (e.g., boredom). Current control and value appraisals (or reappraisals) are also likely to impact subsequent appraisals (e.g., through increased wellbeing which facilitates a positive interpretation of the situation). As such, there is a further increase in subsequent positive emotions, creating a reciprocal loop between reappraisal and wellbeing.

Suppression and Wellbeing

We expect that our findings will show negative reciprocal relations between suppression and wellbeing (see Figure 1). We propose that suppression will negatively impact wellbeing as it fails to reduce the arousal of negative emotions, and may even worsen an individual's internal negative emotional state (Gross & John, 2003; Gross & Levenson, 1993; Webb et al., 2012). As such, young people who frequently use suppression may be at risk of lower wellbeing given that their negative emotional states may be regularly worsened and prolonged (Chervonsky & Hunt, 2019). In addition, young people who rely on suppression may seem ‘inauthentic’ to their peers and have difficulty maintaining connections with them (English & John, 2013), due to the incongruence between their emotional expressions and their internal emotional state. Such a lack of social connection may also undermine students’ wellbeing.

Wellbeing, in turn, may reduce the use of suppression. Students with high wellbeing are likely to have supportive relationships with peers and teachers, and therefore feel comfortable expressing negative emotions openly. This may enable them to maintain social connections, which will likely benefit their wellbeing. Moreover, teachers, classrooms and schools which instil a sense of wellbeing in students may do so by allowing individuals to feel that their emotional expressions are generally accepted within the school environment. This may reduce the need for students to suppress their emotional expressions to conform to behavioural norms (i.e., school display rules); thus, contributing to greater school wellbeing.

In contrast, low wellbeing may increase suppression. According to interpersonal theories of depression (Coyne, 1976), depressed individuals’ expression of negative affect (e.g., showing irritability; Larsen et al., 2013) may cause social rejection and difficulties in relationships. In addition, adolescents are increasingly aware of how others perceive them (Larsen et al., 2013). As such, young people with low wellbeing may be aware of being rejected and negatively evaluated by others if they display negative affect (Larsen et al., 2013). Thus, they may attempt to suppress their expressions of negative emotions to avoid stress in relationships. Students with low wellbeing may also suppress negative emotions in the classroom if they feel the teacher would not accept their emotional displays. This may further contribute to low school wellbeing by not having teachers' emotional support.

Relations Between Reappraisal and Suppression

We do not propose any hypotheses for how reappraisal and suppression might be related. Typically, studies have found no significant correlation between reappraisal and suppression (e.g., Balzarotti et al., 2010, Gross & John, 2003, John & Gross, 2004), which suggests that those who make greater use of reappraisal are no more or less likely to use suppression than others (John & Eng, 2014). Similarly, in studies with adolescents, Chervonsky and Hunt (2019) and Ng et al. (2019) found no significant correlation between the constructs over one year. However, other studies with adolescents reported significant relations between these constructs. For instance, Gullone and Taff (2012) found a small concurrent negative correlation (r = -.13). In contrast, in the study by Martín-Albo et al. (2018), reappraisal positively predicted suppression (β = .18), and suppression positively predicted reappraisal (β = .16) over one month. Given the lack of consistency in these findings, we leave as an exploratory question how reappraisal and suppression are linked over time. However, we also note that extant studies have used between-person analysis to examine this link, thus leaving the within-person relations between reappraisal and suppression open to question. In the present study, we address this gap in the literature.

Aims of the Present Study

Previous research has shown that reappraisal is related positively, and suppression negatively, to wellbeing and mental health. However, studies have yet to examine how emotion regulation and school-related wellbeing are interrelated. Furthermore, previous studies have used between-person analysis, but have not yet used a within-person perspective to investigate relations between these constructs. The present study with 2,365 secondary school students in the UK examined relations between reappraisal, suppression, and wellbeing over 12 months across two school years. The study had two primary aims. Our first aim was to make a novel contribution to the literature by investigating reciprocal relations between reappraisal, suppression, and school-related wellbeing using a three-wave longitudinal dataset. Second, we use two robust latent variable modeling strategies: the CLPM and the RI-CLPM. Juxtaposing these two strategies allows us to compare between- and within-person perspectives on the relations between the three aforementioned constructs.

Research Hypotheses

The CLPM and the RI-CLPM address the following two different research questions: (a) How are emotion regulation and wellbeing related from a between-person perspective, and (b) how are they related from a within-person perspective? For both modelling strategies (the CLPM and the RI-CLPM), we anticipate that reappraisal will be related positively, and suppression negatively to subsequent school-related wellbeing. In addition, we expect that wellbeing has positive reciprocal effects on reappraisal, implying that reappraisal and wellbeing are reciprocally related over time. We also expect that wellbeing has negative reciprocal effects on suppression, implying that suppression and wellbeing are reciprocally related over time (see Figure 1 for the hypothesized effects in the CLPM and the RI-CLPM). Succinctly stated, we tested the following hypotheses:

Hypothesis 1a: In the CLPM, cognitive reappraisal is positively related to subsequent school-related wellbeing, and school-related wellbeing is positively related to subsequent reappraisal.

Hypothesis 1b: In the RI-CLPM, cognitive reappraisal is positively related to subsequent school-related wellbeing, and school-related wellbeing is positively related to subsequent reappraisal.

Hypothesis 2a: In the CLPM, suppression is negatively related to subsequent school-related wellbeing, and school-related wellbeing is negatively related to subsequent suppression.

Hypothesis 2b: In the RI-CLPM, suppression is negatively related to subsequent school-related wellbeing, and school-related wellbeing is negatively related to subsequent suppression.

We left as an exploratory question if reappraisal and suppression are related over time. In addition to examining direct relations between the variables, we also examined indirect relations between the variables at Time 1 and Time 3 by considering the same set of variables as mediators at Time 2 (see Figure 1). Given our hypotheses on reciprocal effects linking reappraisal and wellbeing, we expected that (in both the CLPM and RI-CLPM) wellbeing mediates the effects of earlier (Time 1) reappraisal on later (Time 3) reappraisal. We also expected that reappraisal mediates the effects of earlier (Time 1) wellbeing on later (Time 3) wellbeing. In addition, given our hypotheses on reciprocal effects linking suppression and wellbeing, we expected that wellbeing mediates effects of earlier (Time 1) suppression on later (Time 3) suppression. We also expected that suppression mediates effects of earlier (Time 1) wellbeing on later (Time 3) wellbeing. We left other possible indirect effects as an open research question.

Research Question: Juxtaposing the CLPM and RI-CLPM

We explored whether support for the hypotheses differed for the CLPM and the RI-CLPM. As Hamaker et al. (2015) highlighted, there is no general a priori basis for predicting how estimates from CLPM and RI-CLPMs will vary in direction or size. Nevertheless, based on our hypotheses, we expected the direction of effects to be consistent across the CLPM and the RI-CLPM. We left as an exploratory question how the size of the effects varies across the two models.

Method

Participants and Procedure

Overall 2,365 students (boys = 1,127, girls = 1,164, chose not to disclose = 74) from four secondary schools[1] located in the Northwest of England completed at least one of the assessments. The research team selected schools to participate that were within relatively short travelling distance from the first author's university. This ensured the research team could easily visit the schools and, if requested, communicate face-to-face with the headteacher and other staff members involved in facilitating the research. In addition, the research team had a point of contact within each selected school who was able to liaise with the headteacher to request for students to participate in the study. Five schools were initially contacted and agreed to participate in the study. However, one school withdrew from the study before data were collected due to staffing issues at the school. Out of the total number of participants, 22.4% were from School 1, 27.9% were from School 2, 20.3% were from School 3, and 29.5% were from School 4.

At Times 1–3, sample sizes were 1,756, 1,428, and 1,228 participants. The ethnic heritage of students was predominantly white Caucasian (n = 2081) with smaller numbers from black (n = 24), Asian (n = 53), dual heritage (n = 61), and other backgrounds (n = 52). Seventeen participants did not report their ethnic background. Students were 11–19 years old (M = 14.10 years; SD = 1.98) and were in years 1–7 of secondary school education (M = 2.68; SD = 1.90). There were 682 participants who were eligible for free school meals (FSM; a proxy for low income), 1,626 were not eligible, and 57 did not report their eligibility. When comparing our sample with national data, collected at the same time as our first wave of data collection, our sample had a greater proportion of white participants (national figure of 69.7%; study sample 88.0%), and students from deprived backgrounds (national figure of 12.4%; study sample 28.8.%) based on FSM eligibility, than was typical for England

[1] One of the schools was a sixth-form college which is a tier of upper secondary education for students aged 16-19 years in England, Wales, and Northern Ireland, where students study academic and vocational subjects.

(Department for Education, 2018). The sample had a similar proportion of female participants (national figure of 49.8%; study sample 49.2%) which was typical for England (Department for Education, 2018).

We collected data over three waves, spaced equally at 6-month intervals. We chose six-month intervals to see if relations between constructs were maintained over a relatively long time period; this would enable us to speculate if interventions (to improve wellbeing by enhancing reappraisal skills, for instance) would have a relatively long-lasting effect. Moreover, the time period between data collection points reduced the burden on participating schools and students, as they were only required to complete the questionnaire once or twice during the school year. Students answered the same questionnaire at each wave to report on their reappraisal, suppression, and school-related wellbeing. We administered the three assessments during the autumn term (November) and summer term (May) of one school year and the autumn term (November) of the following school year. We collected the data in the students' classroom. Students created a unique identifier code when completing the first assessment. On the second and third assessments, they also reported this code. The code was then used to match their questionnaires.

The study was approved by the institutional research ethics committee (18/EDN/017) at the first author's university. Participation was made dependent on parental consent through an informed opt-out consent process; parents were sent a letter or email describing the nature of the study and were asked to inform their child's tutor or head of year if they wished for their child to be withdrawn. Six parents from one school requested for their child to be withdrawn. The participant information sheet, which was given to students to read before they completed each questionnaire, made students aware that they did not have to participate in the study if they did not wish to do so. It also informed them that their answers would be kept confidential. In addition, the teacher administering the questionnaire was asked to remind students that they did not have to complete the questionnaire, and that their answers would not be seen by anyone outside of the research team.

Missing Data

The missing data at subsequent data collection waves was due to participants being absent or no longer willing to participate when the questionnaire was administered at Time 2 or 3. This attrition is commonplace in longitudinal studies (Graham, 2009). However, studies must investigate and report why data is missing (Nicholson et al., 2017). To assess whether there was bias in the missing data at times 2 and 3, we used Little's (1988) Missing Completely at Random (MCAR) test. This test was statistically significant ($p < .001$), meaning we could not assume the data was MCAR. Following best practice guidance for identifying missing data sources, we conducted a series of t-tests (Nicholson et al., 2017). Younger participants who did not have FSM were less likely to complete the Time 2 assessments for all constructs. Boys were less likely than girls to complete the Time 3 assessments. Participants who scored lower on the cognitive reappraisal and wellbeing scales were less likely to complete scales at subsequent waves. These results may indicate that students who have lower reappraisal and wellbeing may be less likely to participate in and complete optional classroom-based tasks (see Missing Data Analyses in the Supplementary Materials for a detailed description of the results, and Tables S1 and S2 for results of t-tests for identifying sources of missing data).

Since the missing data could be accounted for by the aforementioned variables, and these variables were included in all subsequent analyses, we treated the data as missing at random (MAR) and used full information maximum likelihood (FIML) estimation. The use of FIML is appropriate to use under assumptions of MAR (Enders, 2010), has been found to be appropriate for managing missing data in large longitudinal studies (Jeličič et al., 2009), and has been shown to result in unbiased standard errors and parameter estimates under MAR (Enders & Bandalos, 2001).

Measures

School-Related Wellbeing

School-related wellbeing was assessed using a six-item self-report scale (Loderer et al., 2016) that measures students' global judgments of their overall wellbeing in school settings (e.g., "I feel comfortable at school"; "School is going well for me"). Students were instructed to rate how they usually think and feel about school/college, and rated their responses on a 5-point Likert Scale (1 = *strongly disagree* to 5 = *strongly agree*). The scale has shown measurement invariance and good internal consistency (αs and ωs = .84–.87) in previous research with adolescents (Loderer et al., 2016; Putwain et al., 2020, 2021).

Cognitive Reappraisal and Expressive Suppression

Cognitive reappraisal and expressive suppression were measured using the 10-item Emotion Regulation Questionnaire for Children and Adolescents (ERQ-CA), designed to measure adolescents' tendency to regulate their emotions by use of cognitive reappraisal and expressive suppression (Gullone & Taffe, 2012). Six items measured the use of cognitive reappraisal (e.g., "When I want to feel happier, I think about something different"). Four items measured the use of expressive suppression (e.g., "I keep my feelings to myself"). Participants rated their responses on a 5-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*). In previous research, internal consistency was αs = .73–.79 for the reappraisal scale and .71–.73 for the expressive suppression scale (Gullone & Taffe, 2012; Liu et al., 2017). It has also demonstrated measurement invariance over a one-year interval (Ng et al., 2019). Previous studies investigating the factor structure of the ERQ-CA have demonstrated support for a two-factor model (e.g., Gullone & Taff, 2012; Martín-Albo et al., 2018; Ng et al., 2019).

Demographic variables

Gender (0 = boys, 1 = girls), age, and free school meals (FSM; 0 = not eligible for FSM, 1 = eligible for FSM) were controlled for in the analysis.

Data Analysis

A latent variable modelling approach was used to test for measurement invariance and estimate latent bivariate correlations using confirmatory factor analysis in Mplus version 8 (Muthén & Muthén, 2017). McDonald's omega (ω) was used to examine the internal consistency of the self-report scales. Omega has been found to provide a more accurate measure of reliability than Cronbach's alpha (Yang & Green, 2011). Structural equation modeling (SEM) was employed to examine reciprocal relations and to estimate mediating effects between suppression, reappraisal, and school-related wellbeing. We tested these associations with a traditional cross-lagged panel model (CLPM; e.g., Finkel, 1995) and a random intercept cross-lagged panel model (RI-CLPM; Hamaker et al., 2015). We used the MLR estimator, which is robust against non-normality of observed variables. Model fits for the CLPM and the RI-CLPM were evaluated using the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and the standardized root mean squared residual (SRMR). A good fitting model is indicated by CFI/ TLI values around .95 or above, RMSEA values $\leq$ .08, and SRMR values $\leq$ .06 (Hu & Bentler, 1999). However, when working with complex naturalistic data, it is recommended to exert caution in using these cut-off values (Heene et al., 2011; Marsh et al., 2004). We included correlations between residuals for identical items across measurement occasions to control for systematic measurement error.

Measurement Invariance

When modelling longitudinal data, it is necessary to demonstrate measurement invariance to ensure the same construct is being measured across time points (Widaman et al., 2010). We tested the measurement invariance of all scales by applying a series of successive constraints for item-factor loadings, item intercepts, and item residual variances over time (Meredith, 1993). A configural model (not including gender, age, and FSM) was specified by the above-described measurement model for each scale. We assessed changes in model fit when item-factor loadings were constrained to be equal (metric invariance), item intercepts in addition to loadings were constrained to be equal (scalar invariance), and when item residuals in addition to loadings and intercepts were constrained to be equal (residual invariance). Measurement invariance is demonstrated when CFI and TLI indices are reduced by $\leq$ .01, changes in RMSEA are $\leq$ .015, and changes in SRMR are $\leq$.30 (Chen, 2007). The cognitive reappraisal and suppression scale demonstrated metric, scalar, and error invariance, and the school-related wellbeing scale showed partial scalar invariance (see Supplementary Materials). Metric invariance is sufficient to model structural paths over time (Widaman et al., 2010); thus, we proceeded with further analyses without imposing residual invariance constraints on any scale items.

Background to CLPM and RI-CLPM

The CLPM examines the prospective relation between individual differences in one specific construct and change in individual differences in another construct (Orth et al., 2021). The CLPM framework has been widely used in educational research to describe longitudinal relationships between constructs. However, it has been criticized for not distinguishing within-person from between-person effects (e.g., Hamaker et al., 2015). In addition, appropriate practical suggestions cannot be derived solely based on the CLPM (e.g., suggestions for designing interventions) as it does not tell us how constructs are related *within* an individual. For most relevant effects, causal mechanisms generating an influence of one construct on another construct occur within rather than between persons (Keijsers, 2016; Murayama et al., 2017; Schenk et al., 2021). The RI-CLPM extends the CLPM by examining whether the within-person temporary deviation from the person-average level in one specific construct influences change in the within-person temporary deviation from the person-average level in a different construct (Orth et al., 2021).

By implication, the CLPM and the RI-CLPM provide different perspectives on longitudinal relations between emotion regulation and wellbeing over time. In the CLPM, cross-lagged paths address how between-person distributions of these variables are related over time. They answer the theoretically and practically important question: Do students who show better emotion regulation than others also show higher wellbeing over time (and vice versa)? These relations of between-person distributions are based on a combination of within- and between-person effects. The RI-CLPM decomposes these overall relations into within- and between- person components; thus, cross-lagged paths in the RI-CLPM represent within-person processes. For example, in the present study the RI-CLPM examines if individuals who use more reappraisal than usual (i.e., than their person-average, trait-like level of reappraisal) will subsequently experience higher school-related wellbeing than usual. The within-person effects in the RI-CLPM reflect temporary fluctuations around individual person means, thereby providing a stronger within-person perspective. However, the RI-CLPM is less useful for assessing the causes that explain differences between persons (Lüdtke & Robitzsch, 2021, 2022). As such, researchers argue that it is theoretically, methodologically, and substantively informative to juxtapose both approaches to theorize that relations between variables exist at both the between- and within-person level (Marsh et al., 2022).

The CLPM and RI-CLPM also differ in how they control for unmeasured potential confounding factors. The RI-CLPM provides potentially stronger control for time-invariant unmeasured confounders (Hamaker et al., 2015), but only if the effects of these unmeasured variables are constant over time; it has limited ability to control for unmeasured confounders, such as demographic variables, when their effects vary over time (Lüdtke & Robitzsch, 2021, 2022). The CLPM with the addition of lag 2 autoregressive effects provides stronger controls for time-varying confounders as well as time-invariant confounders that have time-varying effects (Lüdtke & Robitzsch, 2021, 2022; Marsh et al., 2022). In addition, autoregressive paths in the CLPM represent the stability of rank-order differences between students; in the RI-CLPM, they represent within-person carry-over effects.

The CLPM and RI-CLPM may produce the same pattern of results as the processes linking emotion regulation and wellbeing occur within persons in the first place (i.e., within the individual brain); however, over time these within-person processes can translate into between-person differences in emotion regulation and wellbeing and drive the relations of between-person distributions of the two constructs, as traditionally analyzed in the CLPM. As a result, the within- and between-person relations of the two constructs can be equivalent. For example, the equivalence of within- and between-person relations would entail positive between-person correlations of reappraisal and wellbeing that are equivalent to their positive within-person correlations. However, equivalence cannot be taken for granted but needs to be tested empirically.

To determine if we should run the RI-CLPM in addition to the CLPM, we calculated intra-class correlation coefficients (ICC1 or ρ_I) showing the proportion of variance observed across waves for all three constructs. The calculations showed that approximately 45,%, 48%, and 55% of the variance over time stemmed from between-person differences in reappraisal, suppression, and school-related wellbeing, respectively. Thus, there was sufficient within-person variability in our data to justify estimating a RI-CLPM (Berry & Willoughby, 2017; Hamaker et al., 2015). We analyzed the data using the CLPM to test if and how reappraisal, suppression, and school-related wellbeing are related at the between-person level among young people. We analyzed the data using the RI-CLPM to disentangle the within-person and between-person variance, thereby identifying if the relations between the constructs are also evident at the within-person level. This would allow us to infer more appropriate suggestions for potential interventions than can be derived from the CLPM alone.

Transparency and Openness

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study, and we follow JARS (Kazak, 2018). All data, analysis code, and research materials are available at https://doi.org/10.17605/OSF.IO/W5CPE. Data were analyzed using Mplus, version 8 (Muthén & Muthén, 2017). This study's design and its analysis were not pre-registered.

Results

Descriptive Statistics and Latent Bivariate Correlations

We report descriptive statistics in Table 1. Skewness and kurtosis of all study variables were within +/-1. Internal consistency was good for cognitive reappraisal and school-related wellbeing (ωs ≥ .82) and satisfactory for suppression (ωs = .70). Intra-class correlation coefficients (ICC1 or ρ_I) showing the proportion of variance accounted for by school membership was small (1-2%) for T_1, T_2 and T_3 wellbeing, and < 1% for the other variables. The proportion of variance accounted for by year group was also small (< 4%) for all study variables. Thus, we did not specify any clusters in subsequent analyses.

A CFA measurement model was conducted which included all reappraisal, suppression, and wellbeing variables as well as gender, age and FSM. The model showed a good fit to the data, with χ^2 (1113) = 1760.92, *p* <.001, CFI = .970, TLI = .966, RMSEA = .016, and SRMR = .036, and factor loadings for all items ≥ .40 (see Preliminary Analyses in the Supplementary Materials for details). Latent bivariate correlations are reported in Table 2. Cognitive reappraisal was positively correlated with wellbeing within and across all three waves. With the exception of correlations within Wave 1, suppression was negatively correlated with wellbeing within and across all waves.

Structural Equation Modelling

Nested Models

We compared the reciprocal relations CLPM with three CLPMs nested under the reciprocal relations CLPM, and we compared the reciprocal relations RI-CLPM with three RI-CLPMs nested under the reciprocal relations RI-CLPM. For both the CLPM and the RI-CLPM, we specified the three nested models as follows: (1) a measurement (baseline) model assuming no relations between all constructs, thus all directional paths linking reappraisal, suppression, and wellbeing were set to zero; (2) a model assuming unidirectional relations from emotion regulation to wellbeing; in this model, paths from reappraisal and suppression to subsequent wellbeing, paths from reappraisal to suppression, and paths from suppression to reappraisal were freely estimated, but paths from school-related wellbeing to reappraisal and suppression were set to zero (Model A); (3) a model assuming unidirectional relations from wellbeing to emotion regulation; in this model, paths from reappraisal to suppression, from suppression to reappraisal, and from wellbeing to reappraisal and suppression were freely estimated, but paths from reappraisal and suppression to wellbeing were set to zero (Model B). All CLPM models controlled for the effects of gender, age and FSM on all constructs at each wave. All RI-CLPM models controlled for the effects of gender, age and FSM on the random intercept factors.

Table 3 compares the model fit indices for the CLPM reciprocal relations model with the nested models, and the RI-CLPM reciprocal relations model with the nested models. The reciprocal relations models showed significantly better fit than the other models using the Satorra–Bentler scaled $\chi2$ difference test (TRd; Bryant & Satorra, 2012). Models were also compared using the Akaike Information criterion (AIC). Lower AIC values indicate improved model fit (Hix-Small et al., 2004), and an AIC value > 10 indicates a substantively worse fit for the model with the higher value (Burnham & Anderson, 2002). The reciprocal relations models had the lowest AIC value compared to the other nested models. As such, we accepted the reciprocal relations models for both the CLPM and RI-CLPM, and we proceeded to conduct further analyses using these models.

Standardized ß coefficients for cross-lagged effects > .12 were interpreted as large effects, ßs = .04–.11 as moderate effects, and ßs < .03 as small effects (Orth, 2022). Autoregressive and cross-lagged paths were constrained to be equal across time in both the CLPM and RI-CLPM which is justified when there is no reason to expect changes in the strength of coefficients over time, and when data collection points are equally spaced (Cole & Maxwell, 2003; Little et al., 2007; Orth et al., 2021). The constraints also reduced the number of parameters in the models, to keep them as parsimonious as possible and ensure proper model convergence.

Cross-Lagged Panel Model

We used the traditional CLPM to examine the cross-lagged paths among reappraisal, suppression, and wellbeing while controlling for the concurrent relations between the three variables at all three time points. We controlled for the effects of gender, age and FSM on reappraisal, suppression and wellbeing at each wave. We compared a CLPM which estimated all lag 1 and 2 autoregressive and cross-lagged paths (fully-forward model) with a lag 1 CLPM which estimated lag 1 autoregressive and cross-lagged paths, and a lag 2 CLPM which estimated lag 2 effects for autoregressive paths only. The lag 2 model with autoregressive paths showed a significantly better fit than the other models using the Satorra–Bentler scaled $\chi 2$ difference test (TRd; Bryant & Satorra, 2012; see Table S4 in the Supplementary Materials for model fit indices and goodness of fit for the CLPM models). Thus, we conducted further analyses using this model, controlling for the variance accounted for by the autoregressive paths between all waves for all three variables. This three-wave CLPM showed a good fit to the data, χ^2 (1125) = 1753.72, p <.001, CFI = .969, TLI = .965, RMSEA = .016, and SRMR = .038. We report statistically significant path coefficients in Figure 2. All standardized path coefficients, un-lagged concurrent relations, and the effects of covariates are shown in Table 4. As shown in Figure 2, reappraisal was a positive predictor of school-related wellbeing, and wellbeing was a positive predictor of reappraisal. Suppression was not significantly related to wellbeing over time. Reappraisal negatively predicted suppression; however, suppression was not significantly related to subsequent reappraisal. Gender showed small, significantly negative relations with T_1 and T_2 reappraisal, and T_3 school-related wellbeing. Age showed moderate significantly positive relations with T_1 suppression and T_1 school-related wellbeing.

Random-Intercept Cross-Lagged Panel Model

We used the RI-CLPM to examine within-person cross-lagged paths among reappraisal, suppression, and wellbeing while controlling for concurrent within-person relations between these variables at all three time points. We also controlled for the within-person autoregressive paths from T_1 to T_2 and T_2 to T_3 for all constructs, after partialling out the between-person variance (random intercept factors) for the three variables. Factor loadings for the random intercepts were fixed to 1. The effects of covariates on the random intercept factors were estimated by specifying paths from gender, age, and FSM to global trait factors. This three-wave RI-CLPM also had a good fit to the data, χ^2 (1166) = 1813.53, p <.001, CFI = .970, TLI = .967, RMSEA = .015, and SRMR = .038. We report statistically significant path coefficients in Figure 3, and all standardized path coefficients, unlagged concurrent relations, the effects of the covariates, random intercept correlations, and standard errors in Table 5.

The pattern of cross-lagged within-person effects in the RI-CLPM was identical to the pattern of cross-lagged effects in the CLPM. At the within-person level, reappraisal positively predicted wellbeing, and wellbeing positively predicted reappraisal. Wellbeing was not significantly related to suppression. Reappraisal was a negative predictor of suppression, but suppression was not related to subsequent reappraisal. At the between-person level, gender showed significant negative relations with the random intercepts of reappraisal and wellbeing. Age showed significant positive relations with the intercepts of suppression and wellbeing. The reappraisal, suppression, and wellbeing random intercepts were not significantly correlated with each other. The likely reason was the large standard errors (>.16) relative to the size of the correlation coefficients.

Estimates of Indirect Paths

We created 95% confidence intervals around the point estimates of the indirect effects to assess whether indirect effects of T_1 variables on T_3 variables were statistically significant. Confidence intervals that do not include zero suggest that there is a statistically significant indirect effect ($p < 0.05$; MacKinnon, 2012). We report the total, direct, and indirect effects in Table 6 for significant mediation pathways. For both the CLPM and the RI-CLPM, there were indirect relations between (1) T_1 reappraisal and T_3 reappraisal mediated by T_2 wellbeing, and (2) T_1 wellbeing and T_3 wellbeing mediated by T_2 reappraisal.

Discussion

Our study is the first to examine the link between students' emotion regulation and school wellbeing while juxtaposing between-person analyses (using the CLPM) with within-person analyses (using the RI-CLPM). Supporting Hypotheses 1a and 1b, both the CLPM and the RI-CLPM showed that cognitive reappraisal positively predicted subsequent school-related wellbeing, and school-related wellbeing positively predicted subsequent cognitive reappraisal. The cross-lagged effect sizes were large in the RI-CLPM and medium to large in the CLPM. In both the CLPM and RI-CLPM, suppression was not significantly related to subsequent school-related wellbeing, and school-related wellbeing was not significantly related to subsequent suppression, thereby not supporting Hypotheses 2a and 2b. In addition, cognitive reappraisal was negatively related to subsequent suppression.

Through examination of indirect relations we also found evidence (from both the CLPM and RI-CLPM) that greater use of reappraisal led to subsequent use of reappraisal, mediated by higher school-related wellbeing. Similarly, higher wellbeing led to subsequent wellbeing, mediated by reappraisal. Overall, these findings document positive feedback loops between reappraisal and wellbeing over time. Furthermore, the results show that the pattern of within-person relations between constructs (as shown by the RI-CLPM) was equivalent to the between-person relations between constructs (as demonstrated by the CLPM). As such, the results indicate that between- versus within-person relations between reappraisal, suppression, and school-related wellbeing in secondary school students are likely to be equivalent.

Cognitive Reappraisal and School-Related Wellbeing

Our study is also the first to establish relations between cognitive reappraisal and subjective wellbeing using a specific measure of school wellbeing. Several reasons might explain the statistically significant positive relations from reappraisal to school-related wellbeing. First, students who use reappraisal are more likely to be efficient at regulating their emotions. For instance, they may be better able to recover from stress if they use this strategy (Shapero et al., 2017). Indeed, students are likely to experience stressors within the school environment (e.g., when presenting in front of a class). Therefore, the inability to downregulate (or prevent) negative emotional experiences may mean the young person feels unable to cope with the pressures of school, and may experience low wellbeing. Conversely, students who use reappraisal to reduce the negative impact of stress are likely to feel able to cope with school, and thus experience higher school wellbeing. Second, using reappraisal results in positive psychological, social, and cognitive outcomes because it regulates the emotion before, or just after, it has occurred (Gross & John, 2003). As such, students who use reappraisal may be better able to direct attention away from emotionally relevant information to focus on learning, resulting in improved memory for educational material and better school performance (e.g., Davis & Levine, 2013; Pizzie et al., 2020). This is likely to contribute to a greater sense of school-related wellbeing.

In turn, individuals experiencing high levels of wellbeing may have broadened cognition. They may be more likely to interpret a situation positively (e.g., through control or value appraisals) than those experiencing low levels of wellbeing. As such, they may be more efficient at using antecedent-focused strategies such as reappraisal and are likely to experience more positive emotions (and thus wellbeing) due to using this strategy. It may also be that individuals who experience positive situations in school have high wellbeing, which implies positive emotions and thereby broadens cognition and promotes the use of reappraisal. Conversely, students experiencing negative situations in school may have low wellbeing, experience negative emotions, and make less use of positively reappraising the situation. These students may be more likely to engage in response-focused strategies such as rumination (Tortella-Feliu et al., 2010). Using these strategies can then lead to a further decrease in wellbeing. Further research will be needed, which incorporates measures of other emotion regulation strategies, such as distraction and rumination, to test this claim.

Suppression and School-Related Wellbeing

We did not find support for our prediction that suppression negatively predicts school-related wellbeing, or that school-related wellbeing negatively predicts suppression. One reason may be that suppression (unlike reappraisal) is concerned with regulating the outward expression of emotion and does not regulate the experiential or physiological components of emotion. Thus, reappraisal may have stronger links with wellbeing than suppression as reappraisal attends to regulating the subjective emotional experience.

Another important factor to consider which may account for the lack of significant relations between suppression and school-related wellbeing is that we used a context-specific measure of wellbeing for our study. However, the scale used to measure suppression was not school-specific. It is possible that context-matched suppression and wellbeing scales would have yielded different findings. For instance, if we had asked participants to report on the degree to which they kept their feelings related to school experiences to themselves, this may have shown a significant relation to school-related wellbeing. However, we found a significant relation between reappraisal and school-related wellbeing even though we did not use a context-specific measure of reappraisal. One reason for this could be that regulating subjective emotional experiences (by using reappraisal) across various contexts may be related to wellbeing across various contexts (including school). However, regulating the expression of emotions (by using suppression) may only be related to wellbeing which pertains to the environment in which the emotions are being suppressed. Future studies could consider including both a general and school-specific measure of suppression to examine whether there are differences in how these measures relate to school wellbeing.

It may also be that suppression allows the young person to navigate their school responsibilities and has positive social, cultural, or self-protective functions (Gross and Cassidy, 2019). For instance, a student may suppress their anger at receiving a negative comment from a teacher to avoid being sent out of class. Thus, it may be that suppression does not improve students' wellbeing (as it fails to reduce the arousal of negative emotions) but it does not harm it either (as it allows them to adapt to the school environment). Future studies which examine when and why students suppress their emotions at school (e.g., by collecting qualitative interview data) would be useful to explore this claim.

Cognitive Reappraisal and Suppression

When examining whether reappraisal and suppression were linked, we found that reappraisal negatively predicted suppression. This finding is contrary to Martín-Albo et al.'s (2018) study, which found that reappraisal positively predicted suppression, and suppression positively predicted reappraisal over one month. Much of the previous literature suggests that reappraisal and suppression are independent, in that use of one does not affect the use of the other (John & Eng, 2014); this may be because reappraisal regulates internal emotional experiences whereas suppression regulates outward emotional expressions. However, our results indicate that over time greater use of reappraisal leads to decreased use of suppression to regulate emotions on subsequent occasions. This may have important implications for a young person's wellbeing. Reappraisal could subsequently reduce the reliance on suppression, thereby reducing levels of psychopathology as demonstrated in previous studies (e.g., Schäfer et al., 2017). Indeed, examining how reappraisal impacts subsequent suppression in adolescents, and how this relates to outcomes of wellbeing, would be important for future studies to investigate.

Limitations and Directions for Future Research

The present study is a novel contribution to the education and emotion regulation literature, and it yielded findings that were robust across waves and two different modeling approaches. Nevertheless, there are limitations that need to be considered and can be used to suggest directions for future work. First, we only investigated two emotion regulation strategies, reappraisal and suppression. However, other emotion regulation strategies are also likely to be antecedents to, and outcomes of, school-related wellbeing (e.g., rumination; Garnefski & Kraaij, 2018). Furthermore, at least in some situations, individuals likely use multiple strategies together or in sequence to regulate emotions (Aldao & Nolen-Hoeksema, 2013; Ford et al., 2019). Thus, investigating how multiple strategies impact school-related wellbeing would be a fruitful avenue for future research.

Second, we must exercise caution in assuming that reappraisal will always be linked to greater wellbeing in all situations. Reappraisal may be adaptive or maladaptive depending on the context in which it is used (Troy et al., 2013). For instance, reappraisal may be adaptive when students use it to reduce their anxiety to maintain their study efforts. However, it may be maladaptive when students use it to reduce their anxiety to avoid studying. Indeed, when considering how emotion regulation strategies relate to wellbeing, we must be aware that emotion regulation is a dynamic, context-dependent process. Many situational factors can influence the efficacy of strategies, such as personality/demographic factors, the nature of the stimulus, how the regulation strategies are chosen and implemented, and how the outcome of the regulation is evaluated (Aldao, 2013; Bonanno & Burton, 2013).

Third, a further important limitation of the study is that we measured wellbeing but not specific emotions. Thus, we do not know which emotions need reappraising to impact school wellbeing positively, nor whether school wellbeing affects the frequency of reappraisal for specific emotions. In addition, we cannot rule out that suppressing certain emotions (e.g., sadness) would be negatively associated with school wellbeing. Indeed, studies have found more frequent use of suppression in situations where adolescents experience sadness compared to when they are experiencing anger (Zeman & Shipman, 1997; Zimmerman & Iwanski, 2014). Furthermore, we do not know which school-related factors impact the regulation of emotions, in which academic situations specific emotions and their regulation are activated, and how situation-specific regulation impacts wellbeing. For instance, if anxiety is more likely when students take tests than when completing homework, would students' reappraisal in test-taking have greater benefits for their wellbeing (through reducing anxiety) than reappraisal during homework? As such, future studies should investigate the regulation of specific emotions and consider school-related factors and situations which activate these emotions.

Fourth, the emotion regulation measure used in the study did not investigate the link between the up-regulation or down-regulation of emotions and wellbeing. Down-regulation reduces the intensity of an emotional experience, and up-regulating increases its intensity. In adolescents, down-regulating negative emotions has been shown to have a greater impact on increasing subsequent positive emotions than directly up-regulating positive emotions (Deng et al., 2013). However, it is uncertain whether using emotion regulation strategies to down-regulate negative emotions or upregulate positive emotions has stronger relations to school-related wellbeing. As such, future studies could explore the consequences of up-regulation or down-regulation of emotions.

Fifth, only self-reported data pertaining to school-related wellbeing and emotion regulation were used in the study. No measures of academic performance were included. It would be useful for future studies to include measures of students' academic performance to further investigate the mechanisms linking reappraisal and school wellbeing. For example, it may be that reappraisal promotes academic performance, which, in turn, enhances wellbeing. It would also be useful to use multiple research methods (e.g., follow-up interviews with participants or daily diary studies) to gain deeper insight into how emotion regulation strategies relate to school-wellbeing. For instance, researchers could investigate when students typically use reappraisal at school (e.g., after receiving feedback on tests, or when socializing with peers), and examine how it might enhance their wellbeing. Alternatively, they could ask them to consider times when they are experiencing low or high wellbeing at school, and find out how they regulate their emotions on these occasions. Nonetheless, the principle aim of the present study was not to provide such in-depth insight, but rather to first establish whether the proposed bidirectional links between suppression, reappraisal, and school-related wellbeing exist at all.

Sixth, we define school-related wellbeing as the dominance of positive emotions compared to negative emotions and cognitions towards school life (Hascher, 2003, p. 129). Thus, emotions are an important component of wellbeing. In addition, emotion regulation involves the up-regulation or down-regulation of positive and/or negative emotions. As such, both wellbeing and emotion regulation relate to emotions. This begs the question: Do they show construct overlap? Following theories of emotion regulation, we contend that emotion and the regulation of emotions are distinct constructs that are clearly distinguishable (see also Gross, 2015). Emotions are not part of actions aiming to regulate them; they are the objects (or aims) of these actions. For example, changing the situation to upregulate joy is not the same as joy itself. As such, at least if measured properly, we believe that there is no construct overlap between emotions (or wellbeing) and the regulation of emotions. This reasoning is supported by the present findings. Reappraisal and suppression, on the one hand, and wellbeing, on the other, showed only moderate correlations.

Finally, an important limitation is that we did not measure the mediating variables which might account for the link between emotion regulation and wellbeing. For instance, reappraisal may positively impact school wellbeing through mechanisms such as coping with school pressures or improved learning; suppression may negatively impact wellbeing through mechanisms such as lack of social support. With the present data, we can only speculate about these mechanisms. As such, future studies must measure potential mediators to explain how the constructs are related. Moreover, it may be that reappraisal acts as a mediator variable in explaining how other factors impact students' wellbeing. For example, cognition malleability beliefs might determine subjective wellbeing, with reappraisal mediating this relationship (Zhu et al., 2020). Thus, future studies should examine how reappraisal may act as the mechanism that, wholly or partially, explains the link between factors such as cognitive beliefs and school-related wellbeing.

Implications for Theory

Findings from this study support Fredrickson's (1998) broaden-and-build theory that positive emotions (as implied by wellbeing) and broadened cognition (i.e., use of reappraisal) influence each other reciprocally, leading to an upward spiral of increases in reappraisal and wellbeing over time. Extending this theory further, our findings suggest that cognitive broadening will likely influence how people choose to regulate their emotions. Individuals who regularly experience positive emotions may have greater access to adaptive cognitive emotion regulation strategies such as reappraisal, and using these strategies is likely to enhance wellbeing. In addition, our findings support Harley et al.'s (2019) emotion regulation in achievement situations theory (ERAS). It proposes that using reappraisal (through control and value appraisals) to regulate emotional responses is likely to increase positive emotions, creating a reciprocal loop between reappraisal and wellbeing. Our findings illuminate the theory further by highlighting the importance of positive emotions (i.e., wellbeing) in facilitating the use of cognitive appraisals. Thus, the achievement environment (e.g., one which enhances or diminishes students' wellbeing) may be particularly important to consider when examining what facilitates or constrains the use of cognitive reappraisals to regulate achievement emotions.

Insights for Practice

According to this study, cognitive reappraisal is one contributing factor that enables students to have a sense of subjective wellbeing related to their school. Thus, reappraisal would be beneficial for improving students' sense of school-related wellbeing. As such, interventions that promote students' reappraisal, could have downstream benefits for improving mental health and wellbeing. Cognitive Behavioral Therapy (CBT) interventions typically involve cognitive change techniques in conjunction with response- and behaviorally-orientated strategies (Beck, 2011). This type of intervention has been shown to have benefits (e.g., reducing depression, and increasing wellbeing) when integrating reappraisal techniques that help improve emotion regulation (e.g., Berking et al., 2013). However, there are likely benefits arising from training and practice in reappraisal alone. Longitudinal reappraisal training involves practice in using reappraisal tactics over repeated sessions. This type of intervention has been shown to reduce negative emotions in adults (e.g., Denny & Ochsner, 2014; Denny et al., 2015; Ng & Diener, 2013). Longitudinal intervention research on reappraisal training with young people is lacking. However, training students in using reappraisal would likely have a positive impact on their school wellbeing. The training may involve practice in telling oneself a contextually-appropriate story about an outcome (Denny & Ochsner, 2014), and then using reappraisal over 3 or 4 sessions to regulate responses to aversive photos related to school experiences. This type of intervention is likely to be less costly and time-consuming for schools to implement than a CBT intervention which includes the full range of behavioral and cognitive therapies.

A novel finding from this study is that a sense of subjective wellbeing relative to the school appears to contribute to the use of reappraisal. Thus, by supporting the wellbeing of their students, schools could develop students' reappraisal skills. Schools could promote students' wellbeing by creating positive school environments. This could be done by enhancing school connectedness by enabling students to feel that adults and peers at school care about their learning, their overall wellbeing, and about them as individuals (Marsh et al., 2019). In addition, schools could improve students' perceptions of teacher support (Kidger et al., 2012). Perceptions of teacher support may be enhanced by a positive classroom climate (i.e., the teacher showing positive attitudes towards students), teacher sensitivity (i.e., teacher's responsiveness to students' needs), and regard for student (adolescent) perspectives (i.e., teachers supporting and promoting students' development; Pianta & Hamre, 2009; Romano et al., 2021). These positive school environments that promote wellbeing are likely to have downstream benefits for the development of reappraisal ability.

Conclusion

In longitudinal models of the relations between students' reappraisal, suppression, and school-related wellbeing, we found positive reciprocal relations between reappraisal and wellbeing. These relations were equivalent across two complementary modeling approaches, including the classic CLPM and the RI-CLPM. Thus, from both a between-person and a within-person perspective, reappraisal contributes to school-related wellbeing, and school-related wellbeing contributes to increased use of reappraisal. In contrast, suppression was not significantly related to wellbeing over time. We also found that reappraisal negatively predicted suppression use over time. However, suppression use did not predict subsequent use of reappraisal. All of these relations were also evident at the between-person and the within-person level. Our study suggests that interventions and strategies to encourage students to develop their reappraisal skills can enhance a sense of school-related wellbeing, and a sense of school-related wellbeing can promote the development of cognitive reappraisal.

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Table 1

Descriptive Statistics and Item Factor Loadings

	Mean	*SD*	ω	ρ_I	Skew-ness	Kurt-osis	Factor loadings
T_1 Reappraisal	3.21	0.98	.82	<.01	-.36	-.17	.51 - .76
T_2 Reappraisal	3.21	1.05	.85	<.01	-.37	-.25	.58 - .76
T_3 Reappraisal	3.22	0.98	.85	<.01	-.37	-.08	.53 - .81
T_1 Suppression	3.06	1.36	.70	.02	-.03	-.64	.40 - .74
T_2 Suppression	3.07	1.31	.70	<.01	.02	-.61	.40 - .75
T_3 Suppression	3.10	1.20	.70	<.01	-.05	-.54	.40 - .77
T_1 Wellbeing	3.44	0.90	.86	.06	-.53	.34	.54 - .84
T_2 Wellbeing	3.35	0.98	.87	.03	-.48	.11	.58 - .86
T_3 Wellbeing	3.25	0.90	.87	.02	-.45	.06	.58 - .86

Note. ω = McDonald's omega. ρ_I = intraclass correlation coefficient (ICC1).

Table 2

Correlations Between the Study Variables

	1	2	3	4	5	6	7	8	9	10	11	12
1. T_1 Reappraisal	—	.11***	.36***	.53***	-.06	.32***	.41***	.01	.23***	-.06*	.01	.01
2. T_1 Suppression	.14**	—	-.04	.05	.64***	-.04	-.02	.48***	-.05	-.02	.17***	.06*
3. T_1 Wellbeing	.31***	-.03	—	.28***	-.14**	.69***	.22***	-.07	.55***	-.06*	.12***	.00
4. T_2 Reappraisal	.44***	-.04	.20***	—	.02	.35***	.57***	-.03	.34***	-.07*	.05	-.04
5. T_2 Suppression	-.13***	.52***	-.16***	.07	—	-.21***	-.05	.64***	-.17***	.01	.06	.05
6. T_2 Wellbeing	.23***	-.09*	.59***	.30***	-.17***	—	.32***	-.09*	.65***	-.08**	.06*	-.02
7. T_3 Reappraisal	.34***	-.06	.17***	.48***	-.13**	.27***	—	-.03	.44***	-.06*	.05	-.04
8. T_3 Suppression	-.05	.41***	-.08*	-.09**	.52***	-.11**	.04	—	-.16***	.03	.01	-.01
9. T_3 Wellbeing	.17***	-.10**	.46***	.26***	-.17***	.56***	.37***	-.15***	—	-.11***	.10***	-.05
10. Gender	-.05	-.01	-.03	-.05	.00	-.07**	-.05	-.01	-.10**	—	—	—
11. Age	.01	.12***	.14***	.04	.02	.08**	.04	.00	.12***	—	—	—
12. FSM	.00	.10	.00	-.04	-.01	-.06*	.02	.00	.04	—	—	—

Note. Latent bivariate correlations above the diagonal, manifest Pearson's *r* correlations below the diagonal.

**p* <.05. ***p* <.01. ****p* <. 001.

Table 3

Comparison of the Reciprocal Relations CLPM and RI-CLPM to Their Nested Models

	χ^2 (df)	RMSEA	SRMR	CFI	TLI	AIC	ΔAIC	TRd (df)
CLPM								
Baseline Model	1804.40 (1131)***	.016	.046	.967	.963	158555.21	49.53	49.43 (6)***
Model A	1763.29 (1127)***	.016	.040	.969	.965	158513.19	7.51	9.57 (2)**
Model B	1770.44 (1127)***	.016	.040	.969	.965	158522.00	16.32	16.11 (2)***
Reciprocal Relations Model	1753.72 (1125)***	.016	.038	.969	.965	158505.68	—	—
RI-CLPM								
Baseline Model	1832.93 (1172)***	.015	.039	.970	.967	181100.27	10.86	19.92 (6)**
Model A	1820.41 (1168)***	.015	.039	.970	.967	181093.30	3.89	7.28 (2)*
Model B	1826.75 (1168)***	.015	.039	.970	.967	181100.89	11.48	14.31 (2)***
Reciprocal Relations Model	1813.53 (1166)***	.015	.038	.970	.967	181089.41	—	—

Note. Model A: Relations of school wellbeing to cognitive reappraisal and suppression constrained to zero. Model B: Relations of cognitive reappraisal and suppression to school wellbeing constrained to zero. *p< .05. **p< .01. ***p< .001.

Table 4

Standardized Autoregressive and Cross-Lagged Path Coefficients and Correlation Coefficients for the Reciprocal Relations CLPM

	Reappraisal			Suppression			Wellbeing		
Autoregressive effects									
T1 → T2		**.458** (.041)			**.650** (.042)			**.607** (.034)	
T2 → T3		**.500** (.045)			**.567** (.055)			**.550** (.037)	
T1 → T3		**.109** (.052)			**.140** (.067)			**.115** (.042)	
Cross-lagged effects	*Suppression → Reappraisal*		*Wellbeing → Reappraisal*	*Reappraisal → Suppression*		*Wellbeing → Suppression*	*Reappraisal → Wellbeing*		*Suppression → Wellbeing*
T1 → T2	-.050 (.031)		**.093** (.030)	**-.110** (.033)		.005 (.034)	**.101** (.027)		-.045 (.027)
T2 → T3	-.046 (.029)		**.089** (.030)	**-.114** (.032)		.004 (.031)	**.103** (.028)		-.039 (.023)
Concurrent correlations		*Wellbeing ⇔ Reappraisal*			*Reappraisal ⇔ Suppression*			*Suppression ⇔ Wellbeing*	
T1		**.339** (.031)			**.108** (.043)			**-.105** (.040)	
T2		**.182** (.047)			**.208** (.060)			**-.185** (.056)	
T3		**.299** (.045)			**.166** (.063)			**-.111** (.056)	
Effects of covariates	*Gender*	*Age*	*FSM*	*Gender*	*Age*	*FSM*	*Gender*	*Age*	*FSM*
T1	**-.055** (.026)	.004 (.028)	.008 (.028)	-.012 (.031)	**.169** (.030)	.053 (.031)	-.055 (.025)	**.121** (.025)	.001 (.027)
T2	**-.036** (.028)	.040 (.028)	-.046 (.028)	.010 (.032)	-.062 (.032)	.013 (.031)	-.038 (.024)	-.012 (.025)	-.028 (.025)
T3	-.012 (.029)	.015 (.029)	-.010 (.031)	.017 (.032)	-.034 (.034)	-.052 (.034)	**-.052** (.026)	.048 (.026)	-.035 (.027)

Note. **Bold** coefficients $p < .05$. Coefficients in parenthesis are standard errors.

Table 5

Standardized Autoregressive and Cross-Lagged Path Coefficients and Correlation Coefficients for the Reciprocal Relations RI-CLPM

	Reappraisal		Suppression		Wellbeing	
Autoregressive effects						
T1 → T2	**.305** (.094)		**.408** (.156)		**.323** (.082)	
T2 → T3	**.338** (.100)		**.391** (.161)		**.365** (.085)	
Cross-lagged effects	*Suppression → Reappraisal*	*Wellbeing → Reappraisal*	*Reappraisal → Suppression*	*Wellbeing → Suppression*	*Reappraisal → Wellbeing*	*Suppression → Wellbeing*
T1 → T2	-.076 (.082)	**.168** (.071)	**-.178** (.082)	.025 (.084)	**.220** (.066)	-.055 (.077)
T2 → T3	-.073 (.079)	**.190** (.078)	**-.197** (.090)	.028 (.095)	**.243** (.071)	-.053 (.074)
Concurrent correlations	*Wellbeing ⇔ Reappraisal*		*Reappraisal ⇔ Suppression*		*Suppression ⇔ Wellbeing*	
T1	**.427** (.087)		.140 (.148)		-.005 (.143)	
T2	**.251** (.060)		.152 (.084)		**-.184** (.081)	
T3	**.382** (.054)		.115 (.078)		-.114 (.075)	
Effects of covariates on random intercepts						
Gender	**-.112** (.045)		.007 (.037)		**-.117** (.034)	
Age	.053 (.040)		**.120** (.041)		**.145** (.033)	
FSM	-.027 (.041)		.043 (.037)		-.022 (.033)	
Correlations of random intercepts	*Wellbeing ⇔ Reappraisal*		*Reappraisal ⇔ Suppression*		*Suppression ⇔ Wellbeing*	
	.256 (.179)		.132 (.274)		-.143 (.179)	

Note. **Bold** coefficients $p < .05$. Coefficients in parenthesis are standard errors.

Table 6

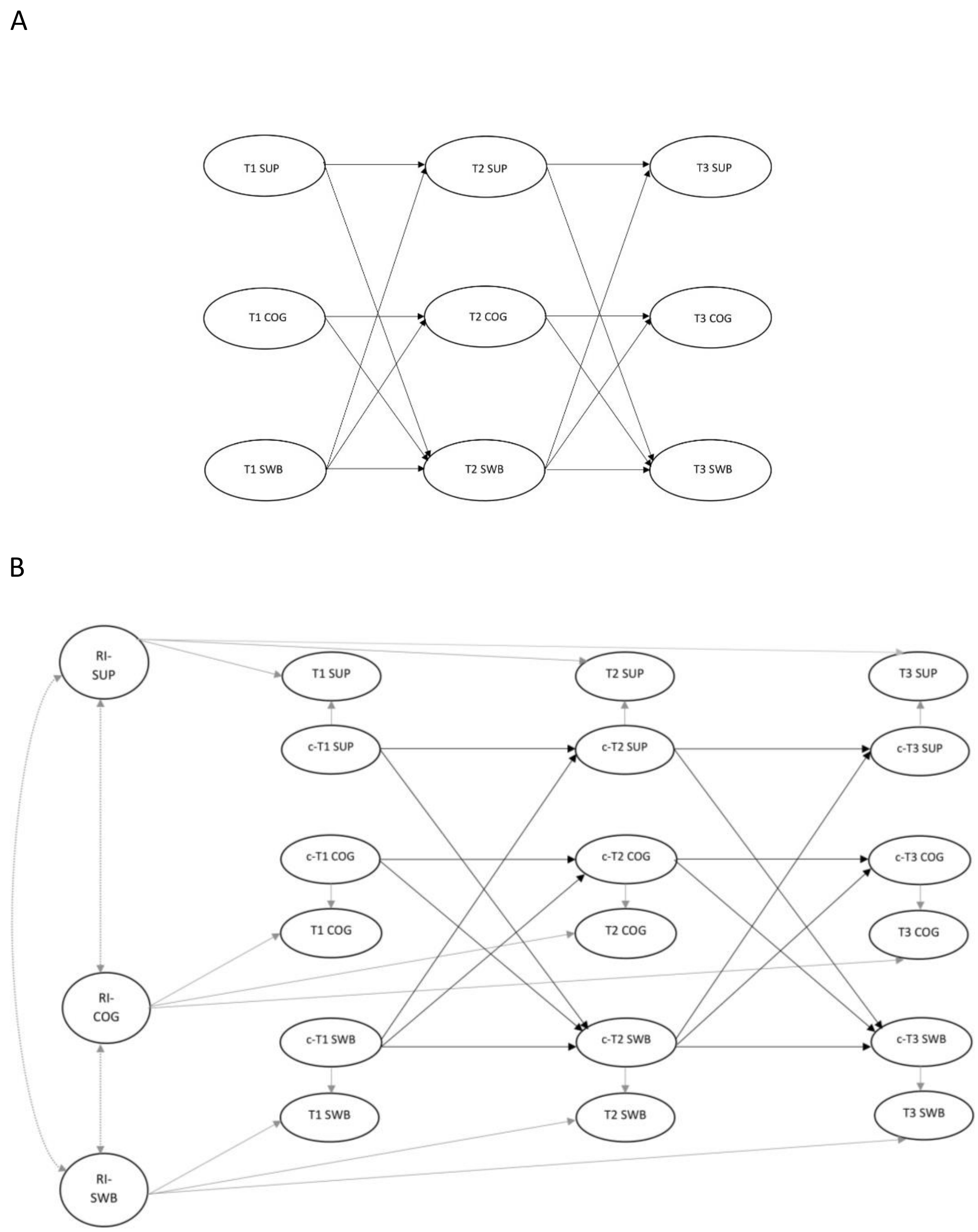
Statistically Significant Mediational Effects in the CLPM and the RI-CLPM

	CLPM estimates			RI-CLPM estimates		
	β	*SE*	95% CIs [*LL; UL*]	β	*SE*	95% CIs [*LL; UL*]
T_1 Reappraisal to T_3 Reappraisal						
Total effect	.352	.043	[.281; .424]	.158	.067	[.047; .268]
Direct effect	.109	.052	[.023; .195]	—	—	—
Indirect effect (via T_2 Wellbeing)	.009	.003	[.003; .015]	.042	.024	[.002; .081]
T_1 Wellbeing to T_3 Wellbeing						
Total effect	.458	.034	[.402; .515]	.158	.063	[.054; .261]
Direct effect	.115	.042	[.046; .185]	—	—	—
Indirect effect (via T_2 Reappraisal)	.010	.004	[.004; .016]	.041	.024	[.002; .080]

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Figure 1

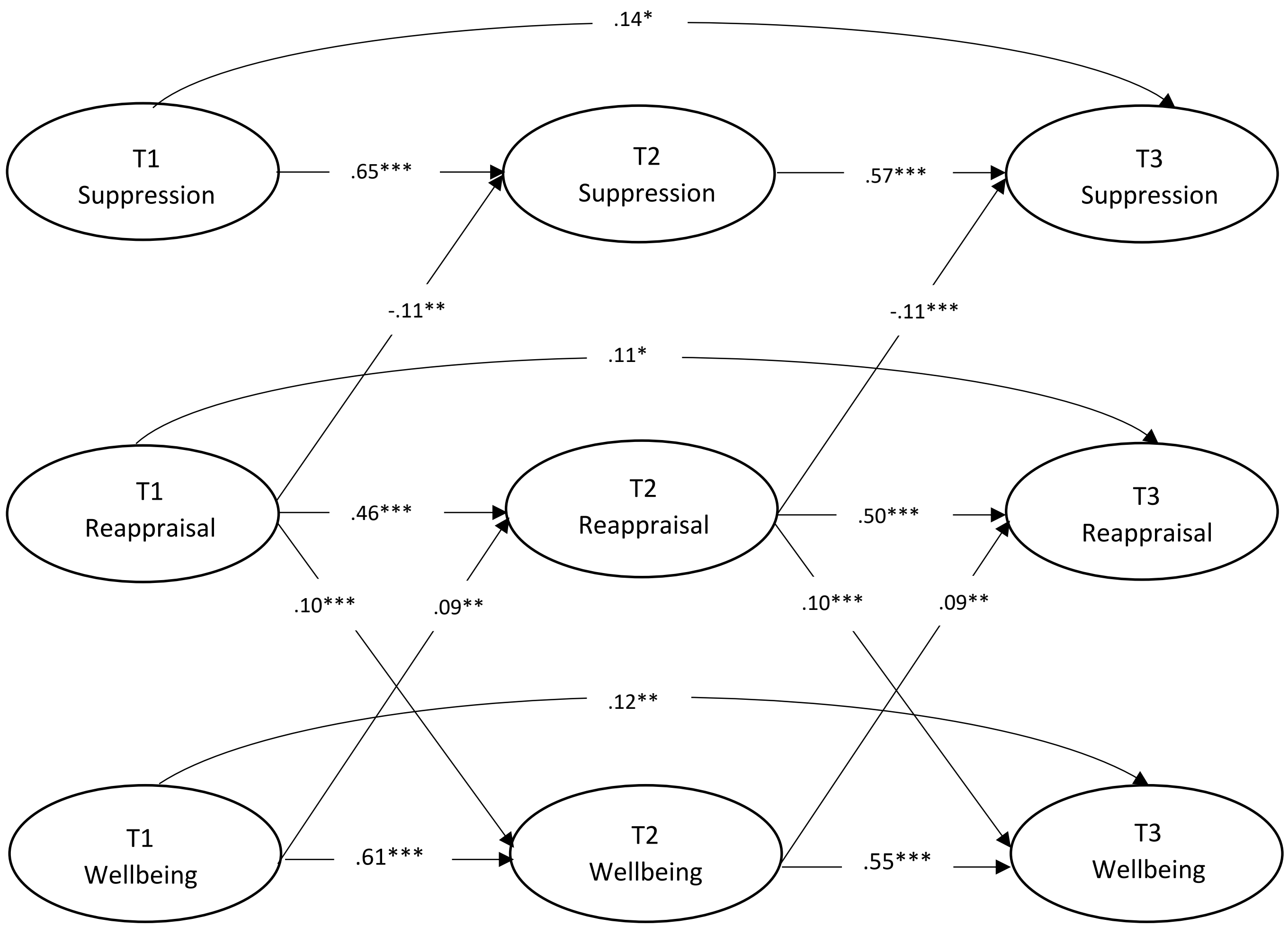
The Hypothesized CLPM (Panel A) and RI-CLPM (Panel B) Depicting Associations Between Reappraisal, Suppression and School-Wellbeing



Note. SUP = latent variable of suppression; COG = latent variable of cognitive reappraisal; SWB = latent variable of school-related wellbeing; c-SUP, c-COG, c-SWB = within-person level variables; RI-SUP, RI-COG, RI-SWB = between-person level factors (random intercepts). Diagonal black arrows depict the cross-lagged paths. Horizontal black arrows depict the autoregressive paths. Concurrent relations are not depicted. Grey dotted lines represent correlations between random intercept factors.

Figure 2

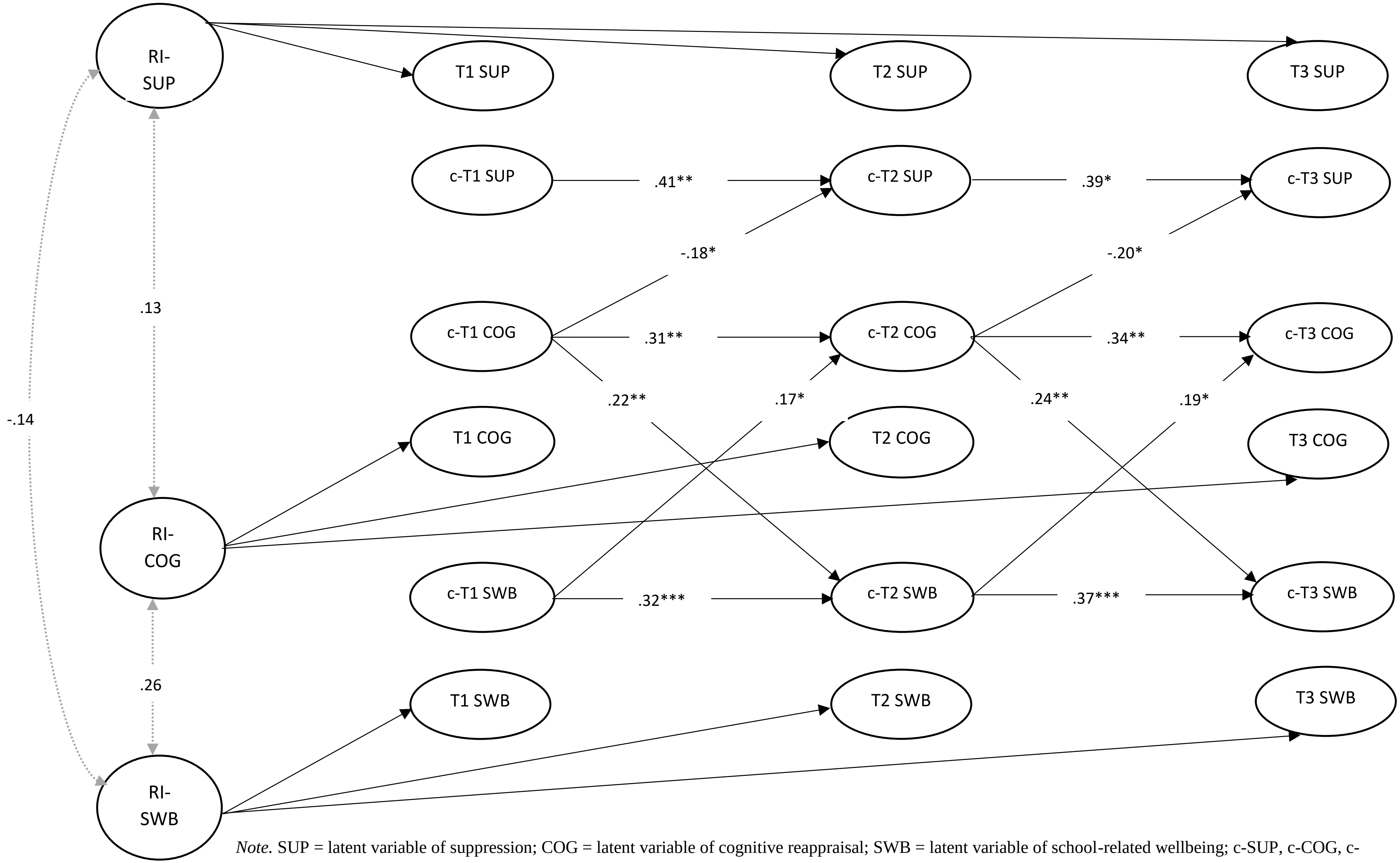
The CLPM Depicting Significant Associations Between Reappraisal, Suppression, and School-Related Wellbeing



Note. Effects of covariates and concurrent relations are not depicted. *p< .05. **p< .01. ***p< .001.

Figure 3

The RI-CLPM Depicting Significant Associations Between Reappraisal, Suppression, and School-Related Wellbeing



Note. SUP = latent variable of suppression; COG = latent variable of cognitive reappraisal; SWB = latent variable of school-related wellbeing; c-SUP, c-COG, c-SWB = within-person level variables; RI-SUP, RI-COG, RI-SWB = between-person level factors (random intercepts). Grey dotted lines represent non-significant correlations between random intercept factors. Effects of covariates and within-person concurrent relations are not depicted. **p*< .05. ***p*< .01. ****p*< .001.

Students' Emotion Regulation and School-Related Wellbeing:

Longitudinal Models Juxtaposing Between- and Within-Person Perspectives

- Supplementary Materials –

This document contains the following materials:

1. Missing Data Analyses

2. Preliminary Analyses

3. References

Tables S1-S4

1. Missing Data Analyses

Table S1 and Table S2 show the results from the t-tests for identifying sources of missing data. We also conducted chi-square difference tests to examine missingness for gender, nationality and FSM. Students who had FSM were more likely to complete the questionnaire at Time 2 than students who did not have FSM ($p < .001$). All other differences for missingness at Time 2 were not statistically significant (*p*s >.05). For Time 3, males were less likely than females to participate in completing the Time 3 cognitive reappraisal scale (p =.019), the Time 3 suppression scale (p =.017), and the Time 3 school-related wellbeing scale (p =.018). All other differences for Time 3 missing data were not statistically significant (*p*s >.05). Since the missing data could be accounted for by FSM and gender, these variables were included as covariates in the SEMs.

2. Preliminary Analyses

To estimate latent bivariate correlations, a measurement model was created that included reappraisal (6 items at T_1, T_2 and T_3), suppression (4 items at T_1, T_2 and T_3), and wellbeing (6 items at T_1, T_2 and T_3). The residuals of corresponding indicators at T_1, T_2, and T_3, were allowed to correlate for all measures. Previous studies examining the factor structure of the ERQ-CA recommend correlating the residual variances for items 1 and 3 on the cognitive reappraisal sub-scale (‘When I want to feel happier I think about something different’ and ‘When I want to feel less bad… I think about something different’) because the items show large correlations between residuals (Gullone & Taffe, 2012; Ng at al., 2019), likely due to the items having similar wording even though they represent contrasting emotional states (Ng et al., 2019). As such, correlating the residuals of these items is justified (Cole et al., 2007), and they were allowed to correlate at each time point. Gender (0 = male, 1 = female), age, and FSM (FSM; 0 = not eligible for FSM, 1 = eligible for FSM) were added to the measurement model as manifest variables.

Measurement Invariance

Tests of measurement invariance are reported in Table S3. The reappraisal and suppression scales demonstrated metric, scalar, and residual invariance, suggesting that the same construct is represented by each of the scales at each measurement occasion. The wellbeing scale showed partial scalar invariance as the item intercepts were the same across all time points for three of the six items on the scale. The items on the scale not displaying scalar invariance were ‘School is going well for me,’ ‘I feel good at school,’ and ‘I like going to school.

3. References

Cole, D. A., Ciesla, J. A., & Steiger, J. H. (2007). The insidious effects of failing to include design-driven correlated residuals in latent-variable covariance structure analysis. *Psychological Methods*, *12*(4), 381-398. https://doi.org/10.1037/1082-989X.12.4.381

Gullone, E., & Taffe, J. (2012). The Emotion Regulation Questionnaire for Children and Adolescents (ERQ–CA): A psychometric evaluation. *Psychological Assessment, 24*(2), 409-417. https://doi.org/10.1037/a0025777

Ng, Z. J., Huebner, E. S., Maydeu-Olivares, A., & Hills, K. J. (2019). Confirmatory factor analytic structure and measurement invariance of the Emotion Regulation Questionnaire for Children and Adolescents in a longitudinal sample of adolescents. *Journal of Psychoeducational Assessment, 37*(2), 139-153. https://doi.org/10.1177/0734282917732891

Table S1

Results of T-Tests for identifying sources of Missing Data for T_2 Reappraisal, T_2 Suppression, and T_2 Wellbeing

Variables	Mean Difference	*SE* Difference	*t*	df	*p*
T_2 Reappraisal					
T_1 Reappraisal	-.105	.035	-2.959	1,714	.003
T_1 Wellbeing	-.249	.035	-7.160	1,552	<.001
Age	-.358	.081	-4.414	2,213	<.001
T_2 Suppression					
T_1 Reappraisal	-.124	.035	-3.535	1,714	<.001
T_1 Wellbeing	-.237	.034	-6.953	1,745	<.001
Age	-.672	.080	-8.397	2,341	<.001
T_2 Wellbeing					
T_1 Wellbeing	-.238	.035	-6.805	1,513	<.001
T_1 Reappraisal	-.096	.036	-2.717	1,714	.007
Age	-.347	.083	-4.181	2,355	<.001

Note. Mean difference refers to the difference in means for participants who had missing data at Time 2 compared with participants who did not having missing data at Time 2 (0 = missing, 1 = completed).

Table S2

Results of T-Tests for identifying sources of Missing Data for T_3 Reappraisal, T_3 Suppression, and T_3 Wellbeing

Variables	Mean Difference	*SE* Difference	*t*	df	*p*
T_3 Reappraisal					
T_1 Reappraisal	-.107	.035	-3.054	1714	.002
T_1 Wellbeing	-.185	.034	-5.404	1751	<.001
T_2 Reappraisal	-.121	.043	-2.800	1135	.005
T_2 Wellbeing	-.245	.042	-5.818	1149	<.001
T_3 Suppression					
T_1 Reappraisal	-.106	.035	-3.028	1714	.002
T_1 Wellbeing	-.184	.034	-5.385	1751	<.001
T_2 Reappraisal	-.121	.043	-2.800	1135	.005
T_2 Wellbeing	-.245	.042	-5.818	1149	<.001
T_3 Wellbeing					
T_1 Reappraisal	-.120	.035	-3.423	1714	.001
T_1 Wellbeing	-.188	.034	-5.487	1746	<.001
T_2 Reappraisal	-.121	.044	-2.766	1086	.006
T_2 Wellbeing	-.247	.042	-5.811	1098	<.001

Note. Mean difference refers to the difference in means for participants who had missing data at Time 3 compared with participants who did not having missing data at Time 3 (0 = missing, 1 = completed).

Table S3

Tests of Measurement Invariance for Reappraisal, Suppression, and School-Related Wellbeing

Models	χ^2(df)	RMSEA	SRMR	CFI	TLI	Δ RMSEA	ΔCFI	ΔTLI
Reappraisal								
T_1	55.65 (8)	.059	.020	.986	.974			
T_2	23.39 (8)	.037	.012	.995	.991			
T_3	15.51 (8)	.028	.012	.997	.995			
Configural	282.52 (111)	.026	.037	.983	.976			
Metric Invariance	295.55 (121)	.025	.039	.983	.978	-.001	<.001	-.002
Scalar Invariance	306.28 (133)	.024	.041	.983	.980	-.001	<.001	+.002
Residual Invariance	339.39 (145)	.024	.041	.981	.979	<.001	-.002	-.001
Suppression								
T_1	6.02 (2)	.039	.012	.995	.986			
T_2	1.37 (2)	.000	.006	1.000	1.002			
T_3	1.99 (2)	.000	.008	1.000	1.000			
Configural	76.04 (39)	.021	.028	.989	.981			
Metric Invariance	77.40 (45)	.019	.029	.990	.986	-.002	+.001	+.005
Scalar Invariance	88.95 (53)	.018	.030	.989	.987	-.001	-.001	+.001
Residual Invariance	111.16 (61)	.020	.041	.985	.984	+.002	-.004	-.003

Models	χ^2(df)	RMSEA	SRMR	CFI	TLI	Δ RMSEA	ΔCFI	ΔTLI
Wellbeing								
T_1	62.34 (9)	.058	.016	.987	.979			
T_2	52.41 (9)	.058	.017	.988	.981			
T_3	66.76 (9)	.072	.023	.982	.969			
Configural	299.697 (114)	.026	.026	.985	.980			
Metric Invariance	312.239 (124)	.025	.028	.985	.982	-.001	<.001	+.002
Scalar Invariance	468.947 (136)	.032	.051	.974	.970	+.007	-.011	-.012
Partial Scalar Invariance[a]	416.867 (136)	.031	.044	.977	.973	+.006	-.008	-.009

Note. χ^2 statistic for all models statistically significant at p <.001.

[a] Equality constraint relaxed on three items: 'School is going well for me', 'I feel good at school' and 'I like going to school'

Table S4

Model Fit Indices and Goodness of Fit for the Lag 1 and Lag 2 CLPMs

	χ^2 (df)	RMSEA	SRMR	CFI	TLI	AIC	ΔAIC	TRd (df)
Lag 1	1768.44 (1128)***	.016	.039	.969	.965	158517.25	13.41	25.80 (9)**
Lag 2: Autoregressive paths only	1753.72 (1125)***	.016	.038	.969	.965	158505.68	1.84	11.15 (6)
Lag 2: CL & Autoregressive Paths	1742.51 (1119)***	.016	.037	.970	.966	158503.84	—	—

Note. CL = Cross-lagged. **p*< .05. ***p*< .01. ****p*< .001.