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A SENSITIVITY ANALYSIS FOR RELATIVE IMPORTANCE WEIGHTS IN THE META-ANALYTIC CONTEXT: A STEP TOWARDS NARROWING THE THEORY-EMPIRICISM GAP IN TURNOVER

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

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Abstract

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Turnover is one of the most important phenomena for management scholars and practitioners. Yet, researchers and practitioners are often frustrated by their inability to accurately predict why individuals leave their jobs. This should be worrisome given that total replacement costs can exceed 100% of an employee's salary (Cascio, 2006) and can represent up to 40% of a firm's pre-tax income (Allen, 2008). Motivated by these concerns, the purpose of this study was to assess the predictive validity of commonly-investigated correlates and, by extension, conceptualizations of employee turnover using a large-scale database of scientific findings. I developed a sensitivity analysis for relative importance weights in the meta-analytic context to answer two research questions. First, I explored the relative importance of 11 theoretically-important correlates of turnover intention. Second, I examined whether or not job satisfaction and organizational commitment are potentially empirically redundant when predicting turnover intention. Results for my first research question indicate that job satisfaction, organizational commitment, and embeddedness (e.g., person-job fit, person-organization fit) may be the most valid proximal predictors of turnover intention. Results for a tripartite analysis of the potential

empirical redundancy between job satisfaction and organizational commitment when predicting turnover intention align well with previous research on this topic (Le, Schmidt, Harter, & Lauver, 2010) and generally suggest that the two constructs may be empirically indistinguishable in the turnover context. Taken together, this study has important implications for the turnover and sensitivity analysis literatures. Specifically, results from this study indicate that job satisfaction, organizational commitment, and embeddedness have the highest degree of explanatory value for predicting turnover intention. In addition, the relative importance results suggest that the direct relations between turnover intention and work-life conflict and turnover intention and individual job performance should not be central to future conceptualizations of turnover intention. With regard to the sensitivity analysis literature, this study demonstrates the application of a sensitivity analysis for relative importance weights in the meta-analytic context. This new method takes into account variance around the meta-analytic mean effect size estimate when imputing relative importance weights and may be adapted to other correlation matrix-based techniques (i.e., structural equation modeling) that are often used to test theory.

Chapter 1. Introduction

Turnover is one of the most important phenomena for management scholars and practitioners. Its importance is partly due to its high costs and, therefore, its effect on organizational performance. The "shocking cost of turnover" (Waldman, Kelly, Aurora, & Smith, 2004, p. 206) has been highlighted by Cascio (2006), who showed that total replacement costs can exceed 100% of an employee's salary, and Allen (2008), who suggested that turnover-related costs can represent up to 40% of a firm's pre-tax income. Indeed, meta-analytic evidence has demonstrated a significant and negative relationship between turnover and organizational performance (Hancock et al., 2013; Park & Shaw, 2013). As such, the economic costs associated with employee turnover likely makes it one of the most important constructs in the organizational sciences (Allen, Bryant, & Vardaman, 2010). Recent data also illustrate that the importance of turnover may be increasing. For instance, data from the Bureau of Labor Statistics (2015) indicated that the U.S national annual turnover rate increased at a consistent rate over the past five years (after 2011 and before 2017). The data also suggested that the average quit rate for the first six months of 2016 was 8% higher (Δ 0.14% points; 1.91% vs. 2.06%) than that for the same period in the previous year. Therefore, an accurate understanding of turnover's antecedents and consequences is vital for research and practice.

For more than 50 years, researchers have attempted to determine why individuals leave their jobs. During this time, turnover research has changed considerably (Hom, Mitchell, Lee, & Griffeth, 2012). For example, a comparison of March and Simon's (1958) two predictor direct effects model and Allen and Griffeth's (2001) more recent moderated-three-path mediated effects model illustrates how turnover models have changed in complexity over the years. Other examples of change include (a) a shift from individual-level outcomes to a focus on the costs associated with unit-level turnover rather than individual-level turnover (Kacmar et al., 2006; Koys, 2001; Shaw, 2011) , (b) an increased focus on more complex relationships in turnover's nomological network, such as the inverted-U formulation of some turnover relations (Abelson & Baysinger, 1984; Dalton & Todor, 1979; Staw, 1980) , and (c) developments in statistical analysis techniques that allow the examination of cross-level moderating effects (Chang, Wang, & Huang, 2013). These changes have brought about a proliferation of theoretical approaches to turnover in order to better explain why individuals leave their job. Yet, this increased complexity has generally failed to increase our cumulative knowledge on turnover in a meaningful way (Holtom, Mitchell, Lee, & Eberly, 2008; Lee & Mitchell, 1994; Russell, 2013). Indeed, many important questions such as which variables are most important for predicting turnover remain unanswered. Meta-analytic reviews on turnover have also failed to produce well-supported conclusions. For instance, Russell (2013) reported that only 45% (20/44) of the meta-analytic effects reported by Griffeth, Hom, and Gaertner (2000) exhibited 95% credibility intervals that did not contain zero. Overall, turnover remains a polarizing subject that is fraught with inconsistent findings, leaving many scholars frustrated over their inability to predict more than 10-15% of variance in turnover (Holtom et al., 2008; Lee & Mitchell, 1994) and practitioners uncertain as to which practices they should implement to most effectively reduce dysfunctional turnover in their organizations.

According to Steel (2002), the problem facing turnover scholars is rooted in a "conceptual-empirical interface" (p. 347), where new turnover theories are developed before old ones are rigorously tested. I refer to this self-perpetuating backlog as the *theory-empiricism gap*

– a situation in which empiricists are unable to test theory at the same rate it is developed. Indeed, this state of affairs may be a by-product of our field's "theory fetish" (Hambrick, 2007, p. 1346). Evidence supports this claim given that only nine percent of the theoretical presentations in *Academy of Management Review* articles are ever tested (Kacmar & Whitfield, 2000). Consequently, one may conclude that our field's leading theoretical outlet provides little guidance with regard to evidence-based management for practitioners.

Similar to the science-practice gap that plagues human resource management in general (Kulik, 2014; Tenhiälä et al., 2014), the theory-empiricism gap depresses scientific and practical progress because it creates an abundance of theory that is not rigorously tested or, perhaps more importantly, replicated. It follows that this creates a "vast graveyard of undead theories" (Ferguson & Heene, 2012, p. 555), which complicates the theoretical landscape (Leavitt, Mitchell, & Peterson, 2010). Indeed, this may especially be true of turnover theories given that one of the leading theoretical perspectives – Mobley et al.'s (1979) conceptualization of the turnover process – has never fully been tested, which may suggest that theory on turnover provides little explanatory value. However, Rynes, Bartunek, and Daft (2001) suggested that our research methods can "increase the relevance and value of published research for both practitioners and academics" and, thus, may help to reduce the divide between both scientists and practitioners. Therefore, one interpretation of Rynes et al.'s (2001) assertion may be that scientists can help to minimize the adverse effects of the science-practice gap by employing research methods that provide accurate and/or robust estimates of scientific findings. I pursue this assertion by introducing a sensitivity analysis that can be used to provide a range of relative importance estimates in the meta-analytic context, a method often used to determine the explanatory power of a set of theoretically-relevant predictors (Banks et al., 2014). Specifically, I augment Tonidandel and LeBreton’s (2015) relative importance analysis method so that it provides lower and upper bound relative weight estimates and apply the sensitivity analysis to a collection of theoretically-relevant turnover intention correlates to address the theory-empiricism gap facing this important area of research.

A difficulty in identifying the conceptual space for some constructs may exacerbate the problems presented by turnover’s theory-empiricism gap. This concern is often referred to as the jingle-jangle problem (Block, 1996; Kelley, 1927; Thorndike, 1913). The jingle fallacy refers to the belief in which two constructs that share the same label refer to two different things. For example, engagement has been used to measure both an individual’s state-like (Sonnentag, Dormann, & Demerouti, 2010) and a trait-like (Schaufeli, Salanova, González-Romá, & Bakker, 2002) “state of mind … in the experience or performance of work” (Christian, Garza, & Slaughter, 2011, p. 95). In contrast, the jangle fallacy refers to instances in which two constructs with different labels represent the same thing. An inadequate knowledge of the many names for a construct may lead to poor discovery behaviors during literature searches and thus distort meta-analytic results. As such, this fallacy drains scientific resources (Zuckerman, 2008) and contributes to difficulty in theory unification and knowledge culmination (Duckworth & Schulze, 2009).

Collectively, the jingle-jangle fallacy has been referred to as the “construct identity fallacy” (Larsen & Bong, 2016, p. 1) and generally increases certain constructs’ degree of ambiguity with regard to meaning, which makes interpreting scientific results even more difficult for practitioners. Indeed, the turnover literature, similar to other research areas like human capital and job engagement (Molloy & Ployhart, 2012; Shuck, Ghosh, Zigarmi, & Nimon, 2013), likely suffers from the jingle-jangle problem. For example, oftentimes job satisfaction and organizational commitment are hypothesized to be negatively related to turnover intention and actual turnover despite recent evidence suggesting that these constructs may be empirically indistinguishable (Le et al., 2010). According to Campbell and Fiske (1959), convergent validity is demonstrated by correlations between measures that are “significantly different from zero and sufficiently large to encourage further examination of validity” (p. 82). Indeed, Le et al. (2010) reported a near-isomorphic construct-level correlation (.91) between organizational commitment and job satisfaction. Therefore, I will follow Campbell and Fiske’s (1959) recommendation and further examine the potential empirical redundancy between these two constructs in the context of predicting turnover. Specifically, I will use meta-analytic data to examine the change in relative importance weights across nine independent variables (IV) after organizational commitment replaces job satisfaction in a “full” model of turnover. If the relative importance weights for the nine IVs common to both “full” models remain fairly stable, after organizational commitment replaces job satisfaction in the model, similar support will be given to the claim that job satisfaction and organizational commitment are potentially empirically redundant.

Taken together, concerns surrounding the aforementioned theory-empiricism gap and construct identity fallacy motivate the current study. I will address both concerns by developing a sensitivity analysis for Tonidandel & LeBreton’s (2011) relative importance analysis technique. First, I will examine a set of theoretically-relevant correlates of turnover intention to determine which ones have the highest degree of importance and are most stable in the prediction of this important outcome. Second, the sensitivity analysis will be used to assess the potential empirical redundancy between job satisfaction and organizational commitment when predicting turnover intention. An important contribution of the sensitivity analysis is its applicability to other areas of research that are faced with similar problems. Therefore, researchers relying on meta-analytically derived correlation matrices in the domains of leadership (Banks et al., 2014), employee engagement (Cole, Walter, Bedeian, & O'Boyle, 2012), personality (O'Boyle et al., 2015), self-regulation (Burnette et al., 2013), emotional intelligence (Joseph, Jin, Newman, & O'Boyle, 2015), and optimism (Alarcon, Bowling, & Khazon, 2013) may be able to use the sensitivity analysis introduced in the current study to address the theoretical and empirical redundancies present in their respective research paradigms.

Chapter 2. Literature Review

Approximately 65 meta-analytic and 2,500 primary studies on turnover behavior or turnover intention exist, which suggests that to illustrate every nuanced theoretical perspective in this literature would be an unrealistic undertaking. Therefore, in this section, I aim to highlight some key theories on turnover intention and actual turnover that serve as the backbone and future of this important area of research. Specifically, I will provide an overview of five turnover models (Lee & Mitchell, 1994; March & Simon, 1958; Mitchell et al., 2001; Mobley, Griffeth, Hand, & Meglino, 1979; Nyberg & Ployhart, 2013) before offering a brief description of extant research that has linked the correlates to be examined in the proposed study to turnover intention and behavior. Given that only a sample of the turnover literature is provided here, I note that Hom et al. (2012) and Shaw (2011) recently offered a more comprehensive review of this research area.

March and Simon's (1958) Model of Turnover

Nearly 60 years ago, March and Simon (1958) introduced their seminal conceptualization of the turnover process. Indeed, most theoretical perspectives on turnover since then are to some degree descendants of the March and Simon framework (e.g., Lee et al., 1999; Mobley, Horner, & Hollingsworth, 1978). To understand March and Simon's process model of turnover, one must first be familiar with Barnard's (1938) theory of organizational equilibrium. According to Barnard, because of an inability to produce the desired level of satisfaction, an individual will develop a cooperative system. One's cooperative system is composed of four subsystems: a physical system, a personal system, a social system, and the organization. The survival of an individual's cooperative system rests on the "the attainment of efficiency" (Barnard, 1938), a satisfied state that is realized when the contribution of the individual is less than the inducements given by the organization. Importantly, the organization is what binds each system together and its sustainability is dependent on the contributions of its employees. As such, equilibrium is achieved when the employee is satisfied with the inducements received in return for his or her contribution and the organization is able to maintain its operations without a deficit. Mano (1994, p. 15) described this exchange process as follows:

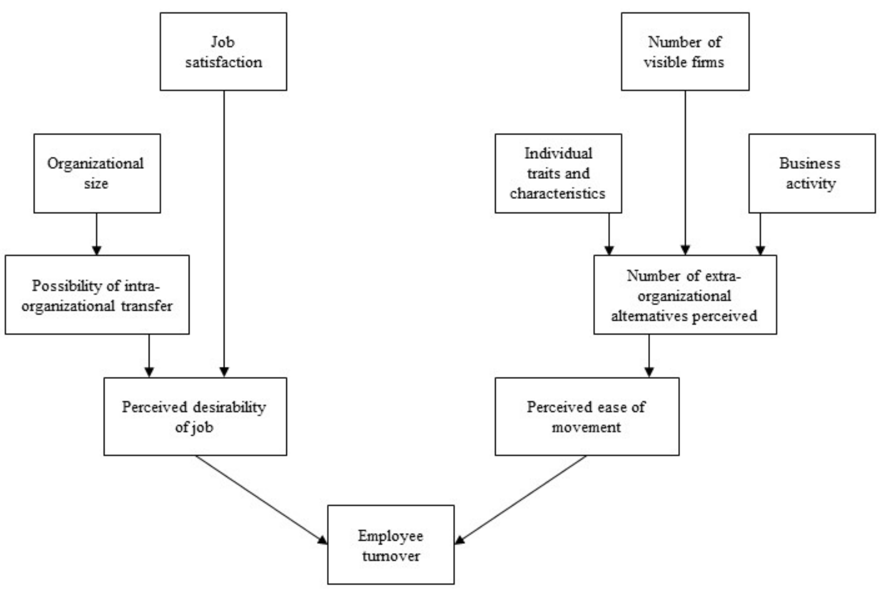
> In other words, the organization gives the contributor what is less valuable to the organization but more valuable to the contributor; and the organization receives from the contributor what is more valuable to the organization and less valuable to the contributor.

Building on Barnard's (1938) theory of organizational equilibrium, March and Simon (1958) posited that equilibrium between an individual's contribution and an organization's compensation is a function of two motivational components – perceived desirability of the job and perceived ease of movement (see Figure 1). Both factors were proposed to operate independently to influence an employee's motivation. On the one hand, contributions to the organization will continue when equilibrium is maintained. Yet, on the other hand, job search behavior will be initiated when a discrepancy occurs and an imbalance is experienced. Moreover, March and Simon (1958) contended that job satisfaction and organizational size, which was argued to be positively associated with the likelihood of intraorganizational transfer (i.e., likelihood of promotion), influenced one's perceptions of his or her current job. In addition, they emphasized one's level of job satisfaction and the state of the job market as key determinants of perceived ease of movement between jobs. It is important to note that subsequent research labelled these components of equilibrium as job satisfaction and perceived number of job alternatives (Jackofsky & Peters, 1983), which is perhaps why March and Simon's (1958) model of turnover is often considered a simple two-predictor model.

Together, March and Simon's (1958) conceptualization of turnover appears to reflect the two dominant perspectives or traditions related to turnover research described by Morrell, Loan-Clarke, and Wilkinson (2001). Specifically, the affective tradition is captured by the perceived desirability of the job factor and the economic tradition by the perceived ease of the movement factor. Interestingly, however, the former has garnered most of the empirical attention and has led to at least ten meta-analytic reviews involving job satisfaction and turnover intention or turnover behavior (see Appendix A).

Figure 1

March and Simon's Model of Turnover

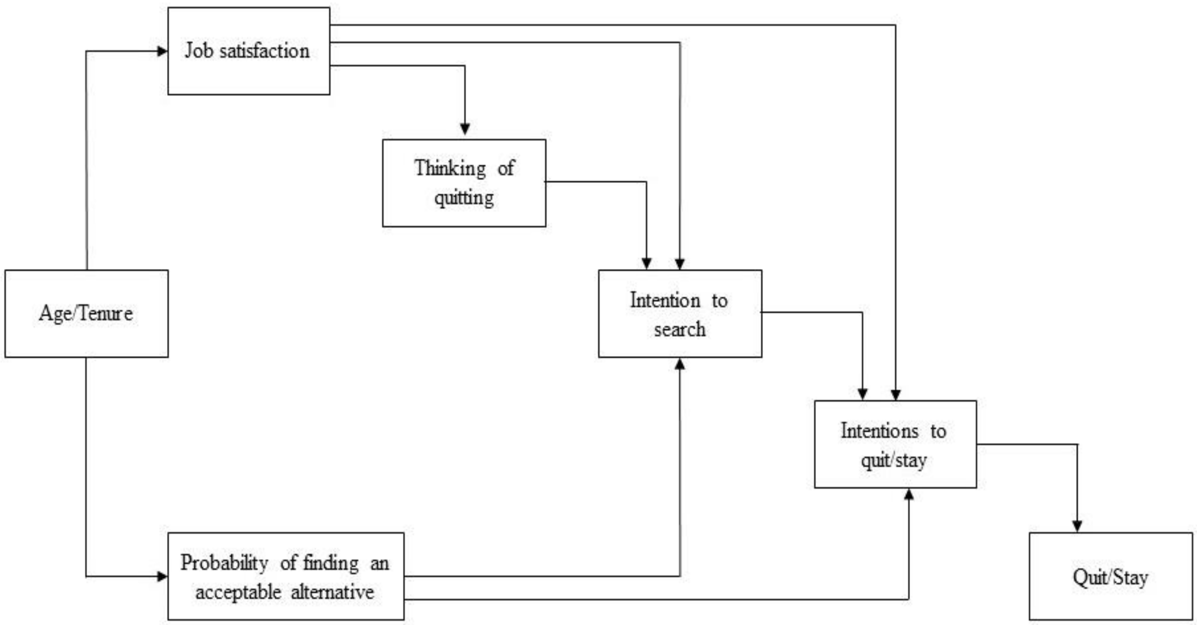


Mobley et al.'s (1979; 1978) Models of Turnover

Drawing on work by Locke (1968, 1969), Mobley and colleagues (1979; 1978) extended March and Simon's (1958) conceptualization of the turnover process in a number of ways (see Figure 2). First, these scholars posited that age and tenure would have an indirect effect on turnover intention and turnover behavior through job satisfaction and the probability of finding an acceptable job alternative. Although a detailed explanation for this hypothesized effect is not offered by Mobley et al. (1978), they suggested that younger workers are more likely to have greater mobility and thus a higher number of alternatives available to them than older workers. Interestingly, many other investigations of the turnover process also failed to explain why the relation between age and turnover was hypothesized (e.g., Arnold & Feldman, 1982; Clegg, 1983; Farris, 1971; Keller, 1984; Kerr, 1947). Still, recent meta-analytic reviews provided support for Mobley et al.'s (1978) claim that age is negatively related to turnover (Healy, Lehman, & McDaniel, 1995; Ng & Feldman, 2009). In addition, Mobley et al. (1978) augmented March and Simon's (1958) conceptualization of turnover by recognizing "that a variety of cognitive and behavioral phenomena are occurring between the emotional experience of job dissatisfaction and the withdrawal behavior" (p. 408). Specifically, these scholars identified thinking of quitting, intention to search, and intention to stay as intervening variables that link job dissatisfaction to turnover behavior. Taken together, the model introduced by Mobley et al. (1978) is perhaps one of the earliest multivariate, multistage models of turnover and posited that intermediate linkages between job satisfaction and the number of perceived job alternatives and turnover likely exist.

Figure 2.

Mobley et al.'s (1978) Representation of Intermediate Linkages in the Employee Withdrawal Process

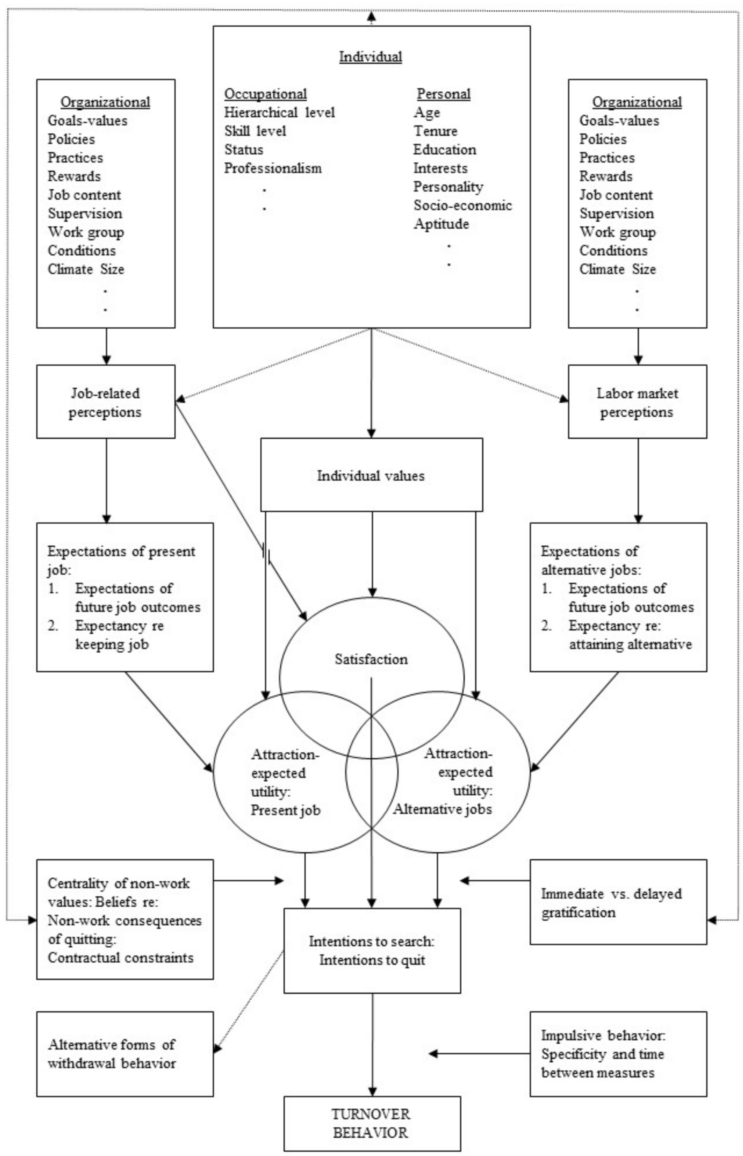


Note. Adapted from Mobley et al. (1978)

A subsequent model offered by Mobley et al. (1979; see Figure 1) displayed how a variety of organizational, individual, and economic variables interact to predict turnover and is displayed here in Figure 3. Included in the list of organizational-related factors that influence employee turnover were human resource policies, reward structures, supervision practices, and organization size. In comparison, the posited individual-related factors included skill level, job level, age, tenure, education, interests, and ability. The model indicated that organizational- and individual-related factors interact to shape one's job-related perceptions. This product in turn forms an individual's job satisfaction and perceptions of current job expectations. In contrast, an individual's labor market perceptions were proposed to be formed by an interaction between individual-related and economic/labor market-related factors (i.e., unemployment rate, advertising levels, recruiting levels, etc.). It follows that one's utility expectations of job alternatives are influenced by these labor market perceptions. Together, the three-way interaction between satisfaction, current job utility expectations, and alternative job utility expectations indicates whether or not an individual will engage in job search behavior.

Figure 3

Mobley et al.'s (1979) Conceptualization of the Turnover Process



Note. Adapted from Mobley et al. (1979)

This multivariate approach to turnover is attractive because it accounts for the numerous forces that influence employee turnover decisions. Yet, its complexity makes it difficult to test. Although Mobley et al. (p. 520, 1979) claimed that “the need for integrative, multivariate, longitudinal research is evident if significant progress is to be made in understanding the psychology of the employee turnover process,” a review of the literature failed to return a single study in which a test of the full model was conducted. Moreover, the literature suggests that several paths to turnover presented in Mobley et al.’s (1979) article have never been empirically tested. For instance, to the best of my knowledge, an examination of the “family responsibility→individual values→attraction-expected utility: alternatives→intentions to quit” path has never been tested. Indeed, many examinations of Mobley et al.’s (1979) large schematic of the primary variables and process of employee turnover have relied on simplified models only (e.g., Dalessio, Silverman, & Schuck, 1986; Michaels & Spector, 1982). Taken together, Mobley et al.’s (1979) model is representative of the paradigm shift that disseminated across turnover theorists at this time. Specifically, it catalyzed the belief that turnover is a complex, multivariate phenomenon that involves direct and multiplicative effects between present- and future-oriented variables. However, “a thorough test of all components of the Mobley et al. (1979) model would undoubtedly be beyond the scope of any single study” (Michaels & Spector, 1982, p. 54), which may bring into question the efficacy of this model itself.

Lee and Mitchell’s (1994) Unfolding Model of Voluntary Employee Turnover

Although some scholars described the dysfunctional aspects of employee separation as “axiomatic” (Dalton & Todor, 1979, p. 225) and as the “sine qua non” (Muchinsky & Tuttle, 1979, p. 43) of the turnover literature, others argued that a lack of operationalization (i.e., a failure to characterize turnover as dysfunctional vs. functional) may lead to an overestimation of the impact of turnover (Dalton, Todor, & Krackhardt, 1982). After all, not all turnover is bad (Allen et al., 2010). Perhaps driven by recommendations to operationalize turnover type and because of its salience and importance to organizations, Lee and Mitchell (1994) presented an unfolding model of voluntary separations. Specifically, using both pull (i.e., concepts external to the employee) and push (i.e., constructs internal to the employee) theories, Lee and Mitchell (1994) conceptualized four decision paths to turnover. Three of these paths outlined actions that an employee may follow in response to a "shock" event. Importantly, a shock event represents a stimulus that generates information and may be positive (i.e., an unexpected job offer from a different firm) or negative (i.e., missed promotion).

The unfolding model of voluntary employee turnover is grounded in Beach's (1990) generic decision-making model and image theory. Several key assumptions underscore these theoretical perspectives (Keren & Wagenaar, 1987; Oden, 1987). In particular, it is assumed that, for *in situ* decision processes regarding one's employment, (a) evaluation seldom is extensive, (b) behavior is largely programmed, (c) decision makers employ several strategies for making choices, and (d) the economic view of decision making is not the only approach to making decisions. Moreover, Beach (1993) suggested that individuals "screen" their options rather than choose them. Furthermore, he argued that individuals will draw on personal and/or referent past experiences – also referred to as decision frames – to guide this screening process. Importantly, information is screened to determine how one's value image, trajectory image, and strategic image may be affected following a shock event. The value image is described as the general values, standards, and principles that govern a person. An individual's trajectory image represents the set of goals that motivates and guides behavior. Finally, an individual's strategic image represents the set of behavior tactics that will help an individual realize his or her goals. According to Beach (1993), the screening process is enacted when a discrepancy exists between information presented by a shock event and any one of the three aforementioned image criteria. Taken together, Lee and Mitchell's (1994) model of employee turnover generally unfolds as follows: First, an event or some shock to the system occurs. A person may or may not consider leaving their job if this event has implications for his or her job. If job termination is a viable option, then job alternatives must be considered. These alternatives constitute decision paths or ways that an employee can terminate their current employment. Lee and Mitchell (1994) used four decision paths to model this general process.

Decision Path #1 is characterized by a shock to the system and a memory probe that results in a match. Specifically, following a shock to the system, an individual will conduct a memory search for similar past experiences, prior decision rules, and learned responses. If a match is identified, the person's previous behavior and subsequent consequences will be judged to determine if similar behavior should be enacted in the current situation. If the individual determines that the current situation closely matches a past event and that a previous behavior produced a positive outcome, a script-driven response will be applied to the current event with little consideration for other behavioral responses. However, a different path will be followed if a match with a rule that governs an individual's value, trajectory, or strategic image is not identified or if the past enacted behavior resulted in an unfavorable outcome.

Decision Path #2 is categorized as a push decision in which no matches or specific job alternatives are identified in the aftermath of a shock event. Therefore, this decision frame holds that an employee can terminate his or her relationship with an organization even when a job alternative is not readily available. Given that no personal or situational experiences can be referenced, a script-driven response cannot be enacted. Therefore, the employee is pushed to engage in additional mental deliberations such that screening the present information centers on the binary decision to either quit or stay with the organization. Indeed, whether or not the shock to the system can be integrated into the employee's value, trajectory, and strategic images determines the outcome of this decision. Should this compatibility test be passed, then the employee is likely to remain with the organization. However, employee separation is likely to unfold without consideration of job alternatives if the compatibility test indicates a lack of fit between the new information and any of the three image criteria. Together, this process differs from Decision Path #1 because the enacted behavior is not automatic. Specifically, the employee evaluates his or her current satisfaction before making a turnover decision because a script is unavailable. In addition, Decision Path #2 is considered a push decision because this approach holds that factors internal to the individual (i.e., individual differences) govern the decision to leave even if a job alternative is not available. Furthermore, negative shocks are more likely to initiate Decision Path #2 because its focus is on leaving without a specific job alternative.

Similar to Decision Path #2, Decision Path #3 is prompted when a match between the experienced shock and a recall of a response to a similar shock in the past does not occur. However, unlike Decision Path #2, the employee's decision is a choice between staying with the current organization and quitting to follow a perceived job alternative. Importantly, the image comparisons associated with Decision Path #3 are generally more complex than for Decision Paths #1 and #2 because the employee engages in a greater number of thought processes and compatibility tests. For example, job search behaviors may be enacted if the employee is (a) unable to rely on a script-driven response to a stimulus and (b) unable to integrate the new information with his or her value, trajectory, or strategic images. Consequently, the employee must evaluate whether or not his or her images fit with each perceived job alternative. An alternative is no longer considered viable if it does not align with the employee's value, trajectory, and strategic images. This winnowing process is enacted until a single alternative remains. Once established, the benefits of leaving for this alternative are directly compared to the benefits associated with staying in the current organization. The option that presents the greatest benefit to the employee's image is selected.

Decision Path #4 is unlike any of the aforementioned decision frames because it does not involve a shock. Specifically, a single event does not occur that elicits mental deliberations about a similar event in the past (Decision Path #1), reevaluation of the employee's job satisfaction and commitment to the current organization (Decision Path #2), or thoughts about the employee's image in an alternative organization (Decision Path #3). Instead, Decision Path #4 holds that an employee will periodically examine the job market to see what alternatives are available and will leave the current organization if this perusal uncovers a better fit. According to Lee and Mitchell (1994), Decision Path #4 can be initiated two different ways. First, the employee or the organization may gradually change over time such that the employee's value, trajectory, or strategic images no longer fit with elements of the job. Indeed, this gradual divergence means that no single shock is salient enough to trigger employee separation and that the decision to leave may be the result of the culmination of several, less prominent events. A second way that Decision Path #4 may be activated is through a series of affective reactions that may bypass cognitive, rational reactions (Lee & Mitchell, 1994; Weiss, Nicholas, & Daus, 1993). Put differently, an employee can become dissatisfied with his or her job even though value comparisons are not made. It is also important to note that two subpaths characterize how Decision Path #4 generally unfolds. First, in some instances, the employee will follow paths that have been suggested by earlier conceptualizations of employee turnover. Similar to what Mobley et al. (1978) presented, for example, the employee may think about quitting, engage in job search behavior, evaluate viable alternatives. However, others may revert to a process that converges with the last part of Decision Path #2. In such a case, the employee, recognizing that a discrepancy regarding fit exists, will simply leave without considering alternatives.

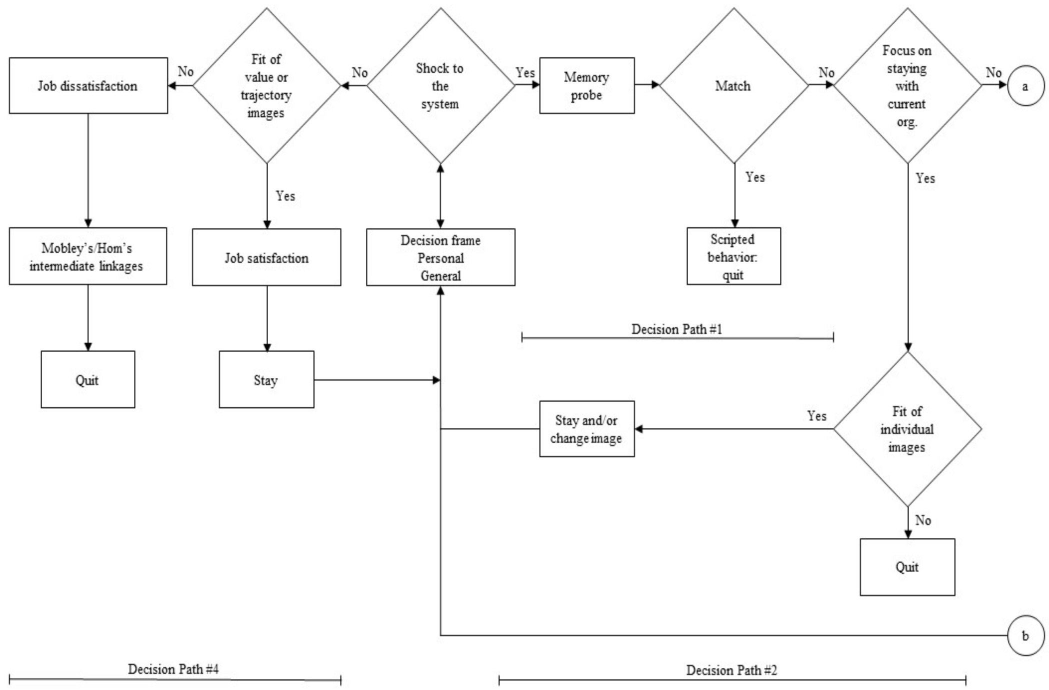
In sum, Lee and Mitchell's (1994) unfolding model of voluntary turnover depicted how different psychological processes can explain the same outcome. Indeed, not every employee shares the same path to quitting an organization. The unfolding model was intended to prompt theory and empirical research on employee turnover. It was hoped this would be achieved by including in the model both economic and rational decision-making processes (March & Simon, 1958) and processes that are more reactive and irrational. Yet, an examination of the literature indicated that few attempts have been made to test Lee and Mitchell's (1994) model. One such attempt was made by Lee, Mitchell, Wise, and Fireman (1996). However, their study achieved just .46[1]. A more stringent test of the model was provided by Lee et al. (1999) who utilized a sample of 229 research participants. The results of this study generally supported the decision paths displayed in Lee and Mitchell's (1994) unfolding model of employee turnover. However, Dauten (1980) reported over 200 examples of quit decisions based on qualitative data derived from intensive interviews. Therefore, the efficacy of Lee and Mitchell's (1994) four path model may be brought into question because the number of paths to turnover identified by their model

[1] A post hoc power analysis was conducted using median effect size (r = .16) information reported by Bosco et al. (2015) and sample size information reported by Lee et al. (1994) (n = 27). A one-tailed exact test for bivariate normal relations using the software GPower version 3.1.9.2 (Faul, Erdfelder, Buchner & Lang, 2009) indicated that just .46 power would have been achieved had direct relations only been examined by Le et al. (1994). However, the statistical power achieved by Lee et al.'s (1994) study was likely less than this given that they conducted path analyses and did not examine simple bivariate relations.

does not converge with the number reported by Dauten (1980). Decision Paths #1, #2, and #4 are presented in Figure 4 and Decision Path #3 in Figure 5.

Figure 4

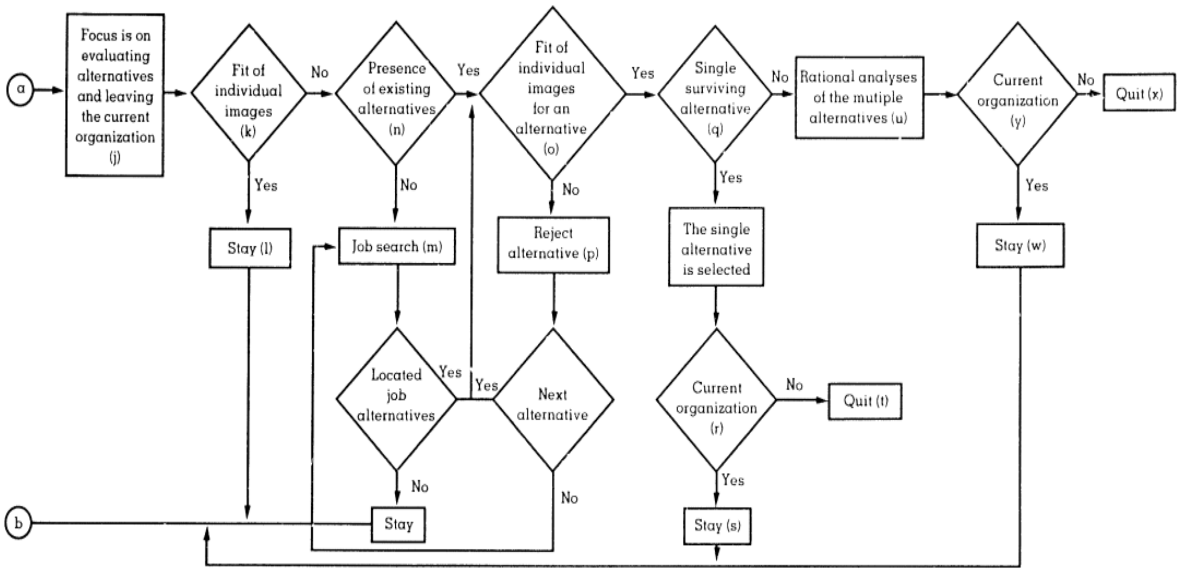
Lee and Mitchell's (1994) Decision Paths #1, #2, and #4



Note. Adapted from Lee and Mitchell (1994)

Figure 5

Lee and Mitchell's (1994) Decision Paths #3



Note. Adapted from Lee and Mitchell (1994)

Mitchell et al.'s (2001) Job Embeddedness Approach to Voluntary Turnover

Research on turnover has indicated that workplace attitudes are not the only factors that govern an employee's decision to quit their job (Griffeth et al., 2000; Hom & Griffeth, 1995). Indeed, other factors beyond traditional attitudinal models are important for understanding turnover (Maertz & Campion, 1998) and a large body of research has found that nonwork factors play an important role in predicting turnover intention and actual turnover (Cohen, 1995; Liu et al., 2015). Job embeddedness (Mitchell et al., 2001) is one theoretical perspective on turnover that posits employee retention is dependent on more than just employee workplace attitudes.

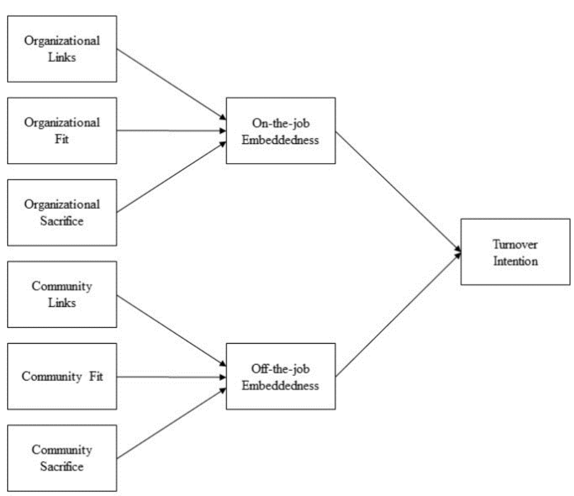
Job embeddedness represents a higher-order factor that considers the influence of three variables in the employee turnover process (Hom et al., 2009; Lee et al., 2004). In general, job embeddedness assesses (a) the extent to which aspects of an employee's job and community converge, (b) the extent to which employees are linked to other individuals in their workplace and community, and (c) the ease with which links can be severed. These assessments are referred to as fit, links, and sacrifice, respectively. Fit is defined as an “employee’s perceived compatibility or comfort with an organization and with his or her environment” (Holtom & O’Neill, 2004, p. 221). Person-fit at the workplace has a diverse and rich literature and, importantly, many types of fit, such as an individual’s compatibility with his or her job (i.e., person-job fit), organization (i.e., person-organization fit), work group (i.e., person-group fit), and supervisor (person-supervisor fit) have emerged as active research domains. Fit in this context also captures nonwork-related fit (Ramesh & Gelfand, 2010) and captures how well an individual fits into his or her surrounding community. As such, the degree of fit between an employee and his or her workplace and community environment together play an important role in the prediction of turnover.

Links are conceptualized as “formal or informal connections between a person and institutions or other people” (Mitchell et al., 2001, p. 1104). Similar to theories on social capital (Arregle, Hitt, Sirmon, & Very, 2007) and social networks (Wang, Fang, Qureshi, & Janssen, 2015), links are characterized in terms of quantity. Put differently, the larger the number of relationships between an individual and his or her colleagues, the more bound he or she is to the job and community. In addition, the number of links between an individual and his or her surrounding community also plays an important role such that a higher number of links is associated with lower likelihood of quitting. The final dimension of job embeddedness, sacrifice, refers to the “perceived cost of material or psychological benefits that may be forfeited by leaving a job” (Mitchell et al., 2001, p. 1105). Indeed, this cost is directly and positively associated with the degree of fit and number of links an individual has in his or her current job and community. Put differently, the cost of leaving a job increases as the level of fit and the number of links between an individual and his or her organization and community increases. For example, although salary may be comparable, the switching costs associated with a new health care or relocating one's family may involve sacrifices and, thus, are real and relevant (Mitchell et al., 2001).

Taken together, job embeddedness theory presents a three-by-two matrix that suggests six dimensions (i.e., links, fit, and sacrifice associated with an individual's organization and community) play important roles when predicting employee turnover. Subsequent research efforts have referred to organizational links, fit, and sacrifice as "on-the-job embeddedness" and community links, fit, and sacrifice as "off-the-job embeddedness" (see Figure 6) (Lee et al., 2004; Sekiguchi, Burton, & Sablynski, 2008). In a meta-analytic examination of these constructs, Jiang et al. (2012) found on-the-job embeddedness was more strongly related to turnover intention (r_{wt} = -.48 vs. -.22; r_{wt} denotes corrected for sampling error) and actual turnover (r_c = -.19 vs. -.12) than off-the-job embeddedness.

Figure 6

Mitchell et al.'s (2001) Job Embeddedness Theory



Note. Adapted from Mitchell et al. (2001)

Collective Turnover (Hausknecht & Trevor, 2011; Nyberg & Ployhart, 2013)

Collective turnover is a burgeoning area of research within the turnover literature and describes aggregate levels of employee departures that occur within teams, work groups, or organizations. As of 2010, more than 100 articles had been published on turnover at higher units of analysis (Hausknecht & Trevor, 2011). Collective turnover is different from individual-level turnover because of its important consequences for human resource management planning and, in particular, human capital depletion (Gardner, Wright, & Moynihan, 2011; Lepak & Shaw, 2008). Yet, “collective level theory has been absent from much of the [collective turnover] research” (Hausknecht & Trevor, 2011, p. 379). The need for theory on turnover at the collective level is attributable to potential fallacies that are committed when research findings at the individual level are assumed to be true at the group level. This myth is referred to the atomistic fallacy (Klein & Kozlowski, 2000; Taggar & Seijts, 2003). Indeed, Bliese (2000) noted that total isomorphism (the degree to which higher- and lower-level phenomenon are identical) is rare. Nyberg and Ployhart sought to address these deficiencies by introducing context-emergent turnover (CET) – a theoretical perspective that holds “collective turnover is the aggregate quantity and quality of employee knowledge, skills, abilities, and other characteristics (KSAOs) depleted from the unit” (2013, p. 109).

It is important to note that collective turnover is an emergent phenomenon and that it originates from individual turnover. As such, the costs associated with individual turnover – which are typically considered in terms of replacement costs – are very different from those associated with collective turnover. Collective turnover represents aggregated individual turnover and, thus, may also involve important social capital losses (Shaw, Duffy, Johnson, & Lockhart, 2005). Moreover, Nyberg and Ployhart (2013) further break from the traditional approach to turnover by suggesting that collective turnover is characterized by both quantitative *and* qualitative components that can change over time. The quantitative component refers to the rate of unit turnover (i.e., the number or percentage of employees that quit the unit). In contrast, the qualitative component refers to the types of KSAOs and captures the idea that the consequences of turnover are not the same across all employees. This means that turnover is not weighted equally for all employees and that the cost of leaving the organization may be greater for certain employees than others. Surprisingly, the qualitative dimension has been generally ignored by traditional approaches to turnover even though it may have greater implications for an organization's stock of human capital (Nyberg & Ployhart, 2013).

The role of time is also captured by CET. Specifically, consideration for the flow of human resources in and out of the organization leads to a greater understanding of the consequences of collective turnover. Nyberg and Ployhart (2013) highlighted the importance of time in the collective turnover context by adapting Dierickx and Cool's (1989) bathtub metaphor. They described an organization's stock of human capital as the amount of water in the bathtub and its quality as the water temperature. To regulate the quantity of human capital, the organization can either open the tap (i.e., hire more personnel) or drain (i.e., release employees). Importantly, they suggested that collective turnover does not necessarily mean the organization's KSAOs are being depleted. Rather, the quality of the organization's human capital can be regulated by adding hot water instead of cold water. In this type of situation, a strong inflow of better quality human capital to the stock of human capital coupled with an outflow of lower quality human capital will result in an increase in unit-level KSAOs even though turnover has occurred. However, if the rate of outflow exceeds the rate of inflow, or if the quality lost is greater than the quality gained, then collective turnover will deplete an organization's human capital. The timing of collective turnover is also accounted for by CET. In particular, the rapid depletion of human capital resources is likely to be more disruptive than a slow depletion. For example, the impact on organizational performance and workplace climate when one employee quits per month for a year will likely be very different than the effect of 12 employees leaving in a single month.

Taken together, CET demonstrates how the consequences of collective turnover cannot be separated from the nomological network of human capital resources. Importantly, the development of CET theory provides a framework to explore collective turnover antecedents and consequences in ways that have not been fully understood using individual-level turnover models. For example, individual-level turnover models general posit that involuntary turnover results in higher performance because poor performers are replaced with higher performers. Yet, according to CET theory, this may not be true in all instances. More specifically, CET holds that collective turnover may be detrimental if the stock of human capital resources is lowered to a point that makes routine operations difficult to maintain or if the quality of the incoming employees does not match or exceed the outgoing ones. Therefore, CET is able to point to the downstream effects of collective turnover and explain why the impact of collective turnover will differ from individual-level turnover. Although in its infancy, early tests of CET theory have demonstrated validity. For example, Reilly, Nyberg, Maltarich, and Weller (2014) found that rates of turnover, transfers, and hiring comprised a dynamic system that influenced patient satisfaction.

Chapter 3. A Contribution to Theory Without Creating New Theory

It is difficult to overstate the importance of theory to the scientific process. It has become the “currency of our scholarly realm” (Corley & Gioia, 2011, p. 12) and is intended to be the answer to queries of how and why (Sutton & Staw, 1995). Campbell described theory as “a collection of assertions, both verbal and symbolic, that identifies what variables are important and for what reasons, specifies how they are interrelated and why, and identifies the conditions under which they should be related or not related” (1990, p. 65). In contrast, DiMaggio characterized theory as “an account of a social process, with emphasis on empirical tests of the plausibility of the narrative as well as careful attention to the scope conditions of the account” (1995, p. 391). However, little consensus regarding what constitutes a theoretical contribution exists despite a rich literature on what theory is (Colquitt & Zapata-Phelan, 2007; Cucina & McDaniel, 2016).

Because there exist a variety of opinions regarding what qualifies as a theoretical contribution, minimum requirements for what constitutes a theoretical contribution are ambiguous. Colquitt and Zapata-Phelan presented an ontology that can be used to capture an empirical article’s theoretical contribution (2007, see Figure 1, p. 1283). They suggested that an article’s theoretical contribution can be assessed using two five-point dimensions. The first dimension refers to the extent an empirical article “builds new theory.” A score of one on this, the vertical axis, suggests the empirical study made an attempt to replicate a previously demonstrated effect and ostensibly reflects the lowest contribution to theory. A score of five on this dimension is given when an empirical study introduces a new construct and thus, according to these scholars, makes the highest contribution to theory. Interestingly, this structure seems to contradict Sutton and Staw's claim that constructs "do not constitute theory" (1995, p. 375).

One may also argue that a discrepancy between theoretical contribution and practical contribution, or scientific value, is observed here and that an increased number of replications should be advocated for given the untrustworthiness of our cumulative scientific knowledge (Kepes, Banks, McDaniel, & Whetzel, 2012; Kepes & McDaniel, 2015; Open Science Collaboration, 2015). Indeed, Vandenberg and Grelle suggested "the greatest scientific value emerges when at least two models are specified representing competing conceptualizations and one emerges the strongest" (2008, p. 170). This seemingly echoes Platt's strong inference perspective and suggests that the importance of "the repeated overthrow of scientific theories and their replacement by better or more satisfactory ones" (Popper, 1965, p. 215). This perspective has been ignored by Colquitt and Zapata-Phelan (2007). Furthermore, I suggest that confounding construct creation with making a theoretical contribution will only exasperate the construct proliferation problem that faces our field and will inhibit our ability to build cumulative knowledge (Block, 1995).

The second dimension presented by Colquitt and Zapata-Phelan (2007) is "testing existing theory" and is found along the horizontal axis. A score of one is given when an empirical study is inductive or grounds predictions with logical speculation. This axis is reverse scored such that a score of one reflects the largest contribution to theory. In contrast, a score of five is given when an empirical study grounds predictions within existing theory and thus provides little theoretical contribution. Taken together, empirical studies that score low on the x-axis and high on the y-axis are said to offer the greatest theoretical contribution because they (a) ground their predictions with logical explanation and (b) introduce a new construct.

Drawing on Kilduff's (2006) editorial comments, Corley and Gioia (2011) seemingly augment Colquitt and Zapata-Phelan's (2007) model and assert that a theoretical contribution can be characterized along two different dimensions. These dimensions are utility and originality. On the one hand, utility is described in terms of scientific and practical usefulness and captures research that creates knowledge or adds value. On the other hand, originality is described in terms of incremental and revelatory and is analogous to Huff's (1999) distinction between contributing to a current conversation and starting a new one. The interaction between these two dimensions is displayed in a 2 × 2 matrix (Corley & Gioia, 2011; see Figure 1). Specifically, papers present a prototypical theoretical contribution when they are original and have scientific usefulness (Quadrant 1). However, papers that only fit one of these dimensions well – for example, are scientifically useful but lack originality (Quadrant 2) or display revelatory insight but lack scientific utility (Quadrant 4) – may fail to surpass the theoretical contribution threshold. Finally, those papers that lack originality and utility (Quadrant 3) are likely to be rejected and thus absent from the available literature.

Inherent in both approaches to what constitutes a theoretical contribution is the need for – in one form or another – something new (i.e., a new construct, new theory, etc.). Yet, an inspection of the etymology of the word *contribution* may suggest that developing new theory and/or constructs is not the only means by which a scholar can make a valuable contribution to theory. Specifically, the word *contribution* is derived from two mid-16th century Latin words: *con*, which means *with*, and *tribuere*, which means *bestow*. Together, these words mean *to bring together*. As such, I argue that to bring together and examine an existing catalogue of theoretical perspectives represents a noteworthy contribution to theory that does not require new theory to be developed.

Indeed, meta-analysis may represent one way such a contribution can be made. Meta-analysis is a set of statistical techniques used to assimilate individual effect sizes and is often considered the primary means for generating cumulative knowledge (Kepes et al., 2012). Schmidt and his colleagues advocated the use of meta-analytic techniques on large datasets to facilitate the creation of "empirical building blocks for theory" (1992, p. 1177). I argue that theory will benefit multiplicatively if meta-analysis and the big data ethos are employed simultaneously. Specifically, I contend that meta-analytic datasets that adhere to the four V's (volume, variety, velocity, and veracity; Guzzo et al., 2015) of big data provide a means to bring together and test a variety of theoretical perspectives. The current study builds on these visions. To this end, I will examine the relative importance of several theoretical perspectives on turnover intention using data from the metaBUS database (Bosco et al., 2015a). Specifically, I will employ a sensitivity analysis that embraces both the big data philosophy and meta-analytic procedures to establish which turnover intention correlate(s) is of greatest relative importance. Finally, this methodology will be adapted to examine the jingle-jangle fallacy in a theoretical context. In particular, I will inspect whether job satisfaction and organizational commitment are empirically redundant when predicting turnover intention. Taken together, I hope to bring together a variety of theoretical perspectives on turnover intention and conclude which branch(es) of this literature's "logic tree" (Platt, 1964, p. 347) may bear the most fruit in the future.

Chapter 4. Purpose

The purpose of the current research is to address the theory-empiricism gap in the turnover literature. To this end, I will draw on (a) Kish-Gephart, Harrison, and Treviño's (2010) meta-analytic examination of individual ("bad apple"), moral issue ("bad case"), and organizational ("bad barrel") antecedents of unethical decisions at work, (b) Bosco et al.'s (2015a) taxonomic classification system and database of scientific findings, and (c) Tonidandel and LeBreton's (2011) relative importance analysis methodology to satisfy three research objectives.

The first objective of the current study is to introduce a sensitivity analysis for relative importance weights in the meta-analytic context. Borenstein, Hedges, Higgins, and Rothstein argued that it is important "to consider not only the mean effect size … but also how true effects are distributed about this mean" when conducting a meta-analysis (2009, p. 127). I argue that an understanding of this distribution is also important when making relative importance analysis inferences. The common approach to relative importance analysis from a single meta-analytically-derived correlation matrix consists of mean effect size estimates only (i.e., meta-analytic mean estimates between all variables in the matrix). However, this method fails to consider the uncertainty around the mean which can be due to both random sampling error, systematic between-study variance such as variance due to moderators, and other sources of heterogeneity (e.g., degree of publication bias). Importantly, this uncertainty can be expressed with a prediction interval, which addresses the dispersion of effect sizes in a meta-analytic distribution of effect sizes (Borenstein et al., 2009). This prediction interval is conceptually similar to a credibility interval in psychometric meta-analysis.

I advocate the use of the 16^{th} and 84^{th} percentile of the prediction interval (i.e., 68% prediction interval), in addition to the mean, when conducting a relative importance analysis because it is wider than the confidence interval and will contain 68% of the effect sizes in the meta-analytic dataset. The “68-95-99.7 rule” holds that 68% of normally-distributed values fall within one standard deviation of the corresponding mean, 95% within two standard deviations, and 99.7% within three standard deviations. Given that it is assumed that meta-analytic distributions are normally distributed, the 68% percentile of the prediction interval was selected to inform the sensitivity analysis. As such, the lower bound estimate of the 68% prediction interval, which represents the 16^{th} percentile of the corresponding meta-analytic dataset, will inform the lower bound relative importance weight. In contrast, the upper bound estimate of the 68% prediction interval, which represents the 84^{th} percentile of the corresponding meta-analytic dataset, will inform the upper bound relative importance weight. As such, the relative importance weights based on the mean effect sizes are considered the main analysis. Relative importance analyses that are based on correlation matrices derived from various combinations of the mean and lower and upper bounds of the 68% prediction interval will inform a sensitivity analysis for relative importance weights in the meta-analytic context. Taken together, the first objective of my study is summarized by the following:

> *Research Objective #1*: Introduce a sensitivity analysis for relative importance weights in the meta-analytic context.

Although the suggested approach will help to provide more robust results by returning lower and upper bounds of relative importance, exponentially more meta-analytically-derived correlation matrices must be created (as described later in the Methods section). Therefore, I propose that the sensitivity analysis be informed by a random sample of 1,000 correlation matrices from all possible correlation matrices that can be created from all combinations of the meta-analytic mean and the upper and lower bound estimates of the mean's 68% prediction interval. Taken together, the 1,000 separate sensitivity analyses will deliver a far more comprehensive analysis of relative importance and uncover the extent to which varying estimates of correlations impact the relative weights.

The second objective of the current study is to conduct a large-scale relative importance analysis of commonly-investigated predictors of turnover. I suggest Kish-Gephart et al.'s (2010) approach can be adapted to the turnover literature using Bosco et al.'s (2015a) hierarchical taxonomic classification system. Research by Kish-Gephart et al. (2010) was driven by the need for a "clearer empirical and theoretical picture of what we know (and don't know) about multiple sources of influence on unethical behavior at work" (p. 1). Recognizing that a variety of theoretical perspectives had failed to provide conclusive evidence on how unethical choice unfolds, these scholars used meta-analytic techniques to provide a clearer picture of the literature by empirically examining which theoretical perspectives (e.g., "bad apple" vs. "bad case" vs. "bad barrel") most strongly predict unethical choice. I suggest that a similar account of the turnover literature should be pursued as there is an abundance of theory on turnover yet scholars generally struggle to identify the mechanisms that explain this important phenomenon.

As such, I examine the relative importance of 11 correlates of turnover intention and, by extension, their corresponding theoretical perspectives using data in the form of correlation coefficients from the metaBUS database. Importantly, these correlates were identified as most pertinent given the frequency at which they are correlated with turnover intention in the metaBUS database and their relevance to existing theoretical perspectives on turnover intention (described later in Chapter 5). A summary of how all 11 correlates relate to theory and meta-analytic reviews on turnover is presented in Table 1.

The taxonomic display developed by Bosco et al. (2015a) starts by arranging almost 5,000 nodes (i.e., variables or constructs) into a number of first-level nodes (e.g., behaviors; attitudes; intentions) (see Bosco et al., 2015a for a detailed description). Nodes are then further categorized into finer taxonomic branches. As an example, attitudes are categorized in terms of their respective targets, each representing a second- and lower-level "child" node (e.g., attitudes toward the job; attitudes toward the organization). More specifically, job satisfaction represents a fifth-level node (Attitudes → Object = Job/Task → General Job Affect → Positive → Job Satisfaction). Categorizing constructs in this manner lends itself well to the current study because it helps depress the potential adverse effects brought about by the jingle-jangle fallacy (Bosco, Uggerslev, & Steel, 2017). According to Bosco et al. (2017), the metaBUS database contains approximately 194 unique variable names that appear to refer to turnover intention, which is the dependent variable of interest in this study. Importantly, data relevant to all 194 records can be captured by querying the metaBUS database using a single taxonomic code. In contrast, 24 and 13 searches are required if using an exact letter-string search or Boolean-based strategy, respectively (Bosco et al., 2017). The Kish-Gephart et al. (2010) method signifies "what" this second objective aims to achieve, albeit in the turnover context. Furthermore, the metaBUS database and taxonomic map, in addition to the newly-introduced sensitivity analysis, characterizes "how" it will be accomplished. Therefore, the following summarizes my second research objective.

Research Objective 2: What are the relative importance weights of commonly-investigated correlates of turnover intention?

Table 1

Theoretical and Meta-Analytic Evidence for Turnover Intention Correlates

Turnover intention correlate	Theoretical relevance	Meta-analytic relevance
Job satisfaction	March & Simon (1958) Mobley (1977) Liu et al. (2012)	Tett and Meyer (1993): $r_c = -.58$ Griffeth et al. (2000)[a]: $r_{wt} = -.19$
Pay satisfaction	Adams (1963) DeConinck and Stilwell (2004) Vandenberghe and Tremblay (2008)	Williams et al. (2006): $r_c = -.31$ Griffeth et al. (2000)[a]: $r_{wt} = -.07$
Organizational commitment	Wasti (2003) Porter, Steers, Mowday, and Boulian (1974) Jaros (1997)	Meyer, Stanley, Herscovitch, and Topolnytsky (2002) $r_c = -.56$ Griffeth et al. (2000)[a]: $r_{wt} = -.23$
Organizational justice	Nadiri and Tanova (2010) Loi, Hang-Yue, and Foley (2006) Aquino, Griffeth, Allen, and Hom (1997)	Cohen-Charash and Spector (2001): $r_c = -.24$[b] Colquitt et al. (2001): $r_c = -.24$[c]
Autonomy	Ahuja et al. (2007) Spector and Jex (1991) Schaufeli and Bakker (2004)	Spector (1986): $r_{wt} = -.19$
Embeddedness	Mitchell et al. (2001) Moynihan and Pandey (2008) Westerman and Cyr (2004)	Kristof-Brown, Zimmerman, and Johnson (2005): $r_{wt} = -.29$ Jiang et al. (2012): $r_c = -.48$ Verquer, Beehr, and Wagner (2003): $r_c = -.21$
Work-life conflict	Smith and Gardner (2007) Spector et al. (2007) Scholarios and Marks (2004) Carr, Boyar, and Gregory (2007) Grandey and Cropanzano (1999)	Amstad et al. (2011): $r_{wt} = .19$ Allen, Herst, Bruck, and Sutton (2000): $r_{wt} = .29$
Age	Mobley et al. (1978)	Healy et al. (1995): $r_c = -.08$
Individual performance	Jackofsky (1984) Williams and Livingstone (1994) Shaw, Gupta, and Delery (2005) Trevor, Gerhart, and Boudreau (1997)	Griffeth et al. (2000): $r_c = -.15$[d] Williams and Livingstone (1994): $r_{wt} = -.19$[b]
Supervisor satisfaction	DeConinck and Stilwell (2004) Harris, Wheeler, and Kacmar (2009)	NA
Climate	Jaramillo, Mulki, and Solomon (2006) Lindell and Brandt (2000) Zacharatos, Barling, and Iverson (2005)	Carr, Schmidt, Ford, and DeShon (2003): $r_c = -.28$ Heavey, Holwerda, and Hausknecht (2013)[a]: $r_{wt} = -.11$

Note. r_c = sample size-weighted mean effect size that is corrected for unreliability. r_{wt} = sample size-weighted mean effect size. [a] Outcome is actual turnover. [b] Represents the average of distributive, procedural, and interactional justices. [c] Represents the average of distributive, procedural, interpersonal, and interactional justices. [d] Outcome was retention. NA = not available.

Construct redundancy has already been examined in several areas of I-O psychology and management (Cole et al., 2012; Gignac, Jang, & Bates, 2009; Joseph, Newman, & Hulin, 2010). Results reported by Le et al. (2010) indicated that job satisfaction and organizational commitment are likely empirically redundant because their construct-level correlation was very high (.91) and both were similarly related to positive affectivity and negative affectivity. Although these constructs are commonly used to predict turnover intention (Poon, 2012; Stanley, Vandenberghe, Vandenberg, & Bentein, 2013; Wasti, 2003), whether they are empirically redundant in the prediction of turnover intention has never been examined. As such, in the current study I examine whether or not these constructs are functionally distinct in their prediction of turnover intention. Specifically, I will build on Le et al.'s (2010) investigation by adopting a tripartite approach to assessing the potential empirical redundancy between job satisfaction and organizational commitment.

First, I will assess the potential empirical redundancy using meta-analytic procedures. Specifically, I will examine convergence with regard to meta-analytic effect size magnitude. Support may be given to the claim that job satisfaction and organizational commitment may be empirically indistinguishable if the difference between the magnitude of the job satisfaction-turnover intention relation and the magnitude of the organizational commitment-turnover intentions relation is small. In addition, I will assess whether or not job satisfaction and organizational commitment are statistically different from one another by examining the 95% confidence intervals associated with the aforementioned relations.

Second, and similar to the approach used by Banks et al. (2014) and McDaniel, Hartman, Whetzel, and Grubb (2007), I examine whether organizational commitment adds incremental validity above and beyond job satisfaction when predicting turnover intention. Third, and finally, I examine the potential empirical redundancy between job satisfaction and organizational commitment using the new sensitivity analysis for relative importance weights. For example, relative importance weights for job satisfaction and organizational commitment from a two predictor turnover intention model will be compared. In addition, I will also examine how relative importance weights change across two "full" models when organizational commitment replaces job satisfaction. The first of these full models will include job satisfaction, not organizational commitment, and is defined as follows:

$$\begin{aligned} \textit{Turnover intention}_1 \quad = \quad & \beta_0 + \beta_1(\text{Job satisfaction}) + \beta_2(\text{Pay satisfaction}) \\ & + \beta_3(\text{ Organizational justice}) + \beta_4(\text{Autonomy}) \\ & + \beta_5(\text{Embeddedness}) + \beta_6(\text{Work-life conflict}) \\ & + \beta_7(\text{Age}) + \beta_8(\text{Individual performance}) \\ & + \beta_9(\text{Supervisor support}) + \beta_{10}(\text{Workplace climate}). \end{aligned}$$

In the second full model, organizational commitment will replace job satisfaction and will be given by the following equation:

$$\begin{aligned} \textit{Turnover intention}_2 \quad = \quad & \beta_0 + \beta_1(\text{Organizational commitment}) + \beta_2(\text{Pay satisfaction}) \\ & + \beta_3(\text{ Organizational justice}) + \beta_4(\text{Autonomy}) \\ & + \beta_5(\text{Embeddedness}) + \beta_6(\text{Work-life conflict}) \\ & + \beta_7(\text{Age}) + \beta_8(\text{Individual performance}) \\ & + \beta_9(\text{Supervisor support}) + \beta_{10}(\text{Workplace climate}). \end{aligned}$$

I contend that relative importance weights for the eight correlates that are common to both "full" models will remain fairly stable should job satisfaction and organizational commitment demonstrate empirical redundancy. Together, I will satisfy the third objective of the current research by addressing the following questions:

Research Objective 3a: Are job satisfaction and organizational commitment meta-analytically distinct in the prediction of turnover intention?

Research Objective 3b: Does organizational commitment account for unique variance in turnover intention above and beyond job satisfaction?

Research Objective 3c: When predicting turnover intention, do relative importance weights for pay satisfaction, organizational justice, autonomy, person-organization fit, emotional stability, age, high performance work systems, and workplace climate remain relatively stable when organizational commitment replaces job satisfaction?

Chapter 5. Justification for Choice of Variables

Turnover is defined as the "individual movement across the membership boundary of an organization" (Price, 2001, p. 600). A myriad of labels such as quits, attrition, exit, leave, migration, and withdraw have been used to measure turnover and thus the "vocabulary problem" (Bosco et al., 2017; Furnas, Landauer, Gomez, & Dumais, 1987) may adversely impact our cumulative scientific knowledge in this important research area. Furthermore, turnover is often measured as a dichotomous variable using company records or self-report measures (Allen, Weeks, & Moffitt, 2005; Boswell, Boudreau, & Dunford, 2004; De Croon et al., 2004). Consequently, a major challenge associated with studying turnover is that the correlations with predictors are highly influenced by the respective base rate of turnover because point-biserial correlations only reach their conceptual maximum when the base of the dichotomous variable is .50. Importantly, this is true for both voluntary and involuntary turnover. Indeed, base rates of turnover are likely to vary substantially across studies and will be a source of large artifactual variance unless this variation is taken into account when meta-analytically cumulating correlations across studies. Given these types of concerns, I chose to not include turnover in my analyses. Instead, I opted for turnover intention.

Turnover intent is defined as the reflection of "the (subjective) probability that an individual will change his or her job within a certain time period" (Sousa-Poza & Henneberger, 2004, p. 1). According to Fishbein and Ajzen's (1977; see also Ajzen & Fishbein, 1977) model of reasoned action, a behavioral intention measure will predict the performance of any voluntary act. This may explain why turnover intention is oftentimes conceptualized as a proximal antecedent of turnover behavior (Michaels & Spector, 1982; Mobley, 1977; Steers & Mowday, 1981). Indeed, Griffeth et al. reported that "quit intentions remain the best predictor" of turnover (2000, p. 480) and offered empirical evidence that suggested turnover intention is a suitable proxy for turnover behavior. In addition, turnover intention is often measured as a continuous variable (Bozeman & Perrewé, 2001; Chen et al., 2011; Raver & Nishii, 2010), which negates the need to correct or account for the effect of idiosyncratic base rates of turnover. Taken together, turnover intention is included in the current analyses because empirical and conceptual evidence indicate it is a suitable substitute for turnover behavior.

Drawing on Ajzen and Fishbein's (1977) theory of reasoned action, Sheppard, Hartwick, and Warshaw argued that "when attempting to access the immediate determinants of a given behavior, researchers need only be concerned with attitudes… and intentions towards that particular behavior" (1988, p. 327). Therefore, there is a robust theoretical justification for including attitudinal variables when trying to forecast turnover intent and behavior. According to Judge and Kammeyer-Mueller, an attitude represents "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" (2012, p. 343). Importantly, attitudes are tripartite in nature and can be formed independently by one's affect, cognition, and behavior (Fazio & Olson, 2007). Although there is a multiplicity of attitude objects, they are only relevant insofar they are associated with the target of interest. As such, in the current study I use several attitudinal variables that have conceptual importance to the prediction of turnover intention and actual turnover. In particular, I focus on attitudinal constructs that have relatively close ties to an individual's job and organization because thinking about or enacting turnover pertains to departure from these entities.

In total, eight attitudinal variables are included in the current study. Note that Table 2 contains a list of all variables included in the current analyses. The first attitude on this list is job satisfaction. Although job satisfaction has been defined in many ways (Brief & Weiss, 2002; Harrison, Newman, & Roth, 2006; Locke, 1976), it generally refers to an individual's evaluative state that expresses how they think and feel about their job. Common measures of job satisfaction include the job descriptive index (JDI; Smith, Kendall, & Hulin, 1969) and Minnesota satisfaction questionnaire (MSQ; Weiss, Dawis, England, & Loquist, 1967)[2]. March and Simon's (1958) model of turnover holds that job satisfaction plays a key role in one's decision to leave the organization such that dissatisfied employees are most likely to leave the organization. Moreover, empirical evidence suggests that job satisfaction is one of the strongest predictors of turnover-related outcomes (Griffeth et al., 2000; Hom & Kinicki, 2001; Kinicki, McKee-Ryan, Schriesheim, & Carson, 2002). Taken together, conceptual and empirical evidence warrants the inclusion of job satisfaction in the current research. Table 3 reports the number of independent samples for all intercorrelations.

[2] I note that the Internomological Network (Larsen & Hovorka, 2012; Larsen, Lee, Li, & Bong, 2010) serves as an integrated theory development application and search engine for semantically related constructs. A link to common scales and items used to measure each constructed used in the current analyses is provided in Table 4.

Table 2

Variable and Taxonomic Code Information for Constructs Examined

Variable Name	Code [a]	Branch
Turnover intentions	20179 [b]	Intentions → Employment intentions → Quit intentions
Job satisfaction	20072	Attitudes → Object = Job → General job affect → Positive → Job satisfaction
Pay satisfaction	20074	Attitudes → Object = Job → Compensation → Compensation evaluations → Pay satisfaction
Org. commitment	20057	Attitudes → Object = People → Organization → Relationship → Loyalty → Org. commitment
Organizational justice	20052	Attitudes → Object = Organization → Organizational policies/procedures → Justice
Autonomy	11338	Attitudes → Object = Job → Job characteristics → Job characteristics mode → Autonomy
Embeddedness[c]	11148 11224 20044	Attitudes → Object = Organization → Embeddedness → Organization fit Attitudes → Object = Job/task → job fit Attitudes → Object = Person/life → Community embeddedness
Work-life conflict	20089	Attitudes → Object = Personal/life → Work-life balance[c]
Age	20457	Person characteristics → Objective → Demographics →Age
Individual performance	40055	Behaviors → As employee → Performance → Individual performance
Supervisor support	20002	Attitudes → Object = People → Supervisors → Supervisor support
Climate	20148	Organizational characteristics → Internal environment → Climate

Note. [a] Taxonomic code associated with Bosco et al.'s (2015a; 2015b) hierarchical map (version 52). [b] This five-digit code is linked with "quit intentions. [c] The majority of data pertained to "work-life conflict" relations. As such, I reversed the "work-life balance" data by multiplying by minus one (i.e., -1) to ensure the data were consistent.. Org. = organizational

Table 3

Matrix of the Number of Independent Samples Following Outlier Removal

	Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1.	Turnover intentions	-											
2.	Job satisfaction	424	-										
3.	Pay satisfaction	29	62	-									
4.	Org. commitment	372	550	35	-								
5.	Organizational justice	62	94	15	126	-							
6.	Autonomy	73	214	12	75	27	-						
7.	Embeddedness[s]	28	46	5	37	3	5	-					
8.	Work-life conflict	59	144	8	63	8	83	3	-				
9	Age	295	602	57	463	170	273	42	187	-			
10	Individual performance	195	420	27	374	158	140	34	60	451	-		
11.	Supervisor support	55	104	6	84	23	95	3	68	140	105	-	
12.	Climate	36	85	5	77	6	38	4	32	106	30	6	-

Note. [a]Included "job fit," "organization fit," and "community embeddedness." Org. = organizational

Table 4

Variables included in the current analyses with web links to respective INN query results

Variable Name	Web link to Internomological Network
Turnover intentions	http://inn.theorizeit.org/Search/Variable?query=turnover%20intention
Job satisfaction	http://inn.theorizeit.org/Search/Variable?query=job%20satisfaction
Pay satisfaction	http://inn.theorizeit.org/Search/Variable?query=pay%20satisfaction
Org. commitment	http://inn.theorizeit.org/Search/Variable?query=organizational%20commitment
Organizational justice	http://inn.theorizeit.org/Search/Variable?query=organizational%20justice
Autonomy	http://inn.theorizeit.org/Search/Variable?query=autonomy
Embeddedness	http://inn.theorizeit.org/Search/Variable?query=person-organization%20fit
Work-life conflict	http://inn.theorizeit.org/Search/Variable?query=work-life%20conflict
Age	http://inn.theorizeit.org/Search/Variable?query=age
Individual performance	http://inn.theorizeit.org/Search/Variable?query=individual%20performance
Supervisor support	http://inn.theorizeit.org/Search/Variable?query=supervisor%20support
Climate	http://inn.theorizeit.org/Search/Variable?query=climate

Note. INN = internomological network; Org. = organizational

The second attitudinal correlate included in the current analyses is pay satisfaction. Pay satisfaction can be defined as the "amount of overall positive or negative affect (or feelings) that individuals have toward their pay" (Miceli & Mulvey, 2000, p. 246). Two theories have guided research on pay satisfaction over the past 50 years: equity theory (Adams, 1963, 1965) and discrepancy theory (Lawler, 1971, 1981). Equity theory calls for a fair balance to be struck between an employee's inputs (e.g., effort, skill level, qualifications) and an employee's outputs (e.g., salary, benefits, rewards). In addition, this theoretical perspective holds that an individual will experience distress when his/her output-to-input ratio is perceived to be less than a peer or colleague who has similar inputs. Indeed, this is in keeping with Lawler's (1971, 1981) discrepancy theory perspective that individuals use perceptions of pay of referent others rather than the absolute amount of pay they receive to evaluate their pay satisfaction. Both equity and discrepancy theories suggest that the experience of distress will lead an individual to take corrective action so that balance is restored. Indeed, this can be achieved in a number of ways. For example, an individual who experiences pay dissatisfaction may decide to terminate his/her relationship with the organization (Huseman, Hatfield, & Miles, 1987). In sum, the inclusion of pay satisfaction in the current analyses is justified because of its conceptual importance to the turnover literature.

Organizational commitment is the third attitudinal correlate included in the present research and measures "an individual's psychological bond with the organization" (Judge & Kammeyer-Mueller, 2012, p. 349). Like job satisfaction, commitment scales also have multiple dimensions. Affective commitment (AC) denotes an employee's emotional attachment to and identification with his/her organization and has been found to be negatively associated with turnover (Rhoades, Eisenberger, & Armeli, 2001). Continuance commitment (CC) refers to the perceived costs associated with leaving the organization and has also been found to be negatively associated with turnover intention (Wasti, 2003). The third dimension of organizational commitment, normative commitment (NC), reflects a perceived obligation to remain in the organization. Empirical evidence suggests that it, too, is negatively related to turnover intent and behavior (Somers, 1995). Meyer and Allen (1991) theorized that common to all three dimensions is the view that commitment has implications for behavioral outcomes. This means that individuals who experience low levels of organizational commitment may be more likely to terminate their membership in the organization. Effectively, it is argued that individuals who no longer identify with their organization (i.e., low AC), believe the benefits of leaving outweigh the costs (i.e., low CC), and cease to feel obliged to remain in the unit (i.e., low NC) are more likely to leave. Importantly, for the current analyses I group together all three dimensions because practically all of extant research indicates that each facet is negatively associated with turnover intent and actual turnover. Put differently, conceptualizations of AC-turnover, CC-turnover, and NC-turnover suggest that a moderating effect of commitment type does not exist for this particular bivariate relation and thus aggregating to the overall organizational commitment level will not impact empirical outcomes.

Organizational justice generally refers to an individual's subjective perception of the fairness of allocations in the workplace and represents the fourth attitudinal variable included in the current study. The theory of perceived organizational justice consists of several sub-dimensions, referring to the allocation of outcomes such as financial rewards (i.e., distributive justice), the process by which allocations are made (i.e., procedural justice), the information provided regarding the process (i.e., informational justice), and the received relational treatment through the process (i.e., interpersonal justice). Meta-analytic evidence suggests that each dimension is negatively related to turnover intention (Colquitt et al., 2001). As such, similar to organization commitment, for the current analyses I aggregate all four dimensions to a single higher-order organizational justice group. The theoretical underpinnings of distributive justice can be traced back to Adams' (1965) equity and Vroom's (1964) expectancy theories. On the one hand, for instance, equity theory posits that distributive justice is fostered when allocation outcomes are aligned with implicit norms like equity or equality. On the other hand, the expectancy theory of motivation states that motivation is influenced by the belief that effort will lead to higher performance (expectancy) and belief that higher performance will lead to better rewards (instrumentality) that are valued (valence) by employees. As previously mentioned, distributive justice pertains to the fairness of allocation outcomes and thus is closely linked to instrumentality. Therefore, distributive justice perceptions will influence an employee's motivation and may motivate him/her to leave the organization when distributive injustice (i.e., not receiving fair compensation) is experienced (Nadiri & Tanova, 2010). Although the theoretical foundations for procedural, informational, and interpersonal justices differ from what was just described in this manuscript regarding distributive justice here, a thesis common to all justice facets is that a violation of justice increases the likelihood of an employee terminating his/her relationship with the organization (Aquino et al., 1997; Aryee & Chay, 2001; Dailey & Kirk, 1992).

Autonomy – the fifth attitudinal correlate of turnover intention included in the current study – refers to the "degree to which the job provides substantial freedom, independence and discretion in scheduling the work and in determining the procedures to be used in carrying it out" (Hackman & Oldham, 1980, p. 162). Autonomy is most often measured with Hackman and Oldham's (1975, 1976) job characteristics model. Several theories of motivation emphasize the importance of autonomy in the workplace and how a lack of it can lead to negative outcomes like burnout and turnover intent. As one example, self-determination theory (SDT; Ryan & Deci, 2000) suggests a limited stock of innate resources essential to one's ability to regulate thought and behavior exists. In an overview of SDT, Deci and Ryan (2012) suggested three needs – the needs for competence, relatedness, and autonomy – aid individuals in these types of self-regulation. Autonomy in this context refers to liberty in directing one's own behavior. Importantly, SDT holds that "environments can either facilitate and enable [one's] growth and integration propensities… or they can disrupt, forestall, and fragment these processes resulting in behaviors and inner experiences that represent the darker side of humanity" (Deci & Ryan, 2012, p. 6). It can therefore be concluded that the future self is shaped by the present self's interaction with the environment. Put differently, an individual may remove him or herself from the current environment (i.e., quit the organization) when it does not satisfy their need for autonomy. Taken together, autonomy is included in the current analyses because it is among the most salient characteristics of the job and has conceptual ties to turnover intention.

Interactionist theories have been postulated in the organizational sciences for more than 100 years (Murray, 1938; Parsons, 1909). Since then, several conceptualization of fit between an individual and his/her environment have emerged, making this one of the most esteemed areas of psychological research (Dawis, 1992). Much emphasis has been placed on the match between peoples' interests and those of others in a vocation (e.g., Holland, 1985) and the compatibility between an individual and his or her job, organization, work group, and supervisor. For these reasons, the sixth attitudinal correlate included in the current research is person-environment fit. Similar to organization justice and organizational commitment, several dimensions (e.g., person-organization fit, person-job fit, etc.) or person-environment fit have been posited to be negatively related to turnover-related outcomes (Carless, 2005; Morley et al., 2007; Ramesh & Gelfand, 2010) and thus are aggregated to a single higher-order group for the purposed of the current analyses.

Person-environment scholars often theoretically ground their research in terms of job embeddedness theory (Mitchell et al., 2001) and attraction-selection-attrition theory (ASA; Schneider, Goldstein, & Smith, 1995). Given that a description of the former is provided in a previous section, I briefly outline the latter, ASA, only. The ASA framework outlines how employees will continue to remain in the organization as long as both entities are mutually attracted to each other. More specifically, an individual may be attracted to an organization – and consequently be selected into the organization – if value congruence between both parties exists (i.e., the individual and organization share the same values). The relationship between both the employee and the organization will continue so long as this congruence exists (Chatman, 1989). A lack of congruence, however, induces dissatisfaction through violation of employee expectations and increases the employee's propensity to terminate the relationship (Verquer et al., 2003).

Research in the area of work-life conflict (WLC) is growing at a fast rate (Eby et al., 2005) and because of its nascent nature is included as the seventh attitudinal variable in the current set of analyses. Scholarly activity in this domain is typically characterized by the examination of different forms "of interrole conflict in which the role pressures from the work and family domains are mutually incompatible in some respect. That is, participation in the work (family) role is made more difficult by virtue of participation in the family (work) role" (Greenhaus & Beutell, 1985, p. 77). The directionality of this conflict can follow two paths. The first occurs when one's work role interferes with the family role (WIF) and the second when the family role interferes with the work role (FIW) (Frone, 2003). Researchers interested in WLB topics often ground their hypotheses in Kanter's (1977) distinction between work and non-work spheres and whether or not they are integrated or separated. Separation implies that there is little or no interaction between the two domains whereas integration suggests an open-systems approach in which definitive boundaries between the two spheres do not exist. Spillover theory (Staines, 1980), which holds that employee emotions and behaviors in one sphere carry over into the other, represents another theoretical perspective that has been employed by WLB scholars. However, perhaps the most common theoretical perspective used to justify WLB hypotheses is conflict theory. Effectively, conflict theory claims that the work and family environments are incompatible because they are governed by different sets of norms and requirements (Zedeck & Mosier, 1990). The conflict that arises from being a member of both work and family environments is often attributable to role overload (Rizzo, House, & Lirtzman, 1970). Such conflict can be minimized by reducing or eliminating one's role in one environment. For instance, an individual could engage in turnover intention or behavior and thus direct all of his or her attention and effort toward just one environment.

The final attitudinal variable included in the current study is supervisor support. Although an assortment of definitions for this construct are available in the literature, it generally refers to an individual's belief that the supervisor offers work-related assistance to aid in the performance of their job. Similarly, scholars have drawn on a rich well of theory to conjecture how and why supervisor support is related to turnover-related outcomes. First, organizational support theory holds that employees develop global beliefs concerning the extent to which their organization values their contributions. According to Stinglhamber and Vandenberghe (2003), employees try to personify their organization by ascribing humanlike characteristics to it. To this end, employees oftentimes view how they are treated by their immediate supervisor to inform their rating of perceived organizational support. Put differently, because supervisors are viewed as agents of the organization, employees' ratings of perceived supervisor support often manifests into ratings of perceived organizational support. Indeed, this has important implications for turnover decisions because employees who believe that the organization has a general negative orientation toward them are more likely to leave. Although not discussed in detail here, social exchange theory and the norm of reciprocity (Maertz, Griffeth, Campbell, & Allen, 2007) posits that receiving support from the supervisor should also cause some form of experienced obligation to the supervisor. This engendered obligation to the supervisor may present itself as lower turnover intention. Taken together, there are several theoretical perspectives on how supervisor support relates to turnover that justify its inclusion in the current set of analyses.

It would be an inferential leap to assume that attitudinal variables are the only ones that influence an employee's decision to leave the organization. As such, I include three non-attitudinal variables in the current set of analyses. First, age can be described as an objective person characteristic. Although, limited conceptual reasoning is presented in the literature for the inclusion of age in the turnover process, it appears in several predominant models of turnover (Mobley et al., 1979; Mobley et al., 1978). Some scholars have leveraged March and Simon's (1958) model of turnover to suggest that younger workers are more inclined to quit because they are likely to be more mobile and have a greater number of alternatives available to them. Assuming that older workers have already "worked their way up," this perspective may suggest that economic conditions at different life stages also accounts for why age influences turnover decisions. Another explanation could be that older workers tend to be more satisfied (Kooij, Jansen, Dikkers, & De Lange, 2010) and, therefore, by extension, are less likely to quit their job.

Individual performance has long been a behavioral predictor of employee turnover (Jackofsky, Ferris, & Breckenridge, 1986; Steers & Mowday, 1981) and thus is also included in the current research. According to Jackofsky (1984), individual job performance can influence turnover in a number of ways. As one example, low performers are a primary cause of poor organizational performance. Therefore, these individuals are most likely to be terminated by the organization (i.e., involuntary turnover). Interestingly, Jackofsky also suggested that poor performers may also be more inclined to voluntary leave the organization under "a mutual agreement pact… to save the employee from a negative evaluation on his or record" (1984, p. 78). This idea was later captured by Hom and Griffeth (1995) when they suggested that organizations at times encourage poor performers to quit in order to allow such employees to save face. Lee and Mitchell's (1994) unfolding model of turnover suggests that a poor performance evaluation (i.e., a shock) may motivate an employee to quit his or her position. Furthermore, as noted by Zimmerman and Darnold (2009) Vroom's (1964) expectancy theory also suggests that negative feedback may signal to employees that they are unlikely to receive valued outcomes from the organization (e.g. promotions) or that they may be fired. Consequently, an employee may choose to leave the organization rather than experience the unpleasant circumstances facing them.

The third non-attitudinal, and final, variable included in the current analyses is workplace climate. A large body of research has focused on whether or not environmental variation can influence individual outcomes (Carr et al., 2003). Climate is commonly defined as the shared perceptions of organizational policies, practices, and procedures, both formal and informal (Reichers & Schneider, 1990) and has been a major focus of this literature. Studies on climate-to-outcome phenomena can be traced back to Fleishman (1953) and have since grown to include a wide variety of dimensions of climate (Brown & Leigh, 1996; Pritchard & Karasick, 1973; Schnake, 1983). Ajzen and Fishbein's (1977) theory of planned behavior and Mobley et al.'s (1979) framework of employee turnover have been widely used to explain why climate perceptions are linked to turnover decisions. Both of these perspectives suggest that an employee's perceptions of the workplace environment are shaped by his or her cognitive and affective states. It follows that these perceptions become antecedents to behavior when they are combined with the opportunity to act (Mathieu & Zajac, 1990). Although not discussed in detail here, I note that theory pertaining to human resource management practices and high performance work systems has also been used to develop climate-related hypotheses (see Hong, Liao, Hu, & Jiang, 2013). Together, the current analyses include a set of 11 variables that are conceptually relevant to prediction of turnover. Their inclusion is intended to provide a coarse overview of the relative importance of theoretical perspectives in the published turnover literature.

Chapter 6. Methods

In this section, I begin by describing my data source. Next, I explain the meta-analytic procedures used in my study. In addition, I explain how I removed outliers from my meta-analytic datasets to reduce heterogeneity. Following this, I briefly describe how the incremental validity tests were performed. Finally, I outline the relative importance analysis procedures used in my study. Specifically, I describe the traditional approach to relative importance analysis in the meta-analytic context (Tonidandel & LeBreton, 2011), which relies on a single meta-analytic correlation matrix only, and the newly-introduced sensitivity analysis approach to relative importance analysis, which draws on 1,000 meta-analytic correlation matrices.

metaBUS: Database, Taxonomical Classification System, and Portal

The metaBUS database (Bosco et al., 2015a; Bosco et al., 2015b) is an open-source search engine of scientific findings. At the time of this study, the publically-available database contains approximately 800,000 zero-order correlation coefficients extracted from approximately 9,000 articles published organizational science journals. Moreover, each effect size is tagged to a hierarchical taxonomic map of the field that consists of approximately 5,000 nodes. Although a full description of metaBUS's taxonomy and curation protocols is provided by Bosco et al. (2015b) a brief description of how this database has been formed is offered next.

The metaBUS platform was built using the following semi-automated extraction process. First, a journal article is screened for relevance. If a correlation matrix based on original data is located in the article, its contents (i.e., variable name, mean, standard deviation, and correlation information) are converted to a set of Excel rows and columns using an extraction software. Next, the extraction output is entered into the coding sheet before a script “cleans” the data. The purpose of this script is to remove any irrelevant characters (e.g., asterisks for statistical significance) that may have been inadvertently captured in the extraction process. Following this step, outstanding irrelevancies are addressed manually. In the next stage, coders augment the extraction output by applying article-level and variable-level codes. A summary of these codes is provided in Table 5.

Against the aforementioned jingle-jangle problem backdrop, one of metaBUS’s primary objectives was to develop a comprehensive, yet user-friendly, map of our field. Although a description of how this map was developed was provided by Bosco et al. (2015a), I note that it adheres to the “IsA” concept (Bosco et al., 2017). In addition, the taxonomy arranges constructs by group membership and follows standards set forth by the National Information Standards Organization (National Information Standards Organization (US), 2005). Specifically, nodes are linked by “is a” connections. For example, emotional stability “is a” dimension of personality; in turn, personality “is a” psychological trait; and a psychological trait “is a” person characteristic.

The metaBUS portal – an online interface – uses a query logic system that draws on metaBUS’s corpus of data and taxonomical map to probe the relation between two constructs. Given that the correlation matrix needed for the proposed study’s analysis of relative importance is comprised of 12 constructs (11 independent variables and one dependent variable), 66 meta-analyses were conducted. Using a combination of letter string matches and taxonomic codes, I queried the metaBUS portal to extract the necessary raw data to conduct all 66 meta-analyses and, in turn, facilitate the relative importance analyses. Recall that Table 2 provides a summary of the variable names examined in the current study and their corresponding five-digit codes and placement in Bosco et al.'s (2015a; 2015b) taxonomic map. Importantly, raw data returned by each query was inspected to ensure all taxonomic codes are accurate.

Table 5

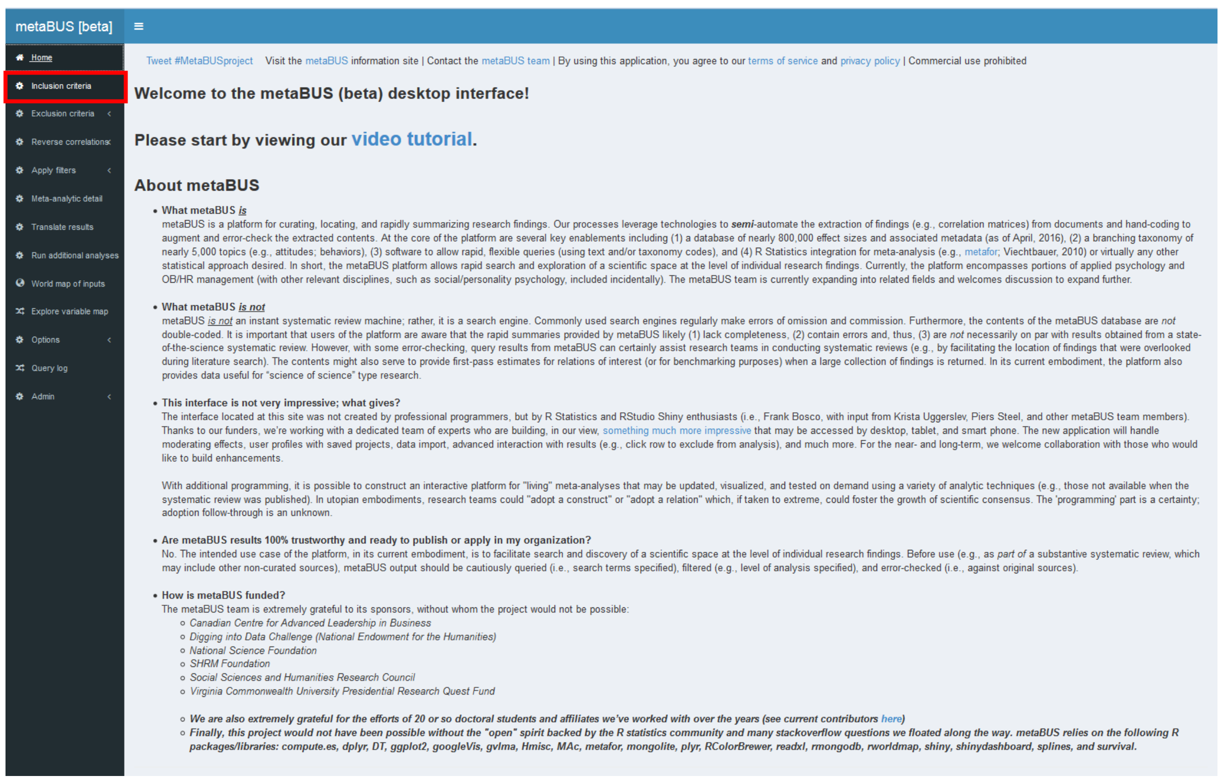
Summary of Article-Level and Variable-Level Codes

Code	Description
Article-level	
Outlet	Details where and when the manuscript was published. Example: JAP-2010-95-4-781 indicates the following the manuscript was published in *Journal of Applied Psychology* in 2010, volume 95, issue 4, start page 781.
Year	Year of publication
Funded	Funded versus nonfunded
DOI	Digital object identifiers are provided so the electronic manuscript can be linked to the database.
Variable-level	
Variable ID	Unique code applied from Bosco et al.' (2015) hierarchical taxonomic display to each variable
Reliability	Used to determine whether or not the reliability is a Cronbach alpha. This code is necessary for artifact corrections
Reverse	Used to indicate if a value needs to be reversed. Example: When employee "performance" is measured as the number of errors, then "performance" actually indicated "lack of performance." Therefore, the code for employee performance is applied and then coded and Reverse = Yes, indicating that the inverse must be applied when conducting analyses.
Time point	Used to indicate if a variable includes a temporal designation. Example: Turnover is often not measured concurrently with other variables. For example, should turnover be measured one year after job satisfaction, then job satisfaction is coded as Time = 1 and turnover as Time = 2.
Response rate	Response rate as reported in the manuscript. If not reported, the response rate is inferred when possible. Example: If 500 surveys were sent to research participants and 250 were returned, then the response rate is .50.
Sample size	Indicates the sample size associated with the individual variable. Importantly, this may vary within a given correlation matrix.
Mean sample size	At times, a sample size range is reported because of missing data. In such cases, the middle value of the range is listed as the sample size and mean sample size is coded as "yes."
Sample number	Used to maintain sample dependence when studies analyze multiple samples or multiple studies.
Coding confidence	Normal versus low confidence.
Pertains	Used to indicate what the data are describing. Examples include: self, general employees, manager, armed forces, students, job applicants, teams, business unit, organization, etc.
Source	Used to indicate where the data came from. Examples include: general employees, managers/supervisors, students, armed forces, teams, subject matter experts, organizational records, government/public records, etc.
Unit of analysis	Indicates the level of analysis. Examples include: individual, dyad, team, unit, organization, etc.
Location	Indicates where the data were collected (e.g., country of origin).

To demonstrate the functionality of the metaBUS portal, I describe how I queried the databased to obtain raw data pertaining to the job satisfaction-turnover intention relation. Note that Appendix B provides a list of the letter strings and taxonomic codes that were used to query the metaBUS database. First, I logged into the metaBUS portal by visiting http://54.164.101.238/. Second, I clicked on "inclusion criteria" in the left panel of the landing page (see Figure 7). This action brings the user to the user interface, in which the metaBUS database can be queried using letter-string matches (see boxes [a] and [b] of Figure 8) and taxonomic codes (see boxes [c] and [d] of Figure 8).

Figure 7

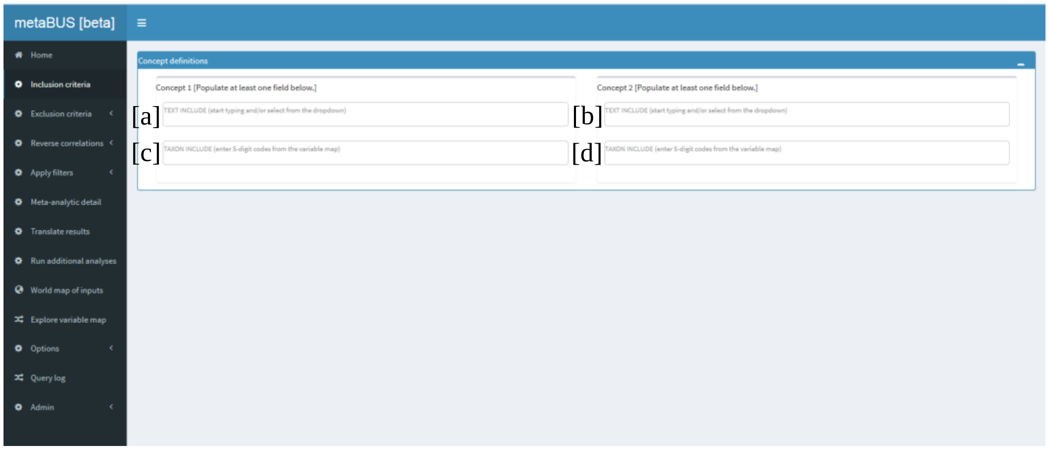
Landing Page of the metaBUS Portal



Note. Online portal can be accessed by visiting http://54.164.101.238/

Figure 8

metaBUS Graphical User Interface

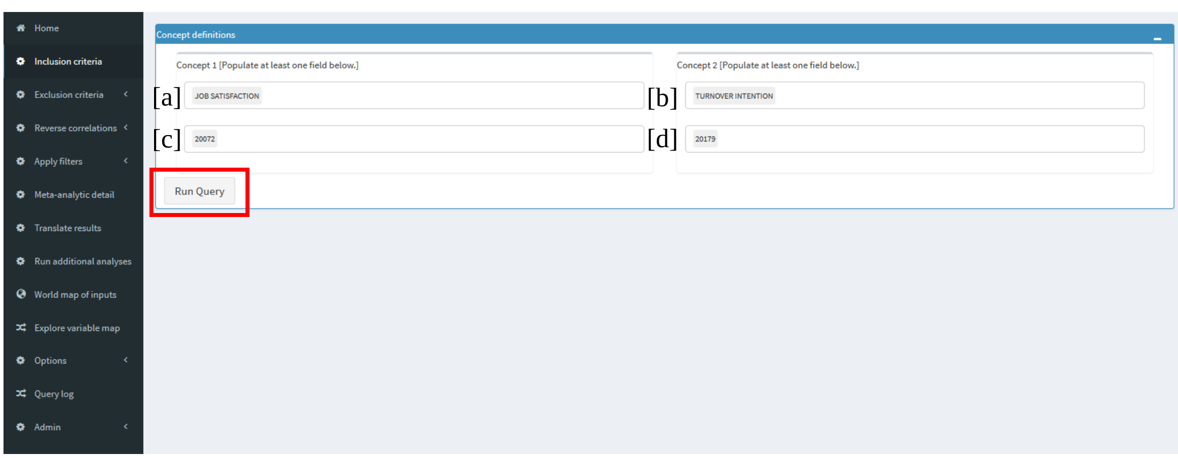


Note. Online portal can be accessed by visiting http://54.164.101.238/

Third, the letter-strings *job satisfaction* and *turnover intention* were inputted into boxes [a] and [b], respectively (see Figure 9). In addition, the corresponding taxonomic codes for job satisfaction (20072) and turnover intention (20179) were entered into boxes [c] and [d], respectively (see Figure 9).

Figure 9

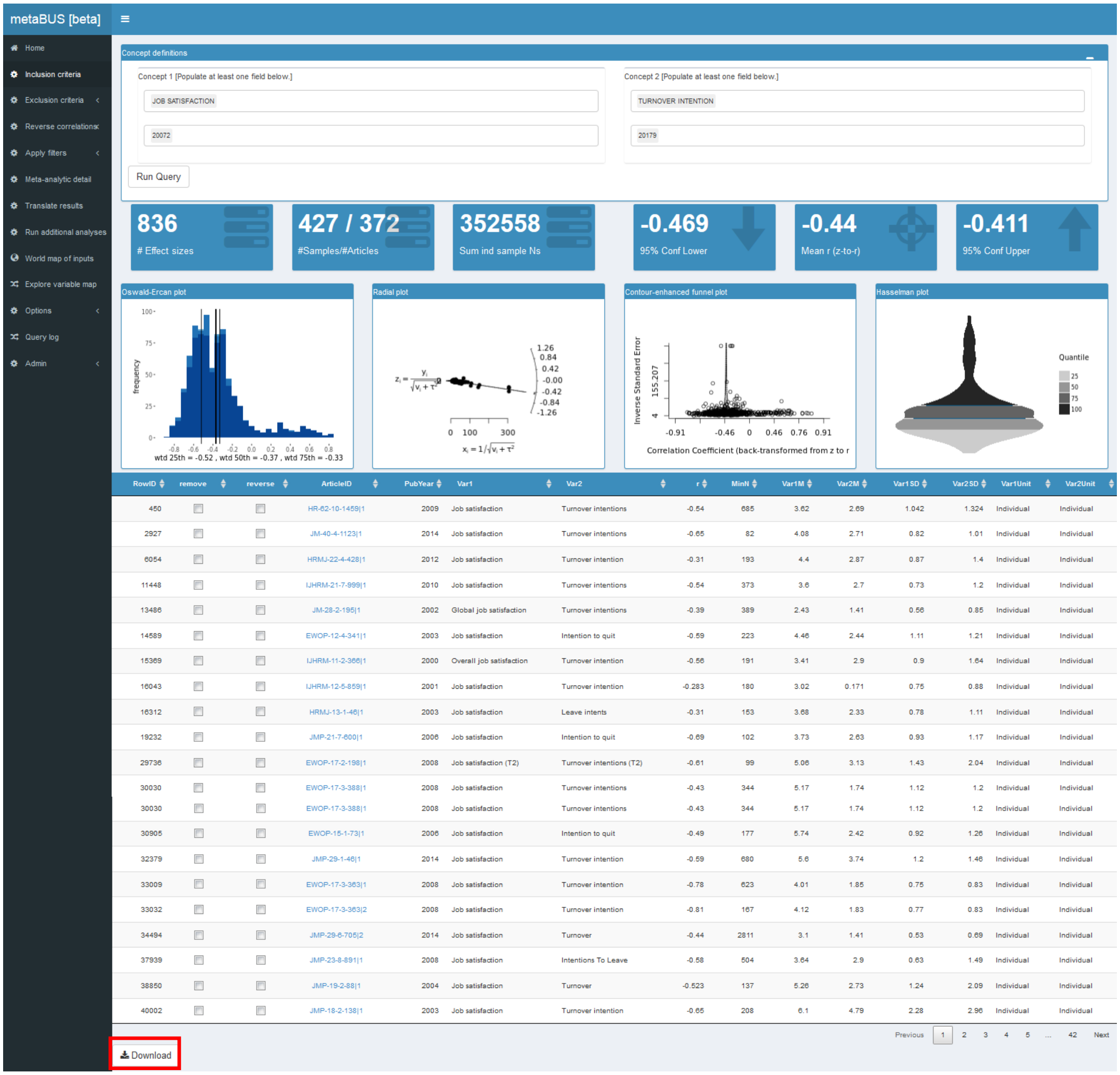
Entering Letter-String and Taxonomic Code Data into metaBUS User Interface



Note. Online portal can be accessed by visiting http://54.164.101.238/

Figure 10

Results Output from metaBUS User Interface



Note. Online portal can be accessed by visiting http://54.164.101.238/

Fourth, I clicked on the "run query" button (see Figure 9) to probe the database using the aforementioned inclusion criteria. An inspection of Figure 10, suggests that this query returned 836 non-independent effect sizes. These effect sizes were drawn from 427 independent samples that were published in 372 articles. In addition, the results output suggests that the meta-analytic mean effect size estimate is -.44. Tett and Meyer (1993) reported a similar meta-analytic mean effect size (-.48; $|\Delta| = .04$ or 9%) for the job satisfaction-turnover intention relation, which gives me confidence in the data provided by metaBUS.

Fifth, I examined the raw data output for errors and unusual cases. For example, a close inspection of Figure 10 reveals that the accuracy of two codes needed to be inspected. Specifically, an examination of the “Var 2” data (see the seventh column) shows that the letter string “turnover,” not “turnover intention,” appears twice in the output, which may indicate that the taxonomic code for turnover intention was erroneously applied to a variable that measures turnover behavior. To inspect the first unusual case (see RowID 34494; first column of Figure 10), I clicked on the corresponding “ArticleID” (fourth column). This action brought me to article’s webpage (Beutell & Schneer, 2014; see http://www.emeraldinsight.com/doi/abs/10.1108/JMP-11-2012-0342). After downloading the article’s PDF, I inspected the text to determine if turnover intention or actual turnover behavior was measured by the original authors.

My search indicated that turnover intention, not actual turnover behavior as indicated by the letter string included in the metaBUS output, was examined in by Beutell and Schneer (2014). Specifically, the authors “consider[ed] the relationship of job satisfaction to turnover intentions among Hispanics” (p. 216). Furthermore, my search found that “one item measured intentions to quit” (p. 716) and that actual turnover behavior was not measured. As such, I concluded that this particular effect size should be retained and, thus, included in my analyses. I followed this process for the other unusual case found in Figure 10 (see RowID 38850; first column). For this particular case, I found that “withdrawal intentions” was measured by Vakola, Tsaousis, and Nikolaou (2004; see p. 98) even though the letter string "turnover" was reported in the article. As such, a judgment call was made to retain this effect size.

The sixth and final step was to download the raw data by clicking on the "Download" button (see Figure 10). This action provides all effect size, sample size, and other relevant information for the corresponding query in a comma separated values (.csv) file. Access to the raw data allows me to perform the analyses needed for the current study. Given that the current study examines the relative importance of 11 predictors of turnover intention, a meta-analytic correlation matrix consisting of 66 inter-correlations must be created. As such, the metaBUS portal was queried 66 times using the aforementioned five step procedure. Importantly, additional data screening occurred at this time. For instance, there were times when effect sizes had to be reversed to ensure that the data were conceptually similar. Specifically, there were instances when a negative effect size had to be changed to a positive one and when a positive effect size had to be changed to a negative one.

For example, there were several instances in which relations involving "job *dis*satisfaction" where returned when I queried the metaBUS database for relations involving "job satisfaction." As an example, an inspection of the "job satisfaction-turnover intention" meta-analytic dataset revealed that the effect size information reported by Webster, Beehr, and Love (2011) may have represented an unusual case. Indeed, one would expect to observe a negative relation between job satisfaction and turnover intention. Yet, the "job satisfaction-turnover intention" meta-analytic dataset returned by metaBUS indicated that Webster et al. (2011) reported a positive relation. However, an examination of the original article revealed that Webster et al. (2011) examined the relation between job *dis*satisfaction and turnover intention, not the relation between job satisfaction and turnover intention. Consequently, I reversed the directionality of the effect size reported by Webster et al. (2011) as to align it with the relation of interest in my study, which was “job satisfaction-turnover intention.” As a result, .69 (Webster et al., 2011; see Table 1, p. 511) was changed to -.69 before meta-analytic and relative importance procedures were performed.

The aforementioned process (i.e., reversing the directionality of an effect size) had to be performed for several relations involving “individual performance.” For example, an inspection of the “individual performance-turnover intention” meta-analytic dataset provided by metaBUS indicated that the effect size information reported by Kossek, Pichler, Meece, and Barratt (2008) may have represented an unusual case. Specifically, according the meta-analytic dataset, Kossek et al. (2008) reported r = .10 for the relation between job performance and turnover intention. This was flagged as an unusual case as “accidents” was used to operationalize job performance. Specifically, job performance was measured by “the number of accidents in the child care setting” (Kossek et al., 2008, p. 382). Indeed, this operationalization indicates that job performance decreases as the number of accidents increases. Therefore, I reversed the directionality of this effect size to conceptually align it with the other “individual performance-turnover intention” data. Interestingly, a number of cases were flagged as unusual but were found to be accurate upon further inspection. For instance, Einarsen, Hoel, and Notelaers (2009) reported a correlation coefficient of .29 for the “individual performance-turnover intention” relation. Indeed, this was deemed unusual as such a large, positive relation is not consistent with the theory in this research area. However, an inspection of the original article indicated that individuals were asked to rate their own job performance by selecting one of five different options that varied from less than 50% to 100%. This operationalization suggests that job performance was measured in the typical direction such that higher scores reflect higher levels of job performance. Furthermore, an inspection of the original articles' results and discussion sections indicated that the correlation coefficient reported by (Einarsen et al., 2009) was not a transcription or publishing error.

Although I queried the metaBUS database for relations pertaining to “work-life balance” (taxonomic code = 20089; metaBUS taxonomy version 52), data returned by these searches were a mixture of relations involving “work-life balance” *and* “work-life conflict.” Given that the majority of the data returned by these searches pertained to “work-life conflict” relations, a judgement call was made to reverse score the effect size data pertaining to “work-life balance” relations. For example, Finkelstein, Frautschy Demuth, and Sweeney (2007) reported a correlation coefficient of -.26 for the “work-life balance-turnover intention” relation. However, this correlation coefficient was changed to .26, a positive effect size to reflect a “work-life conflict-turnover intention” relation, before meta-analytic and relative importance procedures were performed. This action was taken for each relation involving “work-life balance” so that all of the effect size data were conceptually similar. Taken together, data provided by metaBUS were screened for unusual cases before being analyzed. When identified, unusual cases were examined. A detailed description of the screening process is beyond the scope of my study, However, I note that all raw data files can be found on my dissertation project website at https://osf.io/jfv76/.

Finally, it is important to note that raw data provided by metaBUS are at the effect size level and, thus, may not be independent. For example, it is possible that a meta-analytic dataset may include instances in which the bivariate relation in question was measured multiple times using a single sample (e.g., longitudinal research design). In such cases, between-study *and* within-study variances must be accounted for when imputing the meta-analytic mean effect size estimate (for a full description of how this is done see Konstantopoulos, 2011). I outline how dependence issues are addressed in this study later in this section.

Analyses: Meta-Analytic Approach

As previously mentioned, the metaBUS portal was used to locate the necessary data from the published literature for the analyses. Following this initial step, meta-analytic procedures were conducted in R using the *metafor* package (Viechtbauer, 2015). In the interest of scientific transparency, all analytic scripts can be found at my dissertation project website by visiting https://osf.io/jfv76/.

Meta-analysis is a set of quantitative methods used to combine the effect sizes of primary research studies (Kepes, McDaniel, Brannick, & Banks, 2013). There are two primary traditions in meta-analysis. Those schools are (a) the psychometric approach (Schmidt & Hunter, 2015; see also Hunter & Schmidt, 2004), which is typically used in the organizational sciences and (b) the a non-psychometric meta-analysis approach (Hedges & Olkin, 1985; see also Borenstein et al. [2009]). A description and comparison of the approaches to meta-analysis is beyond the scope of the current study (see Kepes et al., 2013 for an overview and description of both approaches). I note that, ideally, one would use the full version of the psychometric meta-analysis because it includes correction for statistical artifacts (e.g., reliability in the independent and/or dependent variable, range restriction). However, I have data in which multiple effects sizes are often available for the same sample which is best addressed with a multi-level meta-analysis (discussed later in this chapter). There does not exist a multi-level psychometric meta-analysis procedure. Thus, I used meta-analysis methods in the non-psychometric tradition. The multi-level analysis in *metafor* calculated the (a) meta-analytic mean effect size estimate, (b) 95% confidence interval, (c) 68% prediction interval, and (d) I^2 statistic for all 66 meta-analyses conducted in the current study. One obtains 66 meta-analysis in that there are 11 meta-analyses of the 11 predictor and turnover intention and 55 meta-analyses calculating the intercorrelations of the 11 predictors.

The meta-analytic mean effect size estimate is precision-weighted mean of all effect sizes included in the meta-analytic dataset. The purpose of the weighting procedure is to assign greater weight to the effect sizes based on larger samples than those based on smaller ones. To this end, the Hedges and Olkin (1985) approach to meta-analysis uses the inverse variances of each study to weight each effect size included in a meta-analytic dataset. I note that the RE meta-analytic mean effect size estimate is calculated using the random effects maximum likelihood (REML) model, which is generally recommended when there is evidence of heterogeneity (e.g., moderators) among the population parameters (Hedges & Olkin, 1985). Furthermore, evidence suggests that the alternate model, the fixed effects one, tends to underestimate the amount of error in the imputed parameters when the true variance between studies is greater than zero (Field, 2001; Hunter & Schmidt, 2000). As a result, statistical problems like inflated Type I error rates and inaccurate meta-analytic results typically arise (Kepes et al., 2013).

A confidence interval, which addresses the precision of the observed meta-analytic mean effect size estimate, represents a range of values in which the “true” population effect size is likely to be found. By convention, meta-analysts typically report the 95% confidence interval associated with the observed meta-analytic mean effect size estimate. Strictly speaking, a 95% confidence interval means that if one were to take 100 different samples and compute a 95% confidence interval for each sample, then approximately 95 of the 100 confidence intervals will contain the "true" mean value. In contrast to the 95% confidence interval, the prediction interval quantifies the dispersion of effect sizes in a meta-analytic dataset and thus indicates the likely range of "true" (i.e., population) effect sizes (Kepes & McDaniel, 2015). A prediction interval is based on sampling error *and* the variance of the studies, τ^2. Overall, confidence intervals reflect only sampling error and prediction intervals reflect sampling error *and* between-study variance. Although an asymptotic decline in both confidence interval and prediction interval width is typically observed as effect sizes are added to the meta-analytic dataset, the latter will always be wider than the former because it includes a between between-variance component, which is not affected by the number of effect sizes included in the meta-analysis. Formulae for both the confidence interval and the prediction interval are present in Borenstein et al. (2009).

The extent of heterogeneity in a meta-analysis partly determines the difficulty in drawing overall conclusions (Higgins & Thompson, 2002). Statistical heterogeneity exists when the underlying parameters being evaluated differ between studies, and may be detectable if the variation between the results of the studies is above the expected level (i.e., by chance). For instance, studies often differ in design (concurrent vs. longitudinal), by participants (managers vs. general employees), intervention (type or level of treatment administered), and measure (subjective vs. objective). To quantify the degree of heterogeneity in each meta-analytic distribution, I report the I^2 statistic (Higgins & Thompson, 2002).

Finally, it is important to note that the meta-analytic procedure used in my study is performed on multilevel data that may not be dependent. Consequently, a multi-level meta-analysis must be performed. Specifically, data gathered from the metaBUS portal are at the effect size level and are not necessarily independent because multiple effect sizes for a given bivariate relationship may be reported in a single sample (Konstantopoulos, 2011). According to Tanner-Smith, Tipton, and Polanin (2016), these independence issues are referred to as "correlated effects" and "hierarchical effects." Given that sample independence is a primary assumption of any meta-analysis (Hedges & Olkin, 1985; Hunter & Schmidt, 2004), datasets that exhibit "correlated effects" and "hierarchical effects" will produce distorted meta-analytic results if the dependencies are ignored. One remedy for these types of problems is to conduct a multilevel meta-analysis, which can be used to estimate and account for the amount of heterogeneity across levels of dependent parameters (Tanner-Smith et al., 2016; Viechtbauer, 2015). This approach is advantageous because it permits the inclusion of statistically dependent effect sizes, and therefore does not require the meta-analyst to discard information contained in the effect sizes reported in primary studies (i.e., the type of data loss that would occur if selection criteria were used to select a set of statistically independent effect sizes). My 66 datasets typically exhibited a "hierarchical effect" such that primary study effect sizes (level 1) are nested within samples (level 2), which, in turn, are nested within articles (level 3).

Konstantopoulos (2011) provided a detailed explanation of how dependency issues are addressed for two and three level data structures. Within-study variance *and* between-study variance must be accounted for when there are two levels in the meta-analytic data structures. The first level of the hierarchy – the within-study model – includes an error term that is normally distributed with a mean of zero and variance v_i, which is assumed to be known

(Konstantopoulos, 2011; see Equation 1). At the second level of the hierarchy – the between-study model – the population parameter varies around an overall mean and includes a study-specific random effect that is normally distributed with a mean of zero and variance τ (Konstantopoulos, 2011; see Equation 2). For the within-study model, it is assumed that the variances of the stochastic errors are different for each study (i.e., heterogeneity of the sampling error). In contrast, for the between-study model it is assumed that the random effects are distributed identically (i.e., homogeneity of random effects). Computations for the three-level model are similar but are more complicated because of variance components at the third level must be included. The model for the first level in a three-level meta-analysis is identical to the within-study model when the data structure is comprised of only two levels. However, in the second level of the hierarchy, the effect size varies around a level three unit mean (Konstantopoulos, 2011, see Equation 10). Finally, at the third level of the hierarchy, the level three unit means vary around an overall mean, which includes a level-three unit specific random effect that is normally distributed and a between-level-three variance (Konstantopoulos, 2011; see Equation 11).

Analyses: Outlier Detection

According the to the *American Psychological Association's* Meta-Analytic Reporting Standards, meta-analytic datasets and results should be submitted to sensitivity analyses (American Psychological Association, 2008, 2010). In general, sensitivity analyses address the question: "What happens if aspects of the data or analyses are changed?" (Greenhouse & Iyengar, 2009, p. 418). In meta-analytic reviews, sensitivity analyses are especially important due to their impact on the scientific literature (Geyskens, Krishnan, Steenkamp, & Cunha, 2009;

Kepes et al., 2013; Schmidt & Hunter, 2015). One sensitivity analysis is the identification of outliers (Kepes et al., 2013).

Outliers are observations that appear “to deviate markedly from other members of the sample in which it occurs” (Grubbs, 1969, p. 1). Not surprisingly, outliers have long been acknowledged to have a potentially distorting influence on statistical analyses and their results (e.g., Grubbs, 1969; Huber, 1980; Tukey, 1960). Due to their influence on the results from primary studies, it has also been recognized that the meta-analytic datasets may contain outliers, which can distort the meta-analytic results (e.g., the mean estimate and the associated standard deviation) and, thus, the validity and robustness of conclusions from meta-analytic reviews (Ada, Sharman, & Balkundi, 2012; Huffcutt & Arthur, 1995; Schmidt & Hunter, 2015; Schmidt et al., 1993; Viechtbauer & Cheung, 2010). Outliers in such datasets may be due to random sampling error, errors in the transcription process or the analysis, or they may reflect some rare characteristic of a study, such as a unique sample or a particularly large sample size. Therefore, the detection of outliers is a reasonable practice prior to estimating meta-analytic statistics.

Viechtbauer and Cheung (2010) adapted to meta-analytic contexts several outlier diagnostic procedures originally designed for standard linear regression analyses. Software does not exist for all the outlier detection methods for multi-level meta-analysis. However I was able to use a residual method, which is also referred to as Cook’s distance and can be interpreted as the Mahalanobis distance between the entire set of predicted values one with the *i*th study included and once with the *i*th study excluded from the model fitting (Viechtbauer & Cheung, 2010; see also Viechtbauer, 2015) A Bonferroni-corrected critical value was used given the often large number of effect sizes. Importantly, Viechtbauer and Cheung’s (2010; see also Viechtbauer, 2015) comprehensive battery of influence diagnostics and multi-conditional decision framework had to be performed multiple times to remove all outliers from the respective meta-analytic dataset. Identified outliers were deleted before meta-analytic and relative importance procedures were performed.

Analyses: Relative Importance Analysis

A variable's relative weight is defined as the contribution it makes to R^2, accounting for both its unique contribution and its contribution in the presence of other variables (LeBreton et al., 2007). Compared to traditional techniques using beta weights from ordinary least squares regression, which can distort statistical inferences in the presence of multicollinearity, relative weights provide interpretable estimates of predictor strength even when predictor variables are correlated (Tonidandel & LeBreton, 2011). Another benefit of relative importance analysis is that the estimates provide an index of the proportionate contribution each predictor makes to total variance explained, such that the contribution made by a predictor with a relative weight of .10 is twice as strong as a predictor with a weight of .05.

Weights can be expressed as "raw" relative weights or rescaled relative weights. The sum of the "raw" relative weights is equal to the model's squared multiple correlation (R^2). "Rescaled" relative weights can be calculated by expressing the "raw" relative weights as a percentage of R^2. As such, the sum of the "rescaled" relative weights will equal 100%. In the meta-analytic context relative importance analysis uses a single correlation matrix in which the cells of the matrix are correlations. When the correlations are meta-analytically derived mean correlations, one is failing to take into account variance around the meta-analytic mean effect size estimate. Consequently, it is possible that relative importance results that employ the meta-analytic means maybe untrustworthy, not to an inadequacy of the relative weights methods but due to the inadequacy of the estimated mean correlations from meta-analyses with substantial heterogeneity. To increase the trustworthiness of relative importance results, I introduce a sensitivity analysis for relative importance weights in the meta-analytic context. Specifically, I advocate an approach to relative importance analysis that uses *multiple* meta-analytic correlation matrices. The matrices are created using the meta-analytic mean effect size estimates and the lower and upper bounds of each corresponding 68% prediction interval (see Equation 8) rather than just a single matrix of meta-analytic mean effect size estimates. Under the proposed approach, each cell of the correlation matrix will have one of three estimates of the meta-analytic mean (a mean estimate and a lower and upper bound estimate).

Importantly, however, an exponential relationship exists between the number of predictors included in the relative importance analysis and the number of correlation matrices required by the proposed sensitivity analysis approach. This is largely due in part to the fact that the number of possible intercorrelations between the predictors increases drastically with the addition of each additional predictor. Plus, if one builds a multiple correlation matrices (e.g., 4 by 4 matrix) by taking all possible combinations in which three estimates of the mean exist for each cell (a mean estimate and a lower and upper bound estimate) one obtains 729 correlation matrices. However, when the number of predictors increases to 5 (i.e., four predictors and one criterion), the number of correlation matrices increases to 65,536. By the time the correlation matrix reaches 12 variables (i.e., 11 predictors and one criterion), 81,402,749,386,839,761,616,226 correlation matrices are required.

As such, I propose that the sensitivity analysis for relative importance weights in the meta-analytic context draw 1,000 correlation matrices from all possible correlation matrices in which the value for each cell is randomly selected from the three options. The three options from which the mean effect size estimate can be selected are (1) the meta-analytic mean effect size estimate, (2) the lower bound of the 68% prediction value, and (3) the upper bound of the 68% prediction value. My decision to select the lower and upper bound of the 68% prediction interval was guided by the “68-96-99.7 rule” (also referred to as the “empirical rule”), which holds that 68% of a normally distributed dataset fall within one standard deviation above and below the mean value. This approach has an added benefit pertaining to non-positive-definite matrices. In particular, in the instance in which a matrix is singular, one can draw an additional non-singular matrix in the same fashion (i.e., randomly selecting a low, medium, or high input value) until the final set of correlation matrices equals 1,000.

Analyses: Incremental Validity

Incremental validity analyses assess the degree to which a construct explains unique variance in a criterion not explained by other constructs included in the model. I tested the incremental validity of organizational commitment beyond job satisfaction using criteria outlined by O'Boyle et al. (2011; see also Banks et al. [2013] and McDaniel, Hartman, Whetzel, & Grubb [2007]). In addition, and similar to Banks et al. (2014), I examine the incremental validity of job satisfaction beyond organizational commitment. I conducted the incremental validity analyses by performing hierarchical linear regressions using a 3 x 3 correlation matrix of turnover intention, job satisfaction, and organizational commitment. In the initial analysis, job satisfaction is first entered into the model of turnover intention. Following this, organizational commitment is entered into the model and the change in variance explained is examined. I can conclude that organizational commitment adds incremental variance above and beyond job satisfaction if the change in variance explained is significant. In the second analysis, organizational commitment is first entered into the model followed by job satisfaction.

The data for this correlation matrix were derived from the meta-analytic mean effect size estimate (introduced later in Table 8). In order to calculate the standard errors, I followed guidelines recommended by Viswesvaran and Ones (1995), which call for the use of the harmonic mean as the sample size. Extant research suggests that the harmonic mean is preferred over the arithmetic mean in organizational research (Colquitt et al., 2001; Hershcovis et al., 2007; Podsakoff, LePine, & LePine, 2007) as it gives less weight to extreme values, thus providing a more conservative approach to testing models. Indeed, this is true in the current study as the harmonic mean (n = 199) is smaller than the arithmetic mean (n = 637). Finally, I note that the incremental validity analyses were performed using SPSS 24 (IBM Corp., 2016) and that all the analytic files can be found at my dissertation project website by visiting https://osf.io/jfv76/.

Analyses: Summary of Methods

Figure 11 outlines the methods flow chart and shows all of the aforementioned methods were brought together to address my research objectives. First, the metaBUS database was queried 66 times using a variety of taxonomic and letter-string searchers. The results of each query were exported to comma separated values (.csv) files. Following this, meta-analytic procedures recommended by Hedges and Olkin (1985) were performed on each of the 66 meta-analytic datasets. Importantly, outliers were identified using Viechtbauer and Cheung's (2010; see also Viechtbauer [2015]) externally standardized residual procedure and, if present, removed from each respective dataset before performing the meta-analysis. Next, a correlation matrix of meta-analytic mean effect size estimates was created. In addition, 1,000 non-singular correlation matrices are created using the meta-analytic mean effect size estimates and the corresponding lower and upper bound estimates of the 68% prediction interval. Each of the non-singular correlation matrices is created through an iterative process in which the value of each cell is randomly selected from the aforementioned meta-analytic parameters. As such, the value of each cell is either the (a) meta-analytic mean effect size estimate, (b) lower bound of the 68% prediction interval, or (c) upper bound of the 68% prediction interval. In turn, the 1,000 matrices are used to perform 1,000 relative importance analyses, which informs the relative importance sensitivity analysis by providing a lower and upper bound estimate of relative importance.

Taken together, the proposed approach to estimating relative importance weights in the meta-analytic context consists of two analyses. First, I estimate the mean raw relative weights and the corresponding rescaled relative importance weights using the traditional approach, which uses a single correlation matrix of meta-analytic mean effect size estimates as input (see Table 6). Indeed, this is exactly how relative importance analyses are currently performed. Second, the lower and upper bound estimates of relative importance are imputed by assessing the range of relative importance estimates across 1,000 correlations matrices, which are created using a random draw of either the (a) meta-analytic mean effect size estimate, (b) lower bound of the 68% prediction interval, or (c) upper bound of the 68% prediction interval for each cell (see Table 7). The lower (upper) bound of the relative importance estimate represents the smallest (largest) relative importance weight estimates across the 1,000 relative importance analyses. This latter step is currently not included when assessing relative importance in the meta-analytic context.

Figure 11

Methods flow chart

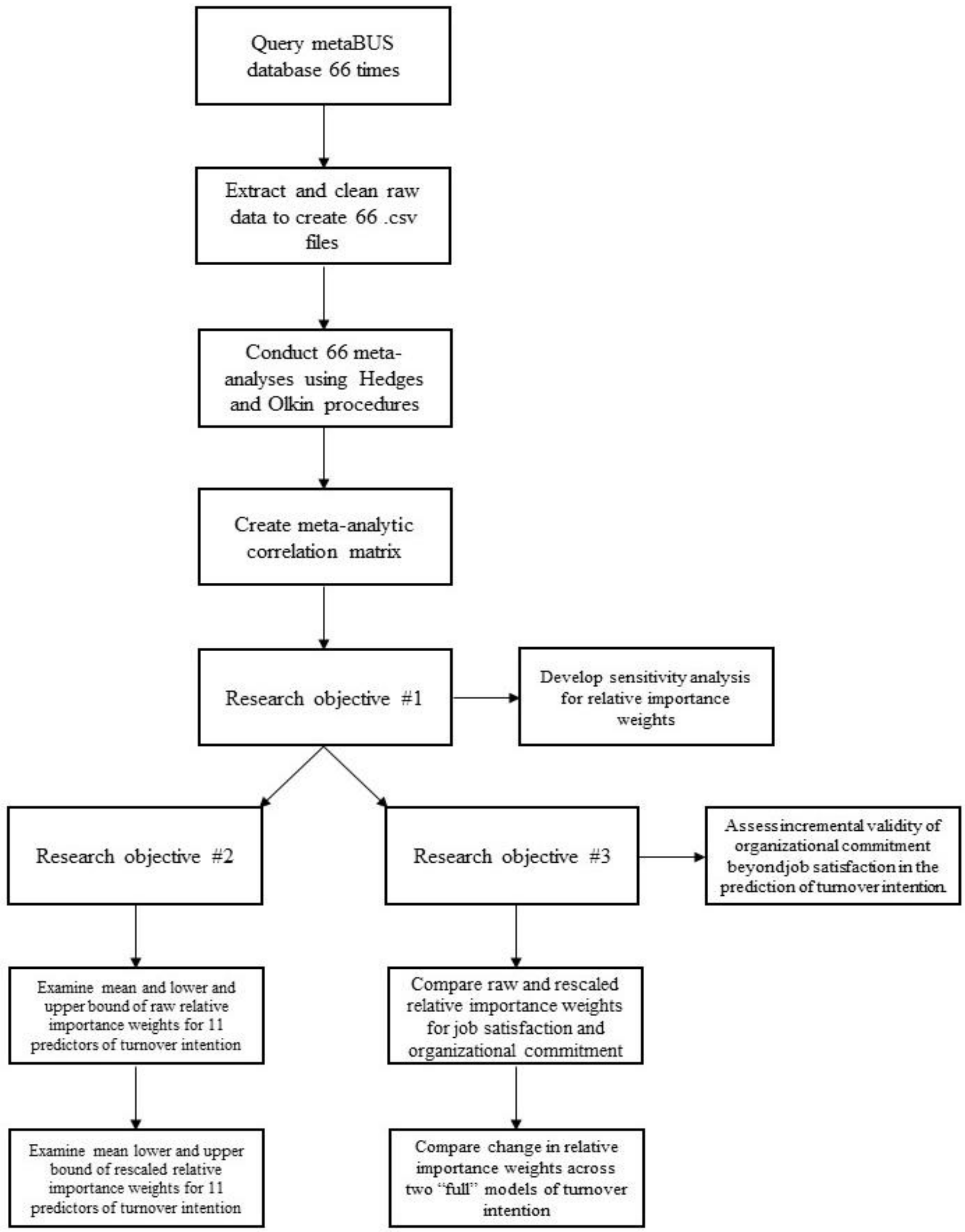


Table 6

Matrix to Illustrate the Traditional Approach to Relative Importance Analysis

Variable	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**	**11.**	**12.**
Turnover intentions	-											
Job satisfaction	M	-										
Pay satisfaction	M	M	-									

Org. commitment	M	M	M	-								
Organizational justice	M	M	M	M	-							
Autonomy	M	M	M	M	M	-						
Embeddedness	M	M	M	M	M	M	-					
Work-life conflict	M	M	M	M	M	M	M	-				
Age	M	M	M	M	M	M	M	M	-			
Individual performance	M	M	M	M	M	M	M	M	M	-		
Supervisor support	M	M	M	M	M	M	M	M	M	M	-	
Climate	M	M	M	M	M	M	M	M	M	M	M	-

Note. [s] Org. = organizational; M = meta-analytic mean effect size estimate.

Table 7

Matrix to Illustrate the One Random Draw Sensitivity Analysis Approach to Relative Importance Analysis

Variable	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**	**11.**	**12.**
Turnover intentions	-											
Job satisfaction	M	-										
Pay satisfaction	L	M	-									
Org. commitment	M	U	L	-								
Organizational justice	U	U	L	U	-							
Autonomy	L	U	L	L	U	-						
Embeddedness	U	L	U	U	U	L	-					
Work-life conflict	M	L	L	L	M	L	L	-				
Age	M	L	M	M	L	U	L	U	-			
Individual performance	L	U	M	M	L	M	L	U	M	-		
Supervisor support	L	U	L	U	M	M	U	L	L	M	-	
Climate	L	M	U	L	M	M	U	M	M	U	M	-

Note. Org. = organizational; M = meta-analytic mean effect size estimate; L = lower bound estimate meta-analytic mean effect size estimate (i.e., lower bound of the 68% prediction interval; U = upper bound estimate of the meta-analytic mean effect size estimate (i.e., upper bound of the 68% prediction interval).

I followed the aforementioned two steps to assess which predictors of turnover intentions are potentially most important (research question #1). Indeed, researchers and practitioners can have increased confidence regarding the relative importance of a predictor if it exhibits low levels of variability with regard to relative importance weight. In contrast, if a predictor presents with a high level of variability with regard to relative importance then potential boundary conditions and other important caveats should be considered. I also use the sensitivity analysis to examine whether or not job satisfaction and organizational commitment present empirical redundancy when predicting turnover intention (research question #2). Specifically, I examine the range of relative importance weights for job satisfaction and organizational commitment. In addition, I examine the change in the range of relative importance weights across two “full” models of turnover intention after organizational commitment replaces job satisfaction as one of the predictors.

Chapter 7: Results

Research Objective #1

The first objective of my study was to introduce a sensitivity analysis for relative importance weights in the meta-analytic context. Tables 8-10 present the three correlation matrices derived from the meta-analytic results. I discuss the meta-analytic results in more detail in the next section. The meta-analytically derived means are found in Table 8, the lower bound of the 68^{th} prediction interval is in Table 9, and Table 10 contains the upper bound of the 68^{th} prediction interval. The sensitivity analysis for relative importance weights in the meta-analytic context builds 1,000 correlation matrices and runs a relative weights analysis of each of the 1,000 correlation matrices. To build each of the 1,000 correlation matrices, the content of each cell of the matrix has a 33.3 % change of being drawn from the corresponding cell in Table 8, or 9 or 10. My approach to relative importance analysis takes into account variance around the meta-analytic mean effect size estimate. Still, the relationship between raw and rescaled relative weights is not always as one might initially expect. In particular, it is important to note that the lowest (highest) raw relative weight does not always correspond to the lowest (highest) rescaled relative weight. This is true because rescaled weights are a function of the amount of variance explained by the entire model (R^2), which will likely change when drawing multiple estimates of each intercorrelation from all possible combinations of intercorrelations. An illustrative example helps to explain this phenomenon.

Table 8

Matrix of Meta-Analytic Mean Effect Size Estimates

	Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1.	Turnover intentions	-											
2.	Job satisfaction	-.45	-										
3.	Pay satisfaction	-.30	.35	-									
4.	Org. commitment	-.43	.51	.28	-								
5.	Organizational justice	-.30	.40	.47	.37	-							
6.	Autonomy	-.20	.32	.33	.28	.21	-						
7.	Embeddedness	-.37	.48	.30	.40	.43	.36	-					
8.	Work-life conflict	.06	-.06	.02	.02	-.15	-.03	-.02	-				
9	Age	-.13	.07	.05	.11	.02	.06	.07	-.01	-			
10	Individual performance	-.12	.19	.12	.20	.18	.16	.27	.02	.03	-		
11.	Supervisor support	-.25	.35	.17	.32	.46	.30	.25	-.08	.00	.20	-	
12.	Climate	-.17	.33	.28	.33	.44	.16	.06	.05	.01	.18	.26	-

Note. Org. = organizational

Table 9

Matrix of Lower Bound of 68% Prediction Interval Estimates

	Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1.	Turnover intentions	-											
2.	Job satisfaction	-.68	-										
3.	Pay satisfaction	-.41	.13	-									
4.	Org. commitment	-.65	.29	.11	-								
5.	Organizational justice	-.45	.19	.26	.17	-							
6.	Autonomy	-.36	.11	.15	.07	.00	-						
7.	Embeddedness	-.59	.29	.04	.13	.04	.20	-					
8.	Work-life conflict	-.15	-.30	-.13	-.19	-.29	-.20	-.22	-				
9	Age	-.25	-.04	-.04	.01	-.06	-.05	-.03	-.12	-			
10	Individual performance	-.29	.03	-.07	.02	.02	-.01	.01	-.15	-.09	-		
11.	Supervisor support	-.41	.10	-.03	.15	.33	.15	-.13	-.31	-.06	.02	-	
12.	Climate	-.43	.01	.04	.05	.16	-.11	-.58	-.26	-.08	-.03	-.14	-

Note. Org. = organizational

Table 10.

Matrix of Upper Bound of 68% Prediction Interval Estimates

	Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1.	Turnover intentions	-											
2.	Job satisfaction	-.13	-										
3.	Pay satisfaction	-.17	.53	-									
4.	Org. commitment	-.15	.68	.43	-								
5.	Organizational justice	-.13	.56	.64	.54	-							
6.	Autonomy	-.03	.51	.49	.46	.41	-						
7.	Embeddedness	-.12	.64	.52	.62	.70	.51	-					
8.	Work-life conflict	.27	.19	.16	.22	.00	.14	.18	-				
9	Age	.00	.18	.13	.21	.10	.16	.16	.09	-			
10	Individual performance	.06	.34	.30	.37	.33	.32	.48	.19	.14	-		
11.	Supervisor support	-.07	.55	.37	.48	.59	.44	.57	.16	.07	.37	-	
12.	Climate	.12	.58	.49	.56	.65	.41	.65	.36	.09	.38	.58	-

Note. Org. = organizational

Suppose that a Model A_m is comprised of three predictors (X_1, X_2, and X_3). Note that the subscript "m" indicates that this model is comprised of meta-analytic mean effect size estimates only. An assessment of Model A_m's meta-analytic correlation matrix reveals that it accounts for 50% of variance in the criterion, Y. Furthermore, a relative importance analysis indicates the respective raw relative weights for X_1, X_2, and X_3 are .250, .175, and .075. Importantly, these raw relative weights correspond to the following rescaled relative weights: 50%, 35%, and 15%.

Next, suppose that, as described above and in the Methods section, that the same set of predictors is estimated using the lower and upper bound estimates of each 68% prediction interval. This model is referred to as Model A_L to denote that only the lower bound estimates of each intercorrelation are inputted into the relative importance analysis. This procedure suggests that Model A_L accounts for 35% of variance in Y. Furthermore, it indicates that X_1, X_2, and X_3 have raw relative weights of .189, .091, and .070, respectively. These raw relative weights correspond to the following rescaled relative weights: 54%, 26%, 20%. Upon closer inspection, we find that the raw relative weights for X_1 and X_3 produced by Model A_M are *larger* than the ones produced by Model A_L. Yet, interestingly, the rescaled relative weights for X_1 and X_3 produced by Model A_M are *smaller* than the ones produced by Model A_L. This phenomenon occurs because the denominator used to calculate the rescaled relative weights (i.e., R^2) varies across both models even though the same set of predictors are included in Model A_M and Model A_L. The variance in R^2 can be explained by the variance in the estimates of X_1, X_2, and X_3 (i.e., meta-analytic mean effect size estimate vs. lower bound of the 68% prediction interval).

Overall, this phenomenon suggests that reporting the lower (upper) bound estimates of rescaled relative importance is not sufficient because it is not always associated with the lower (upper) bound of the raw relative weight. As such, to give the full range of sensitivity analysis results and in the interest of transparency, I report lower and upper bound results pertaining to each raw relative weight and its corresponding rescaled relative weight *and* each rescaled relative weight and its corresponding raw relative weight when applicable.

Research Objective #2

My second research objective involved a large-scale analysis of the explanatory power of a set of theoretically-relevant correlates of turnover intention. Specifically, I asked: Which commonly-investigated correlates of turnover intention presents the greatest degree of meta-analytic and relative importance? To address this question, I meta-analyzed 11 predictors of turnover intention using archival data provided by the metaBUS database. Meta-analytic mean effect size magnitudes were examined to infer the strength of each predictor's association with turnover intention and 95% confidence intervals were used to infer statistical significance. In addition, I conducted a relative importance analysis of the set of 11 predictors in which lower and upper bounds, as well as mean estimates, of relative importance weights were assessed.

Meta-Analytic Results. Table 11 reports the meta-analytic results for the 11 predictors of turnover intention included in my study. A supplemental table that contains all meta-analytic results (i.e., for the 11 predictors of turnover intention and the 55 intercorrelations between predictors) can be found on my dissertation project website by visiting https://osf.io/jfv76/.

Table 11.

Meta-Analytic Results for Turnover Intentions

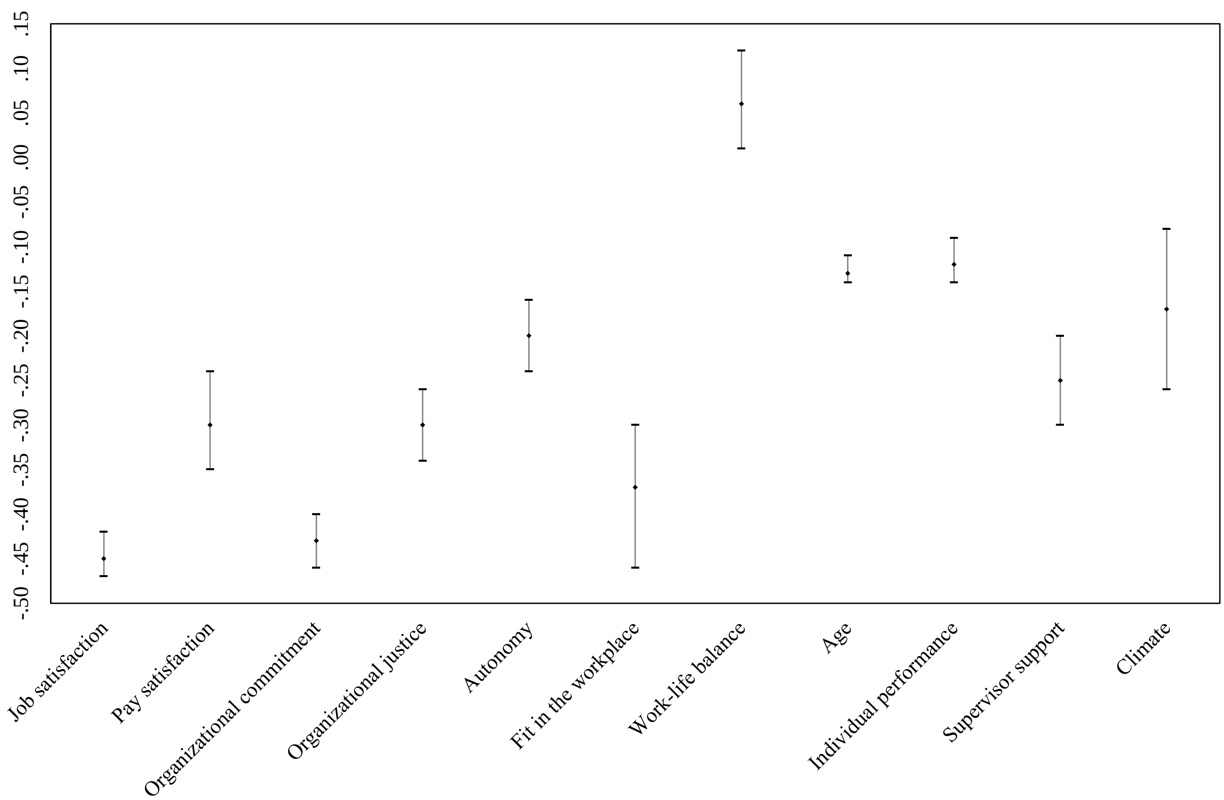
			95% CI		68% PI		
Variable	*k*	$\bar{r}_{o_{RE}}$	Lower	Upper	Lower	Upper	I^2
Job satisfaction	424	-.45	-0.47	-0.42	-0.68	-0.13	98.22
Pay satisfaction	29	-.30	-0.35	-0.24	-0.41	-0.17	89.21
Organizational commitment	372	-.43	-0.46	-0.40	-0.65	-0.15	96.92
Organizational justice	62	-.30	-0.34	-0.26	-0.45	-0.13	89.11
Autonomy	73	-.20	-0.24	-0.16	-0.36	-0.03	94.83
Embeddedness[a]	28	-.37	-0.46	-0.30	-0.59	-0.11	96.51
Work-life conflict	59	.06	0.01	0.12	-0.15	0.27	95.90
Age	295	-.13	-0.14	-0.11	-0.25	-0.00	89.01
Individual performance	195	-.12	-0.14	-0.09	-0.29	0.06	90.37
Supervisor support	55	-.25	-0.30	-0.20	-0.41	-0.07	92.71
Climate	36	-.17	-0.26	-0.08	-0.43	0.12	95.25

Note. [a]Included "job fit," "organization fit," and "community embeddedness." *k* = number of independent samples. $\bar{r}_{o_{RE}}$ = random-effects weighted mean observed correlation. 95% CI = 95% confidence interval. 68% PI = 68% prediction interval. I^2 = ratio of true heterogeneity to total variation.

An assessment of Table 11 indicates that job satisfaction (*k* = 424, $\bar{r}_{o_{RE}}$ = -.45, 95% CI = -.47, -.42) is the strongest predictor (i.e., largest meta-analytic effect size magnitude) of turnover intention, followed by organizational commitment (*k* = 372, $\bar{r}_{o_{RE}}$ = -.43, 95% CI = -.46, -.40) and embeddedness (*k* = 28, $\bar{r}_{o_{RE}}$ = -.37, 95% CI = -.46, -.30). An inspection of Figure 12 suggests that the meta-analytic means of the three predictors are not statistically different from each other as their respective 95% confidence intervals overlap. Interestingly, Figure 12 suggests that job satisfaction and organizational commitment are statistically different from all other predictors of turnover, except embededdness.

Figure 12

Meta-Analytic Results and 95% Confidence Intervals for Turnover Intention



Note. Vertical axis represents effect size magnitude.

Put differently, job satisfaction's 95% confidence interval and organizational commitment's 95% confidence interval do not overlap with 95% confidence intervals for (1) pay satisfaction (k = 29, $\bar{r}_{o_{RE}}$ = -.30, 95% CI = -.35, -.24), (2) organizational justice (k = 62, $\bar{r}_{o_{RE}}$ = -.30, 95% CI = -.34, -.26), (3) autonomy (k = 73, $\bar{r}_{o_{RE}}$ = -.20, 95% CI = -.24, -.16), (4) work-life conflict (k = 28, $\bar{r}_{o_{RE}}$ = -.37, 95% CI = -.46, -.30), (5) age (k = 295, $\bar{r}_{o_{RE}}$ = -.13, 95% CI = -.14, -

.11), (6) individual performance (k = 195, $\bar{r}_{o_{RE}}$ = -.12, 95% CI = -.14, -.09), (7) supervisor support (k = 55, $\bar{r}_{o_{RE}}$ = -.25, 95% CI = -.30, -.20), and (8) climate (k = 36, $\bar{r}_{o_{RE}}$ = -.17, 95% CI = -.26, -.08). Although this may suggest that job satisfaction and organizational commitment are the best predictors of turnover intention, it may also add credence to the claim that they are empirically redundant. This is potentially important for practitioners, especially if they rely on meta-analytic evidence to inform their evidence-based practice decisions. For instance, based on the results presented in Table 11 and Figure 12, a practitioner may decide to implement human resource management (HRM) practices that are intended to increase levels of job satisfaction *and* organizational commitment. However, this may be a waste of resources, and thus lead to unexpected results, if job satisfaction and organizational commitment are empirically indistinguishable from one another.

As shown in Table 11, the I^2 approaches its maximum value of 100 for most of the relations. This suggests that the underlying parameters being evaluated differ between studies and, thus, the majority of variance in each predictor is likely due to one or more phenomenon (e.g., moderators) other than sampling error. Although the I^2 results are not ideal, I suggest that they might be expected given the coarseness of the meta-analytic datasets provided by metaBUS. Put differently, heterogeneity due to outliers is the only type of heterogeneity that is intentionally removed from my datasets. As such, my datasets may be considered coarse as other potential sources of heterogeneity (e.g., moderators like sample type; general employees vs. supervisors) are not accounted for in my study. Still, I am confident that the large I^2 statistics do not threaten the efficacy of the meta-analytic parameters given that my results align with results reported in extant meta-analytic reviews on turnover intention. For instance, Tett and Meyer (1993) reported a sample size-weighted meta-analytic mean effect size estimate of -.48 (k = 88, 95% CI = -.47, -

.42) for the job satisfaction-turnover intention relation, which is only marginally different from the naïve meta-analytic mean effect size estimate (k = 424, $\bar{r}_{o_{RE}}$ = -.45, 95% CI = -.47, -.42) reported in Table 11 for the same relation.

Raw Relative Importance Weights Results.

Table 12 reports results pertaining to the sensitivity analysis of raw relative importance weights. The first column reports the analyzed predictor. Column two reports the mean raw relative weight, which is estimated using the conventional approach to relative importance analysis (i.e., using a correlation matrix of meta-analytic mean effect size estimates). The corresponding mean rescaled relative weight is reported in column five. The lower bound of the raw relative weight, and its corresponding rescaled relative weight, is reported in columns three and six. The upper bound of raw relative weight, and its corresponding rescaled relative weight, is reported in columns four and seven. Values reported in columns three, four, six, and seven are estimated using the sensitivity analysis approach outlined in the Methods section. Specifically, these values represent the smallest and largest relative importance estimates across 1,000 relative importance analyses. As previously mentioned, the required number of correlation matrices are a sample of all possible matrices that can be created using three estimates (mean and 68% prediction interval) of each meta-analytic intercorrelation.

The lower bound raw relative weight (column three) represents the smallest raw relative weight across all 1,000 relative importance analyses. In comparison, the upper bound raw relative weight (column four) represents the largest raw relative weight across all 1,000 relative importance analyses. Importantly, the lower and upper raw relative weights are unlikely to be drawn from the same correlation matrix and, thus, do not share a common R^2 value. As such, the sum of the lower bound rescaled relative weights (column six) and the sum of the upper rescaled relative weights (column seven) do not amount to 100%. However, given that the mean raw relative weights (column two) are imputed from a single matrix of meta-analytic mean effect size estimates, their corresponding mean rescaled relative weights (column five) will sum to 100%.

Table 12

Raw Relative Importance Analysis Results and Corresponding Rescaled Relative Importance Weights

	Raw weights			Rescaled weights		
Variable	Mean	Lower	Upper	Mean	Lower	Upper
1. Job satisfaction	.077	.000	.523	25.89%	0.87%	56.19%
2. Pay satisfaction	.031	.006	.353	10.51%	1.01%	38.98%
3. Org. commitment	.076	.004	.512	25.65%	0.88%	54.40%
4. Organizational justice	.017	.003	.353	5.80%	0.88%	41.08%
5. Autonomy	.006	.002	.232	2.27%	0.23%	28.70%
6. Embeddedness	.051	.003	.456	17.23%	0.59%	52.57%
7. Work-life conflict	.003	.001	.234	0.89%	0.22%	23.49%
8. Age	.010	.000	.134	3.27%	0.06%	16.24%
9. Performance	.002	.001	.182	0.75%	0.12%	20.73%
10. Supervisor support	.017	.003	.340	5.74%	0.59%	34.04%
11. Climate	.006	.005	.358	2.00%	1.20%	38.60%

Note. Org. = organizational.

Results reported in Table 12 indicate that job satisfaction has the largest mean raw relative weight (Raw_M = .077) and largest mean rescaled relative weight (Rescaled_M = 25.89%) among the 11 predictors of turnover intention. However, the corresponding sensitivity analysis results suggest that there exists a large degree of variability in the relative importance estimates. Indeed, the lower bound raw relative importance estimate (Raw_L = .000) and corresponding lower bound of the rescaled relative importance weight (Rescaled_L = 0.87%) indicate that job satisfaction may, at times, carry relatively low importance for predicting turnover intention. In contrast, the upper bound raw relative importance estimate (Raw_U = .523) and corresponding upper bound estimate of the rescaled relative importance weight ($Rescaled_L$ = 56.19%) suggest that, at times, job satisfaction can account for more than 50% of variance in turnover intention. However, an assessment of the distribution of raw relative weights (see Figure 13a) and rescaled relative weights (see Figure 13b) for job satisfaction reveals a noticeable right skew, which may suggest that systematically overestimating the relative importance of job satisfaction is unlikely. Still, the observed variability with regard to the relative importance of job satisfaction should be of concern to researchers and practitioners as it suggests that mean relative importance estimates may not be completely trustworthy.

Figure 13a

Distribution of Raw Relative Importance Weights for Job Satisfaction

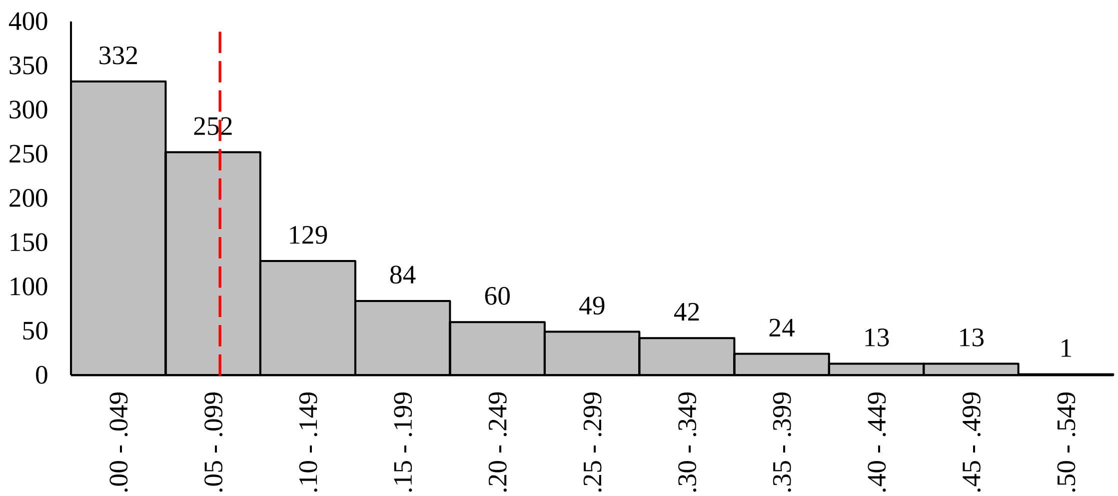
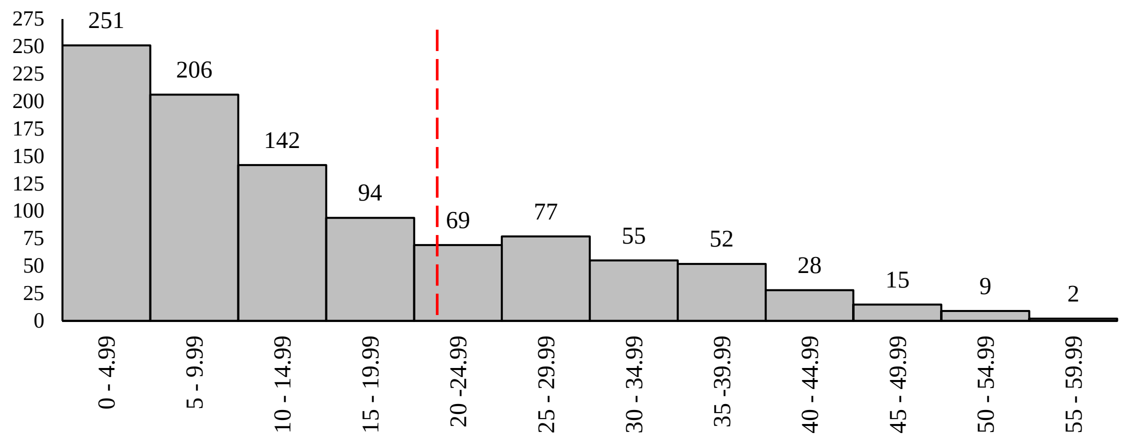


Figure 13b

Distribution of Corresponding Rescaled Relative Importance Weights for Job Satisfaction



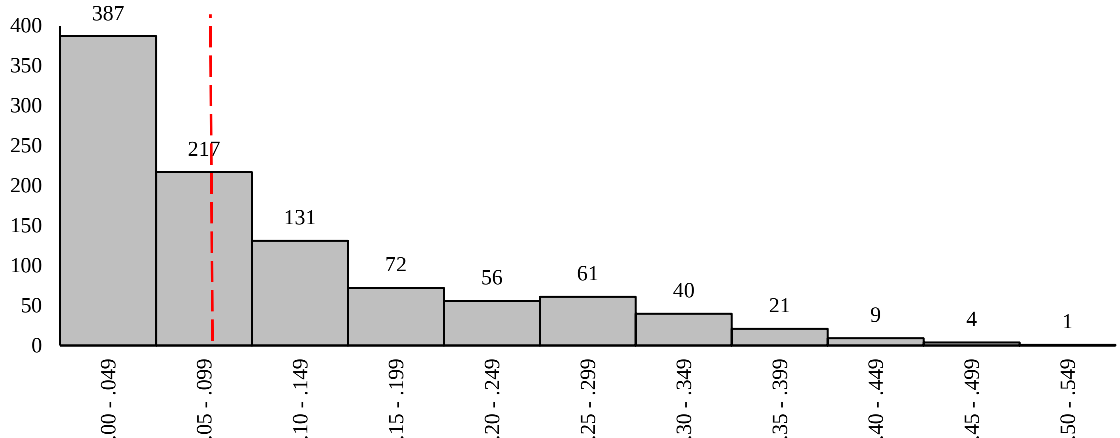
Note. Vertical axis represents raw frequency. The horizontal axis represents bin range for raw (Figure 13a) and rescaled (Figure 13b) relative weights. The dashed red vertical line represents the mean raw (Figure 13a) and rescaled (Figure 13b) relative weight.

An assessment of Table 12 suggests that organizational commitment presents the second the largest mean raw relative weight (Raw_M = .076) and second largest mean rescaled relative weight ($Rescaled_M$ = 25.65%) of the 11 predictors of turnover intention. However, similar to the aforementioned results pertaining to job satisfaction, a large degree of variability in the range of relative importance estimates was observed. Specifically, the sensitivity analysis results revealed that the lower bound of the raw relative importance estimate (Raw_L = .004) and the corresponding lower bound of the rescaled relative importance weight ($Rescaled_L$ = 0.88%) were substantially different from the mean estimates. Likewise, the upper bound of the raw relative importance estimate (Raw_U = .512) and corresponding upper bound of the rescaled relative importance weight ($Rescaled_L$ = 54.40%) for organizational commitment deviated substantially from its mean estimates.

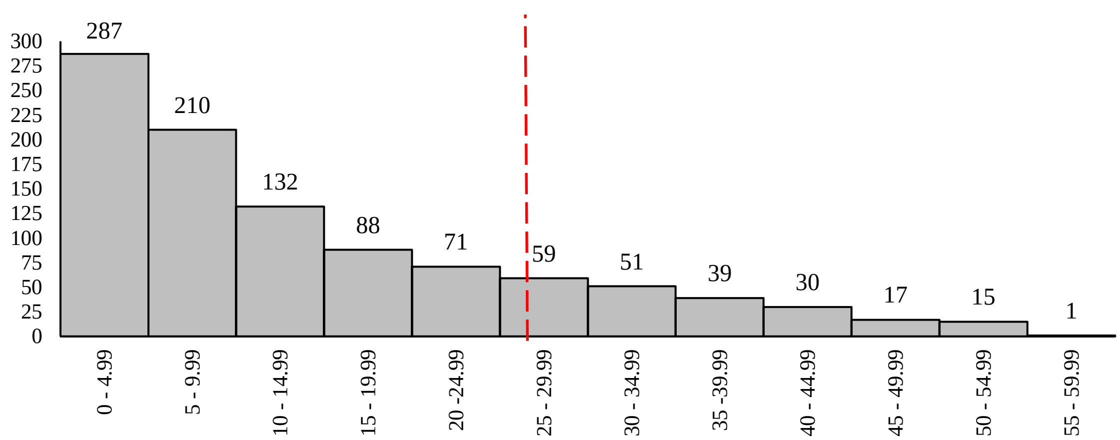
Figure 14a displays the distribution of raw relative importance weights for organizational commitment. Similar to Figure 13a, which displays the distribution of raw relative importance weights for job satisfaction, a noticeable right skew in the distribution is observed. Indeed, this may suggest that the mean raw relative weight (Raw_M = .076) for organizational commitment is unlikely to be overestimated as there is a large concentration of raw relative importance weights at the lower end of the distribution. A similar pattern was observed for the distribution of rescaled relative importance weights for organizational commitment (see Figure 14b).

Figure 14

(a) Distribution of Raw Relative Importance Weights for Organizational Commitment



(b) Distribution of Corresponding Rescaled Relative Importance Weights for Org. Commitment



Note. Org. = Organizational. Vertical axis represents raw frequency. The horizontal axis represents bin range for raw (Figure 14a) and rescaled (Figure 14b) relative weights. The dashed red vertical line represents the mean raw (Figure 14a) and rescaled (Figure 14b) relative weight.

Taken together, these results indicate that it is important to take into consideration variance around the meta-analytic mean effect size when imputing relative importance weights. Furthermore, the results may add credence to the claim that organizational commitment and job satisfaction are empirically redundant when predicting turnover intention. Specifically, all three raw relative importance estimates (i.e., mean, lower, and upper) are almost identical for both constructs, which may suggest that they are near isomorphic when predicting turnover intention.

Embeddedness presents the third largest mean raw relative importance weight (Raw_M = .051) (see Table 12). Its corresponding mean rescaled relative importance weight is 17.23%, which also ranks third largest among the set of 11 predictors of turnover intention analyzed in the current study. The sensitivity analysis results yielded a wide range of raw relative importance estimates. The lower bound estimate of the raw relative importance (Raw_L = .003; $Rescaled_L$ = 0.59%) suggests that, in certain contexts, embeddedness potentially has relatively low relative importance for the prediction of turnover intention. In contrast, the upper bound estimate of the raw relative importance (Raw_U = .456; $Rescaled_U$ = 52.57%) indicates that embeddedness may be a relatively important predictor of turnover intention. An assessment of the distribution of raw and rescaled relative importance estimates (see Figure 15a and Figure 15b) reveals a downward asymptotic pattern. As such, this may indicate that the raw relative importance of embeddedness is unlikely to be overestimated because there is a large concentration of results at the left-hand side of distribution.

Figure 15a

Distribution of Raw Relative Importance Weights for Embeddedness

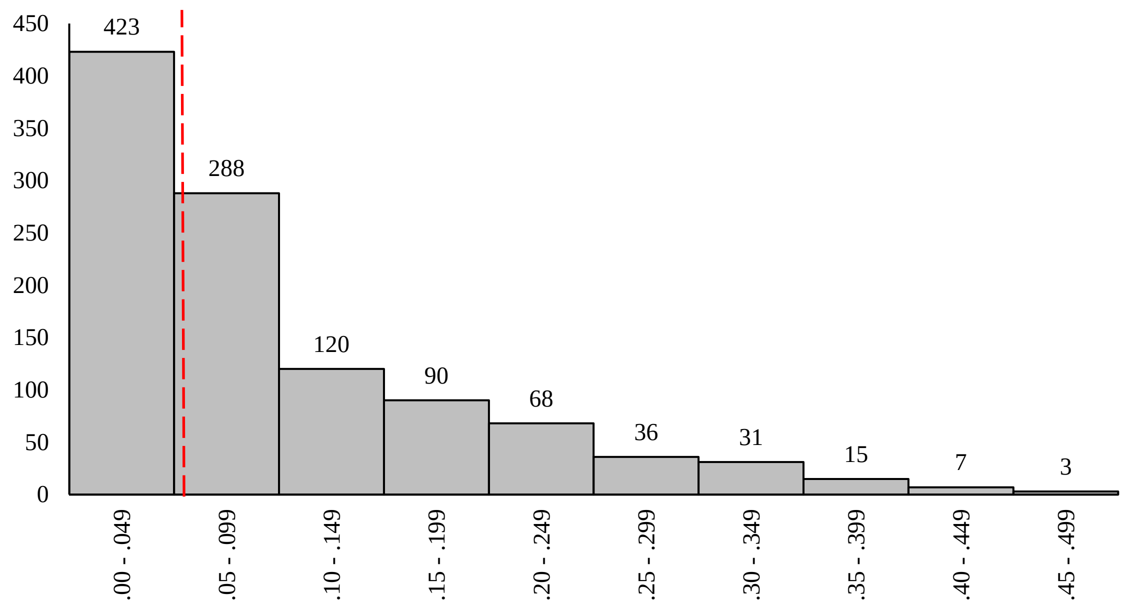
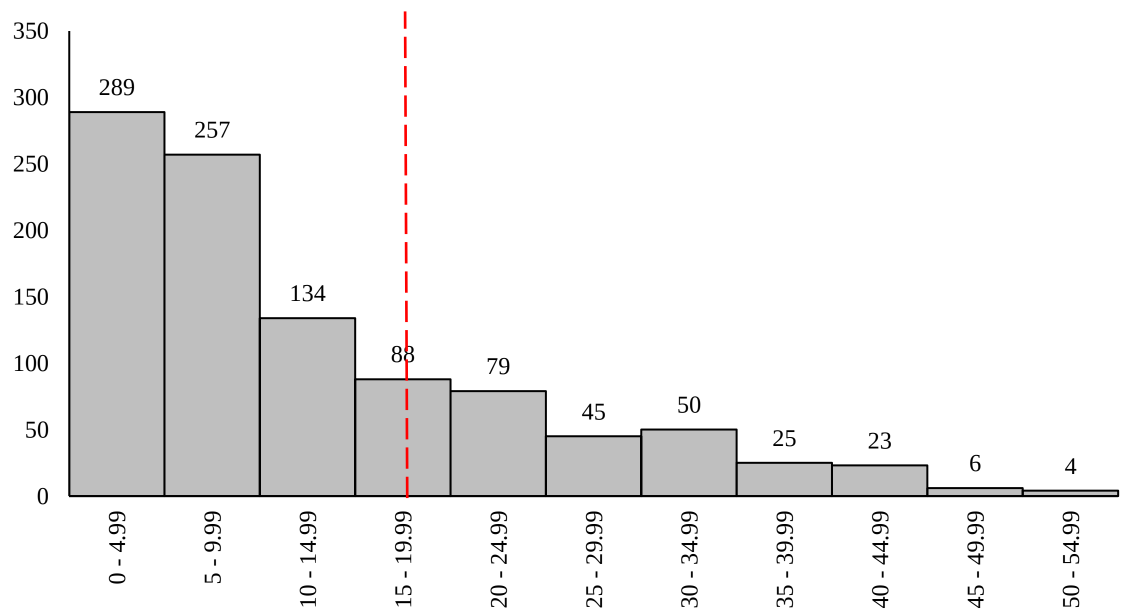


Figure 15b

Distribution of Corresponding Rescaled Relative Importance Weights for Embeddedness



Note. Vertical axis represents raw frequency. The horizontal axis represents bin range for raw (Figure 15a) and rescaled (Figure 15b) relative weights. The dashed red vertical line represents the mean raw (Figure 15a) and rescaled (Figure 15b) relative weight.

The sensitivity analysis results revealed some other interesting findings. For example, the mean relative importance results suggest that organizational justice (Raw_M = .017; $Rescaled_M$ = 5.80%), autonomy (Raw_M = .006; $Rescaled_M$ = 2.27%), work-life conflict (Raw_M = .003; $Rescaled_M$ = 0.89%), age, (Raw_M = .010; $Rescaled_M$ = 3.27%), individual job performance (Raw_M = .002; $Rescaled_M$ = 0.75%), supervisor support (Raw_M = .017; $Rescaled_M$ = 5.74%), and climate (Raw_M = .006; $Rescaled_M$ = 2.00%) have very low relative importance for predicting turnover intention compared to job satisfaction, organizational commitment, and embeddedness. These results are surprising given their theoretical importance in the turnover literature. Indeed, that the relative importance weights are not uniformly distributed (i.e., equal in magnitude) may indicate that the importance of certain theoretical perspectives on turnover has been overemphasized and are not created equally.

Rescaled Relative Importance Weights. Table 13 reports the results for the rescaled relative importance weights and their corresponding raw relative importance weights. Importantly, the mean relative importance results reported in Table 13 match the mean results reported in Table 12 (see Methods section for the explanation). As such, I report results pertaining to the sensitivity analysis only (columns 3, 4, 6, and 7 of Table 13).

In general, the results presented in Table 13 align well with the results reported in Table 12. For instance, similar to Table 12, the results reported in Table 13 indicate that job satisfaction (Raw_U = .465; $Rescaled_U$ = 59.67%), organizational commitment (Raw_U = .472; $Rescaled_U$ = 57.30%), and embeddedness (Raw_U = .421; $Rescaled_U$ = 53.86%) present with the highest rescaled relative importance weights. This convergence may add credence to the claim that these constructs, and their corresponding theoretical perspectives, are most important for predicting turnover intention.

Table 13

Rescaled Relative Importance Results and Corresponding Raw Relative Importance Weights

		Raw weight			Rescaled weight		
	Variable	Mean	Lower	Upper	Mean	Lower	Upper
1.	Job satisfaction	.077	.004	.465	25.89%	0.45%	59.67%
2.	Pay satisfaction	.031	.007	.138	10.51%	0.66%	45.73%
3.	Org. commitment	.076	.005	.472	25.65%	0.64%	57.30%
4.	Organizational justice	.017	.003	.218	5.80%	0.43%	50.29%
5.	Autonomy	.006	.002	.144	2.27%	0.23%	36.05%
6.	Embeddedness	.051	.003	.421	17.23%	0.59%	53.86%
7.	Work-life conflict	.003	.001	.111	0.89%	0.15%	36.87%
8.	Age	.010	.000	.075	3.27%	0.05%	37.32%
9.	Performance	.002	.001	.130	0.75%	0.12%	29.38%
10.	Supervisor support	.017	.004	.333	5.74%	0.43%	43.24%
11.	Climate	.006	.006	.225	2.00%	0.67%	53.14%

Note. Org. = organizational;

Interestingly, the sensitivity analysis results reported in Table 13 were generally more extreme than the ones reported in Table 12. For instance, compared to the results reported in Table 12, the lower bound of the rescaled relative importance weights were closer to zero for eight out of 11 predictors (73%); the remaining three were unchanged. In addition, the upper bound of the rescaled relative importance weights reported in Table 13 were always larger than the corresponding ones reported in Table 12. Taken together, these results may indicate that examining the range of rescaled relative importance weights and their respective raw relative importance weights – rather than the range of raw relative importance weights and their corresponding rescaled relative importance weights – yields the most conservative sensitivity analysis of relative importance weights in the meta-analytic context.

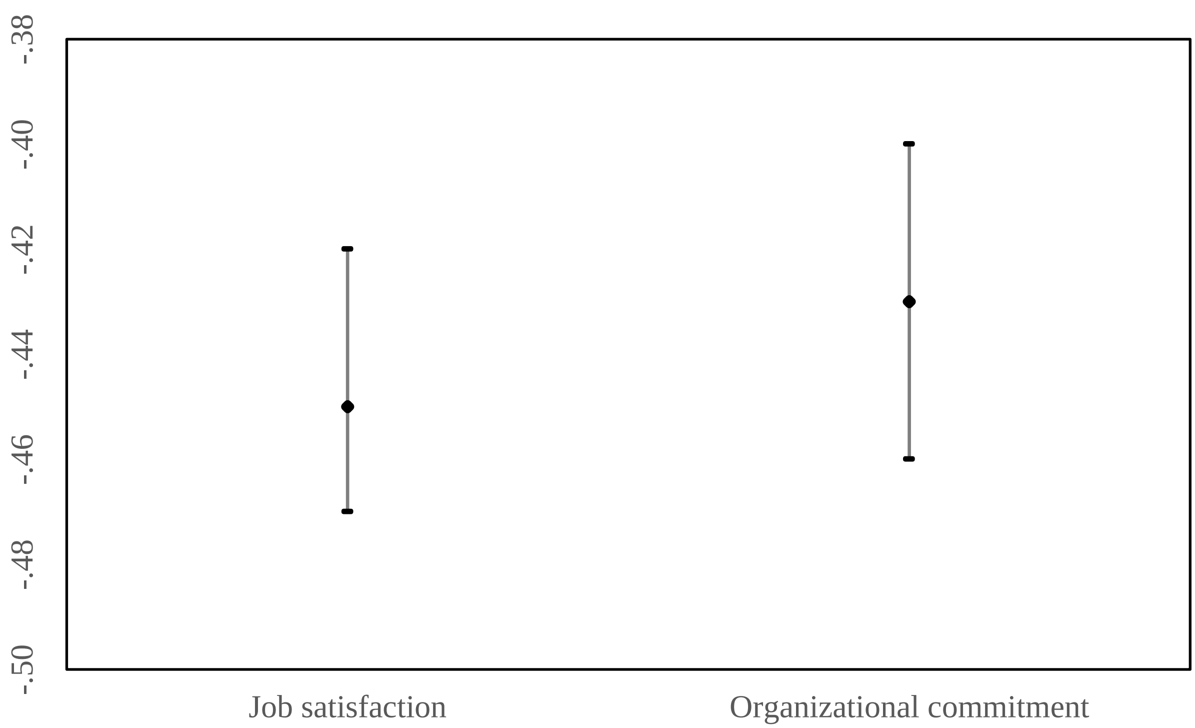
Research Objective #3

For my third research objective, I examined whether or not job satisfaction and organizational commitment presented potential empirical redundancy when predicting turnover intention. To this end, I used a battery of statistical techniques to assess if these constructs and, by extension, corresponding theoretical underpinnings are orthogonal when predicting one of organizational science's most important criteria. First, I used meta-analytic evidence to assess the empirical similarity between job satisfaction and organizational commitment. Specifically, I compared the magnitude of their meta-analytic mean effect size estimates with turnover intention and corresponding 95% confidence intervals. Second, I conducted an incremental validity analysis (see McDaniel et al., 2007 and Banks et al., 2014) to assess whether or not organizational commitment adds incremental variance above and beyond job satisfaction when predicting turnover intention. Third, I used sensitivity analysis to examine which of the two constructs presents the greater degree of relative importance for predicting turnover intention. In addition, I use the sensitivity analysis to investigate the change in relative importance weights across nine predictors that are common to two "full" models of turnover intention. This comprehensive approach to assessing empirical redundancy is advantageous because it uses "multiple reference points to locate an object's exact position" (Jick, 1979, p. 602). Indeed, using multiple methods to assess one phenomenon lead to more robust conclusions if the results converge on one conclusion. As such, a *non causa pro causa* may be avoided, thereby providing a more trustworthy assessment of the potential empirical redundancy presented by job satisfaction and organizational commitment.

Meta-Analytic Results. An assessment of Table 11 indicates that job satisfaction (*k* = 424, $\bar{r}_{o_{RE}}$ = -.45) and organizational commitment (*k* = 372, $\bar{r}_{o_{RE}}$ = -.43) have almost identical meta-analytic mean effect sizes estimates with turnover intention. I observed an absolute difference of .02 between the two estimates. Furthermore, job satisfaction's 95% confidence interval (95% CI = -.47, -.42) overlaps with organizational commitment's 95% confidence interval (95% CI = -.46, -.40) (see Figure 16). As such, this indicates that the two constructs are likely not statistically different from one another when predicting turnover intention.

Figure 16

Meta-Analytic Mean and 95% Confidence Interval Estimates for Job Satisfaction and Organizational Commitment



Note. Vertical axis represents effect size magnitude. Horizontal axis represents variable type.

Table 14

Results of Incremental Validity Tests (Harmonic Mean of n = 199)

	β	*SE*	β	*SE*
	The incremental validity of organizational commitment			
Job satisfaction	-.447***	.064	-.308***	.072
Organizational commitment			-.271***	.072
R^2	.200***		.254***	
ΔR^2			.054***	
	The incremental validity of job satisfaction			
Organizational commitment	-.429***	.064	-.271***	.072
Job satisfaction			-.308***	.072
R^2	.184***		.254***	
ΔR^2			.070***	

Note. β = unstandardized beta coefficient; *SE* = unstandardized standard error
***p < .001

Incremental Validity Results. The results of the incremental validity tests are displayed in Table 14. The top panel of Table 14 reports the incremental validity of organizational commitment above job satisfaction and the bottom panel illustrates the incremental validity of job satisfaction above organizational commitment. The results presented in the top panel suggest that organizational commitment increments job satisfaction in explaining turnover intention (ΔR^2 = .054, $p < .001$), which may suggest that organizational commitment and job satisfaction are not empirically redundant when predicting turnover intention. Although this result is significant, its practical significance may be brought into question given that only 5.4% of additional variance is explained when organizational commitment is added to the model. Results reported in the bottom panel of Table 14 indicate that job satisfaction adds incremental variance beyond organizational commitment when predicting turnover intention (ΔR^2 = .070, $p < .001$), which may add credence to the aforementioned results and also suggest that job satisfaction and organizational commitment are not empirically redundant when predicting turnover intention.

Relative Importance Results. To conserve space, and because the earlier sensitivity analysis results indicated that the set of results pertaining to the rescaled relative importance weights and the corresponding raw relative importance weights yielded the most conservative estimates, I do not report the set of results pertaining to the raw relative importance weights and the corresponding rescaled relative importance weights. It is important to point out that the correlation matrix associated with this relative importance analysis is comprised of only three intercorrelations (i.e., a 3 x 3 correlation matrix). Still, just like before, each cell in the matrix is comprised of either the (a) meta-analytic mean effect size estimate, (b) lower bound of the corresponding 68% prediction interval, or (c) upper bound of the corresponding 68% prediction interval. However, given that only 27 possible matrices can be created, the sensitivity analysis draws on *all* possible meta-analytic correlation matrices instead of 1,000. This means the lower (upper) bound of the rescaled relative weight represents the lowest (highest) rescaled relative importance weight across all 27 relative importance analyses.

Table 15 reports the results of a relative importance analysis of job satisfaction and organizational commitment only. An assessment of the results indicate that the mean rescaled relative importance weights, and corresponding mean raw relative importance weights, for job satisfaction (Raw_M = .135; Rescaled_M = 53.15%) and organizational commitment (Raw_M = .119; Rescaled_M = 46.85%) are fairly similar. Indeed, this convergence suggests that both constructs account for approximately the same amount of variance in turnover intention. Although one possible explanation for this result is that both constructs are equally important, another one might suggest that their near uniformity indicates that they are empirically indistinguishable and compete for the same variance in the criterion.

Table 15

Relative Importance Analysis Results of Job Satisfaction and Organizational Commitment

Variable	Raw weight Mean	Raw weight Lower	Raw weight Upper	Rescaled weight Mean	Rescaled weight Lower	Rescaled weight Upper
1. Job satisfaction	.135	.010	.451	53.15%	2.48%	97.40%
2. Organizational commitment	.119	.012	.410	46.85%	2.60%	97.52%

Sensitivity analysis results reported in Table 15 also suggest that job satisfaction and organization commitment have a similar range of relative importance estimates. On the one hand, the lower bound of the rescaled relative importance weight for job satisfaction (Raw_L = .010; $Rescaled_U$ = 2.48%) is almost identical to the one for organizational commitment (Raw_L = .012; $Rescaled_U$ = 2.60%). On the other hand, the upper bound of the rescaled relative importance weights for job satisfaction (Raw_U = .451; $Resclaed_U$ = 97.40%) and organizational commitment (Raw_U = .410; $Rescaled_U$ = 97.52%) are also very similar. Together, this convergence may suggest that the two constructs are empirically redundant when predicting turnover intention. However, I urge caution when interpreting these results because the range of estimates for both constructs is very large.

However, an inspection of all 27 relative importance analysis results indicates that job satisfaction and organizational commitment oftentimes potentially present with empirical redundancy. For instance, I observed fairly similar rescaled relative importance weights for job satisfaction and organizational commitment even when the correlation matrix used to impute the relative importance weights was comprised of the lower estimates of the meta-analytic mean effect size estimate only (i.e., lower bound of the 68% prediction interval). Specifically, in this particular case, the mean rescaled relative importance weight for job satisfaction (Raw_M = .363;

$Rescaled_M$ = 53.17%) is only slightly larger than the one for organizational commitment (Raw_M = .320; $Rescaled_M$ = 46.83%).

Finally, I analyzed the relative importance of 10 predictors included in two "full" models of turnover intention to provide a more stringent examination of the potential empirical redundancy between job satisfaction and organizational commitment. In the first model, henceforth referred to as $Model_{JS}$, I included the following 10 predictors of turnover intention: (1) job satisfaction, (2) pay satisfaction, (3) organizational justice, (4) autonomy, (5) embeddedness, (6) work-life conflict, (7) age, (8) individual performance, (9) supervisor support, and (10) workplace climate. In the second model, henceforth referred to as $Model_{OC}$, all predictors were the same except for one. Specifically, organizational commitment replaced job satisfaction.

Table 16.

Relative Importance Analysis Results – Job Satisfaction Included in Full Model of Turnover Intention

		Raw weight			Rescaled weight		
	Variable	Mean	Lower	Upper	Mean	Lower	Upper
1.	Job satisfaction	.098	.003	.500	36.59%	0.94%	64.88%
2.	Pay satisfaction	.034	.006	.233	12.78%	0.61%	48.52%
3.	Organizational justice	.020	.003	.145	7.58%	0.61%	43.06%
4.	Autonomy	.008	.001	.180	3.03%	0.20%	37.78%
5.	Embeddedness	.062	.005	.371	23.22%	0.53%	60.08%
6.	Work-life conflict	.002	.001	.141	0.84%	0.15%	37.43%
7.	Age	.012	.000	.073	4.33%	0.01%	29.71%
8.	Performance	.003	.001	.093	0.99%	0.17%	32.83%
9.	Supervisor support	.021	.002	.165	7.76%	0.52%	43.05%
10.	Climate	.008	.007	.207	2.89%	0.74%	52.74%

Table 17.

Relative Importance Analysis Results – Organizational Commitment Included in Full Model of Turnover Intention

		Raw weight			Rescaled weight		
	Variable	Mean	Lower	Upper	Mean	Lower	Upper
1.	Organizational commitment	.096	.004	.375	35.24%	0.49%	65.27%
2.	Pay satisfaction	.037	.005	.171	13.56%	0.84%	51.85%
3.	Organizational justice	.020	.003	.181	7.19%	0.50%	57.02%
4.	Autonomy	.008	.001	.150	3.02%	0.19%	41.94%
5.	Embeddedness	.067	.002	.349	24.51%	0.34%	71.41%
6.	Work-life conflict	.003	.001	.099	1.21%	0.13%	37.01%
7.	Age	.010	.072	.002	3.80%	0.02%	31.72%
8.	Performance	.003	.001	.077	0.96%	0.18%	36.73%
9.	Supervisor support	.021	.003	.174	7.68%	0.40%	43.83%
10.	Climate	.008	.007	.264	2.83%	0.89%	59.34%

Tables 16 and 17 reports the relative importance and sensitivity analysis results for Model_{JS} and Model_{OC}, respectively. Results reported in the former table indicate that job satisfaction (Raw_M = .098; Rescaled_M = 36.89%), embeddedness (Raw_M = .062; Rescaled_M = 23.22%), and pay satisfaction (Raw_M = .034; Rescaled_M = 12.78%) are the three most important predictors of turnover intention. Interestingly, results for the latter model suggest that organizational commitment (Raw_M = .096; Rescaled_M = 35.24%), embeddedness (Raw_M = .067; Rescaled_M = 24.51%), and pay satisfaction (Raw_M = .037; Rescaled_M = 13.56%) account for the most variance in turnover intention.

Independently, these tables reveal very little about the potential empirical redundancy between job satisfaction and organizational commitment. However, cross-referencing their results may help to determine whether or not job satisfaction and organizational commitment are potentially empirically redundant when predicting turnover intention. Specifically, evidence for the claim that job satisfaction and organizational commitment are empirically indistinguishable may be found if the relative importance weights for job satisfaction (from Model$_{JS}$) and organizational commitment (from Model$_{OC}$) are similar. Further support may be given to this claim if the relative importance weights for the nine predictors common to both “full” models remain stable after organizational commitment replaces job satisfaction. Indeed, together this may suggest that job satisfaction and organizational commitment are non-orthogonal, especially in the prediction of turnover intention.

Table 18 compares the relative importance results that were reported for job satisfaction (from Model$_{JS}$) in Table 16 and organizational commitment (from Model$_{OC}$) in Table 17. A close inspection of the results reported in Table 18 indicates that the two constructs present almost identical relative importance and sensitivity analysis results. For instance, only a 1.35 percentage point difference was observed between the mean rescaled relative importance weight for job satisfaction and organizational commitment. With regard to the lower and upper bound of the rescaled weight, the observed differences are only 0.45% and 0.39% percentage points, respectively. Indeed, these results may support the aforementioned meta-analytic results and suggest that these constructs are potentially empirically redundant as they appear to be near isomorphic in the context of predicting turnover intention.

Table 18.

Absolute Change in Relative Importance Weights for Organizational Commitment and Job Satisfaction

		Raw weight			Rescaled weight		
	Variable	Mean	Lower	Upper	Mean	Lower	Upper
1.	Job satisfaction	.098	.003	.500	36.59%	0.94%	64.88%
2.	Org. commitment	.096	.004	.375	35.24%	0.49%	65.27%
		|Δ| = .002	|Δ| = .001	|Δ| = .125	|Δ| = 1.35%	|Δ| = 0.45%	|Δ| = 0.39%

Note. Org. = organizational;

Table 19 reports the change in relative importance weights for the nine predictors that are common to both Model$_{JS}$ and Model$_{OC}$. The results indicate that job satisfaction and organizational commitment may be interchangeable as negligible differences in the ranges of relative importance estimates were generally observed. For example, with regard to the mean rescaled relative weights, I observed differences that ranged from 0.01 percentage points (autonomy; see column five of Table 19) to 1.29 percentage points (embeddedness; see column five of Table 19). Similar results were observed for the lower bound of the rescaled relative importance weights. Specifically, I observed differences that ranged from 0.01 percentage points (autonomy, individual performance, and supervisor support; see column six of Table 19) to 0.23 percentage points (pay satisfaction; see column six of Table 19). Although six out of eight (75%) upper bound estimates of the rescaled relative weight also exhibited small differences, two presented with distinguishable differences.

Table 19.

Absolute Change in Relative Importance Analysis Results After Organizational Commitment Replaces Job Satisfaction in Full Model of Turnover Intentions

		Raw Weight			Rescaled weight		
	Variable	Δ Mean	Δ Lower	Δ Upper	Δ Mean	Δ Lower	Δ Upper
1.	Pay satisfaction	.003	.001	.062	0.78%	0.23%	3.33%
2.	Organizational justice	.000	.000	.036	0.39%	0.11%	13.96%
3.	Autonomy	.000	.000	0.03	0.01%	0.01%	4.16%
4.	Embeddedness	.005	.003	.022	1.29%	0.19%	11.33%
5	Work-life conflict	.001	.000	.042	0.37%	0.02%	0.42%
6.	Age	.002	.072	.071	0.53%	0.01%	2.01%
7.	Performance	.000	.000	.016	0.03%	0.01%	3.90%
8.	Supervisor support	.000	.001	.009	0.08%	0.12%	0.78%
9.	Climate	.000	.000	.057	0.06%	0.15%	6.60%

First, the upper bound of the rescaled relative importance weight for organizational justice in Model$_{JS}$ is 43.06%. However, the rescaled relative importance weight for organizational justice jumped to 57.02% (a 13.96 percentage point difference) in Model$_{OC}$. Second, the upper bound of the rescaled relative weight for embeddedness is 60.08% in Model$_{JS}$. In contrast, the corresponding rescaled relative weight becomes 71.41% (an 11.33 percentage point difference) in Model$_{OC}$. Taken together, the results suggest that relative importance weights for nine theoretically-relevant predictors generally remain stable when organizational commitment replaces job satisfaction in a “full” model of turnover intention. Indeed, this may indicate that job satisfaction and organizational commitment are interchangeable and should not be included in the same model of turnover intention as they may compete for the same variance in the criterion, thereby distorting the overall results.

These findings have important implications for future research on theory. For instance, my results may suggest that future generations of turnover theory should explore whether or not there exists a higher-order factor that is comprised of job satisfaction and organizational commitment (Harrison et al., 2006). This action may help to prune superfluous theory and lead to a less dense theoretical landscape (Leavitt et al., 2010). Alternatively, turnover researchers may consider new and/or alternate approaches to measuring organizational commitment. Importantly, this latter suggestion does not bring into question the legitimacy of organizational commitment theory and instead suggests that the potentially redundancy is strictly empirical (i.e., measurement related).

Summary of Study Findings

The purpose of this study was to (1) introduce a sensitivity analysis for relative importance weights in the meta-analytic context, (2) examine the relative importance of commonly-investigated correlates of turnover intention, and (3) assess whether or not job satisfaction and organizational commitment are potentially empirically redundant in the prediction of turnover intention. I introduced a sensitivity analysis approach for relative importance weights by taking into account variance around the meta-analytic mean effect size estimate. In the interest of scientific transparency, and with the hope of other scholars providing robust relative importance estimates, all analysis scripts and meta-analytic datasets that demonstrate the performance of this sensitivity analysis can be found on my dissertation project website at https://osf.io/jfv76/. A large-scale analysis of 11 correlates of turnover intention indicated that job satisfaction, organizational commitment, and embeddedness may be the most important predictors of turnover intention. Interestingly, my results indicated that work-life conflict and individual performance were the weakest predictors of turnover intention. These results were particularly surprising given the importance of work-life conflict and individual performance to theory on turnover (Hughes & Bozionelos, 2007; Sturges & Guest, 2004).

Finally, my examination of the potential empirical redundancy between job satisfaction and organizational commitment indicated that they are near perfect substitutes when predicting turnover intention. Specifically, my results suggested that the naïve meta-analytic mean effect size estimates and corresponding 95% confidence intervals for the job satisfaction- and organizational commitment-turnover intention relations are very similar. Although, the incremental validity results indicate that organizational commitment (job satisfaction) significantly increments job satisfaction (organizational commitment) in explaining turnover intention, the unstandardized beta coefficients for the original predictor noticeably diminished in step two of the hierarchical multiple regression process. Together, this may be symptomatic of multicollinarity between job satisfaction and organizational commitment and suggest that they are not orthogonal. Furthermore, results comparing the relative importance weights for two “full” models of turnover intention indicated that job satisfaction and organizational commitment are almost perfectly interchangeable when predicting turnover intention.

Supplementary Analyses

To further assess the potential empirical redundancy between job satisfaction and organizational commitment I conducted a relative importance analysis of a third “full” model of turnover intention. In this model, henceforth referred to as $Model_3$, I collapsed job satisfaction and organizational commitment into one construct. Specifically, the job satisfaction-turnover intention and organizational commitment-turnover intention datasets were combined to create a single dataset. As such, the combined dataset contained 796 rows of data as the job satisfaction dataset contained 424 rows and the organizational commitment one contained 372 rows (424 + 372 = 796). In addition to this higher-order factor, $Model_3$ also included pay satisfaction, organizational justice, autonomy, embeddedness, work-life conflict, age, individual performance, supervisor support, and workplace climate as predictors of turnover intention.

Table 20 reports the relative importance and sensitivity analysis results for $Model_3$. An inspection of the mean rescaled relative importance results (see column five) indicate that the combined factor (Raw_M = .091; $Rescaled_M$ = 34.50%) is potentially the most important predictor of turnover intention. Following this is embeddedness (Raw_M = .067; $Rescaled_M$ = 24.51%) and pay satisfaction (Raw_M = .067; $Rescaled_M$ = 24.51%). The rank-ordering of these results compliment the results reported in Tables 16 (Model$_{JS}$) and 17 (Model$_{OC}$), which also suggest that embeddedness and pay satisfaction are potentially the second and third most important predictors of turnover intention, respectively.

Table 20.

Relative Importance Analysis Results for Model$_3$ (Organizational Commitment and Job Satisfaction Are Combined)

	Variable	Raw weight Mean	Raw weight Lower	Raw weight Upper	Rescaled weight Mean	Rescaled weight Lower	Rescaled weight Upper
1.	JS and OC combined	.091	.003	.429	34.50%	0.65%	70.51%
2.	Pay satisfaction	.035	.006	.176	13.12%	0.98%	62.56%
3.	Organizational justice	.020	.004	.228	7.59%	0.62%	56.53%
4.	Autonomy	.008	.002	.100	3.06%	0.32%	58.96%
5.	Embeddedness	.065	.003	.338	24.72%	0.46%	65.25%
6	Work-life conflict	.003	.001	.123	0.96%	0.19%	38.46%
7.	Age	.011	.000	.060	4.18%	0.02%	35.09%
8.	Performance	.003	.001	.089	0.99%	0.29%	40.31%
9.	Supervisor support	.021	.002	.208	7.96%	0.28%	54.03%
10.	Climate	.008	.007	.166	2.94%	1.09%	61.73%

Note. JS = job satisfaction; OC = organizational commitment

Table 21 reports the difference with regard to relative importance weights between (1) job satisfaction and the combined factor and (2) organizational commitment and the combined factor. Results pertaining to the job satisfaction versus combined factor comparison can be found along the fourth row of Table 21. An inspection of these results indicate that job satisfaction and the combined factor present very similar mean relative importance weights (Rescaled$_M$ = 36.59% vs. Rescaled$_M$ = 34.50%; $|\Delta|$ = 2.09 percentage points). Importantly, the mean raw relative importance results and all sensitivity analysis results for job satisfaction and the combined factor are also very similar. Together, the results reported in Table 21 suggest that job satisfaction and the combined factor approach isomorphism, which may offer initial evidence that suggests they are potentially interchangeable when predicting turnover intention.

Table 21.

Absolute Change in Relative Importance Weights (Job Satisfaction vs. Combined Factor and Organizational Commitment vs. Combined Factor)

	Variable	Raw weight			Rescaled weight		
		Mean	Lower	Upper	Mean	Lower	Upper
1.	Job satisfaction	.098	.003	.500	36.59%	0.94%	64.88%
2.	Org. commitment	.096	.004	.375	35.24%	0.49%	65.27%
3.	JS and OC combined	.091	.003	.429	34.50%	0.65%	70.51%
	|1 – 3|	|Δ| = .007	|Δ| = .000	|Δ| = .071	|Δ| = 2.09%	|Δ| = 0.29%	|Δ| = 5.63%
	|2 – 3|	|Δ| = .005	|Δ| = .000	|Δ| = .054	|Δ| = 0.74%	|Δ| = 0.16%	|Δ| = 5.24%

Note. Org. = organizational; JS = job satisfaction; OC = organizational commitment.

Convergence was also observed between organizational commitment and the combined factor yielded (see row five of Table 21). For instance, my results suggest that organizational commitment and the combined factor present almost identical mean relative importance weights (Rescaled_M = 35.24% vs. Rescaled_M = 34.50%; |Δ| = 0.74 percentage points). In general, the relative importance and sensitivity analysis results for organizational commitment and the combined factor converge, which may indicate that they are near perfect substitutes when predicting turnover intention.

Table 22 reports the absolute change in regard to relative importance weights between Model_3 (i.e., the model that contains the combined factor) and Model_{JS} (the model that contains job satisfaction only). Indeed, one would expect to observe small differences in regard to relative importance results across all nine predictors that are common to both models if job satisfaction and the combined factor are empirically redundant. An assessment of Table 22 indicates that the relative importance results reported in $Model_3$ are generally very similar to the ones reported in $Model_{JS}$. For instance, the mean rescaled relative importance weight for eight out of nine (89%; pay satisfaction, organizational justice, autonomy, work-life conflict, age, individual performance, supervisor support, and workplace climate) predictors in $Model_3$ differ by less than half a percentage point from the corresponding rescaled relative importance weights in $Model_{JS}$.

Table 22.

Absolute Change between $Model_3$ and $Model_{JS}$ in Regard to Relative Importance Weights

		Raw weight			Rescaled weight		
	Variable	Δ Mean	Δ Lower	Δ Upper	Δ Mean	Δ Lower	Δ Upper
1.	Pay satisfaction	.001	.000	.057	0.34%	0.37%	14.04%
2.	Organizational justice	.000	.001	.083	0.01%	0.01%	13.47%
3.	Autonomy	.000	.001	.080	0.03%	0.12%	21.18%
4.	Embeddedness	.003	.002	.033	1.50%	0.07%	5.17%
5	Work-life conflict	.001	.000	.018	0.12%	0.04%	1.03%
6.	Age	.001	.000	.013	0.15%	0.01%	5.38%
7.	Performance	.000	.000	.004	0.00%	0.12%	7.48%
8.	Supervisor support	.000	.000	.043	0.20%	0.24%	10.98%
9.	Climate	.000	.000	.041	0.05%	0.35%	8.99%

Although each of the lower bound estimates of rescaled relative importance reported in $Model_{JS}$ were within half a percentage point of the corresponding lower bound estimates reported in $Model_3$, a noticeable degree of variability was observed in the upper bound estimates across both models. Specifically, only five out of nine (56%; embeddedness, work-life conflict, age, individual performance, and climate) predictors that are common to both models differed by less than 10 percentage points. In contrast, I observed fairly large differences in the upper bound of the rescaled relative importance weight across both models for pay satisfaction ($|\Delta| = 14.04$ percentage points), organizational justice ($|\Delta| = 13.47$ percentage points), autonomy ($|\Delta| = 21.18$

percentage points), and supervisor support ($|\Delta| = 10.98$ percentage points). It is likely that these observed differences are a result of job satisfaction and organizational commitment being combined into a single factor in Model_{3}, which was done *ceteris paribus*. Importantly, the upper bound estimates for each of the four aforementioned predictors were larger in Model_3 than in Model_{JS}, which may indicate that including job satisfaction *and* organizational commitment in a model of turnover intention attenuates the relative importance of certain predictors that are also included in the model. Indeed, this has important implications for practitioners who rely on relative importance analysis results in the meta-analytic context as not accounting for this potential phenomenon may lead to ill-informed evidence-based practice and, thus, unexpected results, which could widen the science-practice gap.

I also examined the difference with regard to relative importance weights between Model_{OC} and Model_{3}. Table 23 reports the results of this comparison. In general, the differences between Model_{OC} and Model_{3} are comparable to the ones observed between Model_{JS} and Model_{3}. Specifically, each of the mean rescaled relative importance weights reported in Model_{OC} (see column five of Table 17) are within half a percentage point of the corresponding ones reported in Model_{3} (see column five of Table 23). This may suggest that the combined factor (i.e., job satisfaction + organizational commitment) does not affect the mean relative importance weights of the other predictors included in the "full" model of turnover intention. Similar results were also observed for the lower bound estimates of the rescaled relative importance weight. In particular, each of the lower rescaled relative importance weights reported in Model_{OC} (see column six of Table 17) are within half a percentage point of the corresponding ones reported in Model_{3} (see column six of Table 23).

Table 23.

Absolute Change between Model$_3$ and Model$_{OC}$ in Regard to Relative Importance Weights

	Variable	Raw weight Δ Mean	Raw weight Δ Lower	Raw weight Δ Upper	Rescaled weight Δ Mean	Rescaled weight Δ Lower	Rescaled weight Δ Upper
1.	Pay satisfaction	.002	.001	.005	0.44%	0.14%	10.71%
2.	Organizational justice	.000	.001	.047	0.40%	0.12%	0.49%
3.	Autonomy	.000	.001	.050	0.04%	0.13%	17.02%
4.	Embeddedness	.002	.001	.011	0.21%	0.12%	6.16%
5	Work-life conflict	.000	.000	.024	0.25%	0.06%	1.45%
6.	Age	.001	.072	.058	0.38%	0.00%	3.37%
7.	Performance	.000	.000	.012	0.03%	0.11%	3.58%
8.	Supervisor support	.000	.001	.034	0.28%	0.12%	10.20%
9.	Climate	.000	.000	.098	0.11%	0.20%	2.39%

Interestingly, the discrepancies between Model$_{OC}$'s and Model$_3$'s upper bound estimates (see column seven of Table 23) were almost identical to those observed between Model$_{JS}$ and Model$_3$ (see column seven of Table 22). Similar to the Model$_{JS}$ and Model$_3$ comparison, six out of nine (67%; organizational justice, embeddedness, work-life conflict, age, individual performance, and climate) predictors that are common to both Model$_{OC}$ and Model$_3$ presented with upper bound estimates that differed by less than 10 percentage points. Furthermore, pay satisfaction ($|\Delta|$ = 10.71 percentage points), autonomy ($|\Delta|$ = 17.02 percentage points), and supervisor support ($|\Delta|$ = 10.20 percentage points) were the only predictors that reported noteworthy differences with regard to upper bound estimates.

The purpose of the supplementary analyses was to further examine the potential empirical redundancy between job satisfaction and organizational commitment in the prediction of turnover intention. In general, the results of the supplementary analyses add credence to the claim that these two constructs are potentially empirically redundant. For instance, a combined factor, in which job satisfaction and organizational commitment were collapsed into a single construct (Harrison et al., 2006), yielded similar relative importance and sensitivity analysis results as job satisfaction and organizational commitment alone. Furthermore, I observed similar relative importance and sensitivity analysis results for the nine predictors of turnover intention when either (1) job satisfaction, (2) organizational commitment, or (3) the combined factor were included in the "full" model. Indeed, this supports the claim that job satisfaction and organizational commitment are non-orthogonal and may be near perfect substitutes when predicting important organizational outcomes like turnover intention.

To further examine the potential empirical redundancy between job satisfaction and organizational commitment when predicting turnover intention I also performed a series of multilevel meta-regression analyses in R using Cheung and Chan's (2005) *metaSEM* package. First, I examined whether or not the distinction between job satisfaction and organizational commitment was relevant when predicting turnover intention. To this end, I collapsed the "job satisfaction-turnover intention" and "organizational commitment-turnover intention" datasets into a single dataset. Put differently, I created a dataset that contained all data pertaining to the "job satisfaction-turnover intention" and "organizational commitment-turnover intention" relations. Following this, all correlation coefficients were converted to absolute values and a dummy vector was created to distinguish the two correlates of turnover intention (organization commitment = 0, job satisfaction =1). A three-level meta-regression analysis was performed as the newly-created dataset contained three levels; effects (level one) were nested within samples (level two) and samples were nested within articles (level three). My results indicated that the distinction between job satisfaction and organizational commitment was statistically significant when predicting turnover intention ($\beta = 0.0357132$, 95% CI = [0.0141365, 0.0572899], $p < .01$), which may suggest that they are not empirically redundant in this context. However, I expected to observe a significant result given the relatively large sample size associated with this analysis. As such, it is important to examine the magnitude of the effect when interpreting this result. From this perspective, the distinction between job satisfaction and organization is almost negligible ($\beta = 0.0357132$) and, thus, may indicate that these two constructs are empirically redundant when predicting turnover intention.

Additional meta-regression analyses were performed to determine whether or not the distinction between job satisfaction and organizational commitment was more important for the prediction of turnover intention than (1) a random sample of the data pertaining to the "job satisfaction-turnover intention" relation or (2) a random sample of the data pertaining to the "organizational commitment-turnover intention" relation. To this end, I compared the aforementioned meta-regression result ($\beta = 0.357132$, 95% CI = [0.0141365, 0.0572899], $p < .01$), the one from the analysis of the dummy vector which henceforth is referred to as the "dummy result," to the mean of 500 multilevel meta-regressions performed using random samplings of the data pertaining to (1) the "job satisfaction-turnover intention" relation and (2) to the "organizational commitment-turnover intention" relation. Importantly, similar to my analysis of the dummy vector, I converted all correlation coefficients to absolute values before performing all 1,000 meta-regression. Henceforth I refer to the mean of the 500 multilevel meta-regressions performed using random samplings of the data pertaining to the "job satisfaction-turnover intention" relation and the mean of the 500 multilevel meta-regressions performed using random samplings of the data pertaining to the "organizational commitment-turnover intention" relation as the "mean results."

Taken together, this approach will add credence to the claim that job satisfaction and organizational commitment are empirically redundant if the "mean results" are larger than the "dummy result," as it will indicate that the distinction between the two correlates is less important than a random sampling of data from either dataset. Furthermore, I performed a statistical significance test by examining the 95% confidence interval associated with the "dummy result." This test was performed by examining whether or not the "mean results" fall within the "dummy result's" 95% confidence interval.

Table 24 reports the results of the multilevel meta-regressions that I performed to assess the potential empirical redundancy between job satisfaction and organizational commitment in the prediction of turnover intention. My analysis of 500 random samples of the data pertaining to the "job satisfaction-turnover intention" relation produced a mean unstandardized beta coefficient of 0.038354. Indeed, this result indicates that the distinction between job satisfaction and organizational commitment is *less* important than a random sampling of data pertaining to the "job satisfaction-turnover intention" relation when predicting turnover intention. In contrast, my analysis of 500 random samples of the data pertaining to the "organizational commitment-turnover intention" relation produced a mean unstandardized beta coefficient of 0.0265067. This result is not aligned with the previous one and suggests that the distinction between job satisfaction and organizational commitment is *more* important than a random sampling of data pertaining to the "organizational commitment-turnover intention" relation when predicting turnover intention.

Table 24

Meta-Regression Results to Assess Potential Empirical Redundancy

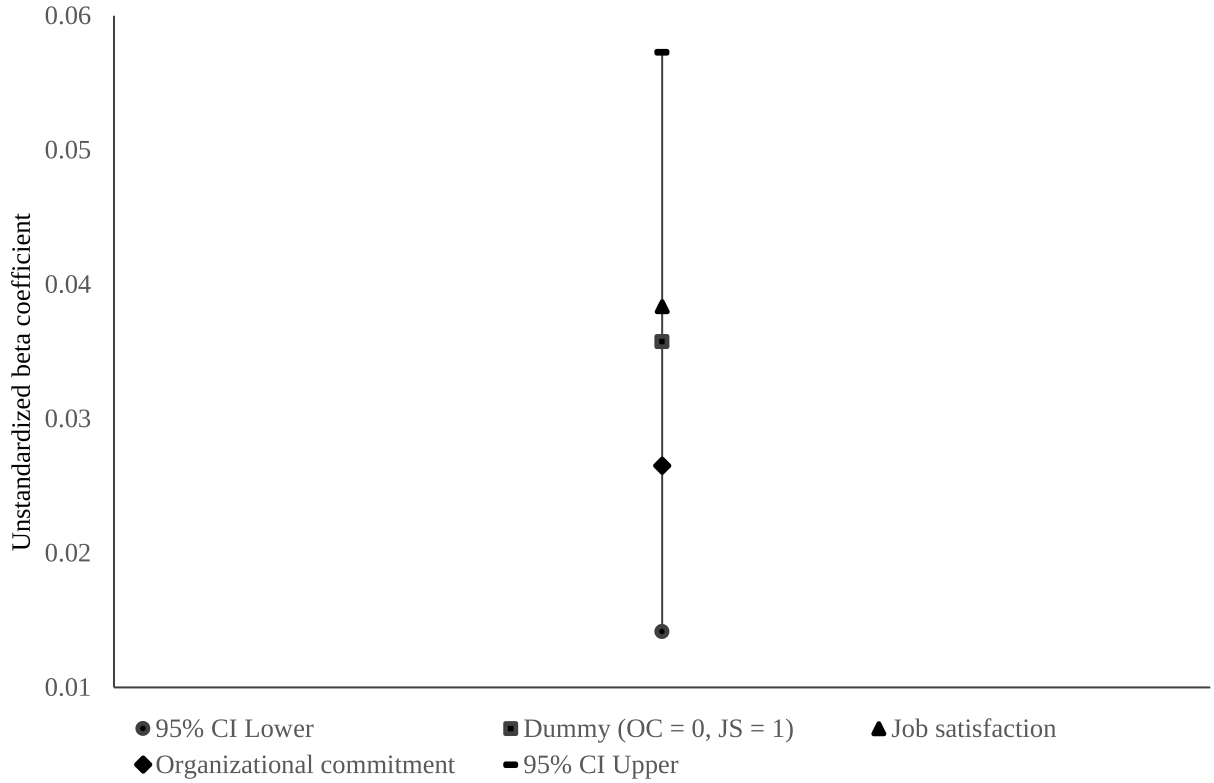
	Dataset	β	SE	95% CI L	95% CI U
1.	Dummy vector (OC = 0, JS = 1)	0.0357132	. 0110087	0.0141365	0.0572899
2.	Random sampling of data pertaining to “job satisfaction-turnover intention” relation	0.0383540	NA	NA	NA
3.	Random sampling of data pertaining to “job satisfaction-turnover intention” relation	0.0265067	NA	NA	NA

Note: β = unstandardized beta coefficient; 95% CI L = lower bound of the 95% confidence interval; 95% CI U = upper bound of the 95% confidence interval. OC = organizational commitment; JS = job satisfaction. NA = not applicable.

To provide a better test of the potential empirical redundancy between job satisfaction and organizational commitment when predicting turnover intention I examined whether or not the “mean results” were within the 95% confidence interval of the “dummy result.” This approach may be considered a “better test” of this question as it allows the difference between the “dummy result” and both of the “mean results” to be tested for significance. Specifically, I could conclude that the distinction between job satisfaction and organizational commitment was not statistically different from the result from (1) a random sample of the data pertaining to the “job satisfaction-turnover intention” relation or (2) a random sample of the data pertaining to the “organizational commitment-turnover intention” relation if the confidence intervals for the “dummy result” and both of the “mean results” overlap. Indeed, this is similar to how statistical differences are examined in the meta-analytic context. However, a 95% confidence interval could not be created for the “mean results” as standard errors cannot be averaged to create mean standard errors. Therefore, I simply examined whether or not the “mean results” were found in the “dummy result’s” 95% confidence interval.

Figure 17

Graphical Display of Meta-Regression Results to Assess Potential Empirical Redundancy



Note. OC = organizational commitment; JS = job satisfaction. 95% CI L = lower bound of the 95% confidence interval associated with the *dummy*; 95% CI U = upper bound of the 95% confidence interval associated with the *dummy*. The result for *dummy* represents the moderating effect associated with distinguishing between job satisfaction and organizational commitment when predicting turnover intention. The result for *job satisfaction* represents the mean meta-regression result of 500 random samples of the "job satisfaction-turnover intention" meta-analytic dataset. The result for *organizational commitment* represents the mean meta-regression result of 500 random samples of the "organizational commitment-turnover intention" meta-analytic dataset. A 95% confidence interval could be calculated for *dummy* only.

An inspection of Figure 17 indicates that the distinction between job satisfaction and organizational commitment and the mean result from (1) 500 random samples of the data pertaining to the "job satisfaction-turnover intention" relation and (2) 500 random samples of the data pertaining to the "organizational commitment-turnover intention" relation are not statistically different. Indeed, Figure 17 suggests that the "mean results" were located within the “dummy result’s” 95% confidence interval and, thus, suggests that job satisfaction and organizational commitment are empirically redundant when predicting turnover intention.

Overall, my examination of the potential empirical redundancy between job satisfaction and organizational commitment in the prediction of turnover intention yielded strong evidence for the claim that job satisfaction and organizational commitment are empirically indistinguishable when predicting turnover intention. First, my meta-analytic (i.e., mean effect size estimates and 95% CIs) results suggested that the two constructs are empirically redundant as I observed a “large” context specific correlation (Bosco et al., 2015a) between job satisfaction and organizational commitment. In addition, their 95% confidence intervals overlapped, which indicated that the effect each construct had on turnover intention is not statistically different from each other. Second, my relative importance analysis results suggested that the job satisfaction and organizational commitment are almost perfect substitutes when predicting turnover intention. Specifically, I observed similar levels of relative importance when job satisfaction and organizational commitment were included in a two-predictor model or turnover intention. Furthermore, the relative importance weights for nine correlates of turnover intention remained relatively stable after organizational commitment replaced job satisfaction in a “full model” of turnover intention. Importantly, this was true even after organizational commitment and job satisfaction were collapsed into a single higher-order factor. Third, a series of meta-regressions revealed that distinction between job satisfaction and organizational commitment is *less* important than a random sampling of data pertaining to the “job satisfaction-turnover intention” relation when predicting turnover intention. Moreover, the meta-regression results indicated that the distinction between job satisfaction and organizational commitment and the mean result from (1) 500 random samples of the data pertaining to the “job satisfaction-turnover intention” relation and (2) 500 random samples of the data pertaining to the "organizational commitment-turnover intention" relation are not statistically different.

Taken together, these results provide strong evidence for the claim that job satisfaction and organizational commitment are empirically redundant when predicting turnover intention. This is surprising given the apparent important role played by both constructs in recent conceptualizations of turnover intention. The results of the current study suggest that future researchers may need to consider using job satisfaction *or* organizational commitment in future conceptualization of turnover intention. Alternatively, the results reported in this study could be used to motivate theory pruning (Leavitt et al., 2010).

Chapter 8: Discussion

Recent research has brought into question the trustworthiness and replicability of our cumulative scientific knowledge (Kepes & McDaniel, 2013; Open Science Collaboration, 2015). Indeed, such concerns have lead scientists to conclude that “most claimed research findings are false” (Ioannidis, 2005, p. 696). Unfortunately, the trustworthiness of some of our literature areas, from strategic management to human resource management (HRM) and industrial and organizational psychology, has recently been questioned (e.g., Banks, Kepes, & McDaniel, 2015; Bettis, 2012; Kepes & McDaniel, 2013). Given concerns about the trustworthiness of organizational sciences, it is important that all methodologies that are used to test theory have some form of sensitivity analysis. Without such sensitivity analyses, researchers are unable to evaluate the robustness of their results and conclusions and practitioners are unable to trust recommendations for practice that are grounded in empirical evidence. Collectively, this may further widen the science-practice gap.

Although the *American Psychological Association’s* Meta-Analysis Reporting Standards encourages the use of sensitivity analysis for assessing the robustness of meta-analytic results (American Psychological Association, 2008, 2010), standards for analyzing the trustworthiness of results derived from meta-analytic correlation matrices are less clear. Relative importance analysis represents one such method and, to the best of my knowledge, currently does not have a sensitivity analysis to determine whether or not its results are robust and trustworthy when meta-analytically derived correlation matrices serve as input. As such, the first purpose of this study was introduce a sensitivity analysis for relative importance weights in the meta-analytic context.

To this end, I developed a technique that takes into account variance around each meta-analytic mean effect size estimate included in the input correlation matrix. This was achieved by building correlation matrices where the cell of matrix had an equal probability of being a meta-analytic mean or the upper or lower bound of the 68% prediction interval.

This approach seemed fitting for a number of reasons. For instance, the prediction interval reveals the distribution of effect size estimates for individual studies. As such, this dispersion quantifies the degree of heterogeneity in each meta-analytic dataset. Importantly, heterogeneity in a meta-analytic dataset can be a result of phenomena like publication bias (Kepes & McDaniel, 2015), outliers (Peters et al., 2007; Terrin, Schmid, Lau, & Olkin, 2003), or moderators (Kepes et al., 2012). Therefore, the prediction interval may account for one or all of these phenomena simultaneously. Taken together, the sensitivity analysis introduced in the current study may help to extend the *American Psychological Association's* Meta-Analysis Reporting Standards to other meta-analytic products (i.e., results derived from meta-analytic correlation matrices), which may lead to more robust recommendations for practice and, thus, better returns on evidence-based practice.

The turnover literature represented a motivating example for the application of this new sensitivity analysis because it is characterized by an abundance of theory. Indeed, the turnover literature is likely often the focus of theoretical speculation because of its importance to the organizational sciences and practice (Allen, 2008). However, recent reviews of the employee turnover literature (Holtom et al., 2008; Hom et al., 2012) did not mention the importance of (or need for) pruning theory in this important area of research, which may signal a belief that all conceptualizations of turnover are useful. However, according to Popper's (1963) basic scientific principle, any theory is defined by its inherent testability and falsifiability. In my study, I analyzed the relative importance of 11 commonly-investigated predictors of turnover intention, which, in a sense, examines the falsifiability of each theoretical perspective *indu* all other theoretical perspective represented in the “full” model.

My results suggest that certain theoretical perspectives on turnover have little explanatory power. This is in spite the fact that the turnover literature is generally characterized by an “incessant stream of confirmations, of observations which "verified" the theories” (Popper, 1963, p. 34). Therefore, one may suggest that the turnover literature has advanced a plethora of pseudotheories, “the scientific equivalent of fool’s gold … [and] the complete opposite of what other fields require for a theory” (Cucina & McDaniel, 2016, p. 1117). This will damaging downstream effects for both science and practice. With regard to science, the inclusion and development of relatively unimportant theories complicates the theoretical landscape unnecessarily (Leavitt et al., 2010), making it difficult to separate signal from noise and to build a trustworthy cumulative scientific knowledge. For practitioners, an overabundance of inconsequential theory – particularly complicated theory (e.g., moderated-mediation, multilevel) – inhibits their ability to assess the generalizability of scientific findings and, thus, constrains the potential of evidence-based practice recommendations.

Still, my findings indicate that certain theoretical perspectives may help to explain a relatively large portion of variance in turnover intention. Specifically, only four constructs (job satisfaction, organizational commitment, pay satisfaction, and embeddedness) accounted for approximately 79% of the explained variance of turnover intention when the meta-analytic mean effect size estimates were used to perform the relative importance analysis (i.e., the traditional approach). However, I note that only 29.75% of variance in turnover intention was accounted for by the 11 predictors when the correlation matrix of meta-analytic mean effect size estimates was inputted into the relative importance analysis. This indicates that the majority of variance in turnover intention may remain unexplained even though 11 commonly-investigated predictors where included in the current analyses. Furthermore, this may add credence to the claim that the turnover literature is potentially comprised of “pseudotheories” (Cucina & McDaniel, 2016) as less than 30% of variance in turnover intention is accounted for by 11 theoretically-relevant predictors. Indeed, one would expect more variance than this to be accounted for by a model of 11 theoretically-relevant predictors.

However, an assessment of my sensitivity analysis results suggests that, at times, the set of predictors included in the current analyses can account for almost none or all of the variance in turnover intention. Specifically, across all 1,000 relative importance analyses a very wide range of R^2 results was observed when variance around the mean, which may represent heterogeneity due to publication bias or moderators, is taken into account. Indeed, this may suggest that existing theories on turnover are able to adequately explain what leads to turnover intention and, ultimately, turnover behavior. Yet, concomitantly, these results may indicate that existing theory falls short of explaining potential boundary conditions or reasons why varying degrees (e.g., levels) of a predictor exist. As such, my results may not necessarily represent an indictment of existing theory on turnover. Instead, they may exemplify the need for more nuanced theory on turnover. Such theory may describe why more than two levels (e.g., low vs. high) of a predictor exists and may better explain how and why different levels of a predictor are associated with the criterion of interest. Taken together, the results of my sensitivity analysis may indicate that nuanced theory, which focuses on intra-construct phenomena, is required to better understand the variations in relative importance weights observed in my study. Indeed, intra-construct theory may help to better explain variance that is currently not understood and thus do for the turnover literature what experience sampling methodology (i.e., intra-person research design) (e.g., Bennett et al., 2016; Gabriel, Diefendorff, Bennett, & Sloan, 2017) has done for organizational research methodology.

There appears to be mounting evidence that suggests many constructs in the organizational sciences are empirically indistinguishable (Banks et al., 2014; Banks, McCauley, Gardner, & Guler, 2016). This situation has been a cause for concern for some time (Morrow, 1983; Rousseau, 2007) and should be worrisome for researchers as it may it signal a failure to adhere to Occam's Razor, which states that "entities should not be multiplied beyond necessity" (William Occam, ca. 1290-1349). Although recent evidence suggests that job satisfaction and organizational commitment are empirically indistinguishable (Le et al., 2010), they still appear together in conceptualizations of turnover-related outcomes (e.g., Brunetto, Teo, Shacklock, & Farr-Wharton, 2012; Fu & Deshpande, 2014). My relative importance results suggest that the empirical distinctness of job satisfaction and organizational commitment should be rigorously discussed as they indicate that they are almost perfect substitutes when predicting turnover intention[3]. Three possible explanations for the apparent empirical redundancy may guide this conversation.

One possible explanation is that theory on organizational commitment (Mowday, Steers, & Porter, 1979) is merely a reincarnation of theory on job satisfaction. Under this perspective, job satisfaction and organizational commitment are ostensibly based on the same underlying phenomenon and, thus, occupy the same conceptual space. As such, it might be suggested that

[3] I concede that my assessment of the empirical redundancy issue produced conflicting results. Still, I argue that partial evidence that supports the claim that job satisfaction and organizational commitment are empirically redundant should motivate a discussion on this topic. Indeed, the same could be argued for the inconclusive results reported in my study, which fail to eliminate the suspicion that job satisfaction and organizational commitment are *not* empirically redundant.

most, if not all, theory on organizational commitment should be eradicated from future conceptualizations of turnover. Following this, job satisfaction could assume the conceptual space that was once supposedly occupied by both it and organizational commitment, thereby reducing the number of explanatory mechanisms in the nomological network from two to one. Although this approach may help to produce a less dense theoretical landscape (Leavitt et al., 2010), it is an extreme measure and ignores the rich literature on organizational commitment that has been written since its inception.

A second possible explanation for the apparent empirical redundancy between job satisfaction and organizational commitment might center on potential measurement issues. Introducing measurement to the discussion on whether or not these constructs are empirically redundant might be appeasing to some scholars – theorists in particular – as it suggests the problem might be an empirical one rather than a theoretical one. Importantly, psychological measurement and measurement theory are fundamental tools that make progress in organizational research possible. One pillar of these perspectives is that the observed variable(s) is representative of the latent variable and its conceptual space. Indeed, both job satisfaction and organizational commitment are latent constructs as they cannot be directly observed and instead must be inferred using latent variables (e.g., survey items). According to classical measurement theory (Nunnally & Bernstein, 1967, 1994), the efficacy of any latent variable for predicting a criterion is depressed to the extent that its corresponding observed variable(s) is not isomorphic with the phenomenon intended to be measured. This might offer an explanation for the apparent empirical redundancy between job satisfaction and organizational commitment. Specifically, it may suggest that items (i.e., the observed variables) used to measure organizational commitment (i.e., the latent variable) do not reflect the intended conceptual space. Instead, the items intended to measure organizational commitment may tap into a diverging conceptual space, which is likely occupied job satisfaction. If this is the case, then the legitimacy of theory on organizational commitment is upheld and a potential remedy may be to rigorously factor analyze existing and new items that are intended to map onto organizational commitment's unique conceptual space.

A third possible explanation for the observed empirical redundancy between job satisfaction and organizational commitment could be that these two work-related attitudes reflect individuals' evaluation of their work experiences. Put differently, it is possible that job satisfaction and organizational commitment are factors of a higher-order general job attitude construct (see Harrison et al., 2006). Credence is given to this argument if the higher-order general job attitude construct is more strongly correlated with a "general *set* of actions" (Harrison et al., 2006, p. 316) than its lower-order components. I queried the metaBUS database to assess the veracity of this possible explanation. Specifically, I conducted a post hoc analysis in which I examined the meta-analytic relation between the (1) higher-order general job attitude and job performance, (2) job satisfaction and job performance, and (3) organizational commitment and job performance[4]. In this context, job satisfaction and organizational commitment are collapsed into one construct to represent the higher-order general job attitude. In addition, job performance, which is comprised of in-role performance, extra-role performance, training performance, and other facets of job performance, represents the general set of actions that "serves as the best criterion construct for overall job attitudes" (Harrison et al., 2006, p. 316). Results of this post hoc analysis support the idea that job satisfaction and organizational

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[4] Note that job performance was selected as the criterion for this post hoc analysis as it is one of the most important outcomes in organizational research. Furthermore, the metaBUS database contains approximately 1,100 effect sizes for both the job satisfaction- and organizational commitment-turnover intention relations, which suggests statistical power should not threaten my results.

commitment may be factors of a higher-order general job attitude construct. Specifically, the meta-analytic mean effect size estimate for relation between the higher-order general job attitude and job performance ($\bar{r}_{o_{RE}}$ = .1969) is larger than the one for the relation between job satisfaction and job performance ($\bar{r}_{o_{RE}}$ = .1897) and organizational commitment and job performance ($\bar{r}_{o_{RE}}$ = .1965). Taken together, these results may suggest that the empirical redundancy between job satisfaction and organizational commitment observed in the current study may be explained by Harrison et al.'s hypothesis (2006) that there exists a higher-order general job attitude factor that consists of job satisfaction and organizational commitment.

Limitations and future research

Although this study introduced an innovative approach to assessing the range of relative importance weights for a set of turnover intention correlates and empirical redundancy between job satisfaction and organizational commitment, it is not without certain limitations. The first potential limitation pertains to the data source. Although metaBUS maintains the world's largest, open-source database of scientific findings, it currently collects data from the published literature only. As such, metaBUS does not systematically assimilate research findings from the "grey literature" (Kepes et al., 2012, p. 627). The grey literature is comprised of research found in conference papers, dissertations, technical reports, and articles in non-English languages (Kepes et al., 2012). It can also include studies that were conducted but not available other than from the author(s) who wrote it. Given that evidence suggests that research findings found in the available literature tend to be more significant and positive than the corresponding grey literature (Greenwald, 1975; Song et al., 2010), it is possible that publication bias threatens my meta-analytic results. Publication bias is a phenomenon that can distort results and conclusions from meta-analytic reviews and occurs when the studies on a topic in the available literature are systematically unrepresentative of all completed studies on that topic (Kepes et al., 2012; McDaniel, Rothstein, & Whetzel, 2006). Extensions of this research should include publication bias analyses. In light of this limitation, I suggest that future researchers try to replicate my findings after relevant data from the "grey literature" (Kepes et al., 2012, p. 627) are added to my datasets, which are available on my dissertation project website at https://osf.io/jfv76/.

Still, some of my meta-analytic results converge with extant meta-analytic findings. For instance, the meta-analytic mean effect size estimate that I observed for the job satisfaction-job performance relation (k = 420, $\bar{r}_{o_{RE}}$ = -.19) (see Table 11) is practically identical to the one (k = 312, $\bar{r}_{o_{RE}}$ = -.18) reported by Judge, Thoresen, Bono, and Patton (2001) in their seminal article. In addition, the meta-analytic mean effect estimate that I observed for the autonomy-turnover intention relation (k = 73, $\bar{r}_{o_{RE}}$ = -.20) (see Table 11) is almost identical to the one (k = 11, $\bar{r}_{o_{RE}}$ = -.19) reported by Spector (1986). Taken together, the convergence of my meta-analytic results with previous meta-analytic results gives me increased confidence regarding my overall conclusions.

A second limitation of my study is that the data source was limited to studies in management-related journals that reported results as correlations. Future research should include effect sizes from non-correlational results. For example, some research could examine turnover intentions with a dichotomously defined employee type variable (traditional workers vs. telecommuters; see Igbaria & Guimaraes [1999] for an example) and report results as t-tests. These types of effect sizes are currently not included in the metaBUS database. Consequently, the data used in my study may not be representative of the population of scientific findings on turnover-related outcomes. Also turnover research is not solely found in management research because turnover is concern in many occupations. For instance, turnover is often the topic of interest in nursing/healthcare journals (Gurney, Mueller, & Price, 1997; Holtom & O'Neill, 2004; Mueller, Boyer, Price, & Iverson, 1994). Yet, currently these data are not included in the metaBUS database. As such, I recommend that future analyses on the relative importance of predictors of turnover include data from management and non-management journals.

A third potential limitation of my study pertains to the degree of heterogeneity observed in several of the meta-analytic datasets. Indeed, evidence suggests that heterogeneity (i.e., between-study variance) can yield upwardly-biased meta-analytic mean effect size estimates (Viechtbauer & Cheung, 2010). My results suggest that the I^2 statistic approaches its maximum value of 100 in many of my meta-analytic datasets (e.g., job satisfaction with turnover intention has an I^2 statistic of 98.22%; see Table 11). Therefore, it is possible that the corresponding meta-analytic results are untrustworthy because of untreated moderating effects. Still, I note that I took steps to remove residual heterogeneity by identifying and deleting outliers using Viechtbauer and Cheung's (2010, see also Viechtbauer, 2015) externally standardized residual procedure. In addition, the purpose of this study was to provide an aerial view of which constructs and, by extension, theoretical perspectives are most relatively important for predicting turnover intention. As such, focus was placed on broad associations with turnover intention rather than nuanced ones. Consequently, the high levels of heterogeneity are likely due in part to the coarseness of the data used to satisfy this study's research objectives. Future extensions of this work should consider the sources of the heterogeneity in each of the meta-analytic distributions to the extent that they can be identified. Replications of current analyses with data drawn from moderator subgroups may be able to meaningfully reduce the heterogeneity. However, I note that this may substantially increase the number of analyses. For instance, if there are two moderator subgroups for each of the 11 predictors, one would effectively be doubling the numbers of predictors. In addition to disaggregating data by substantive moderators, I encourage future researchers to disaggregate by altering the decision rules for this study. For example, in future research one could disaggregate organizational justice into its components (e.g., distributive, procedural, informational).

Fourth, my meta-analytic analyses were conducted using the multi-level meta-analysis procedures in the *metafor* package (Viechtbauer, 2015) and not the psychometric meta-analysis approach typically used in management research. It is argued that the procedures recommended by Schmidt and Hunter (2015) are advantageous because they correct for artifactual variances (e.g., unreliability in the predictor and/or criterion, range restriction) that are not accounted for when using the current approach. Future research should consider how to use psychometric corrections when applying multi-level meta-analysis methods.

Fifth, only one outlier detection method was used in the current study. Ideally, one would use multiple outlier detection methods to access whether or not an effect is an outlier. For example, Viechtbauer and Cheung's (2010; see also Viechtbauer, 2015) multivariate, multidimensional influence diagnostics procedure employs seven outlier detection techniques. This approach may be considered the preferred practice as it is aligned with the concept of "triangulation" (Jick, 1979, p. 602) and would provide multiple reference points to determine if an effect is an outlier. Indeed, if the results of multiple outlier detection analyses converge, evidence for the presence/absence of outliers is provided. However, nearly all outlier detection techniques have not been adapted to the multilevel meta-analytic context. I used the externally standardized residual method (i.e., Cook's distance) only. As such, I encourage future researchers to adapt other outlier detection methods to the multilevel meta-analytic context so that more rigorous sensitivity analyses can be performed, which will likely increase the trustworthiness of our cumulative scientific knowledge.

A sixth limiting characteristic of my study is that only a limited set of predictors of turnover intention is included in my analyses. Indeed, some critics may argue that the turnover literature – or any literature – is not captured by 11 predictors. I concur with this assertion but wish to point out that no benchmark for assessing the relative importance of an entire literature exists. Also, it is unlikely that the 11 predictors included in my study are representative of the entire turnover literature. For instance, personality variables were not included in the current analyses even though they have been shown to be important predictors of turnover decisions (Zimmerman, 2008). Still, to the best of my knowledge, this is the first attempt at partitioning the relative importance of commonly-investigated predictors of turnover intention. As such, I am confident that the results reported in this study will help to inform future theory on turnover, especially given that each predictor was chosen based on its theoretical importance to turnover-related outcomes. Therefore, at worst, my results reveal the relative importance of a sample of theoretical perspectives on turnover and indicate which ones can potentially be pruned (Leavitt et al., 2010), leaving others to be assessed by future research.

I recommend that future studies examine the relative importance of additional predictors of turnover. Indeed, the turnover literature might benefit from a relative importance analysis in which an even larger set of predictors is used. As previously mentioned, my study does not represent an exhaustive relative importance analysis of the turnover literature. Consequently, potentially important predictors of turnover intention (e.g., personality traits) are not assessed or controlled for in my study. As such, I encourage future researchers to build on the current research to explore the relative importance of a large number of turnover intention predictors (e.g., 25 or more predictors). I suggest that this approach to "taking stock and moving forward" (Maitlis & Christianson, 2014, p. 57) in the turnover literature will help inform future theory as it may determine which predictors of turnover are most theoretically (ir)relevant.

Despite the aforementioned limitations, the current research paves the way for potentially exciting future developments in the turnover and research methods literatures. In addition, I believe my results will have important implications for future discussions on philosophy of science topics. With regard to the turnover literature, my findings indicate that future theorists should focus on the association between (1) job satisfaction and turnover intention and (2) embeddedness and turnover intention. Indeed, empirical results derived from meta-analytic output may represent the building blocks of theory (Schmidt, 1992, p. 1177). As such, my results suggest that theorists seeking to better understand what leads individuals to leave their jobs should consider exploring antecedents of job satisfaction and embeddedness (e.g., person-organization and person-job fit). Indeed, this may inform a better understanding of the intermediate and distal predictors of turnover intention.

Although my results indicate that certain constructs (e.g., work-life conflict) hold relatively low importance for predicting turnover intention, I do not discount their potential relative importance to turnover's wider nomological network. Indeed, it is quite possible that such constructs are important to broader theory on turnover. For instance, work-life conflict, which was generally found to have relatively low importance for predicting turnover intention, may be a relatively important predictor of job satisfaction and/or embeddedness. Therefore, I encourage future scholars to assess the relative importance of predictors of job satisfaction and/or embeddedness to determine the potential distal predictors of turnover intention, which may also help practitioners to reduce the negative effects of dysfunctional turnover.

With regard to the research methods literature, my study will have important implications for analyzing the robustness of results derived from meta-analytic correlation matrix-based statistical techniques and assessing the potential empirical redundancy between other constructs. First, there exists a number of meta-analytic correlation-matrix based statistical techniques that currently do not have sensitivity analysis protocols. In the current study, I introduce a sensitivity analysis for relative importance weights in the meta-analytic context, which is a statistical analysis technique that uses a meta-analytic correlation matrix as its basic input. Therefore, I suggest that the sensitivity analysis approach introduced in the current study can be adapted to statistical analysis techniques like meta-analytic structural equation modeling (MASEM) (Cheung & Chan, 2005) and incremental validity analysis as they also use a meta-analytic correlation matrix as their basic input. This may help to produce more robust scientific results. Furthermore, introducing sensitivity analyses for MASEMs and incremental validity analyses may help practitioners make more informed evidence-based practice decisions by providing a range of estimates instead of just one, which may help narrow the science-practice gap. Lastly, the *American Psychological Association's* Meta-Analysis Reporting Standards (American Psychological Association, 2010) and the consumer-centric (Aguinis et al., 2010) approach to reporting research results encourage the use of sensitivity analysis techniques. As such, I recommend that the sensitivity analysis introduced in the current study be adapted to other meta-analytic correlation matrix-based techniques (e.g., MASEM) so that they are aligned with efforts aimed at improving the transparency of scientific output.

I also contend that the current research will have important implications for assessing potential construct redundancy in other areas of research. In this study, I used a tripartite approach to assessing the potential empirical redundancy between job satisfaction and organizational commitment. Specifically, I employed meta-analytic, incremental validity analysis, and relative importance analysis procedures to investigate whether or not these two constructs present empirical redundancy when predicting turnover intention. In general, my results of the application of this comprehensive empirical redundancy analysis compliment extant research (e.g., Harrison et al., 2006; Le et al., 2010) and suggest that job satisfaction and organizational commitment are almost empirically indistinguishable when predicting one of the most important outcomes in organizational research, turnover intention. Importantly, however, it has been suggested that there exists a "broader possibility that the problem of construct empirical redundancy may be quite widespread in organizational research" (Le et al., 2010, p. 121). Indeed, evidence suggests that this assertion may be true (Banks et al., 2016; Meriac, Slifka, & LaBat, 2015; O'Boyle et al., 2015). Given the concerns regarding the trustworthiness of our cumulative scientific knowledge (Bettis, 2012; Kepes & McDaniel, 2013), it is likely that more rigorous methods for examining empirical redundancy will be required. The tripartite approach used in the current study may represent on such method.

In particular, the relative importance analysis approach (i.e., examining "full" models and assessing the change in relative importance weights) is an innovative technique that has never been used before. An important contribution of this methodology is its applicability to other areas of research that are also facing potential empirical redundancy problems. For instance, researchers in the domains of motivation (Marsh, Craven, Hinkley, & Debus, 2003; Murphy & Alexander, 2000), emotional intelligence (Van Rooy, Viswesvaran, & Pluta, 2005), mental toughness (Crust & Swann, 2011), disability (Pollard, Johnston, & Dixon, 2007), sensation seeking (Zuckerman, 2008), organizational citizenship behavior (Organ, 1997), and personality (Block, 1996; Peck, 2007) may be able to use the comprehensive approach to assessing potential empirical redundancy introduced in the current study to address the theoretical and empirical redundancies present in their respective research domains. Although this approach to addressing the construct redundancy problem may have potential, it is important to note it may also have its own set of limitations.

For example, "full models" – like the ones presented in my study – that contain a large number of predictors may limit the efficacy of this method to examine the potential construct redundancy between two variables. This is due to the fact that there is less and less variance left to be explained as more and more variables are added to the "full model." In other words, "full models" become more stable as variables are added. As such, it is possible that the relative weight estimates for the nine correlates of turnover intention that are common to both Model_{JS} and Model_{OC} may be relatively stable by dint of the large number of variables included in each respective model. Indeed, this bring into question my conclusion that job satisfaction and organizational commitment are potentially empirically redundant when predicting turnover intention. I encourage future researchers to adapt my approach to examining the potential empirical redundancy between two constructs such that "full models" are examined in incremental steps. Specifically, it would be beneficial to know whether or not the relative importance weights for the potentially redundant variables are comparable when other variables are added to the "full model" one at a time. Despite this potential limitation, I note that my conclusion that job satisfaction and organizational commitment are empirically redundant when predicting turnover intention is supported my meta-analytic and meta-regression results.

Conclusion

The “shocking cost of turnover” (Waldman et al., 2004, p. 206) likely makes it one of the most important topics to practitioners. Likewise, the abundance of theory on turnover likely makes it one of the most important areas of research for organizational scholars. As my results have indicated, not all theory on turnover is created equally as certain perspectives (e.g., embeddedness) may be relatively more important than others (e.g., job performance). In addition, my findings suggested that the traditional approach to relative importance analysis in the meta-analytic context may produce results that are nonrobust and untrustworthy. Specifically, I introduced a sensitivity analysis for relative importance weights in the meta-analytic context that illustrates the value of taking into account variance around the mean. The sensitivity analysis demonstrated that relative importance results for turnover intention can change drastically when variability around the mean estimates is taken into consideration. This should be worrisome for researchers and practitioners are relative importance results can be used to inform evidence-based practice decisions.

A tripartite analysis of the potential empirical redundancy between job satisfaction and organizational commitment when predicting turnover intention aligned well with extant research and suggested that they may by empirically distinguishable. In particular, I introduced an innovative application of relative importance analysis in which two “full” models are examined to assess potential empirical redundancy between two constructs. My results indicated that job satisfaction and organizational commitment may be interchangeable when predicting turnover intention. This degree of empirical similarity should be worrisome for researchers as it may bring into question the legitimacy of one of the most predominant theories in the organizational sciences, organizational commitment. In addition, the extent to which job satisfaction and organizational commitment are nonorthogonal may lead to substantially weaker returns on investment if practitioners implement human resource management practices that independently target job satisfaction *and* organizational commitment.

In conclusion, aligned with the idea of triangulation (Orlitzky, 2012) and customer-centric science (Aguinis et al., 2010), the reporting of the range of relative importance results, such that variance around the mean estimates is taken into account, should be encouraged by journals. Such steps gives our sciences more transparency, which could help to increase the trustworthiness of our cumulative knowledge. Furthermore, I encourage additional large-scale examinations of potential empirical redundancy in the organizational sciences. This may "help us to weed the garden of organizational studies to keep our garden healthier as a whole" (Leavitt et al., 2010, p. 633) and help us to provide practitioners with unambiguous evidence-based practice recommendations.

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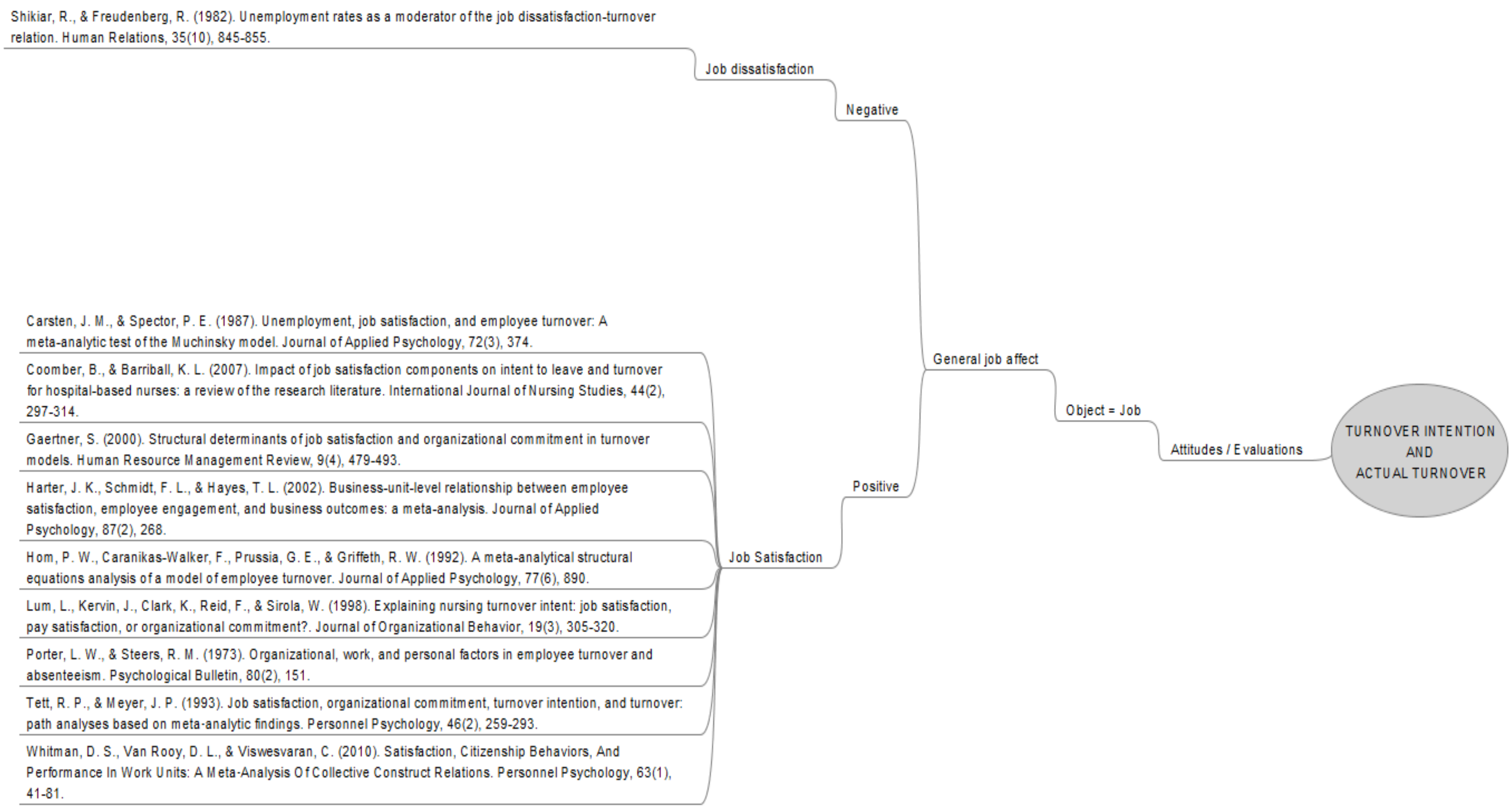
Appendix A

Representation of 10 Meta-Analyses on Turnover Involving Job Satisfaction-Related Correlates



Appendix B

Letter Strings and Taxonomic Codes Used to Query the metaBUS Database

Variable Name	Letter string	Taxonomic code[a]
Turnover intentions	Turnover intention	20179[b]
Job satisfaction	Job satisfaction	20072
Pay satisfaction	N/A	20074
Organizational commitment	Organizational commitment	20057
Organizational justice	Organizational justice	20052
Autonomy	N/A	11338
Embeddedness	N/A	11148+11224+20044[c]
Work-life conflict	Work-life balance	20089[d]
Age	N/A	20457
Individual performance	N/A	40055
Supervisor support	Supervisor support	20002
Climate	N/A	20148

Note. [a] Taxonomic code associated with Bosco et al.'s (2015a; 2015b) hierarchical map. [b] This five-digit code is linked with "quit intentions" in Bosco et al.'s (2015a; 2015b) hierarchical Map (version 52). [c] 11148 = organizational fit; 11224 = job fit; 20044 = community embeddedness. [d] The majority of data pertained to "work-life conflict" relations. As such, I reversed the "work-life balance" data by multiplying by minus on (i.e., -1) to ensure the data were consistent. N/A = not applied because the corresponding letter string produced a high number of false positives or because it did not make sense to include a letter string in addition to a taxonomic code. For instance, a high number of false positives were produced when the letter string "performance" was included in queries for "individual performance."

Vita

James Gerard Field was born January 20, 1987 in Tralee, County Kerry in Ireland. He is currently a Permanent Resident of the United States and an Irish citizen. He graduated from Christian Brothers Secondary School in Tralee, Ireland in 2004. He received his Bachelor of Science in Business Administration from Glenville State College, Glenville, West Virginia in 2008 and his Master of Business Administration from Marshall University, Huntington, West Virginia in 2011.