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Does Burnout Affect Academic Achievement?

A Meta-Analysis of Over 100,000 Students

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Abstract

Burnout is understood to have many adverse consequences for students. However, several equivocal findings in the literature mean that it is currently unclear to what extent burnout affects academic achievement. To address this lack of clarity, the aim of the present study was to provide a first meta-analysis of the relationship between burnout and academic achievement. A literature search returned 29 studies (N = 109,396) and 89 effect sizes. Robust variance meta-analyses indicated that total burnout had a significant negative relationship with academic achievement ($r_c^+ = -.24$). A similar pattern of relationships was found for each of the three symptoms of burnout (exhaustion [$r_c^+ = -.15$], cynicism [$r_c^+ = -.24$], and reduced efficacy [$r_c^+ = -.39$]). There was some evidence that the instrument used to measure burnout moderated the relationship between reduced efficacy and achievement. Taken together, the findings suggest that burnout leads to worse academic achievement in school, college, and university.

Keywords: exhaustion, performance, education, school, college, university

Introduction

The value of education cannot be understated. Academic achievement, in particular, is an especially important societal outcome. Relative to students who might struggle at school, college, and university, students who perform well typically have better health and wellbeing, are better remunerated, and contribute significantly more to the tax-base through higher skills and training (e.g., OECD, 2016). Understanding what contributes to achievement in education, then, is of paramount importance. To date, much research has examined the psychological factors (e.g., motivation and personality) that may contribute to academic achievement. In the present study, we extend this literature by testing whether burnout is another such factor.

Academic Achievement

Academic achievement can be measured in many ways. These include specific test performances (e.g., exams), overall class performances (e.g., grades), or composite performance metrics that are aggregated across classes (e.g., Grade Point Average or GPA). These measures allow educators to evaluate the competencies of students in relation to specific learning objectives (e.g., Schneider & Preckel, 2017). They are also used as criteria for various educational selection processes (e.g., further study). This being said, relying on academic achievement as a measure of “good performance” can be problematic. This is because, for example, exams may promote surface-level learning, rather than promoting a deeper understanding of what has been taught (see e.g., Struyven, Dochy, & Janssens, 2005). These issues aside, there is evidence that these measures (GPA, grades, exams) are reliable both across classes and over time (e.g., Bacon & Bean, 2006). As such, not only are these measures clearly important in practice, but they are also useful when conducting research.

The past ten years have seen an increasing scientific emphasis on explaining variance in academic achievement (see Hattie, 2008). This body of work indicates that the predictors of academic achievement are varied and complex. Personal (e.g., student), social (e.g., teacher), and environmental (e.g., school) factors have all been found to play a part. In particular, constructs such as cognitive ability, social support, effort, deliberate practice, intelligence, motivation, conscientiousness, teacher clarity, feedback, and homework show large positive associations with achievement (Poropat, 2009; Richardson, Abraham, & Bond, 2012; Vedel, 2014). By contrast, constructs such as procrastination, anxiety, stress, absenteeism, insomnia, stereotype threat, television, summer vacations, and moving schools show large negative associations with achievement (Schneider & Preckel, 2017; see also Winne & Nesbit, 2010). Reflecting an increased focus on adaptive functioning in many fields of psychology (i.e., positive psychology), more recent research on the predictors of academic achievement has shifted towards factors associated with the physical and mental wellbeing of students (e.g., Ridner, Newton, Staten, Crawford, & Hall, 2016).

Wellbeing has long been associated with higher achievement (e.g., El Ansari & Stock, 2010). It follows, then, that ill-being would be associated with lower achievement. This has indeed been shown to be the case for transient indicators of ill-being such as stress (Richardson et al., 2012). Interestingly, however, the relationships of chronic factors such as depressive symptoms (low mood, pessimism, and apathy over an extended period of time) is unclear. For example, meta-analytic evidence has shown that depressive symptoms show nonsignificant associations with academic achievement (Richardson et al., 2012).[1] This finding could be partly explained by the context-free nature of depressive symptoms. That is, because depressive symptoms are part of a pervasive affective disorder, their effects in specific contexts such as education might be small. Consequently, chronic factors that apply

[1]Note, however, these findings do not necessarily reflect clinical depression, but instead depressive symptoms (see Richardson et al., 2012).

exclusively to the educational context may have more important implications for academic achievement. One such chronic factor is burnout.

Burnout

Burnout was originally conceived in the human services professions (Maslach & Jackson, 1981). The term was coined to describe the process of gradual exhaustion, cynicism and loss of commitment that had been observed in those working in this context. Based on these observations, burnout was defined as a multidimensional syndrome comprising three symptoms, namely, exhaustion, cynicism, and reduced efficacy (Maslach, Jackson, Leiter, Schaufeli, & Schwab, 1986). Unsurprisingly, these symptoms are associated with an array of negative outcomes in work settings. These include, among other things, social disconnection, absenteeism, and compromised performance (Alarcon, 2011; Lee & Ashforth, 1996; Taris, 2006).

Burnout appears to be particularly prevalent among teachers (Iancu, Rusu, Măroiu, Păcurar, & Maricuțoiu, 2018). This is perhaps unsurprising given the many demands and stressors that teachers experience on a day-to-day basis (McCarthy, Lambert, Lineback, Fitchett, & Baddouh, 2016). In this environment, the symptoms of burnout will manifest in numerous personal and interpersonal consequences. For example, burnout in teachers has been associated with reduced work capacity, absenteeism, and ultimately poorer student performance (Chang, 2009). It is likely that these effects explain, at least in part, the extremely high dropout rate in the teaching profession, especially within the first two years (OECD, 2015).

Burnout readily applies to students too. This is because the activities that students undertake can be considered “work” (Schaufeli, Martinez, Pinto, Salanova, & Bakker, 2002). For example, they attend classes and complete structured activities with specific performance goals (e.g., passing a course, obtaining a degree). In this way, academic burnout refers to a multidimensional syndrome of exhaustion from studying, cynicism directed to one's study, and reduced efficacy in relation to academic work (Salmela-Aro, Kiuru, Leskinen, & Nurmi, 2009; Schaufeli et al., 2002). Like in professional contexts, the symptoms of academic burnout have also been linked with many negative outcomes for students. These outcomes include controlled forms of motivation, low self-esteem, and even suicidal ideation (Dyrbe et al., 2008; IsHak et al., 2013; Walburg, 2014).

Burnout and Academic Achievement

Germane to the focus of the present study, burnout will also likely affect academic achievement. Yet it is surprising that, to date, scant theory exists to explain the potential relationships between burnout and achievement in academic contexts. We believe that reduced effort, interest, and absenteeism are likely central to explaining the potential for burnout to influence academic achievement. Indeed, Schaufeli and Taris (2005) have suggested that burnout may underpin both an inability (a depletion of resources and a lack of energy that comprise exhaustion) and an unwillingness (disengagement as a result of the distance that cynicism creates between the student and their studies) to expend effort (see also Thorndike, 1914). In addition, because reduced efficacy may result in negative self-perceptions about one's ability to complete study-related tasks, it too will result in a substantial loss of effort and interest in one's studies (Bandura, 1997; see also Swider & Zimmerman, 2010). Students experiencing frequent burnout symptoms will, therefore, be unable and unwilling to expend effort on study-related tasks. Accordingly, this lack of effort is likely to inhibit academic achievement (e.g., Richardson et al., 2012).

In regard to absenteeism, burnout symptoms may manifest in a reduction not just of effort and interest but of students' physical presence in the learning environment. In this regard, feelings of frustration and tension about academic achievement that result from exhaustion may be compounded by an attempt to distance themselves from their studies (as a result of cynicism; Petitta & Vecchione, 2011). Moreover, avoidance behaviours such as absence from the learning context may arise from perceptions of incompetence (as a result of reduced efficacy; Bandura, 1997). Hence, it is likely that burnout will leave students both psychologically and physically withdrawn from their studies. We think this withdrawal may also explain why burnout may result in reduced academic achievement.

Existing Research

Numerous studies have examined the burnout-academic achievement relationship. As of yet, however, no systematic summary of this literature exists. This is important because individual studies reveal discrepancies in terms of the magnitude and direction of this relationship. For example, research has found that exhaustion has a nonsignificant (Fiorilli et al., 2017), negative (Kljajic et al., 2017), and even positive (Atalayin et al., 2015) correlation with academic achievement. The same is true of cynicism (e.g., Balogun et al., 1996). One way to reconcile these discrepancies is to use meta-analyses to quantitatively summarise this literature. This would also allow for a robust test of the theoretical relationships we have just outlined.

Moderators

In addition to the estimation of summary effects, meta-analyses can also help to reconcile equivocal findings by testing for potential moderating factors. That is, an examination of study characteristics that explain why there may be systematic differences in effect sizes across studies. There may be several factors that moderate the burnout-academic achievement relationship. In the present study, we focused on what we consider the most important. First, several different instruments have been used to measure burnout in context of academic achievement. There are some notable differences among these instruments including the extent to which they are contextualised to the academic domain. For example, the School Burnout Inventory (SBI) was developed specifically for the school setting (e.g., “I feel overwhelmed by my schoolwork”), whereas the Maslach Burnout Inventory-Student Survey (MBI-SS) is a modified version of the MBI (Salmela-Aro, Kiuru, Leskinen, & Nurmi, 2009; Schaufeli et al., 2002). The MBI-SS is modified with regard to the context (studies vs. work; e.g., “I feel burned out from my studies”) and also includes explicit reference to university (e.g., “I feel used up at the end of a day at university”). As such, these measures differ based on the context (school vs. university) and the content of each item. It is therefore possible that differences in the way burnout is measured influences its relationship with academic achievement.

Second, the strength of the burnout-academic achievement relationship may differ depending on the stage of education (primary, secondary, or tertiary). Here, we theorise that burnout might be most problematic for achievement at secondary levels of education. This is for two reasons. First, students of this age are likely to face a potential barrage of new demands including increasing external pressures (e.g., from parents) and biological changes (i.e., puberty; Folkman, Lazarus, Pimley, & Novacek, 1987). Second, they may not yet have developed the coping strategies necessary to deal with these additional demands (see e.g., Hampel & Petermann, 2005). Consequently, stage of education was the second moderator of the burnout-academic achievement relationship that we examined.

Third, we examined type of academic achievement (GPA, grades, exams) as a potential moderator. Our thinking here is that because GPA represents cumulative performance over time (sometimes over several years) it would show the strongest relations with burnout (as conceptualised as an enduring syndrome), while, on the other hand, exams are normally associated with one aspect of learning (e.g., one module or area), and would therefore be less likely to be affected by burnout symptoms. Finally, we also had a number of more exploratory moderators. These were objective (e.g., GPA from academic records) versus subjective (e.g., self-reported GPA) measurement of achievement (see also Madigan, 2019) and gender differences. In testing these moderators, we had no specific or directional hypotheses.

The Present Study

Against this background, the aim of the present study was to provide a first meta-analysis of research examining the relationships between burnout and academic achievement. Based on the aforementioned theory and research, we hypothesised that all three symptoms of burnout (and a total score) would be negatively related to academic achievement. In terms of moderation, we expected that effects would be larger for more cumulative measures of achievement (i.e., GPA), and that effects would be larger for students at the secondary stage of education. We also tested burnout measure, objective versus subjective measures of achievement, and gender as potential moderators but offer no specific hypotheses.

Method

Literature Search

First, an extensive computerized literature search was conducted using the following databases: PsycINFO, PsychARTICLES, MEDLINE, SPORTDiscus, Education Abstracts and Educational Administration Abstracts. The following search terms were used: “burnout” and “academic OR education OR university OR college OR school” and “grade OR GPA OR exam OR performance OR achievement OR study success” (see Hill & Curran, 2016; Poropat, 2009). The search date was between January 1981 (the year the MBI was developed) and February 2020. Overall, the search returned 3,488 studies. As well as the standardized search, an exploratory search was conducted on GoogleScholar and by scanning the reference lists of relevant reviews, book chapters, and journal articles. After removing duplicates and screening abstracts for relevance, 55 articles remained. These were assessed further using the inclusion criteria below.

Inclusion Criteria

As regards criteria for the meta-analysis, studies were included if they: (a) measured burnout and academic achievement using scales that yielded quantitative values; (b) measured either GPA, grades, or exam performance; (c) included an effect size or sufficient information for estimation of an effect size; (d) were published in English; and (e) were a published journal article, thesis/dissertation, or conference presentation. These criteria resulted in the final inclusion of 29 studies reporting 89 effect sizes capturing the relationship between burnout and academic achievement.

Recorded Variables

Next, a coding sheet was completed for each study. The coding sheet included: (a) publication information (authors/year), (b) instructional environment (primary, secondary, or tertiary), (c) sample size, (d) students' age, (e) the percentage of the sample that were female, (f) instrument used to measure burnout, (g) measure of academic achievement (GPA, grades, or exam), (h) whether the measure of academic achievement was objective or self-reported, (i) reliability of academic achievement and burnout subscales, and (j) bivariate correlations between dimensions of burnout (including a total score) and academic achievement. Table 1 presents the coded information for each study.

Meta-Analytical Procedures

Effect sizes were estimated using correlation coefficients corrected for measurement error (r_c; Schmidt & Hunter, 2015). We used the correlation coefficient for each pair of variables and the reliability coefficient for each variable (Cronbach's α) to calculate r_c with the following formula:

$$r_c = \frac{rxy}{\sqrt{rxx * ryy}}$$

Here, r_c is the corrected estimate of the correlation coefficient, *rxy* is the correlation coefficient between predictor (burnout) and outcome (achievement), *rxx* is the reliability coefficient for the predictor, and *ryy* is the reliability coefficient for the outcome. In cases where no reliability estimates for GPA were reported, reliability was estimated based on Westrick (2017), otherwise where reliability coefficients were not available or not reported, we imputed the grand mean (see e.g., MacCann et al., 2020). Calculated this way, effect sizes reflect the correlation coefficient corrected for measurement error using the artefact distributions of the reliability coefficients.

To meta-analyse effect sizes, inverse variance weighted random-effects models were employed. We used random-effects models because they allow inferences about the correlation of burnout on achievement across a variety of procedures and settings (Hedges & Vevea, 1998). To retain as much information as possible, we meta-analysed all eligible effect sizes in each study by permitting studies to contribute multiple effect sizes. Several studies reported multiple effect sizes (i.e., multiple effect sizes based on multiple samples of students) and we controlled for statistical dependencies at the within-study level with robust standard error (variance) estimation (Hedges, Tipton, & Johnson, 2010). This estimation method permits clustered data (i.e., effect sizes nested within samples) to be meta-analysed by correcting the within-study standard errors for correlations between effect sizes. To do so, this method requires an estimate of the mean correlation between all pairs of within-study effect sizes (ρ), which is used to correct the between-study sampling variance (τ^2) for these statistical dependencies. We set $\rho = .80$ because sensitivity analyses revealed that findings were invariant across different reasonable estimates of ρ. Alongside τ^2, we also reported I^2, which quantifies the proportion of effect size variance due to between-sample heterogeneity. I^2 values of 25%, 50%, and 75% reflect low, medium, and high levels of heterogeneity respectively (Higgins & Thompson, 2002).

Inverse variance weighted random-effects meta-analyses with Hedges et al's (2010) robust standard error estimation were conducted using the robumeta package in R (Fisher & Tipton, 2015; see also Agadullina & Lovakov, 2018). To test the overall r_c^+ of each burnout symptom with achievement, we fitted intercept only meta-regression models. The constant coefficient in these models has the interpretation of the weighted mean r_c (Lipsey, 2009). Next, to test for the possibility that domain, burnout instrument, achievement measurement, achievement instrument, and gender (percentage female) explain between-study differences in the weighted average r_c^+, we added several covariates to our intercept only meta-regression models. Domain (tertiary = 0, secondary = 1), burnout instrument (SBI = 0, MBI = 1), and achievement measurement (subjective = 0, objective = 1) were categorical variables with two levels. Achievement instrument has three levels and therefore necessitated the coding of two categorical variables. The first, GPA, reflected the GPA versus others contrast (GPA = 1, others = 0) and the second, exams, reflected the exams versus others contrast (exams = 1, others = 0). When these dummy variables were entered to the meta-regression model, grades was the reference group.

The robumeta package uses the method of moments estimator to estimate τ^2 (Thompson & Sharp, 1999). As recommend by Tipton (2015), this estimator and its degrees of freedom were adjusted for small sample sizes. This adjustment notwithstanding, robust standard error estimation with small sample adjustment remains biased (i.e., increased type I error rate) when the adjusted degrees of freedom are < 4 (Tanner-Smith & Tipton, 2013). Accordingly, we do not interpret any meta-regression estimates with less than 4 degrees of freedom. Finally, for each meta-analysis, we assessed the potential for publication bias. To do so, the fail-safe N statistic was calculated to estimate the number of unpublished studies with null findings that would be necessary to reduce the effect size to zero (Rosenthal, 1979). If this value is greater than $5n + 10$ (where n equals the number of effect sizes), then the probability of publication bias is low (Rosenberg, 2005).

Results

Overall Effect Sizes

We fit intercept only meta-regression models using robust variance estimation for the r_c^+ of each symptom of burnout with achievement (Table 2). For total burnout (N = 96,169), analyses revealed a small-to-medium negative weighted mean effect size (r_c^+ = -.24, 95% CI = -.31, -.16).[2] Between-study heterogeneity was small (τ^2 = .01) with approximately 98% (I^2 = 97.83) attributable to systematic (i.e., methods and settings) error. For exhaustion (N = 9,095), analyses revealed a small negative weighted mean effect size (r_c^+ = -.15, 95% CI = -.22, -.09). Between-study heterogeneity was small (τ^2 = .02) with approximately 88% (I^2 = 87.77) of variance attributable to systematic error. For cynicism (N = 10,888), analyses revealed a small-to-medium negative weighted mean effect size (r_c^+ = -.24, 95% CI = -.32, -.16). Between-study heterogeneity was small (τ^2 = .02) with approximately 92% (I^2 = 91.80) of variance attributable to systematic error. Finally, for reduced efficacy (N = 6,279), analyses revealed a medium negative weighted mean effect size (r_c^+ = -.39, 95% CI = -.49, -.29). Between-study heterogeneity was small (τ^2 = .02) with approximately 92% (I^2 = 92.45) of variance attributable to systematic error.

Moderator Analyses

Results from intercept only models indicated that there was substantial between-study heterogeneity in the effect sizes of all burnout symptoms (I^2 range = 88-98%). The second purpose of this research, then, was to determine whether study-level moderators predicted the between-study heterogeneity of effect sizes (see Table 2). As robust standard error estimation is biased when the adjusted degrees of freedom are < 4, we only interpret significant moderation effects on > 4 degrees of freedom (Tanner-Smith & Tipton, 2013). For the mean

[2] Because the study of Salmela-Aro et al. (2008) had a very large sample and also measured burnout sometime after they measured achievement, we ran another analysis that excluded the effects from this study, no substantial differences were found.

weighted r_c^+ of reduced efficacy, the instrument used to measure burnout moderated the relationship. Here, studies measuring burnout with the MBI typically yielded larger effect sizes (b = .24, 95% CI = .01, .47). No other moderation effects emerged.

Publication Bias

With regard to potential publication bias, fail-safe N statistics are provided in Table 2. The fail-safe N for total burnout, exhaustion, cynicism, and reduced efficacy exceeded Rosenberg's critical value ($5n$ + 10), indicating that publication bias is unlikely for the results corresponding to total burnout and these three symptoms.

Discussion

The aim of the present study was to provide a first meta-analysis of the relationships between burnout and academic achievement. Aligned with our hypotheses, burnout did indeed emerge as a significant negative predictor of achievement (exams, grades, GPA). In this regard, total burnout and all three burnout symptoms predicted worse academic achievement. There was also evidence that the instrument used to measure burnout (MBI, SBI) moderated the relationship between the reduced efficacy dimension of burnout and academic achievement.

Burnout and Academic Achievement

Burnout has consistently emerged as a factor predicting poorer work performance (Taris, 2006). In the present study, we found that burnout also negatively predicts academic achievement. Against a backdrop of equivocal individual studies, the present findings show that when the literature is aggregated, a consistent relationship emerges. This negative relationship is also consistent across all dimensions of burnout. In addition, when compared to effects typically found in the literature (Bosco et al., 2015), these effects are medium-sized. As such, given the significant consequences of poorer academic achievement for health, wealth, and society, burnout is a critical factor to consider when trying to understand

and improve student outcomes.

A similar pattern of relationships emerged for the three individual symptoms of burnout. In this regard, it is unsurprising that exhaustion is linked with lower achievement. A depletion of resources will leave students both physically and emotionally tired and struggling with academic demands. Exhaustion may also lead to an inability to expend effort or display interest in study-relevant tasks (e.g., revising, completing coursework), which means when their work or competence is evaluated, their performance is judged to be poor. What may be surprising, however, is that this effect is relatively small (and the smallest of the three symptoms). This is contrary to the work context, where exhaustion is the largest negative predictor of performance (Taris, 2006). As to what may explain this, we can only conjecture, but it may be related to whether or not there are still opportunities for students to learn inside and outside of the classroom (e.g., they still attend classes or resources are available online).

As to why cynicism reduces achievement, it is possible that a cynical attitude towards studying will mean that students distance themselves from the academic environment, their teachers, and their work. Such withdrawal will likely mean students overlook key information, do not take up opportunities to seek support, and more generally avoid time studying. Taken together, of course, these behaviours are likely to yield poorer academic achievement relative to students who display comparatively less cynicism. Unchecked, it is very easy to see how cynicism could severely impede academic achievement over the long run.

Perhaps the most salient finding in this research is that, of the three symptoms, reduced efficacy had the largest negative correlation with academic achievement. This is not surprising. Negative self-perceptions are highly likely to contribute significantly to avoidance behaviours in students who subscribe to them. It is also likely that the medium effect of perceptions of reduced efficacy on academic achievement reflects reciprocal causality between these two variables (i.e., reduced efficacy contributes to perceptions of reduced accomplishment, which contribute to reduced achievement, and so on). These findings however are somewhat at odds with previous findings in the work domain, where reduced efficacy is a nonsignificant predictor of performance (e.g., Taris, 2006). Perhaps differences in the way that competence is assessed (e.g., exams versus continual appraisal process) may explain these discrepancies. Further work aimed at understanding the reasons for these differences is needed.

There are many studies that have examined predictors of academic achievement. How does burnout fare in comparison to these? In terms of non-psychological variables, burnout shows larger effects than commonly described (and well publicised) factors including television usage, suspension from school, and movement between schools (Hattie, 2008). In terms of psychological variables, burnout shows larger effects than both general and academic stress, and similar sized effects as procrastination, boredom, and test anxiety (Richardson et al., 2012). In fact, reduced efficacy shows one of the largest effects of any psychological predictor of academic achievement (see also Stajkovic, Bandura, Locke, Lee, & Sergent, 2018). These findings are therefore particularly concerning, and reinforce the need for teachers and parents to be aware of burnout symptoms and their consequences.

Moderators

We examined a series of factors that we thought may moderate the relationships between burnout and academic achievement. These were the instrument used to measure burnout, academic level, measure of achievement, objectivity of achievement measure, and gender. Objectivity of achievement measure and gender did not emerge as moderating factors. Burnout was equally debilitating in terms of achievement for men as it was for women. In addition, we thought that those students at secondary levels of education may face a larger volume of stressors, have fewer coping resources, and perhaps smaller social support networks, and for these reasons would be more susceptible to the effects of burnout. The present findings however seem to challenge these assertions. As such, burnout appears to manifest in a similar way for both male and female and secondary and tertiary students.

In partial support of our hypotheses, the reduced efficacy-achievement relationship was moderated by the instrument that was used to measure burnout. It appears that it does matter how reduced efficacy is assessed (i.e., which subscale from which measure is used). In this regard, relationships were stronger when using the MBI-SS than the SBI. There are several possible explanations for this finding. First, the SBI uses only two items to measure reduced efficacy. Whether these are sufficient to capture the breadth of this symptom is unclear. Second, the MBI includes items that are all positively worded (i.e., efficacy), with relationships reversed. Perhaps students are more adept at identifying levels of efficacy than inefficacy. Overall, based on these findings, we recommend the use of the MBI when examining the relationships between reduced efficacy and academic achievement.

Limitations and Suggestions for Future Research

The majority of the studies included in the meta-analyses utilised cross-sectional designs. As such, the present findings offer initial evidence in terms of relationships, but limited evidence in terms of causation. In this regard, several of the present studies did adopt longitudinal designs (e.g., Palos et al., 2019). These are excellent examples of research that can provide stronger evidence for causal relations between burnout and academic achievement. Of particular note, however, is the fact that few, if any, of these studies examined whether burnout predicted changes in achievement over time. This is an important next step to extend our causal understanding of these relationships.

Next, studies aimed at advancing our understanding of the mechanisms responsible for these relationships are essential. We hypothesised a number of routes through which burnout may result in worse achievement (e.g., effort, absenteeism). Future research is required to provide specific tests of these pathways. In a similar vein, personal, lifestyle, and social factors may serve to moderate the relationship between burnout and achievement. For example, certain personality factors, such as perfectionism, may act to exacerbate the negative consequences of burnout for students (Hill & Curran, 2016). In addition, academic buoyancy (students' ability to successfully deal with academic setbacks and challenges that are typical of the ordinary course of school life; Martin & Marsh, 2008) is likely to act as a buffer of burnout development, and in turn providing some protection against reduced achievement (Martin & Marsh, 2019). There is also a growing body of work that has linked burnout to sleep disturbances (e.g., insomnia), examining whether sleep quality affects the burnout-achievement relationship would be a worthwhile avenue for future work. Although parental expectations have been associated with higher academic achievement (Pinquart & Ebeling, 2019), excessive expectations are likely to be a contributing factor to the development of burnout (e.g., Shin, Lee, Kim, & Lee, 2012), and, as such, should be central to social research in this area. Finally, there is evidence that a surface approach to learning (shallow information processing and an extrinsic motivation to learn) is associated with higher burnout, and that a deep approach (deep information processing and an intrinsic motivation to learn) is associated with lower burnout (e.g., Kuittinen & Meriläinen, 2014). Consequently, encouraging and or creating environments that promote a deep approach to learning may be beneficial in regards to offsetting the effects of burnout for achievement.

All the studies included in the present meta-analysis examined the relationships between burnout and achievement in secondary or tertiary education. Consequently, we currently have no understanding of how burnout affects students' achievement in primary education. Here we would argue that for primary students there is still the potential for stress and burnout development. They still experience pressure from parents and educators, and they are still assessed. One important question, however, is whether the measures we have are suitable for primary school students, or whether specific, simpler measures are required in these instances. This is an obvious question to be answered by future work.

Finally, we are interested to know more about where burnout is coming from for these students. There is a large body of evidence attesting to the relevance of stress in this regard. The stress of exams and assessments may likely be a contributing factor. What is also interesting is the possibility of contagion effects from teachers themselves (i.e., interpersonal transmission of burnout). Therefore, future studies examining whether teacher burnout affects student burnout and achievement would be very worthwhile (e.g., Klusmann, Richter, & Lüdtke, 2016; see also Kim, Jörg, & Klassen, in press). It would also be interesting to examine the possible reciprocal nature of these relationships, doing so would provide us with key information to help address these issues (see Iancu et al., 2018).

Applied Implications

What do the present findings mean for those working in educational contexts? First and foremost, they suggest that it is essential that the implications of burnout are made clear to teachers and students. The recent inclusion of burnout in the ICD-11 by the World Health Organization highlights the increased emphasis on burnout and its recognition as a broad societal problem (World Health Organization, 2018). Given the significant implications of burnout demonstrated here, making the most of this addition by the World Health Organization to affect change in educational policy is a worthwhile endeavour. In this regard, increasing burnout awareness (and literacy) will likely be an effective first step. This is important for all levels of education where detrimental effects are likely similar.

There are many ways to prevent and reduce burnout in students. In this regard, there is some evidence of how to do so that comes from the educational context. In this regard, interventions or prevention strategies can target the individual (e.g., stress training) and/or target the organisation (e.g., reduce exams/exam pressure/parental expectations; Bresó, Schaufeli, & Salanova, 2011). Recent evidence from outside of the educational context suggests that a combination of both individual and organisational interventions is likely to be most effective (West et al. 2016). As such, we call for further research to test the effectiveness of such interventions and prevention strategies in the present context so as to provide educators with a means to moderate burnout and its effects.

Conclusion

The present study provides the first meta-analytic evidence that burnout is related to academic achievement. In this regard, the findings suggest that total burnout and all three burnout symptoms predict worse academic achievement. Consequently, it is important that those working in educational contexts recognise burnout as a significant barrier to academic achievement.

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Table 1.

Characteristics of Studies Included in the Meta-Analysis

	Sample				Measurement			Reliability					Effect sizes			
Study	Domain	*N*	M. Age	%Female	Instrument	Achievement	Ach. Meas.	Achievement	Total	E	C	R	Total-Ach	E-Ach	C-Ach	R-Ach
Atalayin et al. (2015)	Tertiary	329	21.32	50.5	MBI-SS	GPA	O	.75	—	.83	.80	.70	—	.10	-.04	-.20
Balogun et al. (1996)	Tertiary	27	—	53	MBI	GPA	O	.75	—	—	—	—	—	.08	.19	-.14
Burr & Beck Dallaghan (2019)	Tertiary	47	—	—	MBI[3]	GPA	O	.75	—	.91	.84	.89	—	-.21	-.10	-.58
Cadime et al. (2016), sample 1	Secondary	267	16.31	100	MBI-SS	GPA	SR	.75	—	.72	.72	—	—	-.05	-.18	—
Cadime et al. (2016), sample 2	Secondary	222	16.31	0	MBI-SS	GPA	SR	.75	—	.72	.72	—	—	-.27	-.34	—
Dumont et al. (2017)	Secondary	2155	—	—	MBI	Exams	O	.90	—	—	.80	—	—	—	-.20	—
Duru et al. (2014)	Tertiary	383	21.05	60.6	MBI-SS	GPA	O	.75	—	.83	.80	.70	—	-.17	-.25	-.29
Fiorilli et al. (2017), sample 1	Secondary	110	15.5	100	SBI	Grade	SR	—	—	.70	.75	.71	—	-.09	-.49	-.44
Fiorilli et al. (2017), sample 2	Secondary	100	15.5	0	SBI	Grade	SR	—	—	.70	.75	.71	—	-.12	-.46	-.46
Griffin & Wu (2019)	Tertiary	81	—	—	MBI 1-item	Exam	O	—	—	—	—	—	-.03	—	—	—
Herrmann et al. (2019)	Secondary	649	14.2	58.6	SBI	GPA	SR	.75	—	.73	.75	—	—	-.20	-.23	—
Hodge et al. (in press)	Tertiary	395	23.12	87.3	SBI	GPA	SR	.75	—	.80	.74	.58	—	-.15	-.30	-.36
Kljajic et al. (2017)	Tertiary	312	19.17	72.1	MBI-SS	GPA	SR	.75	—	.90	.92	.85	—	-.20	-.30	-.37
Korhonen et al. (2016), sample 1 (reading)	Secondary	576	15.8[4]	100	SBI	Exam	O	—	.87	—	—	—	-.13	—	—	—
Korhonen et al. (2016), sample 1 (word comprehension)	Secondary	576	15.8	100	SBI	Exam	O	—	.87	—	—	—	-.19	—	—	—
Korhonen et al. (2016), sample 1	Secondary	576	15.8	100	SBI	Exam	O	—	.87	—	—	—	-.22	—	—	—

[3]Efficacy score was reversed to reflect reduced efficacy.

[4]Mean age was reported across both samples.

(mathematics)																
Korhonen et al. (2016), sample 2	Secondary	576	15.8	0	SBI	Exams	O	—	.87	—	—	—	-.12	—	—	—
(reading)																
Korhonen et al. (2016), sample 2	Secondary	576	15.8	0	SBI	Exams	O	—	.87	—	—	—	-.19	—	—	—
(word comprehension)																
Korhonen et al. (2016), sample 2	Secondary	576	15.8	0	SBI	Exams	O	—	.87	—	—	—	-.17	—	—	—
(mathematics)																
Kotze & Klynhans (2013)	Tertiary	789	—	43	MBI-SS	Grades	O	—	—	—	—	—	—	.10	-.06	—
Law (2007)	Tertiary	100	—	—	MBI	GPA[5]	SR	.75	—	-.88	—	—	—	-.34	—	—
Li et al. (2018)	Tertiary	262	19.25	58.8	MBI-SS	GPA	SR	.75	—	.88	—	—	—	-.33	—	—
McCarthy et al. (1990)	Tertiary	360	21.5	49.7	MBI	GPA	O	.75	—	—	—	—	-.19	—	—	—
Palos et al. (2019) Time 1	Tertiary	142	21.34	76.1	MBI-SS	Grades	O	—	.76	—	—	—	-.06	—	—	—
Palos et al. (2019) Time 2	Tertiary	142	21.34	76.1	MBI-SS	Grades	O	—	.81	—	—	—	-.07	—	—	—
Rana (2016)	Tertiary	218	—	—	MBI-SS	GPA	SR	.75	.75	—	—	—	—	-.19	-.26	-.05
Romano et al. (2019)	Tertiary	257	23.3	79.8	SBI	GPA	SR	.75	.86	—	—	—	-.29	—	—	—
Salanova et al. (2010)	Tertiary	527	22	67	MBI-SS	GPA	O	.75	—	.74	.77	—	—	-.08	-.07	—
Salmela-Aro et al. (2008), sample 1	Secondary	58657	—	49.8	SBI-S	GPA	SR	.75	.65	—	—	—	-.26	—	—	—
Salmela-Aro et al. (2008), sample 2	Secondary	29237	—	56.8	SBI-S	GPA	SR	.75	.65	—	—	—	-.18	—	—	—
Schaufeli et al. (2002), sample 1	Tertiary	621	21.6	62	MBI-SS	Exams	O	—	—	.74	.79	.76	—	-.12	-.19	-.34
Schaufeli et al. (2002), sample 2	Tertiary	723	24.7	84	MBI-SS	Exams	O	—	—	.79	.82	.69	—	-.01	-.03	-.12
Schaufeli et al. (2002), sample 3	Tertiary	309	22.6	88	MBI-SS	Exams	O	—	—	.80	.86	.67	—	-.08	-.01	-.33
Seibert et al. (2017), sample 1	Tertiary	550	19.63	88.4	MBI-SS	GPA	SR	.75	.77	.92	.92	.89	-.17	-.09	-.24	-.20
Seibert et al. (2017), sample 1	Tertiary	543	19.87	89.6	MBI-SS	GPA	SR	.75	.81	.94	.94	.91	-.13	-.08	-.14	-.18
Suldo et al. (2018)	Secondary	2379	—	62.2	SBI	GPA	SR	.75	.88	—	—	—	-.22	—	—	—
Virtanen et al. (2016)	Secondary	2485	14.66	52.1	BBI	Grade	SR	.81	.91	—	—	—	-.28	—	—	—

[5]Correlations are in context of expected GPA.

Vizoso et al. (2019)	Tertiary	532	22.10	82.3	MBI-SS[6]	GPA	SR	.75	—	.81	.75	.77	—	-.08	-.04	-.39
Wang et al. (2018)	Secondary	1419	16.36	51.4	SBI	GPA	SR	.75	.89	—	—	—	.01	—	—	—
Widlund et al. (2018), sample 1 (time 1)	Secondary	583	13.29	50.3	SBI	Exams	O	.89	—	—	—	—	—	-.11	-.20	-.17
Widlund et al. (2018), sample 1 (time 2)	Secondary	583	13.29	50.3	SBI	Exams	O	.89	—	—	—	—	—	-.23	-.31	-.22
Widlund et al. (2018), sample 2 (time 1)	Secondary	497	15.23	52.5	SBI	Exams	O	.89	—	—	—	—	—	-.09	-.11	-.17
Widlund et al. (2018), sample 2 (time 2)	Secondary	497	15.23	52.5	SBI	Exams	O	.89	—	—	—	—	—	-.18	-.22	-.21
Xie et al. (2019)	Tertiary	1977	19.9	71.2	MBI-SS	Grades	O	—	.90	—	—	—	-.32	—	—	—

Note. SBI = School Burnout Inventory (Salmela-Aro et al. 2009). SBI-S = Short Version of the School Burnout Inventory (Salmela & Naatanen 2006). MBI-SS = Maslach Burnout Inventory-Student Survey (Schaufeli et al. 2002). MBI = Maslach Burnout Inventory (Maslach & Jackson, 1981). BBI = Bergen Burnout Indicator 10 (Salmela-Aro & Naatanen, 2005). GPA = Grade point average. M. Age = Mean age. Total-Ach = Correlation between total burnout and academic achievement. E-Ach = Correlation between exhaustion and academic achievement. C-Ach = Correlation between cynicism and academic achievement. R-Ach = Correlation between reduced efficacy and academic achievement. Ach. Meas. = Achievement measure. O = Objective. SR = Self-reported.

[6] Efficacy score was reversed to reflect reduced efficacy.

Table 2.

Weighted average effects with robust variance estimation, moderation analyses, and publication bias

Variable	*k*	*o*	*b*	*SE*	95% CI LL	95% CI *UL*	*t* (*df*)	Heterogeneity τ^2	Heterogeneity I^2	Fail Safe N
Total Burnout	13	19								6026
Intercept Only								.01	97.83	
Constant			-.24**	.03	-.31	-.16	-6.97 (11.40)			
Moderators								.01	97.88	
Constant			-.48	.15	-1.07	.11	-3.15 (2.23)			
Domain (Tertiary = 0, Secondary = 1)			.13	.06	-.04	.36	2.54 (2.95)			
Instrument (SBI = 0, MBI = 1)			.16	03	-.05	.36	5.54 (1.34)			
Measurement (Subjective = 0, Objective = 1)			.02	.06	-.22	.28	.50 (2.03)			
GPA (Others = 0, GPA =1)			.05	.08	-.39	.50	.65 (1.65)			
Exams (Others = 0, Exams = 1)			.07	.15	-.34	.56	.72 (3.35)			
Percentage Female			.001	.002	-.01	.01	.50 (2.13)			
Exhaustion	23	26								625
Intercept Only								.02	87.77	
Constant			-.15*	.03	-.22	-.09	-5.02 (21.30)			
Moderators								.01	74.54	
Constant			-.23	.10	-.56	.03	-2.73 (3.27)			
Domain (Tertiary = 0, Secondary = 1)			-.03	.06	-.16	.23	-.59 (2.66)			
Instrument (SBI = 0, MBI = 1)			.06	.04	-.08	.20	1.34 (2.72)			
Measurement (Subjective = 0, Objective = 1)			.19	.08	-.01	.38	2.19 (8.50)			
GPA (Others = 0, GPA =1)			-.19	.09	-.46	.08	-2.24 (3.08)			
Exams (Others = 0, Exams = 1)			-.26*	.09	-.51	-.02	-2.98 (3.90)			
Percentage Female			.002	.001	-.0003	.01	2.57 (3.65)			
Cynicism	22	25								1818
Intercept Only								.02	91.80	
Constant			-.24**	.04	-.32	-.16	-6.26 (20.40)			
Moderators								.02	87.37	
Constant			-.54**	.10	-.83	-.26	-5.69 (3.41)			
Domain (Tertiary = 0, Secondary = 1)			-.07	.07	-.25	.11	-1.01 (4.26)			
Instrument (SBI = 0, MBI = 1)			.10	.07	-.08	.28	1.51 (4.13)			
Measurement (Subjective = 0, Objective = 1)			.19	.09	-.01	.39	2.16 (9.72)			
GPA (Others = 0, GPA =1)			.10	.13	-.28	.48	.79 (3.46)			
Exams (Others = 0, Exams = 1)			.06	.15	-.34	.46	.40 (4.46)			
Percentage Female			.001	.001	-.002	.01	.93 (3.06)			
Reduced Efficacy	16	19								1865
Intercept Only								.02	92.45	
Constant			-.39**	.05	-.49	-.29	-8.50 (14.70)			
Moderators								.03	93.05	
Constant			-.94*	.16	-1.75	-.14	-5.75 (1.76)			
Domain (Tertiary = 0, Secondary = 1)			.35*	.12	.001	.70	2.83 (3.87)			
Instrument (SBI = 0, MBI = 1)			.24*	.08	.02	.46	3.00 (4.11)			
Measurement (Subjective = 0, Objective = 1)			-.12	.15	-.48	.24	-.79 (6.17)			
GPA (Others = 0, GPA =1)			.42	.14	-.07	.91	2.93 (2.63)			
Exams (Others = 0, Exams = 1)			.49*	.16	.06	1.03	3.03 (2.73)			
Percentage Female			-.0003	.001	-.01	.01	-.18 (1.35)			

Note. *k* = number of studies; *o* = number of comparisons; *b* = coefficient in the meta-regression model; *SE* = standard error of the coefficient; 95% CI = 95% confidence interval for the coefficient; *LL* = lower limit of the 95% confidence interval for the coefficient; UL = upper limit of the 95% confidence interval for the coefficient; *t* = *t*-statistic calculated based on the predicted mean; *df* = small sample corrected degrees of freedom of the distribution of the *t*-statistic.
$p < .05$*, $p < .01$**