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Not if, but how they differ: A meta-analytic test of the nomological networks of burnout and engagement

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ABSTRACT

The distinctiveness between work engagement and burnout has long been an issue of debate. To address this issue, we use a recently developed technique by Yu et al. (2016) to specify and test a meta-analytic structural equation model (MASEM) which accounts for the non-independence between engagement and burnout as well as the simultaneous effects of all relationships in our model, based on job demands-resources (JD-R) theory. We also estimate the degree of variability of these relationships across subpopulations. We report the findings as a distribution of effect size estimates—each estimate in the distribution representing the true effect size for a potential subpopulation—around the mean average estimate for each relationship in the model. Based on the findings, we conclude that overall burnout and engagement display empirically distinct relationships within the JD-R model (i.e., they are not antipodal), particularly in terms of antecedents. Perhaps most interestingly, rather than a polar opposite pattern of relationships, challenge demands have a similarly positive relationship to *both* burnout ($\beta = 0.35$, SD = 0.10) *and* engagement ($\beta = 0.35$, SD = 0.08), suggesting that challenge demands simultaneously lead—in equal force—to both engagement and burnout. In addition, the distributions of effect sizes are nearly identical for both relationships, indicating that this holds true for nearly all subpopulations. As expected, hindrance demands have a positive relationship with burnout ($\beta = 0.31$, SD = 0.10) and have a relatively weak, negative relationship on average to engagement ($\beta = -0.07$, SD = 0.07); work resources have a negative relationship with burnout ($\beta = -0.15$, SD = 0.06) and are positively related to engagement, but in absolute terms they are a stronger predictor of engagement ($\beta = 0.33$, SD = 0.05). In terms of outcomes, burnout and engagement predict a variety of behavioral and attitudinal outcomes differentially from one another, although the differences are less clear due to wide variation in effect sizes in the population. Future research directions are discussed alongside practical implications.

1. Introduction

A sea change occurred in psychology at the turn of the millennium. Psychologists were called upon to move beyond understanding pathology and begin to investigate how to heighten human flourishing and the so-called positive aspects of psychology (Seligman & Csikszentmihalyi, 2000). In synchrony with this call to focus on the positive aspects of psychology, researchers investigating how to reduce employee responses to chronic stress (i.e., burnout) also began to investigate how to induce employee thriving and well-being at work (e.g., engagement). In the more than 15 years since this change of tides, and particularly after 2002 when a measure of work engagement—an active and positive motivational state toward one's work (Nimon, Shuck, & Zigarmi, 2016)—was validated by Schaufeli and colleagues (Schaufeli, Salanova, González-Romá, & Bakker, 2002), the number of research articles on work engagement produced each year has grown tremendously. Yet, while interest has grown exponentially in researching engagement, so has confusion surrounding its conceptualization and its measurement.

In fact, some have argued that we may have lost sight of what exactly engagement is conceptually (e.g., Newman & Harrison, 2008), and others have noted potential empirical issues with its measurement (e.g., Cole, Walter, & Bedeian, 2012; Maslach, Leiter, & Schaufeli, 2008). In particular, there is heated disagreement as to what the nature of engagement is in its relation to its health-impairing counterpart, burnout. For instance, some conceptualize engagement to be the polar

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opposite of burnout (i.e., the absence of burnout) while others conceptualize it to be a distinct state. This debate continues today.

This study seeks to first address the debate of whether burnout and engagement are simply polar opposite constructs—meaning low burnout is equivalent to high engagement and vice versa—or in fact distinct constructs from one another; we do this by providing a brief conceptual and empirical review of the literature on burnout and engagement. After reviewing the literature and presenting the corresponding evidence that seems to indicate the two constructs are indeed distinct states, we then provide a brief overview of the theoretical model which we use to test our primary research question: *on average, how do burnout and engagement differ in their distinct relationships with theoretical antecedents and outcomes?*

Our study builds off of existing work which has sought to clarify whether and to what degree burnout and engagement are distinct constructs (e.g., Byrne, Peters, & Weston, 2016; Cole et al., 2012; Newman, Joseph, & Hulin, 2010; Shuck, Nimon, & Zigarmi, 2017). On the one hand, there is meta-analytic evidence which highlights the high correlations between engagement and other constructs in its nomological network (e.g., burnout, job satisfaction). For example, Cole et al. (2012) through conventional meta-analyses, critiqued the high correlations between dimensions of the most common measures of burnout, the Maslach Burnout Inventory (MBI; Maslach & Jackson, 1981) and engagement, the Utrecht Work Engagement Scale (UWES; Schaufeli et al., 2002). Other scholars, again through conventional meta-analyses, noted that the UWES provided little unique variance beyond a higher-order factor of three commonly studied job attitudes (i.e., job satisfaction, job involvement, and organizational commitment; Newman et al., 2010).

However, in light of some of the limitations to conventional meta-analysis, other scholars have attempted to "untangle" the complexity of this issue using structural equation modeling (SEM) with large, primary datasets. For instance, Byrne et al. (2016), after controlling for the simultaneous interrelationships in their model, showed that engagement showed discriminant validity with some of these same job attitudes. Furthermore, they found that at the construct level "engagement is not the same as the opposite of the burnout construct", despite Cole et al.'s (2012) meta-analysis suggesting that "the UWES assesses a reverse-scored MBI", (Byrne et al., 2016; p. 1219). In addition, Shuck et al. (2017) investigated the empirical overlap of engagement to the same three job attitudes analyzed in the Newman et al. (2010) meta-analysis by examining an exhaustive number of combinations of these constructs in order to partition out the unique variance of each. In addition, both Byrne et al. (2016) and Shuck et al. (2017) found that two measures of engagement, the UWES and the job engagement scale (JES; Rich, Lepine, & Crawford, 2010), not only had distinct nomological networks, but the measures themselves measured different, theoretical aspects of engagement.

In summary, the current state of the debate as to whether engagement is distinct from burnout and other related job attitudes is, simply put, complicated. On one hand, meta-analytic evidence presents a situation in which the two most commonly used measures of burnout and engagement show correlations so high that they suggest redundancy (Cole et al., 2012). meta-analytic evidence also shows a high degree of overlap with common job attitudes (Newman et al., 2010), which as Shuck et al. (2017) colorfully put it, suggests engagement is "the repackaging of old goods; new label, same old merchandise" (p. 81). Yet on the other hand, when scholars conduct analyses which are more sophisticated than those possible with conventional meta-analyses, engagement appears to show patterns of discriminant validity with both burnout (Byrne et al., 2016) and job attitudes (Shuck et al., 2017).

With this state of the science in mind, we seek to build from the current body of work testing the nomological networks of engagement and burnout using a technique which can leverage the advantages of each approach: the power and generalizability of *meta*-analysis with the sophistication of SEM, wherein the non-independence of constructs (i.e., such as that with engagement, burnout, and related job attitudes) and the complex, simultaneous interrelationships of an entire theoretical model can be accounted for. In this study, we test a theoretical model based on the job demands-resources model (JD-R; Demerouti, Bakker, Nachreiner, & Schaufeli, 2001) using a recently developed technique (Yu, Downes, & Carter, 2016) which uniquely accounts for potential non-independence between constructs, such as burnout and engagement. This technique allows us to simultaneously test all parametric relationships in an entire model, thereby allowing us to see *how* burnout and engagement differ from one another and their nomological networks. The technique we employ also allows us to determine *how often* they differ, by providing an entire distribution of effect sizes (i.e., standardized path coefficients) representing the percentage of subpopulations which fall within the given range of effect sizes. This is useful to locate potential relationships which have high variability, indicating moderation which can be explored with future research. In this way we can more definitively determine not only *if*, but *how* engagement's and burnout's nomological networks differ, thereby advancing theory and practice. Prior to implementing this technique, we provide a brief review of the literature on engagement and burnout to provide a theoretical context for the model which we test.

1.1. Conceptual review of engagement

Conceptually, engagement has often been viewed in two main ways: as antipode (i.e., "polar opposite") or as a distinct state (i.e., negatively related albeit distinct construct from burnout). In the first view, as the antipode or diametric opposite of burnout, employees are thought to begin a certain job with a level of positive motivation or state of mind (i.e., engagement), which if the demands of the job outweigh the resources available to the employee will then begin to erode this motivational high and eventually deteriorate, over time, into the motivational low of burnout (Maslach & Leiter, 1997). In fact, the very name of the concept, *burnout*, implies such a process as of a smoldering fire: "once a fire was burning but that fire cannot continue burning brightly unless there are sufficient resources that keep being replenished" (Schaufeli, Leiter, & Maslach, 2009, p. 205). Under this conceptualization, engagement has been operationalized as the inverse pattern of burnout scores on the MBI.

Yet others have conceptualized engagement as a qualitatively different state, a distinct construct from burnout. Under this "distinct states" view, engagement is typically conceptualized as a positive and persistent work-related state characterized by the affective-cognitive dimensions of vigor, dedication, and absorption (Schaufeli et al., 2002). Engagement and burnout are still conceptualized, in this view, as antithetical in nature, but rather than "perfectly complementary and mutually exclusive states, burnout and engagement are independent states that—because of their antithetical nature—are supposed to be negatively related" (Schaufeli & Bakker, 2004; p.294). Schaufeli and colleagues have argued that, defined as distinct states, burnout and engagement are best assessed with independent measures, such as the MBI for burnout (Maslach & Jackson, 1981) and the to-date most commonly used measure of work engagement, the UWES.

Another "distinct states" conceptualization and corresponding measure is that of the JES (Rich et al., 2010). The JES is based on early work by Kahn (1990), who conceptualized engagement as a unique psychological state in which an employee "harnesses" their physical, emotional, and cognitive energies to complete their work. Schaufeli (2013) has noted that the content of the UWES and JES share similar dimensions (with different labels) and items. Furthermore, others have noted that each measure taps into different aspects of the same construct (Byrne et al., 2016; Shuck et al., 2017). See Byrne et al. (2016) for distinctions on when each scale might be applied to specific research questions. However, considering their similarities and to gain a fuller picture of the engagement construct's nomological network, we include both measures of engagement in our study.

In summary, there are two main camps regarding how engagement has been conceptualized: the "antipodes" (i.e., polar opposites) camp and "distinct states" (i.e., burnout and engagement are distinct constructs albeit negatively related) camp. These conceptual differences are important, because they determine how we theorize, operationalize, and understand the true nature of engagement, burnout, and their relationships within theoretical frameworks, such as the JD-R model. As such, it is important then to understand the evidence supporting these conceptualizations.

1.2. Empirical review of burnout and engagement

Given the conceptual differences, scholars have attempted to deepen our understanding empirically on the nature of burnout and its positive counterpart, engagement. Considering several quantitative reviews, the empirical evidence when taken as a whole seems to indicate that burnout and engagement are in fact distinct constructs. In other words, the body of evidence supports the "distinct states" view over the "antipodes" view. However, there are remaining issues regarding the measurement of burnout and engagement to consider first. Specifically, the *inefficacy* dimension of the MBI appears to be the most problematic. Cole et al. (2012) found dimension-level correlations as high as −0.85 (i.e., corrected true-score correlation, or ρ, between the MBI's *inefficacy* dimension and the UWES' *vigor* dimension; $k = 21$, $N = 15{,}271$); they further showed that the MBI's *inefficacy* dimension of the MBI was most strongly related to all three of the engagement dimensions of the UWES (i.e., *dedication, vigor,* and *absorption*), with an average ρ of −0.79, suggesting overlap nearly sufficient to be considered redundant or to have convergent validity (i.e., any correlation of 0.80 or greater is considered "redundant"; Byrne et al., 2016; Kline, 2005), at least with this dimension of the MBI (i.e., *inefficacy*). In other words, the problem is that the MBI's *inefficacy* subscale (i.e., reverse-coded professional efficacy items) is so highly correlated with the UWES that this supposed burnout scale acts as an alternative engagement measure. These measurement issues have added fuel to the fire on the debate as to whether the *construct* of engagement as to whether it is simply the antipodal, "mirror image" of burnout. To address this issue, Schaufeli and Salanova (2007) argued for and found support for the inclusion of a scale which explicitly measures *in*efficacy (in lieu of reverse-scored efficacy).

Despite the potential problems of the MBI's *inefficacy* dimension, its other dimensions, such as *exhaustion*, showed a much weaker relationship with the UWES engagement dimensions (mean ρ = −0.36). Taken as a whole at the construct level, burnout and engagement—as measured by the MBI and UWES, respectively—had a mean observed (i.e., uncorrected[1]) correlation of −0.40 (Cole et al., 2012), which is on the threshold between a moderate and strong effect size according to benchmark guidelines outlined by Bosco et al. (2015), but well below any thresholds considered for convergent validity. Thus Cole et al. (2012) showed that there are indeed legitimate measurement concerns with the dimensions of the MBI (i.e., specifically *inefficacy*) and the UWES dimensions, although there was not enough evidence to definitively conclude that engagement was "new wine in the old bottle" of burnout; in other words, there was not enough evidence to support the "antipodes" conceptualization of burnout and engagement.

In another meta-analysis which simultaneously analyzed burnout and engagement, Crawford et al. (2010) analyzed a larger number of samples and found that engagement and burnout—again, primarily measured by the UWES and MBI scales—had a mean observed (i.e., uncorrected) correlation of −0.39 ($k = 54$, $N = 25{,}998$; ρ = −0.48, when correcting for sampling error and unreliability, per Schmidt & Hunter, 2014), which is at the top of the benchmark threshold as a moderate effect size in applied psychology (Bosco, Aguinis, Singh, Field, & Pierce, 2015).

Thus as a whole, these various quantitative syntheses show that indeed the constructs of engagement and burnout are significantly, negatively related, and that the strength of this relationship is between moderate to strong. Despite many of the legitimate issues raised by Cole et al. (2012), the cumulative evidence regarding burnout and engagement at the construct-level seems to support the notion proposed by Schaufeli and Bakker (2004), that burnout and engagement are neither wholly independent nor antipodal, but rather somewhat distinct states whose relationship appears "to be moderately to strongly negative" (p. 294). Indeed, if these constructs were truly polar opposites, as conceptualized by the antipode view, then the measures (e.g., MBI, UWES)—of supposedly opposite ends of the same construct per this view—would show effect size magnitudes suggestive of convergent validity, such as $|r = 0.70|$ (Carlson & Herdman, 2012) or $|r \geq 0.80|$ (Byrne et al., 2016). Thus, as a whole, despite some dimension-level overlap with the to-date most common engagement scale (i.e., UWES) and the most common burnout scale's (i.e., MBI) dimension of *inefficacy* as presented in Cole and colleagues' study (2012), the evidence indicates that engagement and burnout are in fact distinct constructs whose relationship is negative and moderate to strong in nature.

Therefore, while we echo the need and call for increasing refinement of measures which are theoretically appropriate (Byrne et al., 2016; Shuck et al., 2017), it seems as though the question is not if burnout and engagement are different, but how and when they differ. The evidence above supports the notion that burnout and engagement are, at the construct level, distinct states. Yet still within this distinct states view there remain many questions conceptually and empirically. For example, if burnout and engagement are in fact distinct constructs, how do their respective nomological networks differ? That is, even if we understand that burnout and engagement are distinct states whose measures, to a degree, are tapping distinct constructs, this is simply an understanding of their bivariate relationship to one another; beyond their relationship to one another, how do their relationships with various antecedents and outcomes differ? Furthermore, how do these relationships differ while accounting for the simultaneous effects of all variables within an entire theoretical model?

1.3. Our approach: meta-analytic structural equation modeling (MASEM)

Past quantitative reviews of burnout and engagement have either focused on the bivariate relationships of burnout in isolation with its theoretical antecedents and/or outcomes (e.g., Alarcon, 2011; Kurtessis et al., 2015; Swider & Zimmerman, 2010), or with engagement in isolation with its theoretical antecedents and/or outcomes (e.g., Christian, Garza, & Slaughter, 2011; Mackay, Allen, & Landis, 2016). Many of these reviews examine these bivariate relationships within the context of the JD-R model, although until recently the ability to test entire models—at least models whose variables are not assumed to be completely independent (i.e., as in the case between burnout and engagement)—meta-analytically did not exist (Cheung, 2014). Thus, most reviews have taken a piecemeal approach, which fails to account for the simultaneous effects of the other variables in a model.

Another approach taken has been to utilize meta-analytic path modeling, which although accounts for simultaneous effects of other variables, does not account for potential subpopulation differences and assumes the independence of effect sizes among these variables (Viswesvaran & Ones, 1995). However, in the case of burnout and engagement this is neither conceptually nor empirically so. That is, as

[1] Cole et al. (2012) report both corrected and uncorrected meta-analytic estimates; we note the uncorrected correlation here so as to make an appropriate comparison to the guidelines proposed by Bosco et al. (2015) for effect size magnitudes in psychology for attitude–attitude relationships, which are based on uncorrected ($|r|$) effect sizes. Note that we chose this benchmark due to its direct applicability to applied psychology research; other benchmarks (e.g., Cohen, 1988) are broader estimates and not domain-specific.

noted above, burnout and engagement are in fact significantly related to one another in a negative, moderate-to-strong fashion, and we therefore cannot assume independence. Furthermore regarding potential subpopulation differences, there is preliminary evidence to suggest that there may be differences among subpopulations (i.e., heterogeneity of effect sizes), as is indicated in over 80% of relationships examined by Crawford et al. (2010) with a significant *Q* statistic, meaning a significant amount of heterogeneity in effect size for these relationships. This means there are likely subpopulations (e.g., certain industries, sample demographics) where the relationships among burnout, engagement, and their nomological networks differ. Thus, despite best efforts to quantitatively synthesize and thereby advance our understanding of *how* burnout and engagement and their nomological networks relate to one another within a given theoretical model, we have heretofore had to rely primarily on either analyzing these relationships piecemeal (i.e., as sets of bivariate relationships), or with path analyses (e.g., Crawford, LePine, & Rich, 2010; Nahrgang, Morgeson, & Hofmann, 2011) which rely on the inaccurate assumption of independence and do not account for any potential subpopulation differences. Thus, given that conceptually burnout and engagement—even within the distinct states view—-are thought to be non-independent (Schaufeli & Bakker, 2004), and the evidence outlined above supports this claim, even the best efforts of using traditional meta-analyses and meta-analytic path models falls short to help us understand the true nature of relationships between the nomological network of burnout and engagement.

As such, the purpose of this study is to provide clarity on *how* these related constructs differ in the hopes of shedding light on promising directions for future research by utilizing a technique which both harnesses the strengths and addresses the weaknesses of conventional meta-analytic approaches. Our overarching research question is: *within the most commonly used theoretical framework used to examine them, the JD-R model, how and when do burnout and engagement and their nomological networks differ?* We address our primary research question, *how do they differ,* by utilizing a form of meta-analytic structural equation modeling (MASEM) which accounts for non-independence of effects sizes (Yu et al., 2016). We address our secondary research question, *to what degree do these relationships differ,* indirectly by using the Yu et al. (2016) technique which accounts for heterogeneity of meta-analytic effect sizes. In other words, by accounting for potential subpopulation differences, we can determine to what degree (i.e., the percentage of subpopulations) burnout and engagement relate to various antecedents and outcomes within a given range of values. In addition, as a supplementary analysis, we can also determine to what degree burnout and engagement may behave more as antipodes than as distinct states for a given relationship (see Fig. 3). This knowledge can help us shed light on potential moderators for future research.

The MASEM approach allows us to test a multivariate model, such as the proposed differentiated JD-R model (see Fig. 1), using meta-analytic estimates. Essentially, this technique combines the benefits of meta-analysis with the benefits of structural equation modeling (SEM). Meta-analysis, specifically the random effects model of meta-analysis commonly used in applied psychology, is a technique which allows researchers to determine the mean effect size between two variables among a distribution of effect sizes (Borenstein, Hedges, Higgins, & Rothstein, 2010; Schmidt & Hunter, 2014). In other words, we are able to determine the mean average effect size for a given relationship (e.g., resources − burnout) as well as the distribution of effect sizes for this relationship, often represented through 80% credibility intervals (CVs). CVs represent how generalizable a meta-analytic estimate is by indicating the degree of variability (or heterogeneity) of the effect size in the entire population (Schmidt & Hunter, 1977; Yu et al., 2016).

The benefit of this to research is that we are able to correct for various errors (e.g., measurement error, sampling error) which can significantly affect a given study and biases (e.g., publication bias) in research and thereby identify the population parameter estimate of a relationship—the overall size of an effect between two variables—as well as the precision of that effect (i.e., the number of subpopulations which one would expect to be above or below a certain range of effect sizes). Often meta-analyses are used to quantitatively synthesize a literature, theoretical framework, or to help resolve discrepancies in past primary studies which may have found conflicting results. Our study uses already existing meta-analytic estimates of the mean effect size (i.e., ρ or "rho") and the precision (or sometimes referred to as "heterogeneity") of this effect size (i.e., SD_ρ, used to construct credibility intervals around ρ). In this way, we can determine the most valid and precise estimate for a given relationship. However, a drawback to conventional meta-analyses is that it analyses only bivariate relationships. In this way, meta-analysis allows us to understand the nature of bivariate relationships. However, it does not allow us to understand simultaneous effects among an entire multivariate model, such as the JD-R model. Thus, when combined with the benefits of SEM (i.e., simultaneously analyzing the interrelationships among multiple variables for a given model), MASEM allows us to understand the best estimate of all relationships in a given multivariate model. In addition, the Yu et al. (2016) technique also accounts for heterogeneity of effect sizes, which allows us to further understand the precision or distributions of those relationships in the model.

As such, SEM is often used to test or confirm models. In our case, there is ample evidence through a multitude of previous meta-analyses that the overall premises of the JD-R model are supported. Thus we are not testing the JD-R model, per se, but rather testing to see how the previously confirmed relationships in that model differ—particularly in light of burnout and engagement—once all the relationships are accounted for simultaneously in the model. Until recently, techniques which allowed researchers to do such analyses were lacking (Cheung, 2014). Earlier attempts at MASEM firstly relied on the assumption that each bivariate effect size was independent from the other relationships in the model, which has been criticized as an inaccurate assumption for many of the models scholars often test (Cheung & Chan, 2005). Furthermore, the conventional technique also relied on an imperfect logic: studies employing conventional MASEM first analyzed bivariate relationships and their heterogeneity (i.e., tests for moderation), and then conducted a multivariate SEM which "technique requires the assumption that the bivariate relationships are drawn from a population with zero effect size heterogeneity" (Yu et al., 2016; p. 2). In other words, tests of moderation in meta-analyses are typically a test to find certain subpopulations (e.g., samples in different cultures, samples from different industries) wherein the strength of the relationship differs. This test assumes that there is not one "true score", but an average score around which a range of scores—from different subpopulations—exist within a given interval (i.e., typically 80% credibility interval) (Borenstein et al., 2010; Schmidt & Hunter, 2014). However, previous attempts at MASEM took a "snapshot" of the data as if the average meta-analytic effect size were the one, true score across all subpopulations.

This logical inconsistency is addressed by techniques developed by Cheung (2014, 2015) and Yu et al. (2016). These techniques utilize a bootstrapping method to randomly sample values from the distributions of relationships in the theoretical model (using ρ and SD_ρ) and thereby create a distribution around each path estimate as it relates to all other estimates in the model. Put simply, the Yu et al. (2016) technique allows us to test an entire parametric model (i.e., based on population-level or meta-analytic estimates) and ascertain the level of variability for each relationship in that model (i.e., the heterogeneity of that relationship). In this way, we can determine *how* burnout and engagement differ in their distinct nomological networks on average—as we test a MASEM which accounts for the non-independence of all effects in the model simultaneously, a crucial aspect when analyzing burnout and engagement in particular. Furthermore, by accounting for the heterogeneity of population effect sizes, this technique allows us to estimate the extent—as a percentage of subpopulations determined by intervals

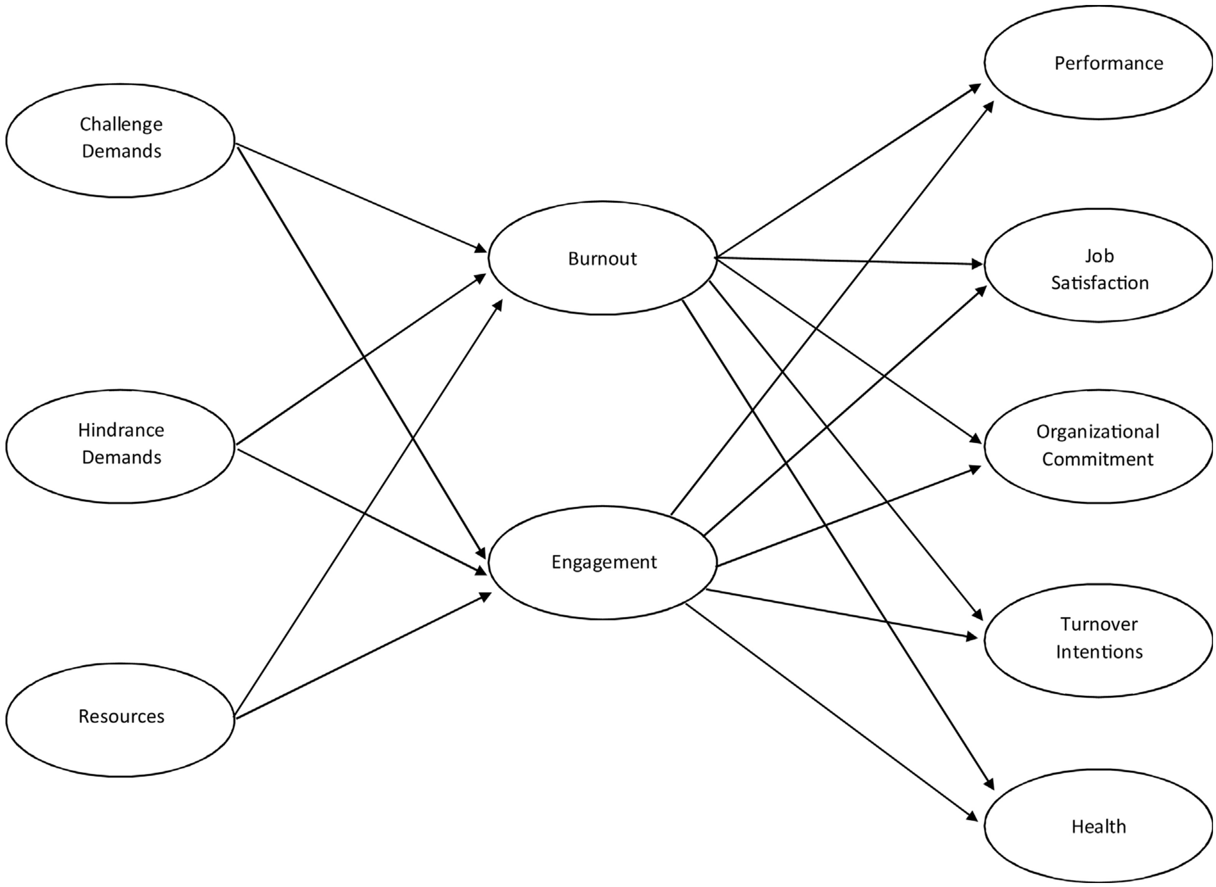

Fig. 1. Proposed Differentiated JD-R Model.

calculated around the average effect size of the path coefficient (e.g., ± 1.285 SD for conventional 80% CVs)—that subpopulation moderators exist within a given range of effect size.

Furthermore, our study addresses a limitation raised by Cole et al. (2012) who analyzed a coarser set of antecedents (i.e., demands and resources) of burnout and engagement, but noted the need to use finer categories of variables, such as by differentiating types of demands. We build off of the work by Crawford et al. (2010) who tested a

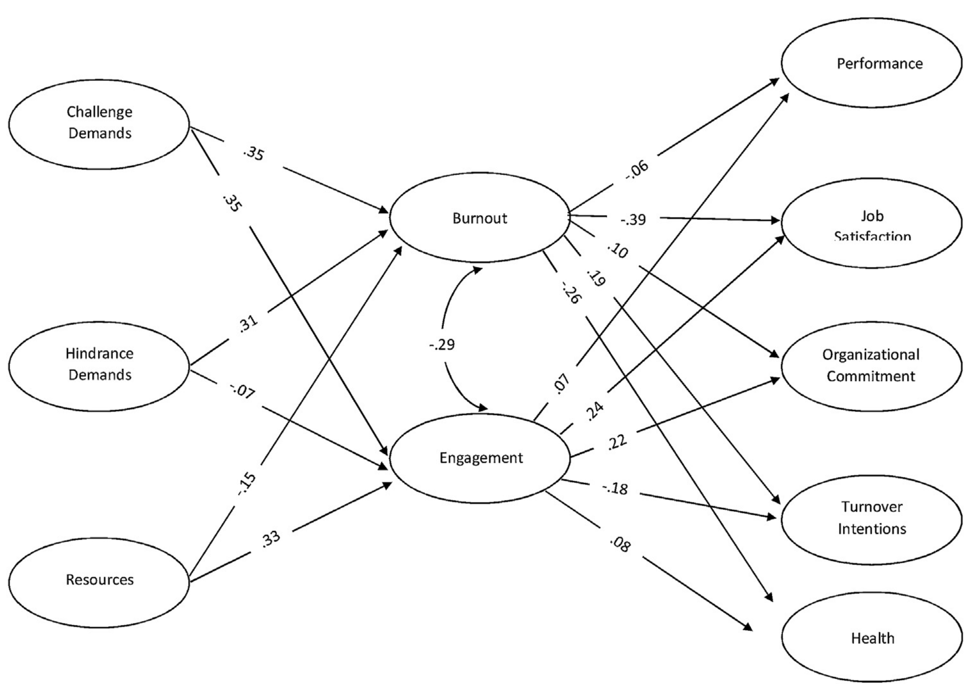

Fig. 2. Results of MASEM Mean Average ß Model of Differentiated JD-R Framework **Note.** Values are average standardized beta coefficient for the entire population distribution of possible values.

differentiated JD-R model using path analyses by separating *types* of demands (i.e., challenge vs. hindrance demands). We further expand the model to include performance behaviors, an outcome which has not been included in any existing meta-analyses which have simultaneously investigated burnout and engagement in the same study. By including outcomes beyond job attitudes (i.e., performance, health) our JD-R model is consistent with many aspects outlined by a review of the JD-R literature by Taris and Schaufeli (2016). Essentially, we are expanding our current understanding of a full range of antecedents and outcomes of burnout and engagement within the JD-R model by using a technique which allows us to simultaneously test the entire differentiated JD-R model while accounting for the interrelationships and variance for each relationship within the model.

In summary, we are using a technique which is particularly suited to accomplish our purpose (i.e., to test how the nomological networks of burnout and engagement differ) which addresses the weaknesses of conventional meta-analysis yet maintains its strengths. We use the differentiated JD-R model as our theoretical framework. We test this differentiated JD-R model with the Yu et al. (2016) MASEM technique and present the finished model which represents the overall nature of relationships among burnout, engagement, their antecedents, and outcomes based on meta-analytically derived correlations and standard deviations. The results are presented first in the summarized figure (Fig. 2) which provides the average strength of relationships in the entire population, indicating the overall pattern of *how* burnout and engagement differ in their relationships to other variables. Second, we provide a summary of *how often* these relationships differ, as a distribution of effect sizes around the mean effect size, in Fig. 3. This allows us to see the degree to which the average strength of relationship varies across subpopulations. We conclude with implications for practice, research, and avenues for future research.

2. Methods

2.1. Procedure

The MASEM procedure of Yu et al. (2016) which we use in the current study consists of four main steps. The first step is to conduct meta-analyses or find existing meta-analytic estimates for all relationships being tested in the theoretical model. We found existing meta-analytic estimates for the JD-R model variables we included in our theoretical model (Fig. 1). These estimates are contained in the meta-analytic correlation table provided as Table 1. As our model contains variables which are psychological in nature, we found existing meta-analyses which used the Schmidt and Hunter (2014) psychometric meta-analytic approach which corrects for potential error in measuring latent variables. For any relationships which we were not able to obtain from existing studies, the research team followed rigorous coding and inclusion procedures to conduct "mini-meta-analyses" to obtain ρ and SD_ρ to be used as input for the meta-analytic correlation tables in the next step.

The next step is to then pool the effect size estimates and their corresponding variances (i.e., ρ and SD_ρ) into a complete meta-correlation table. It is important that the entire table be filled out so that there is a meta-analytically derived estimate in each cell of the table, for both ρ and SD_ρ. See Table 1 for the matrix with corresponding citations used in our study. The third step is to specify the model to be tested, identifying regression paths and covariance paths. The last step is to initiate the MASEM bootstrapping technique using the FIMASEM program in *R* to resample the ρ and SD_ρ matrices; Yu et al. (2016) recommend setting the bootstrapping simulation to 500 iterations.

This technique is consistent with Bayesian logic, meaning that the strength of this technique is in determining the distribution of values around the average path coefficient using credibility intervals. Each iteration of the simulation represents the meta-analytically resampled relationships among the model variables for a potential subpopulation. After all resampling iterations are complete, the Yu et al. (2016) technique provides an average for each standardized path coefficient (*ß*) and its variance ($SD_ß$). However, the interpretation is more nuanced than simply taking the average path coefficient; the average path coefficient is the mean of a population distribution of path coefficients. We construct 80% credibility intervals (CVs) which represent 80% of the entire population of all samples which fall within that range of effect sizes.

We use the mean path coefficient to first interpret the overall JD-R model on average considering all subpopulations, thereby answering the overarching research question: *how* do burnout and engagement differ within their distinct nomological networks? The average SD_ρ for a given relationship is then used to construct 80% CVs around this mean average standardized path coefficient; this represents the distribution of potential path coefficients in various subpopulations. Relatively wide variability in the range for a given path coefficient—particularly if that range overlaps with zero—indicates substantial subpopulation variation, meaning likely moderating factors for that relationship. Thus the interpretation is presented in terms of *how* burnout and engagement differ—in terms of the average of the estimates in the model—and *when*—as an estimated percentage of subpopulations where a given relationship falls within a certain range of values.

2.2. Identification and inclusion criteria of meta-analytic estimates

In order to complete the first and second steps of the MASEM procedure, the research team held to a protocol to systematically identify and select existing meta-analytic estimates for each relationship. Fig. 4 provides a flowchart of our searches. The protocol's first step was to search online databases (i.e., PsycINFO, Google Scholar, ABI Inform) to find any existing meta-analyses for a given relationship in our meta-correlation table of JD-R variables. We searched for keywords for a given bivariate relationship (e.g., "challenge demands" and "hindrance demands") *and* if the title contained a "meta"-related keyword (e.g.; "meta" or "meta-analytic" or "meta-analysis" or "quantitative review"); in accordance with titling requirements and meta-analytic reporting standards (MARS; American Psychological Association, 2008). This returned 1405 meta-analyses (see Fig. 4). We then applied a filter to find only those meta-analyses which had cited any version of Schmidt and Hunter; effectively narrowing down the number of studies to only psychometric meta-analyses. For example; Google Scholar has a "Cited by" function which allowed us to conduct our keyword search for only articles which had cited Schmidt and Hunter (2014); we made an assumption that a meta-analytic study which used this method would necessarily have to cite it. This returned 288 studies. We then sorted through each of these by title and abstract to filter out any which were irrelevant (e.g.; meta-analyses which were region- or country-specific or occupation-specific); resulting in 132 potentially relevant meta-analyses (i.e.; approximately 3 meta-analyses per relationship on average across the 45 relationships of interest).

Next, in the event multiple meta-analyses existed for a particular relationship—which was almost always the case except for the Crawford et al. (2010) meta-analysis which was the only currently published study providing estimates for the relationships between challenge demands and hindrance demands to resources, burnout, and engagement—the meta-analysis with the highest *k* (i.e., highest number of studies analyzed) was selected. A higher *k* provides a more accurate and reliable population estimate (Schmidt & Hunter, 2014). These estimates were then input into the meta-correlation table needed to conduct the MASEM. This resulted in a final number of 10 meta-analyses used which covered 26 of the 45 relationships in the table, as some studies covered multiple relationships. Finally, there were two studies of these ten which did not clearly report $SD\rho$; in these cases we calculated an estimate for it using the interval data reported (e.g., 80% CVs).

We note here that the preponderance of meta-analytic data on

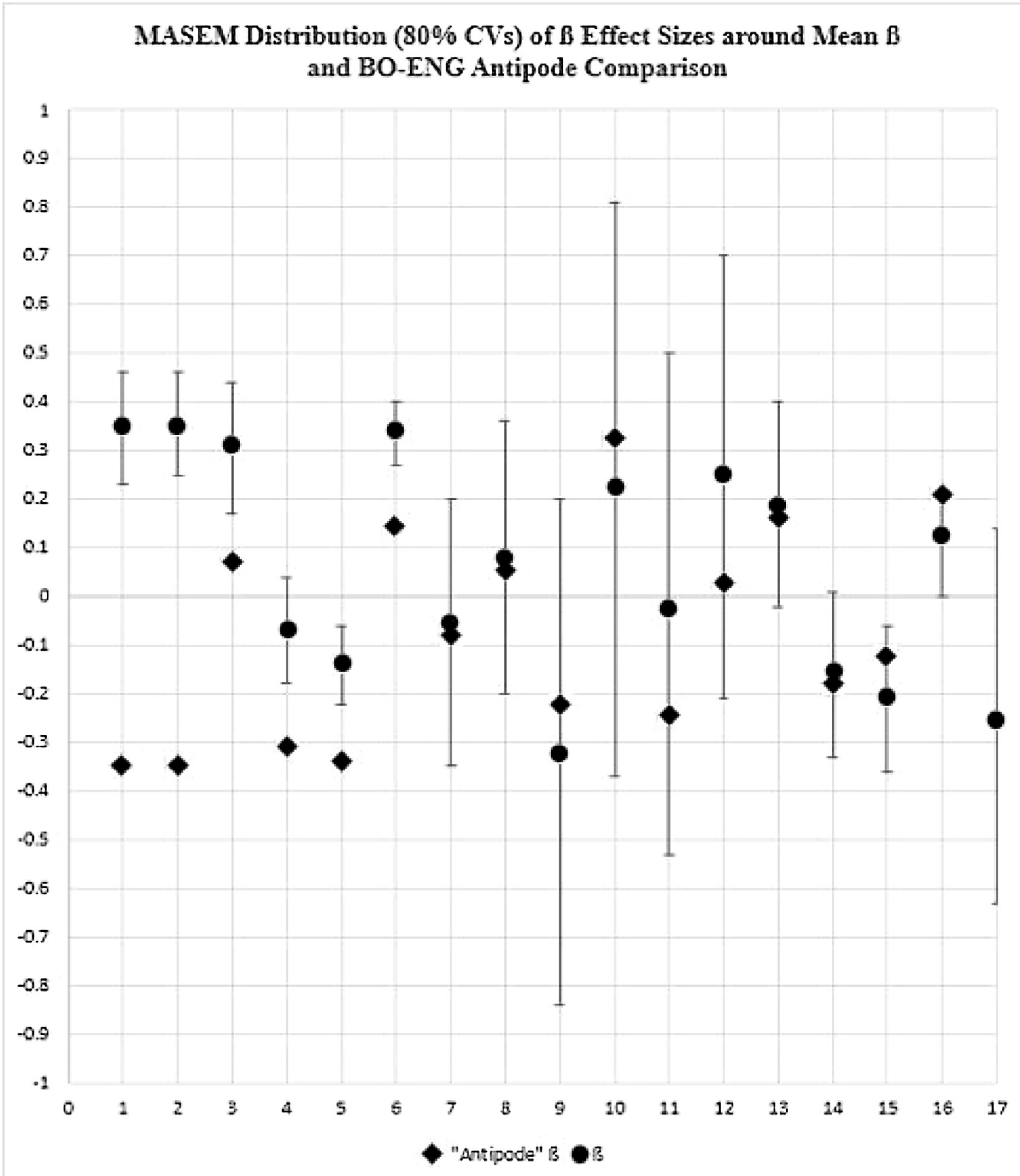

Fig. 3. MASEM Distribution of Effect Sizes around Average ß, with "Antipode" Comparison **Note**. Relationship number is on the *x*-axis and represents variable paths in the MASEM; the magnitude of the standardized beta (ß) effect size calculated from the MASEM is on the *y*-axis. The error bars represent the range within which 80% of all subpopulation parameters fall: only 10% of all subpopulations will have ß values greater than the upper value error bar, and only 10% of all subpopulations will have ß values less than the lower value error bar. A wide range which includes 0 indicates high variability in the greater population of effect sizes. To compare the overall relationships as more "antipodal" or distinct, the value with the corona represents engagement as if it were the antipode of burnout in a given burnout relationship, calculated by multiplying the engagement ß value by −1. When the corona overlaps with the burnout ß point estimate for a given relationship, this indicates a relationship where engagement may behave more as the antipode of burnout on average. The path coefficients are presented in the following order: 1) Challenge demands → Burnout, 2) Challenge demands → Engagement, 3) Hindrance demands → Burnout, 4) Hindrance demands → Engagement, 5) Resources → Burnout, 6) Resources → Engagement, 7) Burnout → Task performance, 8) Engagement → Task performance, 9) Burnout → Job satisfaction, 10) Engagement → Job satisfaction, 11) Burnout → Organizational commitment, 12) Engagement → Organizational commitment, 13) Burnout → Turnover intentions, 14) Engagement → Turnover intentions, 15) Burnout → Health, 16) Engagement → Health, 17) Burnout←→ Engagement covariation.

engagement and burnout correlations consist of the UWES and MBI, respectively, as noted in the meta-analyses corresponding to those relationships (i.e., Alarcon, 2011; Christian et al., 2011; Cole et al., 2012; Crawford et al., 2010; Mackay et al., 2016; Swider & Zimmerman, 2010). For example, Crawford and colleagues state that at the time of their meta-analysis, engagement was "measured predominantly using the Utrecht Work Engagement Scale," (2010, p. 838), that burnout was measured "almost exclusively using some form of the Maslach Burnout Inventory" (p.839), and that their "results and conclusions (were) virtually identical" (p. 839) whether they used the UWES or other engagement measures or MBI or other burnout measures in their analyses. Furthermore, the other meta-analyses listed state similar methods and findings. In other words, most of the engagement data in existing meta-analyses appear to have been measured with the UWES and the burnout data with the MBI; whether other measures were included or not does not seem to substantively change findings. Therefore, we must assume that since we are using these estimates as our input for the current MASEM, that the findings of the current study

Table 1
Matrix of meta-analytically derived population estimates (ρ) and standard deviation (SDρ) used to construct MASEM.

Variable	1	2	3	4	5	6	7	8	9	10
1. Challenge demands	**1.00**	0.09	0.05	0.06	0.05	0.12	0.04	0.06	0.06	0.22
2. Hindrance demands	0.23[a]	**1.00**	0.07	0.07	0.04	0.14	0.06	0.04	0.04	0.05
3. Resources	−0.01[a]	−0.13[a]	**1.00**	0.04	0.03	0.06	0.02	0.04	0.04	0.06
4. Burnout	0.16[a]	0.30[a]	−0.27[a]	**1.00**	0.03	0.14	0.13	0.14	0.15	0.12
5. Engagement	0.16[a]	−0.19[a]	0.36[a]	−0.48[a]	**1.00**	0.11	0.19	0.05	0.11	0.09
6. Task performance	0.15[b]	−0.15[b]	0.16[b]	−0.25[c]	0.26[d]	**1.00**	0.21	0.10	0.15	0.00
7. Job satisfaction	−0.06[b]	−0.17[b]	0.35[b]	−0.47[e]	0.53[f]	0.30[g]	**1.00**	0.13	0.10	0.06
8. Organizational commitment	0.00[b]	−0.19[b]	0.37[b]	−0.36[e]	0.54[d]	0.18[h]	0.65[i]	**1.00**	0.08	0.15
9. Turnover intentions	0.14[b]	0.24[b]	−0.27[b]	0.34[e]	−0.35[d]	−0.15[j]	−0.19[j]	−0.23[j]	**1.00**	0.24
10. Health	−0.06[b]	−0.21[b]	.03[b]	−0.32[k]	0.22[k]	0.07[b]	0.07[b]	0.24[b]	−0.17[b]	**1.00**

Note. All correlations were calculated using the Hunter-Schmidt method. Health variable includes reverse-scored health complaints. Beneath the diagonal are the values for the population estimate (ρ), above the diagonal are the values for the corresponding standard deviation (SDρ). If SDρ was not reported in a given study, it was calculated by the authors using the reported 80% CVs.

[a] Crawford et al., 2010.
[b] estimates calculated for current study.
[c] Swider and Zimmerman (2010).
[d] Mackay et al., 2016.
[e] Alarcon (2011).
[f] Christian et al., 2011.
[g] Judge, Thoresen, Bono, & Patton, 2001.
[h] Riketta (2002).
[i] Meyer, Stanley, Herscovitch, & Topolnytsky, 2002.
[j] Griffeth, Hom, & Gaertner, 2000.
[k] Cole et al., 2012.

also deal primarily, if not nearly exclusively, with the UWES and MBI as the measures of the respective constructs of engagement and burnout.

After searching for existing meta-analyses to fill in the meta-correlation table (Table 1), there were still 19 relationships remaining for which meta-analytic estimates did not exist. For these, we conducted "mini-metas" (i.e., coded only minimal data such as the sample size, correlation between the two key variables, and scale reliabilities) in order to run a meta-analysis to ascertain the appropriate ρ and SDρ values for each remaining relationship. After we identified the relationships for which there were no existing meta-analytic estimates, we then conducted keyword searches using the same electronic databases (i.e., PsycINFO, Google Scholar, ABI Inform) as before. However, for this set of searches, we were searching for primary studies (i.e., not meta-analyses) which contained bivariate, quantitative data for the two variables of interest. Therefore, in order to increase the likelihood that our search would return studies with quantitative, empirical data for a given relationship we added essential psychometric keywords (e.g., "α" or "alpha" or "Cronbach") to the search. This still resulted in over 270,000 potential studies (across the remaining 19 relationships) which might contain relevant data. We then searched the titles of these studies to eliminate irrelevant studies (e.g., studies pertaining to high schoolers). To expedite this process, we used Anne Harzing's "Publish or Perish" software (Harzing, 2007) which crawls Google Scholar and exports the data into more manageable data files; this resulted in a total of 2653 studies identified as potentially containing usable data which were considered for inclusion. Eventually, after sorting through these studies, we had a total of 302 studies which we coded to obtain the remaining 19 meta-analytic estimates found in Table 1. The lowest k was for the relationship between job performance and health ($k = 8$), the highest was resources and turnover ($k = 27$), the mean average k was 15.9 (i.e., meaning on average each estimate was based on 16 studies) and the median was 16.

Regarding task performance, we only included other-report measures (i.e., often supervisor-reported measures) of individual-level task, in-role, or job performance. Extra-role behaviors (i.e., organizational citizenship behaviors, OCBs) or measures of deviant behaviors (i.e., counterproductive work behaviors, CWBs) were not included in our analyses. Regarding health, we restricted our inclusion to *physical* health which consisted of either objective measures (e.g., cardiovascular indicators of health) or self-reported physical health complaints (e.g., sleep problems, aches and pains) which we then reverse-coded. We did not include mental health measures (e.g., depression, life satisfaction, mental stressors). Cole et al. (2012) included both *physical* and *mental* indicators of health; however, given the "fuzziness" of this construct and its potential overlap with JD-R antecedents (e.g., work overload, time stressors), we limited our inclusion to only *physical* indicators of health.

2.3. Analysis

The Yu et al. (2016) technique utilizes a series of bootstrapping simulations, with a recommended number of 500 iterations. The technique is based on Bayesian logic which does not report a test of significance, as its primary use is to answer questions beyond "if" a relationship differs from a null hypothesis (e.g., if the relationship between demands and engagement does not differ from 0). Previous meta-analyses have already established significance (i.e., relationships which exist beyond chance) for nearly all relationships between burnout, engagement, and their antecedents and outcomes. Our study is concerned about seeing *how* and *how often* (i.e., "when") these relationships differ while accounting for all of the other relationships in an entire model. Thus we note here that an interpretation of "significance" of path coefficients in MASEM is less appropriate, as the reported value is in fact the average *parameter* estimate among an entire distribution of effect sizes created using 80% CVs (Yu et al., 2016).

Because we are reporting on the distribution of effect sizes to gain an understanding of both how and when a relationship differs, consistent with Bayesian logic we report and interpret the results in terms of distributions (Yu et al., 2016; Zyphur & Oswald, 2015). That is, results are displayed as an average, standardized beta (*ß*) for a given path coefficient in our model (Fig. 2). Then the width of the distribution for all effect sizes contained in 80% of the population is given (Fig. 3). This distribution provides us with the degree of variability of a given relationship in 80% of all possible subpopulations. In this way, the average *ß* value answers *how,* on average, burnout and engagement differ, and represents the mean value of a given distribution. The 80% $CV_{ß}$, constructed with the $SD_{ß}$ around the average *ß* value, answers *when* or rather *how often* they differ and represents the percentage of subpopulations which fall within a given range of effect sizes.

For example, if the *ß* value for the path between variables $A \rightarrow B$

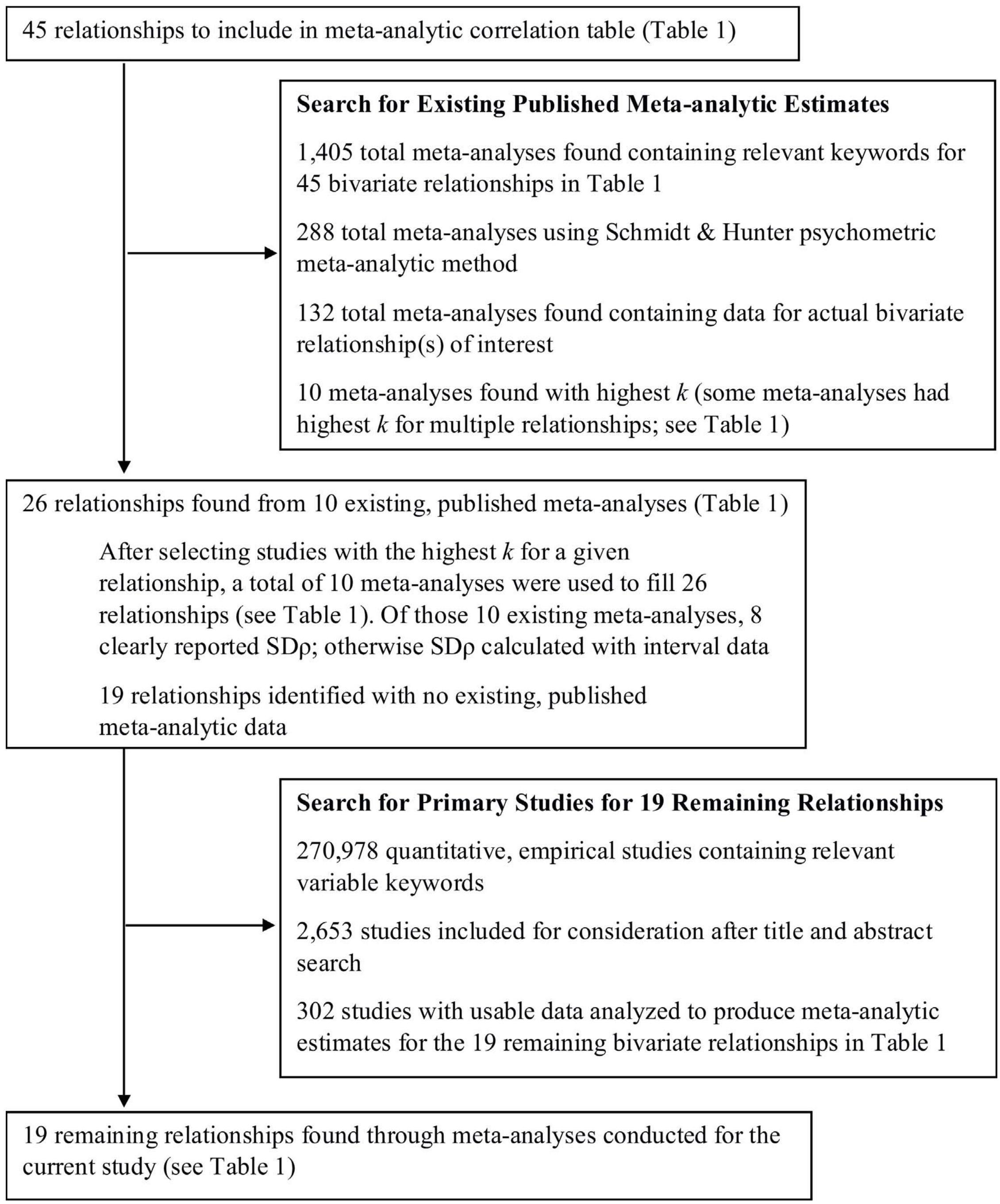

Fig. 4. Flowchart of included meta-analytic estimates to conduct MASEM.

were 0.50, this would indicate that as all other variables in the model are held constant, a 1-SD increase in *A* would result in a 0.50-SD increase in *B* on average. In addition, if the 80% $\text{CV}_{ß}$ for this same $A \rightarrow B$ relationship were [.44, 0.56], then this would mean that for approximately 90% of the population this relationship is greater than or equal to 0.44 (i.e., the 80% of subpopulations included in the interval from 0.44 to 0.56, *plus* the upper 10% of subpopulations above 0.56). Furthermore, as all path coefficients are standardized we can easily compare the relative strength of any number of relationships in the model. For example, in the same model an $A \rightarrow C$ path of 0.25 would indicate that *A* has twice the magnitude of effect on *B* than on *C* on average in the population. This use of Bayesian logic is consistent with recent calls to move beyond simple null hypothesis testing (e.g., Orlitzky, 2012) to help us gain a more accurate and nuanced understanding of psychological phenomena. Results are presented below in light of the study's research questions and summarized in Table 2.

3. Results

Results pertaining to our first research question—how do the nomological networks of burnout and engagement differ overall—are presented in Table 2 and summarized by Fig. 2. The standardized beta coefficient (*ß*) reported in the figure represents the average *ß* value for a given relationship in the model after 500 iterations in the MASEM bootstrapping simulation. We begin by reporting the average strength of the various path coefficients in the model, which allows us to interpret broadly *how* the nomological networks of burnout and engagement differ on average. We will then continue from there to a more nuanced view of the degree of subpopulation variability for each relationship in the JD-R model.

Table 2
Results of mean average ß path coefficients, $SD_{ß}$, and corresponding 80% CVs.

	Relationship	Avg. ß	$SD_{ß}$	80% $CV_{ß}$	80% $CV_{ß}$ width
Burnout Antecedents					
	Challenge demands	0.35	0.10	0.22, 0.47	0.25
	Hindrance demands	0.31	0.10	0.18, 0.44	0.25
	Resources	−0.15	0.06	−0.22, −0.07	0.16
Engagement Antecedents					
	Challenge demands	0.35	0.08	.24, 0.46	0.21
	Hindrance demands	−0.07	0.07	−0.16, 0.03	0.19
	Resources	0.33	0.05	0.27, 0.40	0.13
Burnout Outcomes					
	Task performance	−0.06	0.25	−0.38, 0.26	0.64
	Job satisfaction	−0.39	0.43	−0.94, 0.15	1.10
	Org. commitment	0.10	0.44	−0.47, 0.67	1.14
	Turnover intentions	0.19	0.19	−0.06, 0.43	0.49
	Health	−0.26	0.20	−0.51, −0.01	0.50
Engagement Outcomes					
	Task performance	0.07	0.21	−0.19, 0.33	0.53
	Job satisfaction	0.24	0.45	−0.33, 0.81	1.15
	Org. commitment	0.22	0.38	−0.28, 0.71	0.99
	Turnover intentions	−0.18	0.15	−0.37, 0.01	0.38
	Health	0.08	0.19	−0.16, 0.32	0.48
Burnout-Engagement		−0.29	0.28	−0.65, 0.06	0.71

Note. Results using the Yu et al. (2016) bootstrapping simulation technique using the recommended 500 resampling iterations. Avg. ß = the mean average standardized beta coefficient for the entire population distribution of ß coefficients for a given relationship within the differentiated JD-R model. $SD_{ß}$ = standard deviation of the distribution of ß coefficients; 80% CV = 80% credibility interval, representing 80% of all subpopulations falling within this range of effect sizes for a given relationship in the model.
80% $CV_{ß}$ width less than 0.18 indicates small heterogeneity (i.e., consistency in relationship strength and direction across all subpopulations), between 0.18 and 0.54 indicates moderate heterogeneity (i.e., moderate potential subpopulation differences), and greater than 0.54 indicates large heterogeneity (i.e., significant subpopulation differences in relationship effect size and/or directionality).

3.1. Antecedents of burnout and engagement

The mean average strength of relationships of the paths from challenge demands to burnout and challenge demands to engagement was 0.35 for both paths. In other words, challenge demands have an equivalent, positive effect on both burnout and engagement. The path from hindrance demands, however, was positive for burnout ($ß = 0.31$) and negative for engagement ($ß = -0.07$), on average. Conversely, on average the path between resources and burnout was negative ($ß = -0.15$) and positive for engagement ($ß = 0.33$). Thus, regarding antecedents, instead of a pattern of exact opposite relationships—as would be expected from an antipodal view—there appears to be unique patterns for each construct. Perhaps one of the more interesting findings is that challenge demands has quite far from an exact opposite relationship to burnout and engagement, but rather an equivalent, positive effect on both.

3.2. Outcomes of burnout and engagement

The mean average strength of relationships for the paths between burnout and job performance was −0.06, and 0.07 for engagement. We also examined the mean average strength of paths between burnout and engagement to three important job attitudes: job satisfaction, organizational commitment, and turnover intentions. The path from burnout to job satisfaction was negative ($ß = -0.39$), whereas the path from burnout to organizational commitment, on average, was interestingly positive ($ß = 0.10$). The paths from engagement to job satisfaction and organizational commitment were both positive (respectively $ß = 0.24$, $ß = 0.22$). The path from burnout to turnover intentions was on average positive ($ß = 0.19$) but negative, albeit in almost the same absolute magnitude, from engagement ($ß = -0.18$). Finally, the relationship to physical health was not surprisingly negative for burnout ($ß = -0.26$) and albeit weaker in magnitude, positive for engagement ($ß = 0.08$). Now to understand the more complex picture, we must look at the width of the credibility intervals, or in other words the distribution of effect sizes for a given relationship to clarify the variability of these relationships within the population.

3.3. Variability in effect size among various subpopulations

Using the Yu et al. (2016) technique, we can discern relationships in the JD-R model which have high levels of variability in effect size in the population. High variability (i.e., 80% $CV_{ß}$ widths ≥ 0.55; Bosco et al., 2015; Yu et al., 2016)—particularly if the 80% $CV_{ß}$ includes estimates where the sign (+/−) of the path estimate switches—indicates the presence of significant boundary conditions within the population. The implication, as discussed below, is that there are certain subpopulations (e.g., samples within certain industries, cultures, or various individual differences) which moderate such relationships within the JD-R model. We identify relationships based on suggested benchmarks set forth by Bosco et al. (2015) as an update to Cohen's (1992) conventional benchmarks, and calculated for use in interpreting MASEM effect size distributions by Yu et al. (2016) per the following: small heterogeneity (i.e., the relationship is consistent across the entire population; 80% $CV_{ß}$ width of less than 0.18), moderate heterogeneity (i.e., 80% $CV_{ß}$ width between 0.18 and 0.54), and large heterogeneity (80% $CV_{ß}$ width greater than 0.54).

Regarding the antecedents to burnout and engagement, there is small to moderate heterogeneity as well as consistency in the sign of the relationships. As can be seen in Fig. 3 for a side-by-side comparison, the two relationships between challenge demands → burnout and challenge demands → engagement (number 1 and number 2 in the figure, respectively) show nearly identical distributions. Both distributions have a mean average ß of 0.35 and the 80% $CV_{ß}$ s range from (0.22, 0.47), (0.24, 0.46), respectively. This means that of all subpopulations, only 10% will show a strength of relationship below 0.22 for challenge demands to burnout or below 0.24 for challenge demands to engagement. Furthermore, although on the low end of the benchmark for moderate heterogeneity of effect size for both relationships (80% $CV_{ß}$ width of 0.25 for challenge demands → burnout, 0.21 for challenge demands → engagement; see Table 2), this does indicate there may be some slight subpopulation differences which act as boundary conditions for these relationships.

Regarding the effects of hindrance demands on burnout and engagement, interestingly hindrance demands has a nearly equivalent effect as challenge demands on burnout, with only slightly greater variability. However, hindrance demands has an equivocal relationship to engagement: as seen in Fig. 3, for the majority of subpopulations hindrance demands has a weak, negative relationship with engagement. However, in at least 10% of subpopulations it is either null or positive. Regarding resources, resources → burnout is consistently negative, showing at least a weak, negative relationship to burnout within at least 97.5% of the population (using 1.96 $SD_{ß}$ to determine 95% intervals). There is small heterogeneity in this distribution, meaning there is little variation in this effect across the entire population. Similarly but in a positive direction, the relationship from resources → engagement shows a consistently positive distribution of effect sizes around the mean ß of 0.34 with an even smaller—in fact the tightest distribution in the entire JD-R model—(80% $CV_{ß}$ interval width = 0.13). This indicates that the relationship from work resources leading to engagement is very consistent and generalizable across the entire population. In all, the paths from the JD-R antecedents to burnout and engagement are surprisingly consistent.

However, the paths *from* burnout and engagement *to* their outcomes are not as consistent, and in fact speak to the large amount of research yet to be done in exploring the boundary conditions (i.e., moderators) influencing such large heterogeneity of effect size in the population. After accounting for the effects of all variables in our MASEM, burnout and engagement are actually relatively poor predictors of task performance (-0.06, 0.07, respectively) with distributions which range from positive to negative for both sets of paths. Regarding work attitudes, there was the greatest heterogeneity between burnout and engagement and the attitude of job satisfaction, with respective widths of 1.10 and 1.15—the largest of any in the JD-R model. This finding is somewhat troubling, because it indicates that for at least 10% of subpopulations, the relationship between engagement and job satisfaction is −0.337 or stronger. This finding flies in the face of our typical image of an engaged employee being one who is happily investing their energies into their work. However, for the 10% at the other end of the distribution, the relationship is 0.81 or stronger, supporting this image of engaged employees being almost one and the same as satisfied employees. Such large heterogeneity indicates the presence of extreme boundary conditions.

The distribution for the path from burnout → organizational commitment interestingly shows the second highest degree of variability, with values ranging within the 80% CV from nearly −0.47 to as high as 0.67. Engagement → organizational commitment was only slightly less variable, with a mean *ß* of 0.22, +/− 0.50 on either side. The paths *to* turnover intentions showed only moderate heterogeneity, with both the lower range of the distribution from burnout and the upper range of the distribution from engagement indicating a null or even change-in-sign effect (see relationship numbers 13 and 14, respectively, Fig. 3). Thus, practically speaking—and perhaps not surprisingly—in most of the population, burnout tends to have a positive effect on turnover intentions while engagement tends to have a negative effect on the same. Before discussing the final finding regarding the pattern of antipode vs. distinct states relationships between burnout and engagement, the final outcome we examined in the model was from burnout/engagement to health. The relationship from burnout → health is consistently negative, showing only moderate heterogeneity as to how negative the effect is within the population. That is, for at least 90% of all subpopulations, burnout has a negative effect on individual's physical health. Furthermore, this negative effect can be higher than −0.51 for 10% of subpopulations. The relationship from engagement → health was not as clear, however, indicating that sometimes engagement actually leads to poorer physical health.

3.4. Antipodes

Finally, regarding the supplemental assessment of whether engagement acts as the antipode of burnout within the JD-R model, we provide Fig. 3 which marks the opposite-score of engagement (with a corona-point) for a given burnout relationship. For example, relationship number 1 in the figure represents the distribution of *ß* effect sizes for the relationship of challenge demands → burnout. The data point from which 80% CV bars extend is the average *ß* value for burnout; the corona is the average *ß* effect size for engagement if engagement truly behaved as the antipode of burnout for this particular path (i.e., from challenge demands to burnout/engagement). To calculate this, we simply multiplied the engagement *ß* value for a given burnout relationship by −1; inasmuch as the engagement corona data point overlaps with the burnout average *ß* estimate, the two constructs behave as antipodes for that given relationship. In addition, if the corona falls within the distribution of effect sizes for a given burnout relationship, this also indicates some degree of "antipodality", at least for a given percentage of subpopulations. However, the exact degree or percentage of antipodality is difficult to determine; the only definitive conclusions which can be made here are that for task performance and turnover intentions, there is a high degree of overlap indicating that for these relationships at least, burnout and engagement do tend to behave more as antipodes. However, this is not the case for other variables in their nomological networks, particularly so for antecedents which show not a reverse pattern of relationships but in fact a similar pattern—as in the case of challenge demands.

4. Discussion

4.1. Key findings

The purpose of this study was to add to the growing body of work (e.g., Byrne et al., 2016; Cole et al., 2012; Shuck et al., 2017) which has helped to untangle the complex nature of relationships among the two central constructs of the JD-R model, burnout and engagement. We accomplished this through the use of MASEM which allowed us to meta-analytically determine the simultaneous interrelationships within the JD-R model. The overall finding is that burnout and engagement do in fact appear to operate distinctly in the population. This finding, in combination with previous meta-analytic findings (e.g., Crawford et al., 2010), substantiates the "distinct states" view proposed by Schaufeli and Bakker (2004); that is, burnout and engagement are moderately, negatively related constructs with distinct nomological networks.

This distinctiveness is most noticeable regarding their antecedents, although it is less clear regarding their outcomes. Regarding antecedents, quite interestingly challenge demands have a nearly identical relationship with both burnout and engagement. Not only is the population *average* for this relationship the same (i.e., *ß* = 0.35), but their distributions of effect sizes across various potential subpopulations (i.e., the 80% CVs) are nearly identical, with the relationship to engagement being only slightly tighter. This is interesting, because far from being "antipodal" (i.e., sharing perfectly opposite relationships), the effect of challenge demands on both constructs is equivalent in magnitude, likely simultaneous, and consistent throughout the population. This could indicate that beyond a certain level of burnout, any gains seen to engagement through increased challenge demands may be lost as the individual begins to experience exhaustion.

Regarding work resources, we see they can be used to both simultaneously increase engagement and—although to a lesser degree—reduce burnout. In fact, in terms of absolute value, resources have more than twice the strength of effect, on average, on engagement (in a positive direction; *ß* = |.33|) than on burnout (in a negative direction; *ß* = |.15|). In addition, it is noteworthy to point out that the width of the CVs for the relationships involving work resources are the narrowest among all the relationships in the JD-R model, meaning this pattern of relationships is relatively consistent throughout the population.

Hindrance demands, as expected, are a stronger predictor of burnout than they are of lower engagement, supporting findings from

Crawford et al. (2010). What is interesting in the MASEM results though, is that the distributions of effect sizes for the paths from hindrance demands to burnout and challenge demands to burnout (i.e., relationship numbers 1 and 3, respectively, in Fig. 3), are quite similar. What this means is challenge demands and hindrance demands have similar effects on burnout in terms of magnitude and consistency throughout the population.

In contrast to the consistency of the antecedents side of the JD-R model, our findings for outcomes of burnout and engagement were not as clear. Focusing first on work attitudes, burnout had a positive relationship to organizational commitment on average, but there is extreme variation in the population. Broadly, the extreme variation means the relationship is likely complex (e.g., a recursive relationship) and that there are most certainly a number of moderators influencing this relationship (e.g., high power-distance cultures). Another interesting finding is the high variability in the population for the path from engagement to job satisfaction. On average engagement leads to higher levels of job satisfaction, and for some subpopulations very high levels (i.e., 10% of subpopulations have a *ß* value above 0.81). However, considering the high degree of heterogeneity—in fact, the greatest level within the JD-R model—there are subpopulations for which high levels of engagement lead to lower satisfaction. One example might be emergency room doctors who may derive great meaning from their work and are required by the circumstance to show high levels of vigor and absorption in it, but who may find at the work exhausting and less satisfying than the work of their physician peers.

The work attitude which had the lowest heterogeneity between both burnout and engagement was turnover intentions. For the most part, the findings here are as expected: burnout leads to higher levels of turnover intentions whereas higher engagement leads to lower levels of turnover intentions. However, for slightly more than 10% of subpopulations, engagement has a positive effect on turnover intentions. Although the reasons people turnover are varied and complex, one possible explanation may be that engaged employees leave to find a more challenging job or occupation. Indeed, one potential subpopulation where this may be true is with Finnish managers: in Mäkikangas and colleagues' longitudinal study, they found Finnish managers' work engagement predicted their turnover over a two-year period (Mäkikangas, Schaufeli, Tolvanen, & Feldt, 2013). One interesting note regarding turnover intentions is that this is the one work attitude for which engagement and burnout do appear to act more as antipodes (see relationship numbers 13 and 14, Fig. 3), *on average*. The overlapping corona in relationship number 13 (Fig. 3) indicates this.

The key takeaway regarding attitudinal outcomes is that despite *average* effect sizes which we might expect (i.e., negative paths from burnout to positive work attitudes and positive paths from engagement to positive work attitudes) the moderate-to-high degree of heterogeneity indicates the presence of moderators affecting various subpopulations. Simply put, this means there are a large number of factors, no doubt many of which are yet to be examined, which moderate the relationships between burnout, engagement, and their effects on work attitudes.

Regarding task performance, an unexpected finding was the weak path coefficients from either construct—and particularly engagement—to task performance. Not only do burnout and engagement both share relatively weak effects on task performance, but there is a high degree of variability as well, including subpopulations where the relationship is nil. This finding is somewhat perplexing considering that one of the two primary mechanisms through which the JD-R model is theorized to operate—a health impairment process via burnout and a motivational process via engagement (Schaufeli & Bakker, 2004)—is not strongly supported, at least inasmuch as we can assume higher motivation leads to greater performance. The antecedent side of the JD-R supports this motivational process. That is, engagement is primarily influenced by a mix of challenge demands and resources, leading to the investment of one's energies into their work. However, engagement's effects on task performance is ambiguous. One possibility is that engagement may be a better predictor of extra-role performance (i.e., OCBs) or innovation behaviors than it is of in-role performance. In fact, Christian et al.'s (2011) meta-analysis on engagement and performance indicates that, at least for studies which use a more rigorous time-lagged study design (see Table 6 of Christian et al.'s study), engagement has a stronger influence on contextual performance (i.e., OCBs; $\rho = 0.44$, $k = 3$) than on in-role performance ($\rho = 0.31$, $k = 3$).

Another possibility is that the complexity of the relationships between burnout, engagement, and performance is simply not captured by our MASEM. For example, over a period of time, engagement may initially lead to increased performance. However, eventually—in the absence of psychological maintenance to replenish spent resources—this same engaged level of performance leads to a gradual exhaustion, and perhaps the inability to maintain the same level of performance.

The health impairment process of the JD-R model, however, is much more strongly supported, from antecedents to outcomes. As we see in our JD-R MASEM, primarily influenced by the exhausting of one's psychological energy through increased hindrance demands, burnout consistently and relatively strongly leads to decreases in physical healthy functioning.

4.2. Practical implications

Through our MASEM investigation of JD-R theory, organizations interested in inculcating positive work attitudes, increasing retention of motivated employees, or reducing the costs of lower employee health should lower employee levels of burnout and raise their engagement through careful management of work demands and resources. Specifically, considering work resources have the most consistent effects of the entire JD-R model, organizations should find ways to increase resources as much as possible. This can be done by increasing social support (e.g., improved leadership training), improved work design (e.g., imbuing work with meaning), or by enhancing employee psychological capital (i.e., resilience, optimism) through training. The consistency of resources effects means that practitioners can be assured that these relationships will hold almost universally in the population—regardless of any moderating factor (e.g., culture, industry, employee individual differences). This may be due to the fact that resources, particularly those proposed by Kahn (1990), appeal to fundamental, innately human needs which are the hallmark of many intrinsic motivational theories (e.g., self-determination theory). All people, regardless of culture or profession, respond—as a fundamental part of being human—to necessary psychological "nutriments" of meaning, autonomy, and feelings of competence (Ryan & Deci, 2000).

Although the relationship of work resources is unequivocal and relatively simple, the management of challenge demands in an organization is more nuanced. Perhaps the most interesting finding of our MASEM study, we found that challenge demands are generally good, but only in moderation, as too much, too fast can also lead to burnout. In this way, challenge demands may operate as a TMGT effect (i.e., "too much of a good thing"; Pierce & Aguinis, 2013). Therefore, in practice it is important to not simply "apply more gas" (i.e., challenge demands), but to closely monitor an individual's levels of stress before providing additional challenges for them.

Regarding hindrance demands, although it may seem obvious, organizations should do all they can to eliminate hindrance demands entirely. However, considering that hindrance demands operate primarily through a health impairment process via burnout, organizations who are particularly interested in reducing burnout and its effects should focus here. Organizations whose interest is primarily in increasing engagement should focus primarily on resources, which have twice the magnitude of promoting the positive (i.e., engagement) than reducing the negative (i.e., burnout). Thus, overall organizations should do the following three things: 1) Eliminate hindrance demands (e.g., role ambiguity, role conflict, red tape) entirely, as much as possible; 2) increase work resources (e.g., social support via leadership, psychological resources via work design) as much as possible; and 3) monitor challenge demands carefully to ensure employees are challenged but do not "run faster than they have strength", so to speak.

The implications of these findings regarding the distinct nomological networks of burnout and engagement are that the interventions used in the workplace for each will in fact be different; that is, "because efforts to address deficits are quite different from those that promote gains" (Leiter & Maslach, 2010; p. 165), organizations seeking to reduce burnout will need to focus on the following two key recommendations: first, reduce hindrance demands (e.g., providing clarity on job roles, clarity on performance expectations, enhancing work-life balance, reducing office politicking and red tape); second, provide challenge demands (e.g., "stretch goals", increased job responsibility, challenging—albeit reasonable—timeframes to complete work goals) to employees *while monitoring* their levels of stress. The current study shows that this second step, to carefully monitor the stress levels in the presence of increased challenge demands, is of key importance—this finding is similar to the common wisdom in sports: it is essential to push one's limits, but a trained "spotter" or "coach" also knows how to prevent injury.

This study, by showing that engagement and burnout operate differentially—particularly regarding their initial causes or antecedents, answers the question proposed by Leiter and Maslach, "whether leading someone from a neutral state to work engagement uses the same processes as leading someone from burnout to a neutral state" (2010, p. 167). Indeed, for organizations whose focus then is to promote the positive, the two key recommendations we provide then to increase engagement are as follows: first, increase the levels of resources such as by increasing perceptions of increased meaning in employees' work, creating an atmosphere of psychological safety, or providing social support such as through servant leadership. Employees provided with these resources and support should then have what is necessary to accomplish work goals. Second, similar to the recommendation above regarding burnout, provide challenging demands while carefully monitoring stress levels. By following these recommendations, organizations can not only reduce ailments but strategically and proactively promote positive work states.

4.3. Future research

In light of other recent work on the nomological networks of burnout and engagement in combination with our quantitative synthesis using a MASEM, we conclude that the question truly is not *if* burnout and engagement differ, but *how* they differ and *when*. One of the most striking aspects of the JD-R MASEM is the consistency of effects of burnout and engagement's antecedents—which strongly supports JD-R theory—in contrast to the large heterogeneity in the outcomes. Thus, a ripe area for future research is in investigating the reasons behind this large heterogeneity. Potential moderators can be classified into two main categories of variables: personal factors or individual differences and situational or environmental factors.

As one example, a person high in the psychological resource of dispositional optimism—a stable, trait-like individual difference variable—is likely to adapt more effectively to handle the stressors of work than someone who is inherently more pessimistic (e.g., Forgeard & Seligman, 2012). As the scope of our study was to explore how and the degree to which burnout and engagement differ in the population, we did not investigate specific boundary conditions. However, our findings clearly indicate that there are such boundary conditions, many of which are yet to be discovered. The ideal finding would be one in which researchers could find under which personal and situational factors individuals can enjoy the maximum benefits of resources and challenge demands and optimally reduce the negative effects of hindrance demands. Examining the distributions of effect sizes (see Table 2), we see that there are at least 10% of subpopulations or samples (i.e., beyond the upper end of the 80% $CV_{ß}$) which have the right balance of personal and situational factors, with effects as high as or higher than $ß = 0.46$ and $ß = 0.40$ for challenge demands and resources on engagement, respectively. In other words, there are samples wherein a 1-SD increase in challenge demands and a 1-SD increase in work resources can cumulatively result in a 0.86-SD increase in engagement. As future research continues to uncover these moderating factors, this can have important practical implications for organizations seeking to both increase engagement and decrease burnout.

A second avenue for future research which we noticed while accumulating meta-data to conduct the MASEM was that the preponderance of primary studies are cross-sectional in nature. Certainly the process of burning occurs through a period of time, and one's levels of engagement can vary from moment to moment. Yet, cross-sectional data fails to capture these phenomological nuances. For example, an employee may begin with a high level of engagement in a challenging job. Yet throughout time these challenges simultaneosly erode their psychological resources leading eventually to decreased levels of performance. Although it is beyond the scope of the current study and in fact beyond the current capability of MASEM to model such a complex relationship between burnout, engagement, and performance, what is clear is that we may not be capturing these kinds of complex relationships in the primary studies conducted. Indeed, to conduct such studies will require more emphasis on longitudinal designs to capture such processes as they unfold over time. Future research can continue to examine, for example, how an individual can be engaged through challenging demands while simultaneously beginning the gradual process of burning out.

4.4. Limitations

The first limitation of this study, and any meta-analytic investigation, involves the quality of the original input. The quality of any meta-analysis relies on the quality of the primary studies included. As such, we wish to emphasize to areas which, although they are perennially included in discussion sections, we feel should be noted here. This study provides clarity regarding particularly the antecedents to burnout and engagement. There is a discernibly distinct pattern between challenge demands, hindrance demands, and resources and their relationships to burnout and engagement. Yet, this relationship is anything but clear regarding many of the outcomes examined. This is likely due to a level of complexity in these relationships which may not often be captured in most cross-sectional primary studies. Therefore, we urge the increased future use of longitudinal study designs.

In addition, we also note the need to use specific, theoretical reasoning—over convention—in determining which variables and measures of those variables are used. For example, concerning engagement specifically, if a study is focusing on the role of psychological needs-fulfillment and its influence on job performance through engagement, it may be more appropriate to use a conceptualization based on Kahn's (1990) work and a corresponding measure based on that conceptualization (e.g., JES measure by Rich et al., 2010) as this conceptualization specifically focuses on core psychological needs as antecedents to engagement in one's work performance. Schaufeli's conceptualization is broader and considers work more generally, not targeted toward a specific work role or task, which is "persistent and pervasive" (Schaufeli et al., 2002; p. 74). See Byrne et al. (2016) for further treatment of this issue.

Other limitations include the lack of individual difference variables in the MASEM we tested. No doubt, myriad individual differences moderate these relationships. Another limitation relates to the high variability found for the outcomes of burnout and engagement. This variability—particularly if the 80% CV included effect size estimates where the sign (+/−) of the path estimate switches—indicates the presence of significant boundary conditions. As this is the first MASEM of the JD-R model, it was outside the scope of our study to begin testing conditional indirect effects (i.e., moderated mediation MASEMs). However, testing these boundary conditions meta-analytically may be an area for future studies

5. Conclusion

In summary, this study first reviews the evidence that burnout and engagement are distinct constructs, in support of Schaufeli and Bakker's (2004) "distinct states" conceptualization. Our exploration of *how* burnout and engagement differ within their distinct nomological networks reveals a clear pattern that the root causes are different. This implication for practice is that the strategies to reduce burnout are not the same as those to increase engagement. The pattern of relationships for outcomes, however, is less clear. Our hope is this study not only helps to elucidate areas for future research and offer practical suggestions on improving the workplace, but that it also puts to rest—to some degree—the debate about *if* they differ. Indeed, burnout and engagement *do* differ, and the future for research and practice is to continue to understand better *how* they differ.

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