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School burnout is related to sleep quality and perseverative cognition regulation at bedtime in young adults

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ABSTRACT

The relationship between school burnout and sleep is largely unexplored, especially in emerging adults. Two studies investigate this relationship, including associations with academic achievement. Study 1 ($N = 350$) documents robust relationships between school burnout and self-reported indices of poorer sleep quality, over and above negative affect (i.e. depression, anxiety, stress) using survey data collected from undergraduates. Higher school burnout also corresponded with lower grade point average after accounting for sleep quality. Studies 2a ($N = 681$) and 2b ($N = 474$) examined school burnout and perseverative cognition regulation across time using latent cross-lagged panel analyses and latent growth models with survey data collected three times over a semester. Findings suggested that although only a few predicted paths emerged between burnout and perseverative cognition regulation, increasing school burnout was associated with slower improvements in perseverative cognition regulation during bedtime. Limitations, study implications, and future research directions are also discussed.

1. Introduction

The 21st century has seen a rise in the pursuit of postsecondary education among emerging adults (18–25 years of age, Arnett, 2007). In the United States, the National Center for Education Statistics (NCES, 2019) reported that enrollment in postsecondary education institutions rose from 13.2 million in 2000 to 16.8 million in 2017. Moreover, enrollment is expected to increase by 3% between 2017 and 2028 (NCES, 2019). Fueling the demand for higher education is labor markets that leave little room for the unqualified and unskilled (Bynner, 2005; Schulenberg & Schoon, 2012). Although completion of postsecondary education provides increased earnings across a lifetime and is associated with greater life expectancy (Cutler & Lleras-Muney, 2006), experiencing academic stress in emerging adulthood is deleterious to psychological and physiological health (Barber & Santuzzi, 2017; Byrne, Davenport, & Mazanov, 2007; May, Sanchez-Gonzalez, & Fincham, 2014). Accordingly, school burnout, a construct representing contextualized school-related stress, has successfully extended the occupational burnout literature into the context of academia where it is an important construct of inquiry (Salmela-Aro, Kiuru, Leskinen, & Nurmi, 2009).

School burnout is a multidimensional affective response to academic stress representing feelings of exhaustion stemming from schoolwork, cynicism toward the meaning of school, and a belief of inadequacy regarding school-related accomplishment (Salmela-Aro et al., 2009). Approached from the demand-resource model (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001), burnout is an outcome attributed to the chronic depletion of resources used to cope with work stress. School burnout is linked to a host of deleterious outcomes, including increased absenteeism, school dropout rates, academic underperformance (May, Bauer, & Fincham, 2015; Salmela-Aro et al., 2009), negative affect, suicidal ideation (Dyrbye et al., 2008; Salmela-Aro et al., 2009), interpersonal phenomena such as intimate partner violence (Cooper, Seibert, May, Fitzgerald, & Fincham, 2017), and cardiotoxic physiological functioning (May, Sanchez-Gonzalez, Brown, Koutnik, & Fincham, 2014; May, Sanchez-Gonzalez, & Fincham, 2014; May, Sanchez-Gonzalez, Seibert, & Fincham, 2016). Furthermore, developmental research indicates the need for early detection as burnout is likely to spill over to additional mental health challenges (e.g., depression, addiction) and poorer academic achievement (Bask & Salmela-Aro, 2013; Salmela-Aro, Upadyaya, Hakkarainen, Lonka, & Alho, 2017; Tuominen-Soini & Salmela-Aro, 2014; also see the review provided by Salmela-Aro, 2017). Although school burnout is linked to numerous indicators of suboptimal physiological, psychological, and behavioral functioning, constructs that might ameliorate these negative

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relationships with school burnout remain relatively underexplored.

One construct that may help explain (as well as alleviate) the link between school burnout and adverse functioning is sleep quality. Higher sleep quality is known to restore cognitive and physiological resources that positively promote health and well-being. (Barber, Grawitch, & Munz, 2013; Barber & Munz, 2011; Hagger, 2010; Pilcher, Morris, Donnelly, & Feigl, 2015). Research linking school burnout and sleep is largely absent in primary to post-secondary academic populations. Investigations using medical school students indicate that burnout is associated with indices of poorer sleep quality, such as sleep latency and duration, frequency in use of sleep medication and subjective sleep quality (Arbabisarjou et al., 2016; Pagnin et al., 2014; Shad, Thawani, & Goel, 2015). However, the cross-sectional nature of the data precludes casual inference and limits understanding of the temporal relations and developmental progression between burnout and sleep.

Although not pertaining to an academic context, occupational research regarding the relationship between burnout and sleep has been informative. Occupational burnout is related to an absence of feeling refreshed in the morning and increased daytime fatigue and sleepiness (Grossi, Perski, Evengård, Blomkvist, & Orth-Gomér, 2003). Additionally, emotional and physical exhaustion, two components of burnout, are predictive of sleep complaints (Brand et al., 2010) with recovery from burnout relating to a host of indices corresponding to improved sleep (e.g. less fatigue, greater subjective sleep quality, and improved polysomnographic values; Ekstedt, Söderström, & Åkerstedt, 2009). Interestingly, Armon, Shirom, Shapira, and Melamed (2008) demonstrated a recursive relationship between work burnout and insomnia; however, only two time points were evaluated precluding analysis of longitudinal change across times. Thus, as with medical school burnout, occupational research has yet to unravel the developmental progression between burnout and sleep.

Occupational research has also been instructive in identifying potential antecedents to diminished sleep quality. A promising but underdeveloped avenue of occupational stress research is in the area of perseverative cognition. Perseverative cognition has been defined as "the repeated or chronic activation of the cognitive representation of one or more psychological stressors" (Brosschot, Gerin, & Thayer, 2006, p. 114). Importantly, perseverative cognition is hypothesized to prolong or sustain the activation of a psychosocial stressor(s) in its representational form (even if the original stressor is not actively present). While not yet broached as a topic of research within the school setting, occupational research has shown that work-stress perseverative cognition is both directly related to poorer sleep quality and also mediates the relationship between work-related stress and sleep quality (i.e. providing a pathway from which a stressor induces influence on the body; Van Laethem et al., 2015). In fact, a longitudinal two wave study found some evidence of bidirectionality, suggesting that work-stress, perseverative cognition, and sleep quality may mutually influence each other over time (see Van Laethem et al., 2015). Identification of the ability for early adults to regulate perseverative cognitions during bedtime may greatly enrich sleep intervention research, especially in the context of increased school stress (i.e. school burnout).

Transactional models of stress may provide insight on how school burnout and sleep affect each other. In the transactional model of stress, stress is a transactional process between individual and environmental components (Dewe, O'Driscoll, & Cooper, 2012). Consequently, psychological theories of stress that address the transaction (i.e. exchange or interaction) between individual and environmental factors (e.g., Conservation of Resource Theory; COR; Hobfoll, 1989) have largely been utilized to understand the experience of work-related stress (Dewe et al., 2012), occupational burnout (Vela-Bueno et al., 2008) and personal burnout with sleep (Barber & Santuzzi, 2017).

Extending the transactional model of stress to school burnout suggests that prolonged exposure to school-related stress depletes the resources needed to successfully navigate tasks and responsibilities within the academic environment. This would increase vulnerability to school burnout further leading to poorer outcomes. In contrast, adequate sleep quality may inhibit or reduce school burnout by replenishing cognitive capacities necessary to manage academic stress. The perseverative cognition hypothesis provided by Brosschot et al. (2006) would also be consistent with the transactional model of stress in that prolonged cognitive activation of school-related stress representations would induce negative sleep outcomes (conversely better regulation of perseverative cognition at bedtime would improve sleep quality).

Given the limitations of prior studies on the relationship between burnout and sleep-related quality, the current research examines these constructs over two studies. Study 1 utilized a cross-sectional approach to establish an association between school burnout and a comprehensive self-report measure of sleep quality among a large sample of undergraduate students. Based on the earlier noted findings on occupational and medical resident burnout, we hypothesized a positive relationship between school burnout and poorer sleep quality. We also explored relationships between burnout and sleep quality with academic performance. Addressing the lack of temporal data in prior research, Study 2 employed a longitudinal methodological approach over the course of an academic semester while also introducing the assessment of regulated perseverative cognition. We then examined the potential causal relationship between school burnout and perseverative cognition in a sample of undergraduate students. Specifically, we examined whether school burnout and perseverative cognition recursively predict one another over time and the relationship they have with academic performance. Replication of temporal findings were then attempted in an independent sample using an alternative measure of burnout. The current research is designed to provide novel contributions to the burnout and sleep literatures by underscoring the importance of accounting for the role both burnout and sleep-related qualities play in activating each other over time.

2. Study 1

2.1. Introduction

Although previous research has demonstrated an association between work burnout and sleep problems, research has not yet examined school burnout in relation to sleep quality. Consequently, Study 1 examined potential relationships between school burnout and sleep quality, while exploring their relationships with academic performance. We hypothesized a positive relationship between school burnout and sleep-related problems (i.e. poor sleep quality) and explored the relationship of school burnout and poor sleep quality with academic performance (grade point average; GPA).

2.2. Method

2.2.1. Participants

Undergraduate students (N = 350) from multiple undergraduate courses at a 4-year public university located in the southeastern region of the U.S. participated in this study. The majority of students identified as female (87%) with an average age of 19.86 years (SD = 1.84). A large portion of the sample (67%) reported their ethnicity as Caucasian followed by 15.5% African American, 11.5% Latino/Hispanic, 1.5% Asian, and 5% endorsed either biracial or non-disclosed ethnicity.

2.2.2. Measures

2.2.2.1. School burnout. School burnout was assessed using the nine item self-report School Burnout Inventory (SBI; Salmela-Aro et al., 2009). The SBI measures three first-order factors of school burnout: (a) exhaustion, (b) cynicism toward the meaning of school, and (c) sense of inadequacy using four, three and two items respectively. For example, exhaustion is captured by the item, "I feel overwhelmed by my school work", whereas the item "I feel that I am losing interest in my school work" captures cynicism, and sense of inadequacy is captured by the item, "I often have feelings of inadequacy in my school work." Participants respond on a 6-point Likert scale ranging from (1) *completely disagree* to (6) *completely agree* with higher scores indicative of higher levels of school burnout. First-order scores were summed to define the global second-order school burnout score. Higher global SBI scores indicate greater school burnout, and reliability in the present sample was $\alpha = 0.87$.

2.2.2.2. Sleep quality. Sleep quality was measured using the Pittsburgh Sleep Quality Index (PSQI: Buysse, Reynolds, Monk, Berman, & Kupfer, 1989). The PSQI demonstrates convergent validity with alternative measures of sleep and sleep logs with a sensitivity and specificity for capturing the presence or absence of sleep impairments (Cole et al., 2006). The PSQI is a 19-item self-report questionnaire that includes seven clinically derived sub-scales measuring: subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleeping medications, and daytime dysfunction. Responses range from open ended to Likert type scales. Sub-scales are comprised of unique algorithms containing one or more of the 19-items. For example, subjective sleep quality is measured using the item, "during the past month, how would you rate your sleep quality overall?" Responses range from (0) *very good* to (4) *very bad*, with higher scores indicating poorer sleep quality. Sleep efficiency is computed as a percentile ranging from 0 to 100 with higher scores indicating improved sleep efficiency and lower sleep problems. The algorithm for sleep efficiency exists as the value of the item "during the past month, how many hours of actual sleep did you get at night?" divided by the difference in hours between the two items "during the past month, when have you usually gone to bed?" and "during the past month, when have you usually gotten up in the morning?" multiplied by 100. Combined sub-scale scores are then used to derive the construct of total sleep disturbance. To achieve unilateral direction indicating higher total sleep disturbance, the sub-scales of sleep efficiency and duration of sleep were reverse coded to match algorithms for sleep disturbance, sleep latency, day dysfunction due to sleepiness, overall sleep quality, and use of sleep medication. Higher scores on each subscale independently and summed together indicate poorer sleep. All PSQI subscale reliabilities in the present sample were greater than $\alpha = 0.83$.

2.2.2.3. Negative affect. Depression, anxiety and stress were measured using the short-form (21 item) version of the Depression Anxiety Stress Scale (DASS-21; Henry & Crawford, 2005). Items measuring depression, anxiety and stress include, "I couldn't seem to experience any positive feeling at all", "I felt I was close to panic" and "I felt that I was using a lot of nervous energy," respectively. Responses to the DASS-21 were on a 4-point Likert scale ranging from (0) *did not apply to me at all* to (3) *applied to me very much or most of the time* with higher scores in each domain indicating increased levels of depression, anxiety, and stress. The sample reliabilities for the DAS-21 subscales of depression, anxiety, and stress were 0.85, 0.87, and 0.88, respectively.

2.2.2.4. Academic performance. Academic performance was measured by participant reports of their cumulative undergraduate grade point average (GPA). The GPA scale ranges from 0 to 4.00 with higher GPA's indicating higher academic performance.

2.2.3. Procedure

University instructors who were not involved in the study permitted investigators to recruit participants through class announcements. Participants were provided the opportunity to earn a small amount of extra course credit for participating in the study. All participants provided written consent prior to engaging in the study using the institutional review board approved form. To be included in the study, students had to have completed at least 1 collegiate semester. Participants completed an online questionnaire that included the measurement scales. Data was collected between the 3rd and 6th weeks of the academic semester.

2.2.4. Analysis strategy

Initial data inspections revealed 14 cases with missing data. These cases were removed from analyses resulting in a study N of 336. As Study 1 aims to establish a relationship between school burnout and sleep, Pearson correlations between the constructs were first examined. Furthermore, as affective disorders may have symptomatology that overlaps with school burnout, investigators suggest controlling for depressive and anxiety symptoms in exploratory burnout research (Melamed, Shirom, Toker, Berliner, & Shapira, 2006; Schaufeli & Buunk, 2003; Shirom, 2009). Therefore, hierarchical multiple regression (HMR) analyses were conducted to demonstrate the incremental contribution of school burnout over and above that of negative affect in accounting for variance in sleep scores. Model 1 of the HMR contained the anxiety and depression predictors and Model 2 introduced school burnout as a predictor. Finally, school burnout and sleep quality were compared in predicting GPA while controlling for negative affect in a HMR model. All analyses were conducted via IBM SPSS version 22 (IBM, 2013). Residuals and scatter plots indicated assumptions of linear relationships, normal multivariate distribution, and homoscedasticity were met.

2.3. Results & discussion

Pearson correlations show significant negative relationships between GPA ($M = 3.23$, $SD = 0.65$) and school burnout scores, including the global burnout ($r = -0.24$, $p < .001$, $M = 28.93$, $SD = 8.66$) and subscale burnout scores ($r = -0.18$, $p < .01$, $M = 13.54$, $SD = 4.0$ for exhaustion, $r = -0.16$, $p < .01$, $M = 8.91$, $SD = 3.74$ for cynicism, and $r = -0.30$, $p < .001$, $M = 6.50$, $SD = 2.43$ for inadequacy). GPA was also significantly correlated with the global Pittsburgh sleep score ($r = -0.11$, $p < .05$, $M = 6.44$, $SD = 3.19$) and subscales of duration of sleep ($r = -0.16$, $p < .01$, $M = 0.71$, $SD = 0.88$) and subjective sleep quality ($r = -0.18$, $p < .01$, $M = 1.17$, $SD = 0.66$). However, GPA was not related ($p > .05$) to subscales representing sleep latency, day dysfunction due to sleepiness, sleep efficiency, or needing medication to sleep (the full correlation table can be found in the supplemental materials).

Regarding the relationship between sleep quality and school burnout, global burnout scores were significantly positively related to the global Pittsburgh sleep scores ($r = 0.40$, $p < .001$) and all seven Pittsburgh sleep subscales (r's range from 0.14 $p < .05$ to 0.41 $p < .01$, see supplemental materials). This pattern also emerged with the burnout subscales. Thus, the correlations indicate that greater burnout is related to poorer sleep quality.

The relationship between global burnout and global sleep quality scores also held after controlling for negative affect (depression, anxiety, and stress from the DASS-21 subscales). The hierarchical multiple regression revealed that after controlling for the negative affect covariates in Model 1, school burnout significantly contributed to the prediction of global Pittsburgh sleep scores in Model 2, $\Delta F(1, 331) = 12.15$, $p < .001$. School burnout accounted for an additional 3% of the variance in global Pittsburg sleep scores. Turning to burnout and sleep quality as predictors of academic achievement, after controlling for DASS-21 subscale scores in Model 1, Model 2 of the HMR demonstrated global school burnout ($\beta = -0.27$, $p < .001$) but not global Pittsburgh sleep scores ($\beta = 0.03$, $p > .05$) accounted for GPA variance, Model $\Delta F(2, 330) = 7.37$, $p < .001$, $\Delta R^2 = 0.047$.

Overall, these findings help establish a relationship between increased school burnout and poorer sleep quality. The relationships also appear robust as burnout scores related to numerous subscales of a comprehensive sleep measurement tool. Furthermore, they also indicate that school burnout, even after accounting for sleep quality,

Table 1
Means, standard deviations, and correlations among study 2a observed variables.

Variable	M	SD	1	2	3	4	5	6	7
GPA	3.33	0.43							
School burnout T1	3.26	0.95	−0.07	**0.87**					
School burnout T2	3.44	0.98	−0.03	0.59***	**0.90**				
School burnout T3	3.38	1.04	−0.04	0.60***	0.62***	**0.91**			
PCR T1	4.25	2.01	0.08*	−0.35***	−0.25***	−0.30***	**0.80**		
PCR T2	4.52	2.01	0.00	−0.25***	−0.30***	−0.26***	0.58***	**0.84**	
PCR T3	4.69	2.01	0.01	−0.32***	−0.25***	−0.31***	0.55***	0.64***	**0.87**
Absenteeism T3	5.32	4.69	−0.14**	0.08	0.19***	0.16***	−0.03	−0.09	−0.07

Note. N ranges from 482 to 611 due to missing data. T1 = Time 1. T2 = Time 2. T3 = Time 3. PCR = perseverative cognition regulation. Coefficient α is presented in bold on the diagonal.
*$p < .05$. **$p < .01$. ***$p < .001$.

relates to poorer academic achievement. Although the findings support the hypothesized relationship between school burnout and poorer sleep quality, this study relies on cross-sectional data and thus cannot speak to the temporal ordering of the relation between school burnout and sleep quality.

Study 2 sought to address this temporal limitation while also seeking to better understand the regulation of a potential antecedent of sleep quality – perseverative cognition. Perseverative cognition has been directly related to sleep quality and has been identified as an important link between a stressor and bodily systems (e.g. physiological activation, Brosschot et al., 2006). However, unlike work-stress, to date its relationship to school burnout in early adults has yet to be evaluated. Thus Study 2 also serves to evaluate the temporal relationship between school burnout and the regulation of perseverative cognition during bedtime.

3. Study 2

3.1. Introduction

Study 2 improves upon the cross-sectional limitation of Study 1, by employing a longitudinal data collection approach over the course of an academic semester. Furthermore, this study evaluates the potential relationship between school burnout and perseverative cognition regulation in undergraduate students. The study uses structural equation modeling to examine measurement invariance across time, and to conduct latent cross-lagged panel analyses, and examine latent growth models. Additionally, the study uses alternative measures of school burnout in two independent samples (Study 2a uses the School Burnout Inventory and Study 2b uses the Maslach Burnout Inventory-Student Survey) to determine the replicability of the findings. Furthermore, as in Study 1, relationships with academic performance indicators (GPA and absenteeism) were evaluated.

3.2. Study 2 method

3.2.1. Participants

As in Study 1, undergraduate students from multiple undergraduate courses at a 4-year public university located in the southeastern region of the U.S. were participants. Participants in Study 2a were 681 students (85% females, M_{age} = 20.05 years, SD = 2.11). Sample demographics include: 70% Caucasian, 11% African American, 3% Asian, 14% Hispanic, 0.5% Middle Eastern, 0.5% Native American/American Indian, and 1% endorsed either biracial or non-disclosed ethnicity with 17% Freshmen, 29% Sophomore, 28% Junior, and 26% Senior. Participants in Study 2b were 474 students (90% females, M_{age} = 20.83 years, SD = 2.93). Sample demographics include: 76% Caucasian, 10% African American, 4% Asian, 5% Hispanic, and 5% endorsed either biracial or non-disclosed ethnicity with 26% Freshmen, 34% Sophomore, 17% Junior, and 23% Senior.

3.2.2. Measures

3.2.2.1. School burnout. School burnout was assessed in Study 2a using the nine-item School Burnout Inventory (SBI; Salmela-Aro et al., 2009) as in Study 1. For Study 2b the Maslach Burnout Inventory-Student Survey (MBI-SS; Schaufeli, Martínez, Pinto, Salanova, & Bakker, 2002) was used to measure school burnout. The MBI-SS consists of 15 items that constitute three scales: exhaustion (five items), cynicism (four items), and professional efficacy (six items). Items include "I feel emotionally drained by my studies", "I have become less enthusiastic about my studies", and "I can effectively solve the problems that arise in my studies" for exhaustion, cynicism, and professional efficacy, respectively. MBI items are scored on a 7-point frequency scale ranging from 0 (*never*) to 6 (*always*). Higher scores on exhaustion and cynicism and low sores on efficacy are indicative of greater burnout. MBI efficacy scores were reverse coded for use in composite scores. For both the SBI and the MBI, scores on each dimension of burnout were averaged; dimension averages were averaged to create global scores for use in calculating correlations (see Tables 1 and 4).

3.2.2.2. Perseverative cognition regulation. Three items were extrapolated, according to the suggestions provided by Åkerstedt, Perski, and Kecklund (2011), to represent regulating perseverative cognition pertaining to general stress, worry, and rumination at bedtime. The three items include, "How well are you able to turn off thoughts of daily responsibilities (e.g. work tasks, school deadlines, family obligations) before going to sleep?", "How well are you able to sleep when you know you have to wake up early?", and "How well are you able to sleep when you know you have to wake up early because of an unpleasant task you need to accomplish?". Responses were recorded on a Likert-based scale (1 = *not well at all*, 9 = *very well*). Therefore, higher scores correspond to better regulation of perseverative cognition.

3.2.2.3. Academic performance. As in Study 1, academic performance was measured using participant reports of GPA. Major universities in the United States use a scale ranging from 0.0 to 4.0, which represents the total average of earned points accumulated by a student throughout their college career. A higher GPA is reflective of higher academic achievement.

3.2.2.4. Absenteeism. Absenteeism was only measured in Study 2a using participants' self-report of the number of classes they missed during the semester of the study.

3.2.3. Procedure

Three waves of survey data were collected for each sample over the course of one academic semester. School burnout and perseverative cognition regulation were assessed on each survey, whereas academic performance (Study 2a and 2b) was assessed on the first survey and absenteeism (Study 2a) was measured on the third survey. All participants provided written consent prior to engaging in the study protocol as approved by the university's institutional review board. All students were recruited from classes in which professors offered opportunities to earn extra credit. One of the opportunities involved the present study. Only students who had completed at least 1 collegiate semester were included in the data collections. Upon providing informed consent and meeting inclusion criteria, participants completed an online questionnaire that included the measurement scales. For these samples, each wave of data was collected approximately six weeks apart. Due to missing data across time points, Little's (1988) missing completely at random (MCAR) test was run. Results revealed that data were MCAR for Study 2a [$\chi^2(338) = 355.84$, $p = .242$] and Study 2b [$\chi^2(166) = 176.75$, $p = .270$].

3.2.4. Study 2 analysis strategy

Study 2 utilized a SEM framework; measurement models, tests for measurement invariance across time, latent cross-lagged panel analysis, and latent growth models (LGM) were run using Mplus 7.1. Hu and Bentler's (1999) recommendations were used to evaluate model fit, which is considered good when chi-square is nonsignificant, CFI is > 0.95, SRMR is lower than 0.08, and RMSEA is lower than 0.06. The cross-lagged panel analysis was conducted to establish the temporal ordering of burnout and perseverative cognition regulation and progressed in two steps: (1) the Autoregressive Model included autoregressive paths and correlations among variables within a time point, and (2) the Full Cross-Lag Model added all cross-lag paths. The path from a variable at Time 1 to itself at Time 2 (e.g., school burnout at Time 1 predicting school burnout at Time 2) is an autoregressive path, and paths between different variables (e.g., school burnout at Time 1 predicting perseverative cognition regulation at Time 2) are cross-lagged paths. The cross-lagged paths from school burnout to perseverative cognition regulation and vice versa provide evidence for temporal order. Then, absenteeism at Time 3 was added to the Full Cross-Lag Model as an outcome of school burnout and perseverative cognition regulation at Time 2 and a correlate of these Time 3 variables. The addition of absenteeism served as an exploration of the effects of school burnout and perseverative cognition regulation on classroom attendance. These models were run with 5000 bootstrap samples (MacKinnon, Lockwood, & Williams, 2004; Preacher & Hayes, 2004).

Finally, latent growth models (LGM) explored whether burnout or perseverative cognition regulation changed within person over the course of the semester. Unconditional growth models (i.e., a model with a single construct and no covariates or controls) were run first to establish whether a given construct changed over time. Then, parallel process growth models examined whether the initial level or rate of change in school burnout was associated with the initial level or rate of change perseverative cognition regulation. For Study 2a, the LGM were estimated using the curve-of-circles approach (Little, 2013) where latent factors are loaded onto the latent intercept and slope factors. The slope was coded 0, 6, 12 so that a 1-unit change would correspond to one week.

Study 2b used an almost identical analytic strategy to Study 2a for all analyses; there were three differences. First, Study 2b utilized a different school burnout measure (i.e., the SBI in Study 2a and the MBI-SS in Study 2b). Because of this, school burnout is modeled differently across the two studies. This choice was made in accordance with prior validation research, which has shown that the SBI and the MBI-SS have different factor structures (e.g., Salmela-Aro et al., 2009; Schaufeli et al., 2002; Seibert, Bauer, May, & Fincham, 2017). Second, Study 2b did not include absenteeism, which in combination with the first difference resulted in differences in degrees of freedom for the analyses. Third, due to the smaller sample size, the latent growth models were estimated using the curve-of-boxes approach (Little, 2013) where observed scale scores are loaded onto the latent intercept and slope factors. The slope was again coded 0, 6, 12 so that a 1-unit change would correspond to one week.

3.3. Study 2 results and discussion

3.3.1. Study 2a results

Means, standard deviations, and Pearson correlations among variables appear in Table 1. School burnout correlated positively with itself over time and negatively with perseverative cognition regulation; perseverative cognition regulation was positively correlated with itself over time. Perseverative cognition regulation at Time 1 was positively, and absenteeism at Time 3 was negatively, correlated with GPA. Absenteeism was also positively correlated with school burnout at Time 2 and Time 3.

Measurement models were run separately for each measure at each time point. Research shows that the SBI is best modeled as a second-order factor structure (Salmela-Aro et al., 2009; Seibert et al., 2017). Because of the complexity of the analytic strategy and identification issues with the 2-item inadequacy measure (see Salmela-Aro et al., 2009), the three burnout scale scores were loaded onto a single latent school burnout factor. The observed scale scores were averages as recommended by Little, Rhemtulla, Gibson, and Schoemann (2013). Perseverative cognition regulation was modeled by loading items onto a latent factor.

After establishing the measurement models, we tested for measurement invariance using Little's (2013) procedure. Strong or scalar invariance (i.e., factor loadings and item means are equated over time) is desired for longitudinal analyses. Strong invariance was established for school burnout. For perseverative cognition regulation, the mean for item 2 at Time 1 had to be freely estimated. Little (2013) noted that small departures from measurement invariance are not a problem.

Next, the cross-lagged panel analyses were conducted along with the exploration of the effects of school burnout and perseverative cognition regulation on absenteeism ($N = 681$). Model fit is presented in Table 2, and Fig. 1 presents the bootstrapped results of the Full Cross-Lag Model after adding absenteeism. We only present the final model because path estimates did not change after adding absenteeism. For these models, cumulative GPA served as a covariate at Time 1; it was significantly correlated with both variables. As can be seen in Table 2, model fit was good for all models. The addition of the cross-lagged paths in the Full Cross-Lag Model marginally improved fit over the Autoregressive Model, $\Delta\chi^2(4) = 9.21$, $p = .056$. However, none of the cross-lagged paths were significant. Note that the effect of perseverative cognition regulation at Time 2 on school burnout at Time 3 was marginally significant, $\beta = -0.09$, $SE = 0.05$, $p = .052$, and that this effect was significant before bootstrapping ($\beta = -0.09$, $SE = 0.04$, $p = .025$). The exploratory analyses for absenteeism revealed that it was uncorrelated with school burnout and perseverative cognition regulation at Time 3, but school burnout at Time 2 positively predicted absenteeism, $\beta = 0.18$, $SE = 0.05$, $p < .001$.

Finally, model fit for the unconditional ($N = 681$ and 677 for school burnout and perseverative cognition regulation, respectively) and parallel process ($N = 681$) growth models is again presented in Table 2. Unstandardized results are reported in Table 3. The unconditional LGM established that initial levels of school burnout and perseverative cognition regulation were moderate and increased over time. The slope value for school burnout suggests that for every one week of the semester, school burnout scores increased by 0.011 points. The slope value for perseverative cognition regulation suggests that for every one week of the semester, perseverative cognition regulation improved by 0.033 points. There was significant variability in the intercept but not in the slope for the variables, suggesting that students varied in the initial levels of school burnout and perseverative cognition regulation but increased at the same rate over the semester. Turning to the parallel process model, initial levels and rates of change in the variables were nearly identical to the unconditional LGM. The initial level of school burnout was correlated with a greater initial level of perseverative cognition regulation, $\psi = -0.572$, $SE = 0.080$, $p < .001$. However,

Table 2
Model fit for SEM analyses in Study 2a and Study 2b.

Model tested	χ^2	*df*	*p*	RMSEA	RMSEA 90%CI	CFI	SRMR
Study 2A							
Cross-lag panel analysis							
Autoregressive model	428.58	141	< 0.001	0.055	[0.049, 0.061]	0.958	0.083
Full cross-lag model	419.38	137	< 0.001	0.055	[0.049, 0.061]	0.959	0.071
Full cross-lag model + Absenteeism	447.37	152	< 0.001	0.053	[0.048, 0.059]	0.957	0.069
Latent growth modeling							
Unconditional burnout model	251.81	26	< 0.001	0.113	[0.100, 0.126]	0.937	0.197
Unconditional PCR model	165.05	26	< 0.001	0.089	[0.076, 0.102]	0.955	0.103
Parallel process model	627.21	129	< 0.001	0.075	[0.069, 0.081]	0.927	0.121
Study 2B							
Cross-lag panel analysis							
Autoregressive model	1298.40	706	< 0.001	0.042	[0.038, 0.046]	0.944	0.081
Full cross-lag model	1258.08	682	< 0.001	0.042	[0.039, 0.046]	0.945	0.068
Latent growth modeling							
Unconditional EXH model	7.76	1	0.005	0.120	[0.053, 0.205]	0.972	0.040
Unconditional CYN Model	7.54	1	0.006	0.118	[0.051, 0.203]	0.972	0.038
Unconditional rPE Model	0.75	1	0.387	0.000	[0.000, 0.116]	1.000	0.013
Unconditional PCR Model	2.14	2[a]	0.343	0.012	[0.000, 0.093]	0.999	0.012
Parallel Process Model - EXH	14.13	8	0.078	0.041	[0.000, 0.074]	0.989	0.027
Parallel Process Model - CYN	18.73	8	0.016	0.054	[0.022, 0.086]	0.977	0.037
Parallel Process Model - rPE	17.11	8	0.029	0.049	[0.015, 0.082]	0.979	0.029

Note. EXH = exhaustion. CYN = cynicism. rPE = reversed professional efficacy. PCR = perseverative cognition regulation.
[a] The residual variance for the Time 1 PCR scale score was slightly negative; therefore, it was fixed to 0.

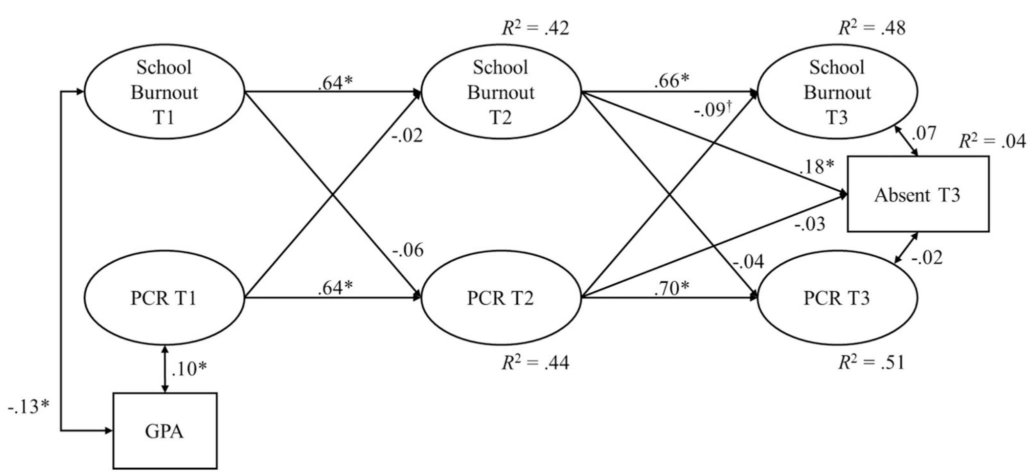

Fig. 1. Study 2a full cross-lag model with absenteeism (Absent). Standardized regression estimates are shown. Correlations between school burnout and perseverative cognition regulation (PCR) within a time point are not shown for clarity. Single-headed arrows are regression paths; double headed arrows are correlations. T1 = Time 1, T2 = Time 2, and T3 = Time 3. Model fit was: $\chi^2(152)$ = 447.37, $p < .001$, RMSEA = 0.05, CFI = 0.96, SRMR = 0.07. N = 681. *$p < .05$; †$p < .10$.

the slopes were not significantly correlated, $\psi = 0.000$, $SE = 0.001$, $p = .759$, suggesting that the observed increase in school burnout over the semester was not associated with the rate of change in perseverative cognition regulation.

3.3.2. Study 2b results

Means, standard deviations, and Pearson correlations among variables are presented in Table 4. Facets of school burnout were generally positively intercorrelated over time. However, reversed professional efficacy did not always significantly correlate with exhaustion. Perseverative cognition regulation scores were related to each other positively over time and negatively correlated with school burnout over time. On average, school burnout was negatively and perseverative cognition regulation was positively correlated with GPA.

Measurement models were run separately for each measure at each time point. The MBI-SS is best modeled with a correlated 3-factor structure (Schaufeli et al., 2002; Seibert et al., 2017). We began by modeling the correlated 3-factor structure at each time point. However, when moving to the measurement invariance analyses, it became clear that the sample size to parameter estimate ratio was insufficient (i.e., df = 906 for strong invariance and N = 467) and model fit was below recommended standards (i.e., CFI = 0.93).[1] Therefore, we created parcels for exhaustion and reversed professional efficacy using the item-to-construct balance method (Little, Cunningham, Shahar, & Widaman, 2002). For cynicism, modification indices revealed the need for a residual correlation between items 1 and 2 at all three time points. Perseverative cognition regulation was modeled by loading items onto a latent factor.

Next, Little's (2013) procedure was used to test for measurement invariance. Strong invariance was established for school burnout. Perseverative cognition regulation did not pass the weak invariance test (i.e., factor loadings are equal over time). The factor loading for item 3 at Time 3 had to be freely estimated. After releasing the factor loading, perseverative cognition regulation passed the strong invariance test. As noted in Study 2a, small departures from invariance are not problematic (Little, 2013).

Then, the cross-lagged panel analyses were conducted (N = 474). Model fit is presented in Table 2, and Table 5 presents the bootstrapped

[1] Results of the initial measurement models and invariance tests are available from the third author upon request.

Table 3
Unstandardized estimates (Standard errors) of the latent growth models in Study 2a and Study 2b.

Variable	Mean initial Status	Variance in initial status	Mean slope	Variance in slope	Covariance (Initial status and slope)
Study 2a					
Unconditional models					
School Burnout	3.403 (0.044)***	0.549 (0.077)***	0.011 (0.003)**	0.000 (0.001)	0.007 (0.007)
PCR	4.116 (0.091)***	2.376 (0.304)***	0.033 (0.007)***	0.006 (0.004)†	−0.018 (0.026)
Parallel process model					
School burnout	3.411 (0.044)***	0.561 (0.077)***	0.011 (0.003)**	0.001 (0.001)	0.004 (0.007)
PCR	4.115 (0.090)***	2.404 (0.301)***	0.033 (0.007)***	0.007 (0.004)†	−0.020 (0.025)
Study 2b					
Unconditional models					
EXH	2.782 (0.062)***	1.020 (0.210)***	−0.008 (0.006)	0.002 (0.003)	−0.007 (0.020)
CYN	1.455 (0.059)***	1.196 (0.223)***	0.016 (0.006)**	0.005 (0.003)†	−0.030 (0.021)
rPE	1.766 (0.049)***	0.767 (0.145)***	0.027 (0.005)***	0.000 (0.002)	−0.016 (0.014)
PCR	4.317 (0.102)***	4.301 (0.303)***	0.018 (0.009)†	0.015 (0.003)***	−0.188 (0.023)***
Parallel process model - EXH					
EXH	2.776 (0.062)***	1.079 (0.206)***	−0.008 (0.006)	0.003 (0.003)	−0.014 (0.019)
PCR	4.324 (0.102)***	4.327 (0.306)***	0.017 (0.010)†	0.016 (0.003)***	−0.195 (0.024)***
Parallel process model - CYN					
CYN	1.456 (0.059)***	1.145 (0.226)***	0.016 (0.006)**	0.005 (0.003)	−0.025 (0.022)
PCR	4.317 (0.102)***	4.305 (0.304)***	0.017 (0.009)†	0.016 (0.003)***	−0.190 (0.024)***
Parallel process model - rPE					
rPE	1.767 (0.049)***	0.769 (0.144)***	0.027 (0.005)***	0.001 (0.002)	−0.016 (0.014)
PCR	4.314 (0.102)***	4.300 (0.303)***	0.018 (0.009)†	0.015 (0.003)***	−0.188 (0.023)***

Note. PCR = perseverative cognition regulation. EXH = exhaustion. CYN = cynicism. rPE = reversed professional efficacy.
†*p* < .10. **p* < .05. ***p* < .01. ****p* < .001.

Table 4
Means, standard deviations, and correlations among Study 2b observed variables.

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	
1. GPA	3.37	0.43													
2. EXH T1	2.74	1.27	−0.09	0.89											
3. CYN T1	1.41	1.21	−0.27***	0.51***	0.88										
4. rPE T1	1.74	1.02	−0.33***	0.13**	0.37***	0.86									
5. EXH T2	2.84	1.35	−0.02	0.62***	0.35***	0.08	0.93								
6. CYN T2	1.66	1.33	−0.18**	0.40***	0.63***	0.32***	0.50***	0.94							
7. rPE T2	1.96	1.10	−0.28***	0.07	0.33***	0.63***	0.22***	0.46***	0.89						
8. EXH T3	2.64	1.27	0.00	0.60***	0.35***	0.01	0.62***	0.43***	0.09	0.94					
9. CYN T3	1.60	1.25	−0.15*	0.35***	0.59***	0.27***	0.37***	0.59***	0.28***	0.57***	0.94				
10. rPE T3	2.08	1.06	−0.23***	0.11	0.36***	0.58***	0.09	0.24***	0.43***	0.10	0.41***	0.90			
11. PCR T1	4.32	2.09	0.13**	−0.34***	−0.11*	−0.10	−0.25***	−0.23**	−0.14	−0.18**	−0.12	−0.10	0.83		
12. PCR T2	4.55	2.14	0.19**	−0.29***	−0.22**	−0.14*	−0.28***	−0.21**	−0.19**	−0.24***	−0.14*	−0.04	0.71***	0.85	
13. PCR T3	4.50	1.95	0.15*	−0.17**	−0.13	−0.19**	−0.22**	−0.28***	−0.16*	−0.28***	−0.26***	−0.26***	0.54***	0.45***	0.85

Note. *N* ranges from 204 to 392 due to missing data. EXH = exhaustion. CYN = cynicism. rPE = reversed professional efficacy. PCR = perseverative cognition regulation. T1 = Time 1. T2 = Time 2. T3 = Time 3. Coefficient α is presented on the diagonal.
**p* < .05. ***p* < .01. ****p* < .001.

Table 5
Standardized regression weights (Standard errors) of the full cross-lag model in Study 2b.

	EXH	CYN	rPE	Sleep
Predictors at T1	Outcomes at T2			
EXH	0.72 (0.08)***	0.04 (0.10)	−0.04 (0.08)	0.05 (0.08)
CYN	−0.04 (0.10)	0.65 (0.10)***	0.11 (0.09)	0.02 (0.09)
rPE	−0.00 (0.07)	0.09 (0.07)	0.63 (0.07)***	−0.09 (0.06)
PCR	0.08 (0.07)	−0.05 (0.08)	−0.10 (0.08)	0.80 (0.05)***
R^2	0.46	0.52	0.48	0.64
Predictors at T2	Outcomes at T3			
EXH	0.58 (0.06)***	0.08 (0.06)	−0.07 (0.08)	0.08 (0.08)
CYN	0.21 (0.09)*	0.57 (0.09)***	0.09 (0.10)	−0.21 (0.10)*
rPE	−0.16 (0.07)*	0.03 (0.07)	0.46 (0.08)***	0.01 (0.09)
PCR	−0.01 (0.06)	0.05 (0.06)	0.02 (0.07)	0.50 (0.06)***
R^2	0.45	0.39	0.25	0.29

Note. EXH = exhaustion. CYN = cynicism. rPE = reversed professional efficacy. PCR = perseverative cognition regulation. T1 = Time 1. T2 = Time 2. T3 = Time 3.
**p* < .05. ***p* < .01. ****p* < .001.

results of the Full Cross-Lag Model. For these models, cumulative GPA served as a control variable at Time 1 and was significantly negatively correlated with cynicism ($r = -0.29$, $p < .001$), reversed professional efficacy ($r = -0.37$, $p < .001$), and perseverative cognition regulation ($r = 0.17$, $p = .001$) but was uncorrelated with exhaustion ($r = -0.09$, $p = .082$). As can be seen in Table 2, model fit was good for both models. The addition of the cross-lagged paths in the Full Cross-Lag Model improved fit over the Autoregressive Model, $\Delta\chi^2(24) = 40.32$, $p = .020$. Although none of the cross-lagged paths from Time 1 to Time 2 variables were significant, there were three significant paths from Time 2 to Time 3 variables. Cynicism ($\beta = 0.21$, $SE = 0.09$, $p = .017$) and reversed professional efficacy ($\beta = -0.16$, $SE = 0.07$, $p = .016$) predicted exhaustion and cynicism predicted perseverative cognition regulation ($\beta = -0.21$, $SE = 0.10$, $p = .042$).

Finally, model fit for the four unconditional and three parallel process growth models ($N = 467$) is again presented in Table 2. Unstandardized parameter estimates for these analyses are reported below and in Table 3. For the school burnout unconditional growth models, initial levels of exhaustion, cynicism, and reversed professional efficacy were low. Exhaustion did not change over time, whereas both cynicism and reversed professional efficacy increased over time. The slope values suggest that for every one week of the semester, cynicism increased by 0.016 points and reversed professional efficacy increased by 0.029 points. There was significant variability in the intercept for all three facets, but no significant variability in the rate of change, suggesting the students changed at the same rate over the semester. For the unconditional perseverative cognition regulation growth model, the residual variance of the Time 1 scale score was slightly negative; therefore, it was fixed to 0. Initial levels of perseverative cognition regulation were moderate and increased marginally over time ($p = .064$). The slope value suggests that for every one week of the semester, perseverative cognition regulation improved by 0.018 points. There was significant variability in both the intercept and slope, suggesting the students varied in the initial levels and rate of change over the semester.

Across the three parallel process models, initial levels and rates of change of the facets of school burnout and perseverative cognition regulation were nearly identical to the unconditional linear growth models. The initial level of exhaustion ($\psi = -0.892$, $SE = 0.137$, $p < .001$), cynicism ($\psi = -0.329$, $SE = 0.124$, $p = .008$), and reversed professional efficacy ($\psi = -0.231$, $SE = 0.104$, $p = .027$) negatively correlated with the initial level of perseverative cognition regulation. Similarly, the rate of change in exhaustion ($\psi = -0.006$, $SE = 0.001$, $p < .001$) and cynicism ($\psi = -0.003$, $SE = 0.001$, $p = .012$) negatively correlated with the rate of change in perseverative cognition regulation. The negative correlation implies that the greater the increase in burnout, the slower the rate of change (i.e., improvement) in perseverative cognition regulation. The reversed professional efficacy and perseverative cognition regulation slopes were not significantly correlated.

3.3.3. Study 2 summary of results and discussion

Using two independent samples and two measures of school burnout, Study 2 evaluated school burnout and perseverative cognition regulation at three time points over a semester. To summarize the results of Study 2, four points are noteworthy. First, across the correlational and LGM analyses, it is clear that students who experience higher levels of burnout also experience lower levels of perseverative cognition regulation. This result further supports the Study 1 findings. Second, however, the results of the cross-lag panel models failed to elucidate clearly the temporal ordering of school burnout and perseverative cognition regulation. Specifically, in Study 2a no cross-lag paths were statistically significant, but perseverative cognition regulation at Time 2 predicted school burnout at Time 3 at a less stringent p-value (i.e., $p < .10$). In Study 2b, the only significant cross-lag path was from cynicism at Time 2 to perseverative cognition regulation at Time 3. Together these findings suggest the potential for a reciprocal relationship. We urge future researchers to explore these relationships to confirm our speculation.

Third, the LGM results demonstrated that both school burnout and perseverative cognition regulation increased over the course of the semester. Although school burnout and perseverative cognition regulation slopes were not significantly correlated in Study 2a, the slopes for two of three facets of school burnout were negatively associated with the perseverative cognition regulation slope in Study 2b. Therefore, the pattern of results suggests that increases in school burnout are associated with slower improvements in perseverative cognition regulation over the course of a semester. In other words, feeling more burned out from school over time is associated with having more perseverative thoughts over time (or worse perseverative cognition regulation over time).

Finally, increased school burnout and lower perseverative cognition regulation are related to poorer academic performance. In the cross-lagged models in Study 2a and 2b, cumulative GPA was negatively associated with school burnout and positively associated with perseverative cognition regulation. Moreover, in Study 2a, students who had higher levels of school burnout at Time 2 were absent more often.

4. General discussion

Findings from the American College Health Association-National College Health Assessment II (ACHA-NCHA, 2018) suggest that a major challenge to collegiate academic success is maladaptive affective functioning (i.e. depression, anxiety, and stress). In fact, highlighting the impact of negative affect, academic stress is reported as the largest academic impediment in undergraduate students across the nation (ACHA-NCHA, 2018). Accordingly, the current research examined school burnout, a multidimensional affective response to academic stress derived from the occupational literature, and explored its relationship with sleep-related qualities and indices of academic achievement over 2 studies (3 samples).

To date, the school burnout–sleep relationship has been largely unexplored, especially in emerging adults emphasizing the novelty of the current studies. Given that school burnout has been linked to numerous indicators of diminished well-being and that constructs such as sleep may ameliorate these negative relationships, the present research is both timely and informative, serving to push both the burnout and sleep literatures forward constructively. Furthermore, gaining a better understanding of sleep hygiene is becoming increasingly relevant as it is linked to numerous aspects of well-being, including memory, immune system functioning, cardiovascular risk, and all cause-mortality (see Kopasz et al., 2010; Opp & Krueger, 2015; Covassin & Singh, 2016; Cappuccio, D'Elia, Strazzullo, & Miller, 2010, respectively with an insightful review of these factors in adolescent and young adult populations by Owens, 2014). A comprehensive understanding of sleep hygiene is especially urgent in the emerging adult population as the era of 24/7 digital connectivity intensifies (Pew Research Center, 2019) and with data suggesting social media immersion corrodes sleep quality (Garett, Liu, & Young, 2018; Long, Zhu, Sharma, & Zhao, 2015).

Regarding the main findings, Study 1 established a robust and consistent relationship between increased school burnout and indices of poorer sleep quality, over and above constructs reflecting negative affect (i.e. depression, anxiety, stress). More specifically, burnout was related to the global Pittsburgh sleep quality score and all seven of the Pittsburgh sleep quality subscales (i.e., subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleeping medications, and daytime dysfunction). Interestingly, this link between burnout and indices of poorer sleep quality seems to be more robust (i.e. involving all PSQI subscales) than what has been previously reported in academic samples of medical students (Pagnin et al., 2014). Also, after accounting for sleep quality, higher school burnout corresponded with lower GPA, a finding consistent with prior burnout research on academic achievement (May et al., 2015).

Addressing the cross-sectional limitation of Study 1, Studies 2a and 2b examined longitudinal trends with survey data collected at three times in an academic semester using two different measures of school burnout, the SBI in Study 2a (Salmela-Aro et al., 2009) and the MBI-SS in Study 2b (Schaufeli et al., 2002). Although findings suggested that only a few predicted paths emerged between burnout and perseverative cognition regulation, school burnout increased and perseverative cognition regulation improved over the course of the semester. Interestingly, increased burnout over the semester suppressed the improvement in perseverative cognition regulation. This is a complex but novel temporal finding that provides initial clues to how the potential causal relationships between burnout and sleep quality may unfold. Regarding the educational outcomes, findings in Study 2a linked higher levels of school burnout (but not perseverative cognition regulation) to absenteeism. Study 2a and 2b demonstrated higher school burnout and lower perseverative cognition regulation to be related to reduced academic performance (cumulative GPA).

The current research in Studies 2a/b model data waves collected six weeks apart thus arguably providing a good snapshot of change within a semester for college students. However, examining differing temporal lags will better determine the ideal intervals between measurements and build a more thorough understanding of the speed at which the influence between burnout and sleep-related indices unfold. For example, daily assessments over a week's span may illuminate differing weekday versus weekend burnout-sleep relationship patterns (see Ekstedt, 2005 for this approach taken in examining sleepiness) or assessments spanning multiple academic years may reveal cohort differences in burnout-sleep patterns (see Talih, Daher, Daou, & Ajaltouni, 2018 for a cross-sectional approach taken with medical students that could be adapted into a longitudinal design).

Importantly, the current research highlights the need to account for school burnout when modeling constructs associated with poorer sleep. This is especially true regarding aspects of negative affect, as burnout accounted for additional variance in sleep scores beyond depression, anxiety, and stress symptomatology. The current research also allows for growth in the domain intersecting the burnout and sleep literatures, as the findings support predictions pertaining to the perseverative cognition hypothesis and both the transactional model of stress (i.e. interaction between an individual and their environmental context) and the demands-resource model (i.e. school demands place upon a student vs. available coping skills) of burnout regarding diminished sleep quality.

4.1. Limitations and directions for future research

Notwithstanding the novel contributions of this research, important limitations and study considerations need to be addressed. A general limitation pertains to the study samples, as they are disproportionately female and Caucasian (although it can be noted that women and Caucasians are the predominant demographic according to higher education enrollment statistics, NCES, 2019). Furthermore, it should also be noted that the data are limited to self-report. Additional research may find it worthwhile to explore burnout-sleep relationships using more objective sleep measures (such as actigraphy and polysomnography) both within the laboratory setting and in more natural settings (i.e. in one's home) through use of ambulatory equipment.

A more specific limitation is the lack of fit for many of the LGM models. In Study 2a, RMSEA was high for the unconditional burnout model, the model chi-square was significant and SRMR was high for all three models. In Study 2b, RMSEA was high for the unconditional exhaustion and cynicism models. We would first note that traditional rules of thumb for a good fitting model do not directly apply to growth models. As Wu, West, and Taylor (2009) point out, prior work on SEM model fit has focused on the covariance structure but growth models have additional sources of misspecification; there is a paucity of work investigating model fit for LGM. Additionally, RMSEA is often inflated when there are a small number of degrees of freedom (Kenny, Kaniskan, & McCoach, 2015), which was the case in Study 2b. That said, the misfit could also be due to an incorrectly specified growth trajectory. The limited work available suggests that RMSEA, and less so SRMR, is sensitive to misspecifications of the shape of the growth curve (Leite & Stapleton, 2006, 2011). Because the current study only had three waves of data, it was not possible to model more complex growth curves. However, the observed means suggest a plateau effect (i.e., an increase from Time 1 to Time 2 and a leveling off from Time 2 to Time 3). Therefore, we encourage future research that measures burnout more frequently and explores the correct shape of the growth curve.

Another area deserving future attention is longitudinal examination of burnout in relation to a more comprehensive sleep measure, such as the Pittsburgh sleep scale used in Study 1. Although Study 2 utilized an index of perseverative cognition regulation, it may instead be beneficial to use a thorough, well-established sleep quality measure. This may be particularly true given the emerging stage of a new research paradigm (i.e. burnout-sleep research). Our measure of perseverative cognition regulation relates to cognitions of stress, worry, and rumination in the context of sleep habits. The magnitude of the concurrent (cross sectional) relationships between school burnout and perseverative cognition regulation identified in Study 2 are similar to that of prior research examining work stress and perseverative cognition. For example, perseverative cognition has been positively related to both distressing work shifts (Radstaak, Geurts, Beckers, Brosschot, & Kompier, 2014) and work-related stress (Van Laethem, et al., 2015) at moderate effect sizes. However, bidirectional relationships, like those identified between perseverative cognition and work-related stress in Van Laethem et al. (2015), were not identified in the current work. Given the differing measures (i.e. perseverative cognition regulation vs. perseverative cognition) and samples (i.e. working adults vs. undergraduate emerging adults), additional research seems necessary to further clarify the discrepancy in findings. Given that perseverative cognition is conceptualized as serving a potential pathway linking a stressor to a body's system (Brosschot et al., 2006), future research may find it beneficial to evaluate perseverative cognition and its regulation as mediators between stress (in this context school burnout) and sleep quality. This has been a successful endeavor within the occupational literature (see Radstaak et al., 2014; Van Laethem et al., 2015).

Additionally, regarding other antecedents or adaptive skills and coping strategies, self-control may be a promising construct for future inquiry to better understand the relationship between school burnout and sleep. Defined as the cognitive capacity to inhibit immediate desires in order to pursue more fruitful long-term outcomes (Tangney, Boone, & Baumeister, 2004), self-control is linked independently to both sleep (Barber et al., 2013; Baumeister, Wright, & Carreon, 2018) and academic burnout (Cooper et al., 2017; Seibert, May, Fitzgerald, & Fincham, 2016). More precisely, quality sleep is deemed pivotal for achieving optimal psychological and physiological functioning and critical to replenishing internal cognitive resources (Barber et al., 2013; Hagger, 2010; Pilcher et al., 2015). That is, sleep contributes to a feedback loop wherein effective sleep restores a person's capacity to exert regulatory controls (Pilcher et al., 2015), and alternatively, poor sleep inhibits the replenishment of self-regulatory resources likely leading to increased sensitivity and heightened reactivity to stressors (Barber & Munz, 2011; Baumeister et al., 2018). The effects of school burnout on academic performance are potentially contingent upon levels of self-control. Specifically, individuals with low self-control and high academic burnout have reported poorer grades and more absenteeism (Seibert et al., 2016). Thus, self-control may be integral to understanding the burnout-sleep relationship and help to provide a more nuanced understanding of the interplay between these two constructs. Doing so will help fill the need in contemporary research to identify individual difference as well as potential contextual (or confounding) variables influencing health and wellness, especially in youth and emerging adults (Rodríguez-Fernández et al., 2016).

5. Conclusion

In conclusion, this research began the process of documenting the largely unexplored relationship between burnout and sleep in emerging adult samples. The cross-sectional findings documented in Study 1 show robust relationships between increased school burnout and indices of poorer sleep quality. The temporal evaluations between school burnout and perseverative cognition regulation in Studies 2a and 2b revealed that both school burnout and perseverative cognition regulation increased over the course of the semester. However, even though only a few predicted paths over time emerged, increases in school burnout were related to slower improvements in perseverative cognition regulation over time. Thus, on average, students who showed the greatest increase in burnout also experienced the least amount of improvement in perseverative cognition regulation. These findings warrant additional longitudinal analyses with more comprehensive sleep measures to thoroughly understand the temporal relationship between burnout and both sleep quality and perseverative cognition regulation. The current work progresses both the burnout and sleep literatures as well as provides motivation for additional longitudinal research.

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