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Job satisfaction researchers typically assume a tripartite model, suggesting evaluations of the job are explained by latent cognitive and affective factors. However, in the attitudes literature, connectionist theorists view attitudes as emergent structures resulting from the mutually reinforcing causal force of interacting cognitive evaluations. Recently, the causal attitudes network (CAN; Dalege et al., 2016) model was proposed as an integration of both these perspectives with network theory. Here, we describe the CAN model and its implications for understanding job satisfaction. We extend the existing literature by drawing from both attitude and network theory. Using multiple data sets and measures of job satisfaction, we test these ideas empirically. First, drawing on the functional approach to attitudes, we show the instrumental-symbolic distinction in attitude objects is evident in job satisfaction networks. Specifically, networks for more instrumental features (e.g., pay) show stable, high connectivity and form a single cluster, whereas networks regarding symbolic features (e.g., supervisor) increase in connectivity with exposure (i.e., job tenure) and form clusters based on valence and cognitive-affective distinction. We show these distinctions result in "small-world" networks for symbolic features wherein affective reactions are more central than cognitive reactions, consistent with the affective primacy hypothesis. We show the practical advantage of CAN by demonstrating in longitudinal data that items with high centrality are more likely to affect change throughout the attitude network, and that network models are better able to predict future voluntary turnover compared with structural equation models. Implications of this exciting new model for research and practice are discussed.

Keywords: attitude theory, causal attitude network, job satisfaction, network analysis

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Job attitudes are central to understanding and predicting workplace behavior. Contemporary research on job attitudes operationalizes an individual's attitude as the aggregate of a person's level of endorsement to statements expressing evaluative reactions to different aspects of their job (Krosnick, Boninger, Chuang, Berent, & Carnot, 1993; Schleicher, Watt, & Greguras, 2004). This approach is consistent with traditional latent variable theory, in which latent attitudes are thought to exert causal force on the respondent, serving as the mechanism that explains item response behavior. Although this approach has the benefit of simplicity, particularly in understanding relations between attitudes and important outcomes, recent research has called into question the merits of these contemporary approaches to understanding the complex nature of attitudes, including their formation, structure, and stability (e.g., Dalege et al., 2016; Eagly & Chaiken, 2007; Van Overwalle & Siebler, 2005). Specifically, attitude research has typically assumed one of two models for describing the structure of attitudes: the *tripartite* model and, more recently, the *connectionist* model.

The tripartite model of attitudes assumes that the structure of an attitude has three major components: *affective* responses constituting emotional reactions toward the attitude object, *cognitive* responses consisting of thought-based appraisals of the object (Locke, 1969), and specific *behavioral* reactions toward the attitude object (Eagly & Chaiken, 1993; Judge & Ilies, 2004; Weiss, 2002). Under the tripartite model, past research on job satisfaction has almost exclusively focused on attempting to disentangle specific components into causal relations (Ilies & Judge, 2004), rather than how the various components are interconnected as a whole. In contrast, in the broader attitudes literature, connectionist models of attitudes assume attitudes are best represented as dynamic systems in which attitudes form and change due to the interactions between only cognitive evaluative reactions toward the attitude object (Conrey & Smith, 2007; Monroe & Read, 2008). As Dalege and colleagues (2016) point out, the connectionist approach seems to better reflect the complex structure of attitudes compared with the tripartite perspective, but unfortunately it cannot be fit to actual data. Instead, the connectionist approach has so far relied on statistical simulations that explicate how cognitions interact to form and propagate attitude structures. Further, whereas tripartite models address cognitive, affective, and behavioral portions of attitudes, connectionist models refer only to cognitive evaluations (Monroe & Read, 2008) and ignore its affective and behavioral portions. Therefore, neither the tripartite nor connectionist models sufficiently address the complexity of attitude structure and operation.

Given the problems noted above with tripartite and connectionist models of attitudes, a third approach to attitudes—the Causal Attitude Network (CAN) model—has recently been proposed that retains the complexity inherent in connectionist models, can be fit to actual data, and unifies the tripartite and connectionist models by focusing on all three components of attitudes (affect, cognition, and behavior). The CAN model views attitudes as dynamic systems of interacting affective, cognitive, and behavioral reactions. The attitude therefore is considered an emergent structure resulting from the interactions between evaluations of the attitude object. Thus, the CAN model does away with the idea of a latent variable inherent to tripartite models and instead views the interaction between evaluations of the attitude object as the explanatory mechanism for item responses (Dalege et al., 2016). Such an approach also eliminates the assumption of *local independence*, which states that the relationships between evaluations are outcomes of a main effect of the latent variable. Under the assumption of local independence, evaluative reactions cannot interact and are interchangeable because the latent variable affects all evaluations similarly.[1] Although the elimination of the latent variable in a theoretical model of attitudes could be viewed as rather inconvenient, Dalege et al. point out that the idea that evaluative reactions do not interact (i.e., local independence) is at odds with theories of cognitive consistency in attitudes. These authors further point out that the idea that different evaluative reactions to an attitude object (or survey items) are interchangeable—in particular, the notion that changes in the latent variable impact all indicators similarly and simultaneously—is out of step with theories of evaluative inconsistency within complex attitudes.

The idea behind the CAN model is that network-theoretic models and network analysis techniques can be utilized in cross-sectional data to describe and investigate the between-subjects interrelations of survey item responses. The patterns of relations between item responses in turn represent the system of reactions to attitude objects (i.e., the attitude). Adopting the network lens in studying attitudes leads to exciting and intriguing hypotheses. Network models have shown stunning generality, explaining everything from ant colony behavior (Gordon, 2014) to the Bose-Einstein condensate (Bianconi & Barabási, 2001), interpersonal relations, and processes in the social sciences (Borgatti, Mehra, Brass, & Labianca, 2009). In applied psychology, network-based theorizing has already lead to promising developments in leadership theory (e.g., Carter, DeChurch, Braun, & Contractor, 2015; Contractor, DeChurch, Carson, Carter, & Keegan, 2012). A recent shift toward understanding the formation, structure, and functioning of individual differences in network-theoretic terms has seen similarly impressive results in application to personality (Cramer et al., 2012), depression (Cramer, Waldorp, van der Maas, & Borsboom, 2010), psychopathology (Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011), and most recently in the CAN model of attitudes. Further, it promises many potential applications in survey analysis that would allow for identification of particular reactions that if altered are more likely to lead to attitude change (Dalege et al., 2016).

In this paper, we present a fresh examination of the structure of job satisfaction under the recently proposed CAN model (Dalege et al., 2016). First, we begin by explaining this new framework and its advantages for understanding the formation, structure, and stability of job attitudes. We point out the impli-

[1] As one reviewer pointed out, this may seem to be a bit of an overstatement, partially because new evaluations (or indicators) can emerge later than others even when there is a common latent factor driving all of them. However, whereas the CAN model does posit a theory for *why* new indicators may emerge, the latent variable model does not. Further, it is notable that, as pointed out by Dalege et al. (2016), Jöreskog's (1971) work on latent variable theory arises from the assumption that the correlation between congeneric tests when corrected for error is unity. Thus, although we do agree that this assumption is unrealistic, we do contend that it is one of the theoretical tenets of latent variable theory. However, the point is debatable (see Bollen, 2002 for an alternate way of thinking about latent variables and a case for the restrictiveness of the local independence assumption).

cations of, and derive hypotheses and research questions for, job satisfaction that are implied by the CAN model. Finally, we test these hypotheses using item responses from data collected on the Job Descriptive Index (JDI) and Job Satisfaction Survey (JSS; Spector, 1985), the data for the 2009 JDI norming study (Lake, Gopalkrishnan, Sliter, & Withrow, 2010), and the longitudinal Health and Retirement Survey (HRS) job satisfaction and employment data (2006 to 2012) with the goal of better understanding the structure of job satisfaction in general, and satisfaction with facets of one's job. In doing so, we hope to elucidate the CAN model, develop and test new hypotheses implied by the CAN mode, as well as point out its implication for the study of job attitudes and organizational survey practices.

The Causal Attitude Network Model and Job Satisfaction

As noted previously, under the CAN model, attitudes are—in theory—dynamic systems that emerge from the interconnectedness of evaluative reactions to an attitude object. In a network perspective, this is most easily understood through graphical representations wherein each evaluative reaction is represented as a circular *node*. The causal connections between evaluative reactions (nodes) are represented by *edges*, depicted by lines in which line thickness reflects the strength of relationship between two evaluative reactions. The strength of relation is also indicated by the distance of one node to another, with the closest nodes having stronger positive relationships, and those furthest away from one another having negative relationships. Additionally, the color of edges is often used to indicate the direction of the relationship (i.e., negative or positive). These graphical depictions are utilized to represent the emergent structure of the attitude that results from the dynamic interactions between attitude object evaluations.

It is important to note here that the advantages to the CAN approach to attitudes does not lie in some new numerical trick that increases accuracy of estimation of attitudes. As we note in Appendix A, the CAN model has much in common with latent variable models. In fact, when examining the fit of network models to the data, fit is almost always (not surprisingly) near perfect.[2] Indeed, the model is akin to allowing for correlations between error terms in confirmatory factor models. Its true promise comes in the way we think about how attitudes work and how they are formed. Thus, we encourage the reader to view the two models as complimentary rather than as competing. Additionally, CAN has great potential for application to organizational attitude surveys by providing indicators of pathways to attitude change, that—as discussed later—cannot be surmised from typical indicators such as factor loadings. In the following, we apply the CAN model to what is quite likely the most commonly examined job attitude in contemporary applied psychology: job satisfaction.

Attitude Formation and Strength

The formation of attitudes under the CAN model is derived from the *free-energy principle*, which posits that systems maintain themselves by minimizing the energy required to maintain their order. Applied to attitude theory, the free-energy principle predicts individuals use the evaluations and inferences they make about an attitude object to form predictions about the object, leading to new, related evaluations that require little energy to maintain the preexisting structure of the attitude system (Friston, 2009; Friston, Daunizeau, Kilner, & Kiebel, 2010). New evaluations that are unrelated to preexisting evaluations require more energy for the system to maintain order and, therefore, are less likely to be introduced. Thus, the CAN model assumes that attitudes form through either one, or a small number of, initial evaluative reactions. For example, Figure 1 illustrates the formation of job satisfaction over time, based on the example given by Dalege et al. (2016). After the first few days on the job, one might start to think they enjoy their job. This single evaluative reaction might then give way to subsequent evaluations of the job as *good* and *pleasant*, which then gives way to believing the job is not *bad* nor *undesirable*.

Notably, the CAN model extends our understanding of attitude formation in that it posits that evaluative reactions differ in how they influence (and interact to influence) new evaluations. Specifically, Dalege and colleagues (2016) point out three major factors that may simultaneously impact the addition of new evaluations to a preexisting attitude object: (a) strength of the readiness (i.e., strength of connections), (b) similarity of valence (i.e., positive vs. negative evaluations), and (c) popularity of current nodes (i.e., how often nodes are connected). Strength of the readiness refers to how similar the new evaluative reaction is to certain evaluations that already exist in the network. For instance, think of an employee's attitude of job satisfaction as a network. An employee has previously evaluated that their job is both (a) respected by others but is also (b) repetitive. Over time, this employee makes a new evaluation in terms of job satisfaction, that their job (c) gives them a sense of accomplishment. The CAN model would suggest that the prior evaluation of their job as respected by others has stronger readiness to this new evaluation of feeling a sense of accomplishment. Thus, the new evaluation is more strongly affected by evaluation of that job as respected because these evaluations are highly related (i.e., high readiness), whereas the prior evaluation of having a repetitive job is not as consistent with the evaluation of feeling a sense of accomplishment.

The second evaluations factor, similarity of valence, directly relates to the strength of the readiness of certain evaluations (Dalege et al., 2016). This factor draws from the idea that evaluations with similar valence (e.g., two positive evaluations like *pleasant* and *good*) have higher readiness toward each other than evaluations with differing valence (e.g., *good* and *undesirable*). This can be seen in Figure 1 by the distance between the negative and positive evaluations, which are further apart than neighboring nodes sharing the same valence. As Dalege points out, this is because evaluations with differing valences are relatively independent (see Cacioppo & Berntson, 1994). Building on our example, an employee may have both positive and negative evaluations of their job satisfaction: positive in that they feel others respect their job but negative in that they feel their duties are repetitive. As new evaluations are made (e.g., a sense of accomplishment), preexist-

[2] In the data examined here, this was certainly true. For example, for the job descriptive index scales in a sample of 1,485 persons; model-data fit for scales ranged from CFI and TLIs of .99 to 1.00, and RMSEAs $< .001$ to .022.

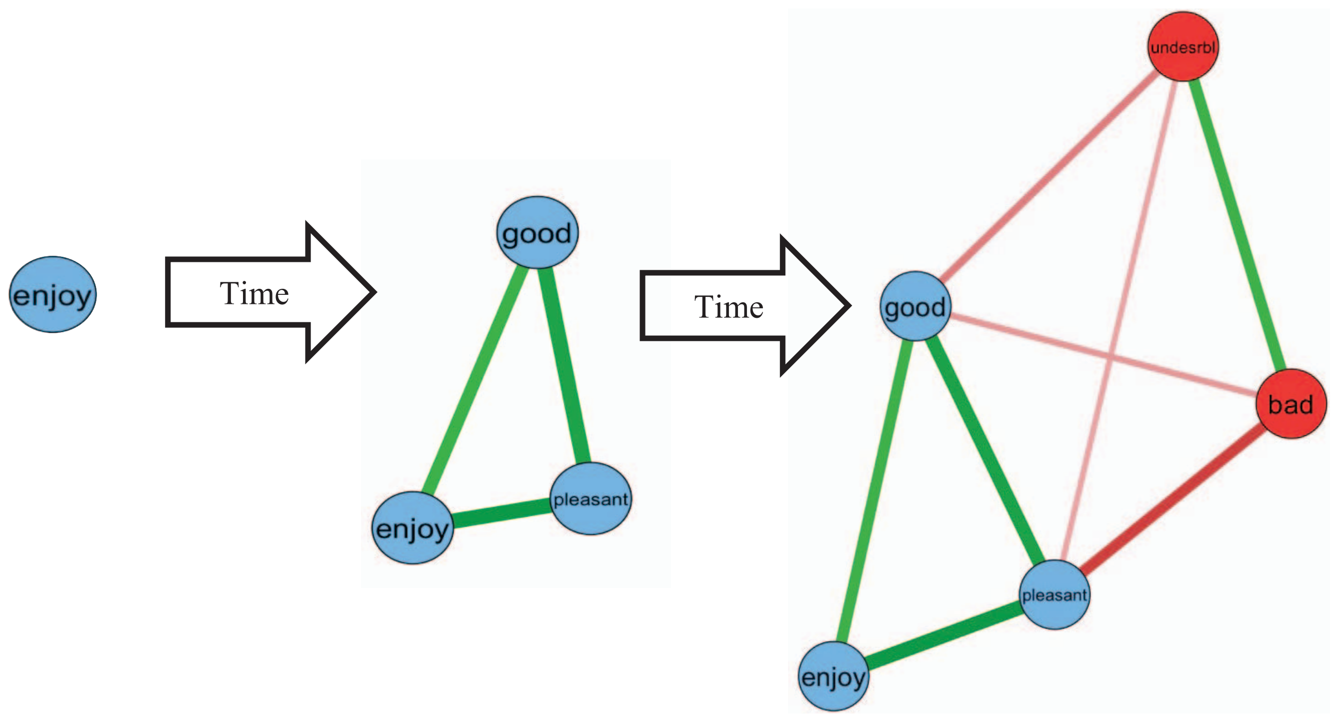

Figure 1. Hypothetical example of the formation of job satisfaction over time. Blue/light gray nodes indicate positive evaluations and red/dark gray nodes indicate negative evaluations; green/solid lines represent positive relations between evaluative reactions and red/dashed lines indicate negative relations. See the online article for the color version of this figure.

ing positive evaluations will be more likely to increase the readiness of new positive evaluations, and preexisting negative evaluations such as feeling their job is repetitive increases the readiness of new negative evaluations. Alternatively, preexisting positive evaluations are less likely to lead to lead to new negative evaluations and vice versa.

Finally, popularity refers to the combined number and strength of connections of a preexisting evaluation with other preexisting evaluations. The popularity of an evaluation affects whether, and how strongly, new evaluations connect to other evaluations in the network (Dalege et al., 2016). Building on our example, imagine that the most popular evaluation in our hypothetical person's attitude network is that they feel their job is respected. The connections of this evaluation with other evaluations will also affect future evaluations of the attitude object. For example, because there is a relation between the feeling that one's job is respected and a sense of accomplishment, but neither has a positive relation with the evaluation that the work is repetitive, one is more likely to make new positive evaluations rather than negative evaluations.

The temporal aspects of the theory inherent to CAN represent an important grounding for measuring attitudes statically. Although the CAN model views links between evaluations as *directional* ties (i.e., one evaluation causing another) during attitude formation, the ties in attitude networks are bidirectional unless the observation of attitudes occurs in real time (see Simon, Krawczyk, & Holyoak, 2004). That is, related evaluations of the attitude object reinforce one another in a mutually causal fashion. These features are drawn on the application of the Ising (1925) model of ferromagnetism, which implies that the reason that attitude object evaluations are correlated *because* of their interactions with one another, and that the function of these interactions is to optimize consistency among evaluations as the system evolves.

Despite the fact that attitude formation is very difficult to observe empirically (Dalege et al., 2016), the theoretical temporal dynamics in the CAN model allow for some specific predictions regarding the *strength* of attitudes. Namely, the extent of *connectivity* in a network can be thought of as a mathematical formalization of the concept of attitude strength. The connectivity in a network increases over time as (a) the number of connections between nodes increases, and/or (b) the size of the weights describing the relation between nodes increases (Dalege et al., 2019). Attitude networks with high connectivity represent strong attitudes, implying that they are more resistant to change (Eagly & Chaiken, 1998; Watts, 1967; Wood, 1982). Given that it is well-established in the attitude literature that attitude strength increases as one interacts with the attitude object (Fazio & Zanna, 1981), the CAN model would predict that persons with higher interaction with the attitude object would show attitude networks with higher connectivity. In the context of job satisfaction, interaction with the attitude object should increase with job tenure given that tenure would increase (a) the volume of knowledge one has about the job, (b) the accessibility of information about the job in the evaluator's memory, (c) elaboration on the good and bad aspects of their job, and (d) the level of certainty an employee has about their evaluation of the job, all of which are noted attitude features that relate to attitude strength (Howe & Krosnick, 2017). Thus, we would generally expect the connectivity of attitude networks to be higher for those with higher levels of tenure in their job (i.e., higher levels of interaction with the attitude network).

An important qualifier to consider is the expectation that some attitude objects are easier to evaluate and thus require less time for the processes of knowledge accumulation and elaboration that leads to greater attitude strength. In particular, drawing from the functional approach to attitudes—which maintains that attitudes serve particular functions—one can make the distinction between more *instrumental* attitude objects and more *symbolic* attitude objects. Instrumental attitude objects have more tangible and objective characteristics and serve a *knowledge function*, in that the attitude serves the function of allowing the evaluator to maximize rewards and minimize punishment, with a primary focus on utility (Katz, 1960). Symbolic attitude objects, on the other hand, have more subjective, intangible features, relying on the attitude holder's formed image of the object. Attitudes toward symbolic attitude objects serve a *social identity*, or self-expressive function, that communicates identity to others and informs the attitude holder of their place in the world (Carter & Highhouse, 2014).

In considering functional theories of attitudes in understanding increased attitude strength with exposure to the attitude object, we propose that—because of their more tangible nature—the strength of attitudes toward instrumental features of the job (e.g., pay, promotions) will emerge quickly. In contrast, attitudes toward symbolic features of the job (e.g., work itself, coworkers) will be slower to emerge because their intangible nature requires subjective image formation, requiring more time to emerge as a strong attitude. Indeed, Carter, Carter, and DeChurch (2018) noted a similar phenomenon in that more observable features of teams (e.g., information sharing) require less time to become perceptible to team members than intangible team-level characteristics (e.g., team trust). Thus, we would expect that (a) attitudes toward more instrumental features of the job will strengthen quickly, and thus show generally higher connectivity than attitude networks for more symbolic features of the job, and (b) increases in connectivity in attitude networks characterized by higher job tenure will be easier to observe for more symbolic attitude objects, but will be difficult to observe for more instrumental objects, for which attitude networks will more immediately strengthened. Therefore, we hypothesize the following:

> *Hypothesis 1a:* Attitude networks for more symbolic facets of job satisfaction (e.g., the work itself, coworkers, supervisors) will show increased connectivity with greater job tenure, whereas more instrumental facets (e.g., pay, promotions) will not change with greater tenure.

> *Hypothesis 1b:* Attitude networks for more instrumental facets of job satisfaction will show greater connectivity overall compared with symbolic networks.

Attitude Structure

Not only does the theoretical perspective of CAN provide a simple and logical explanation for how an attitude develops, it also has implications for how we think about the structure of attitudes. A hypothesis that follows from the CAN model is that attitudes will generally take on a *small-world* structure. The term *small-worldness* (Watts & Strogatz, 1998) is derived from the notion that a resident of Athens, Georgia, may only need to go through a few number of acquaintances to indirectly know someone who lives in Athens, Greece—creating a connection between two smaller networks in separate cities within one much larger network of the world. Thus, the seemingly large world feels smaller by indirect associations. Small-world structures are defined by two network properties. First, a small-world network has high *clustering*. Clusters refer to groups of nodes that are strongly interrelated. In the case of an attitude network, clustering refers to evaluations that are highly positively related. For example, an attitude may exhibit two main clusters: positive evaluations of the attitude object, and negative evaluations of the attitude object. Additionally, we can incorporate the tripartite conception of *cognition*, *affect*, and *behavior* as three potential clusters that may emerge. The second network property, *global connectivity,* refers to the average minimum path length between all nodes in a network and informs attitude strength (Dalege et al., 2016). A path length is the number of edges one would have to cross to get from one node to another. An attitude network would have high connectivity if—for example—a cluster of positive-valence evaluations had relatively shorter path lengths to nodes in the negative-valence cluster. A small-world network is characterized then by highly clustered nodes with relatively short path lengths between nodes in different clusters that Dalege and colleagues refer to as shortcuts between clusters. Formulaically, small-world structures have higher clustering than a random network, but because random networks are already generally high in connectivity, small-world structures have connectivity similar to or not much higher than a random network.

To measure how closely a network approximates a small-world structure, one can compute the *small-world index*, which incorporates the concept of the amount of clustering in the network, *C*, and the connectivity of the network is represented by length, *L*. The clustering coefficient, *C*, is the number of closed triangular patterns in the network (i.e., triplets of attitude object evaluations that are strongly related to one another) divided by the number of triplets that are connected (but not necessarily all related to one another). The length coefficient, *L*, is the average length of the paths between evaluative reactions. A small-world network would be expected to have higher clustering, *C*, but have similar or slightly greater connectivity than a randomly generated network of the same size, L_{rand} (Albert & Barabasi, 2002; Watts & Strogatz, 1998). The small-world index can therefore be computed as:

$$SW = \left(\frac{C}{C_{rand}}\right) \Big/ \left(\frac{L}{L_{rand}}\right). \tag{1}$$

Values of *SW* greater than one suggest that the structure of the attitude object evaluations exhibits a small-world structure. The statistical significance of the small-world index is determined by constructing confidence intervals based on 1,000 or more randomly generated graphs to compute confidence intervals for L_{rand} and C_{rand} using Monte-Carlo simulations (Dalege et al., 2016; Humphries & Gurney, 2008). Thus, to conclude that a network has a small-world structure, we must find that: (a) the small-world index is greater than 1; (b) the average Length, *L*, of the shortest path in the network is either within the 95% confidence interval of L_{rand} or is higher than the upper-bound of that interval; and (c) the clustering, *C*, is greater than the upper bound of the confidence interval of C_{rand}. This index is essentially a quantification of how may times more clustering there is within a network than connectivity (with each standardized by their random-network counterparts); more clustering and less connectivity leads to a higher value of *SW*. For example, a small-worldness of 1.50 would suggest that there is 50% more clustering than connectivity in the network. Although clear guidelines for what constitute large and small values of *SW*—particularly with regard to psychometric data—have not been established, the majority of networks in the available literature fall between 1 and 2. For example, in Dalege et al. (2016), small-worldness values for attitudes toward Ronald Reagan and Walter Mondale were 1.16 and 1.25, respectively, only about .06 greater than what would have been expected for their respective random networks.

Small-world structures have been observed in a variety of emergent structures including power grids, brain networks (Douw et al., 2011), semantic networks of languages (Kenett, Kenett, Ben-Jacob, & Faust, 2011), and connections between authors in scientific fields (see Dalege et al., 2016; Watts & Strogatz, 1998). Additionally, in psychometrics small worlds have been shown to describe symptoms of psychopathology (Borsboom et al., 2011). Thus, the CAN model places attitudes into a framework that is consistent with a general theory of the patterning of emergent structures. In relation to attitudes specifically, Dalege et al. (2016) posited that attitudes should generally show a small-world because the evaluations of the attitude object are highly clustered and these clusters are connected by a moderate number of nodes that form shortcuts that fill structural holes in the network by providing the sole connection between two clusters. Dalege et al. (2016) illustrated this point by demonstrating that attitude structures for presidential candidates Ronald Reagan and Walter Mondale exhibit small-world structure.

A notable reason that attitude evaluation networks emerge as small-world structures is *assortativity*. Assortativity refers to the phenomenon that nodes tend to be connected to other nodes that are similar to them in some way (Newman, 2003). In Dalege et al.'s (2016) attitude networks regarding political candidates, assortativity is evident in (a) the fact that positive and negative evaluations tend to cluster with evaluations of the same respective valence, and (b) items that are alike with regard to whether the sentiment is more akin to an affective (e.g., judgments about the warmth of the candidate) versus cognitive evaluation (e.g., judgments about the competence of the candidate) tended to cluster nearer to one another. Additionally, these clusters have some nodes that form connections between these distinct clusters, adding to the connectivity of the structure. This expected pattern of clustering is notably well-aligned with theories of cognitive consistency in the attitudes literature (Gawronski & Bodenhausen, 2006; Simon, Snow, & Read, 2004).

Job satisfaction is an attitude that can be defined as an individual's evaluations reflecting contentment and positive associations with their job (Locke, 1969). Job satisfaction can be studied at the global level (overall job satisfaction) or at the facet level (satisfaction with specific aspects of the job such as satisfaction with pay, supervisor, or the work itself; Smith, Kendall, & Hulin, 1969). Thus, prior theory on job satisfaction suggests that job attitudes are formed by affective and cognitive evaluations, and require an individual to evaluate the attitude object of interest in terms of their own personal values (Eagly & Chaiken, 2007; Judge & Kammeyer-Mueller, 2012). However, traditional tripartite conceptions of job satisfaction typically invoke a latent variable perspective on attitudes wherein evaluations are the *result* of a temporally preexisting hidden variable (i.e., the attitude). Thus, we argue that—as with all attitudes—the CAN model is more aligned with theoretical perspectives on what job satisfaction is: an emergent structure that results from evaluations of the attitude object (the job overall and/or its specific features) and their interactions. However, at the facet-level, we may expect a small-world structure with some facets but not with others. As noted above, the small-world structure arises primarily because of the clustering of negative- versus positive- evaluations and—most importantly—by cognitive and affective evaluations.

As noted above, one can distinguish between more *instrumental* and more *symbolic* attitude objects. Whereas more symbolic attitude objects (e.g., the work itself, coworkers, supervisors) will evoke both cognitive and affective evaluations that are self-expressive, more instrumental attitude objects (e.g., pay and promotions) will evoke mostly cognitive evaluations that can only form clusters based on the valence of object evaluations (Katz, 1960). This indicates that whereas clusters will form for symbolic attitude objects based on both valence and the cognitive-affective distinction, attitudes toward instrumental objects will show high clustering *and* high connectivity. That is, more instrumental attitude object networks will constitute a single, highly connected cluster, rather than a small-world structure consisting of several clusters that communicate with one another via select nodes. Therefore, we hypothesize:

> *Hypothesis 2a:* Evaluations of satisfaction with the job's features (coworkers, pay, promotions, supervisors, the work itself) will cluster based on their valence.

> *Hypothesis 2b:* Evaluations of satisfaction with the job's symbolic features (coworkers, supervisors, the work itself) will cluster based on whether they or more cognitively- or affectively laden, but not for more instrumental features (pay, promotions).

Because of the alignment of the CAN model with job satisfaction, Dalege et al.'s illustration that small-world structures fit attitudes toward politicians, we expect the small-world structure to fit job satisfaction to the extent that sufficiently independent clusters form, which is expected for symbolic features of the job. However, as our first hypothesis suggests, because of highly cognitive nature of evaluations of instrumental attitude objects, we do not expect such differential clustering to occur. For more instrumental objects, we expect to see highly dense networks that do not exhibit the type of clustering associated with small-world networks.

> *Hypothesis 3:* Satisfaction with the job's more symbolic features (e.g., coworkers, supervisors, work itself) will constitute a small world network, whereas satisfaction with more instrumental features (e.g., pay, benefits) will *not* constitute a small-world network.

Attitude Stability and Change

By applying CAN to understand how evaluations interact to form the emergent structure of an attitude, we might also begin to understand how change in that attitude network could take place. The CAN perspective on attitudes holds that evaluations of one type make other similar evaluations more likely. The existence of similar evaluations means they will feed off one another, with each feeling or thought reinforcing other similar feelings or thoughts over time, and making dissimilar feelings less likely, repelling them away from the network. Stated differently, attitude networks are dynamic systems that gravitate toward equilibrium, a structure that has been noted in personality data (Cramer et al., 2012).

Similar to the free-energy principle in attitude formation, the idea of equilibrium is based around energy expenditure. Attitudes that consist of evaluations that feed off one another in small, highly connected clusters require little energy of the system. For example, it is easy to evaluate one's job as *respectable* and *good*, and maintaining those two positions requires little energy; alternatively, expressing a poor evaluation of a job's respectability while maintaining that the job is good will require substantial energy expenditure. This scenario is a simple one. However, the CAN model also provides a sensible approach to understanding how more complex attitude structures might be held. Although it is true that taking opposite positions on whether the job is respectable and good (e.g., respectable but *not* good) requires high energy expenditure, the expenditure can decrease in the presence of another negative preexisting evaluation such as *repetitive*. That is, if viewing the job as repetitive exerts negative force on the feeling that the job is good but is unrelated to how respectable the job is then this will decrease the energy expenditure in the system. More specifically, energy expenditure can be operationalized in the following formula:

$$H(X) = -\sum_{i} \tau_i X_i - \sum_{ij} \omega_{ij} X_i X_j \qquad (2)$$

where $H(X)$ is the energy expended by holding a particular set of evaluations, X, toward the attitude object. Alternatively, X can be thought of as a response pattern consisting of -1 for an unfavorable evaluation, and $+1$ for a favorable evaluation.[3] The τ_i term represents the threshold of the evaluation (i.e., how likely a random person would be to endorse an evaluation, X_i, independent of the relations between evaluations), and ω_{ij}, the strength of interaction between that evaluation, X_i, and a different evaluation, X_iX_j. The probability of an individual having a set of evaluations can be calculated as an inverse relation to the energy expenditure required relative to other patterns of evaluations, or:

$$P(X = x) = \frac{\exp(-H(X))}{\sum_X [\exp(-H(X))]}. \qquad (3)$$

Returning to our example (see Table 1), imagine the evaluations respectable, good, and repetitive, and that each of these has a similar probability of being selected by a random individual, controlling for their interrelations (all $\tau = .3$). Now, also imagine that respectable and good are positively correlated at .50, and that repetitive is negatively correlated with both of the other evaluations at $-.40$. In this case, the least energy expenditure comes from saying the job is respectable and good but is *not* repetitive, resulting in a probability of .40 for this pattern. Because all of these evaluations are likely to be endorsed ($\tau = .3$), this evaluative pattern takes less energy than believing the job is *not* respectable, *not* good, and *is* repetitive, which has a probability of .22. However, if the thresholds were lower such that all these evaluations were unlikely—say $-.1$ – the order of magnitude for these probabilities reverses as shown in the right-hand side of Table 1. All other patterns of evaluation require a lot of energy (e.g., the job *is* respectable and *not* good, but *is* repetitive).

Now, imagine a person for whom the repetitiveness of the job greatly negatively impacts how strongly they evaluate the job as good ($\omega = -.70$), but repetitiveness does not impact how strongly they evaluate the job as being respectable ($\omega = 0$). Further, respectability is not very important for determining that the job is good ($\omega = .10$). As shown in the left-hand side of Table 2, when all thresholds equal .3, the most likely pattern of responses is that the job is good and respectable but *not* repetitive.[4] However, this pattern is now less likely because of the changes in weights (i.e., .27 vs. .40), and is only slightly more likely than the pattern of respectable and repetitive but *not* good, which now has a probability of .22 (vs. .07 for the weights in Table 1). Now, imagine that in reality the job is indeed very repetitive, and therefore the threshold for this evaluation is much higher than others at .90 (i.e., almost anyone would say it is repetitive; see right-hand side of Table 1). Under this scenario, the least energy is expended when one evaluates their job as being respectable and repetitive, but *not* good.

The properties of attitude networks discussed above have important consequences for how we think about attitude stability and consequently, mechanisms for changing attitudes. Attitude evaluations that serve as bridges from similar evaluations to more dissimilar evaluations can be viewed as key to attitude change. By changing one evaluation, we may hope to see change ripple through the rest of the attitude network as the structure works toward equilibrium. However, as Dalege et al. (2016) note, the more clustered different evaluations of the attitude object are, the more difficult it will be to affect change in the entire network. That is, changing only one evaluation will likely lead to only changes in similar evaluations clustered nearby (e.g., a cognitive evaluation influencing other cognitions); evaluations belonging to other clusters (e.g., affective evaluations) will be unaffected to the extent to which there are no bridges between these clusters. Importantly, a defining feature of small worlds is that they have high clustering, and therefore, in many instances, it will be difficult to change an attitude through changing a single evaluation. However, impacting certain specific evaluations is more likely to lead to changes spreading throughout the network than impacting others, particularly when the evaluations are well-situated in the network and serve as bridges to other clusters.

A key feature of network analysis that facilitates identifying which evaluations might, if changed, produce ripple-effects of change is *centrality.* The concept of the centrality refers to how important a particular evaluation is relative to other evaluations in the attitude network. Three particular types of centrality are important here: (a) *betweenness*; (b) *strength*; and (c) *closeness*. An evaluation will be high in betweenness centrality to the extent that it: (a) connects with a high number of other evaluations; and (b) has strong ties to those evaluations (see Opsahl, Agneessens, & Skvoretz, 2010). Thus, high betweenness centrality indicates the evaluation is the shortest path from one cluster of evaluations to another. Closeness centrality can be defined as the average length of the shortest path between one node

[3] Note that these examples are based on the assumption of dichotomous responses for simplicity, whereas our actual data analysis involves the Gaussian Graphical Model, which is an Ising model for continuous, Guassian data.

[4] Note that this is the same pattern as in the first quadrant of Table 1 even though the weights between evaluations have changed considerably, but is less likely attributable to the changes in weights.

Table 1
Example of Hypothetical Response Patterns, Energy Expenditure, and the Probability of the Pattern Under the Network Model With Higher Versus Lower Thresholds

Pattern (X)	Respectable	Good	Repetitive	H(X)	P(X = x)	Respectable	Good	Repetitive	H(X)	P(X = x)
1	−1	−1	−1	1.20	.02	−1	−1	−1	.00	.09
2	1	−1	−1	.80	.04	1	−1	−1	.40	.06
3	−1	1	−1	.80	.04	−1	1	−1	.40	.06
4	1	1	−1	−1.60	.40	1	1	−1	−1.20	.29
5	−1	−1	1	−1.00	.22	−1	−1	1	−1.40	.36
6	1	−1	1	.20	.07	1	−1	1	.60	.05
7	−1	1	1	.20	.07	−1	1	1	.60	.05
8	1	1	1	−.60	.15	1	1	1	.60	.05
Respectable	$\tau_i = .30$					$\tau_i = -.10$				
Good	$\omega_{ij} = .30$	$\tau_i = .30$				$\omega_{ij} = .30$	$\tau_i = -.10$			
Repetitive	$\omega_{ij} = -.40$	$\omega_{ij} = -.40$	$\tau_i = .30$			$\omega_{ij} = -.40$	$\omega_{ij} = -.40$	$\tau_i = -.10$		

and all other nodes. Finally, strength centrality—perhaps the simplest measure of centrality—is the number of connections (weighted by the strength of those connections[5]) for a node.

We propose that measures of closeness and strength centrality will be more important to understanding how to affect change in a network based on Borgatti's (2005) classification of different types of *flow* in networks. Flow is the process by which change would theoretically occur in a given network. Although Borgatti applies the example to how attitudes are transmitted throughout a social network, we believe that it applies similarly to the transmission of changes in—say—a cognitive evaluation to an affective evaluation. That is, in keeping with the basic concept of the CAN model, attitudes can be thought of as an influence process in which nodes influence one another through interaction. Further, change in a psychometric attitude network would also fit Borgatti's idea that attitude change happens due to replication, or duplication, rather than transference (i.e., the cognitive evaluation does not disappear because it influences an affective evaluation, consistent with Petty, Tormala, Briñol, and Jarvis [2006]). Further, duplication can happen in multiple places in the network at the same time, called *parallel duplication.* In other words, if an affective evaluation of whether or not one feels recognized at their job changes their cognitive evaluation of their compensation package, the feeling of recognition does not go away; rather, they both continue to exist, reflecting parallel duplication. Notably, under Borgatti's classification scheme, betweenness centrality would be more appropriate for understanding processes wherein change happens via transference rather than duplication. We argue this is insensible for attitudes, because its use would imply that we believe the affective evaluation ceases to exist as soon as it is transferred to the cognitive evaluation. Although Borgatti identifies closeness as appropriate for either type of network flow process, strength centrality is identified as particularly suited to parallel duplication processes.

If one of the three measures of centrality were more fitted to a particular attitude network, we believe they would be more strongly related to theoretical structure of attitudes and in turn, would better measure attitude change. More specifically, we hypothesize that the ability to predict the centrality of nodes from their qualifying attributes (e.g., cognitive vs. affective, negative vs. positive) would emerge more strongly for those more suited to identifying mechanisms for affecting change in a network. Thus, we make the following hypothesis:

> *Hypothesis 4:* Strength centrality will be more closely related to the features of attitude object evaluations (i.e., cognitive v. affective; valence) than betweenness and closeness.

As previously stated, the ability to identify central evaluations in an attitude network is a crucial feature of the CAN model that has important scientific and practical importance for understanding attitude change and affecting it. In particular, this feature has great promise in organizational survey work and in determining the course of action for affecting attitude change in organizations. By focusing on sentiments that are likely to spread change throughout the attitude network, it is possible that more efficient interventions can be devised for changing the attitude. Items high in centrality are particularly likely to spread change, especially when networks constitute a small-world network. On the basis of the *affective primary hypothesis*, which states that activation of emotional reactions temporally precede cognitive evaluations of the attitude object (see Cervellon & Dube, 2002; Crano & Prislin, 2006; Huskinson & Haddock, 2006; Judge & Kammeyer-Mueller, 2012), we propose that affective evaluations will be more central to the attitude network than cognitive evaluations. However, as we noted earlier, we believe that attitude networks regarding more instrumental job features (e.g., pay and promotions) mostly involve cognitive evaluations and, therefore, will not contain affective evaluations needed to cluster based on the affect-cognition distinction.

> *Hypothesis 5:* Affective evaluations will be most central in attitude networks regarding symbolic features of the job, but not in attitude networks regarding instrumental features.

With regard to the potential for attitude change, it is particularly interesting to consider how behavioral reactions to the attitude objects can be integrated into the context of the CAN model. Of course, most measures of attitudes—and particularly job satisfaction—focus primarily on the cognitive and affective evaluations of the attitude object. However, the utilization of the CAN approach allows us to examine behavioral intentions and/or observed behavior in the context of an attitude network structure. Decades of research have shown a relationship between job satisfaction and turnover intentions (Chen, Ploy-

[5] For weighted networks, strength centrality is referred to as degree centrality in unweighted networks.

Table 2
Example of Hypothetical Response Patterns, Energy Expenditure, and the Probability of the Pattern Under the Network Model With Higher Versus Lower Thresholds for a Single Evaluation

Pattern (X)	Respectable	Good	Repetitive	H(X)	P(X = x)	Respectable	Good	Repetitive	H(X)	P(X = x)
1	−1	−1	−1	1.50	.02	−1	−1	−1	2.10	.01
2	1	−1	−1	1.10	.03	1	−1	−1	1.70	.01
3	−1	1	−1	−.30	.12	−1	1	−1	.30	.05
4	1	1	−1	−1.10	.27	1	1	−1	−.50	.12
5	−1	−1	1	−.50	.15	−1	−1	1	−1.10	.22
6	1	−1	1	−.90	.22	1	−1	1	−1.50	.33
7	−1	1	1	.50	.06	−1	1	1	−.10	.08
8	1	1	1	−.30	.12	1	1	1	−.90	.18
Respectable	$\tau_i = .30$					$\tau_i = .30$				
Good	$\omega_{ij} = .10$	$\tau_i = .30$				$\omega_{ij} = .10$	$\tau_i = .30$			
Repetitive	$\omega_{ij} = .00$	$\omega_{ij} = -.70$	$\tau_i = .30$			$\omega_{ij} = .00$	$\omega_{ij} = -.70$	$\tau_i = .90$		

hart, Cooper, Anderson, & Bliese, 2011; Tett & Meyer, 1993). However, we hope to take this finding a step further by examining which evaluations of job satisfaction are most likely to lead to changes in turnover intentions if those evaluations are changed. Thus, we ask the following research question:

Research Question 1: What Type of Evaluations Will Be Most Likely to Affect Change in the intention to Quit?

Under the CAN model, an employee's intentions to quit will generally be driven by those items that are most important to the energy expenditure of the entire network (i.e., those with the highest centrality). That is, intentions to behave a particular way will be most readily determined by cognitive or affective evaluations that minimize the energy necessary to actually exhibit the behavior. Notably, this runs counter to the potentially intuitive approach to determining which attitude evaluations should be changed by examining the evaluation with the largest *direct* relationship to behavioral intentions. In actuality, the CAN model suggests that the path to influence turnover intentions would likely be an *indirect* one, particularly in a small-world structure. By activating an evaluation that is connected with nodes that have are highly clustered with (and therefore have direct influence on) the behavioral intention, the combined influence of them all will be greater than targeting a single node that lies close (i.e., is highly correlated with) the behavioral intention. Notably, the information conveyed by centrality estimates is fully unique from psychometric information from—for example—factor analytic models. Examining all items from the data discussed in this article, we found that the correlation between factor loadings from a factor analysis of each scale correlated only between .08, .11, and .13 with the betweenness, closeness, and strength centrality measures discussed here.

Finally, we come to the question of efficacy of prediction in the CAN model and whether it represents a tool for increased predictive power. As with considering fitting a network versus confirmatory factor models, the variance explained in psychometric network models *using only cross-sectional data* is not one of the more unique benefits of psychometric network models; the variance explained when all variables are collected at the same time point will be very similar to that of a structural equation model. Indeed, in examining six scales from the job descriptive index (JDI) in a sample of 1,485 employees, the R^2 of network models for each scale (respectively Job in General, Work Itself, Pay, Promotions, Supervisor, and Coworkers) predicting intentions to quit (ITQ) were .36, .21, .15, .17, .18, and .14 versus .32, .22, .14, .17, .18, and .11, for the respective structural equation models, suggesting similar predictive efficacy.

Rather than being a model that can increase variance explained in purely cross-sectional data, the network models discussed here show their primary advantage in (a) understanding the structure of attitudes; and (b) determining *how* to affect change in attitudes by finding the most central cognitive and/or affective evaluations, rather than attempting to make changes based on the general, somewhat ambiguous latent variable that represents their common variance. Importantly, point (b) implies that psychometric network models *should* be better at identifying the attitude object evaluations that—if changed—would lead to changes throughout the network of evaluations (i.e., the attitude). If this is true, then it also stands to reason that network models would be better at predicting *future* outcomes, such as voluntary turnover. Thus, we hypothesize:

> *Hypothesis 6a:* Cross-sectional estimates of centrality will be able to identify attitude object evaluations whose change is most predictive of change in other evaluations.

As noted previously, based on Borgatti's (2005) framework for understanding the relation between centrality and network flow, we expect:

> *Hypothesis 6b:* Strength centrality will better identify attitude object evaluations whose change is most predictive of change in other evaluations than other centrality metrics.

Of course, because of the high relatedness of the psychometric network and latent variable models, it is possible that the same information could be gleaned from the factor loadings of a confirmatory factor model. Thus, we pose the following hypothesis:

> *Hypothesis 6c:* Strength centrality estimates in a psychometric network model will perform better than factor loadings at identifying those attitude object evaluations whose change is most predictive of change in other evaluations.

Finally, point (b) above also implies that psychometric network models *should* be able to explain more variance in *future* outcomes, such as subsequent voluntary turnover, compared with a structural equation model that utilizes latent variables as predictors. Meta-analyses have suggested that there is a small negative correlation between job satisfaction and voluntary turnover (e.g., $r = -.17$, $K = 67$; Griffeth, Hom, & Gaertner, 2000), and is an important organizational outcome with large costs for organizations. Thus, we hypothesize:

> *Hypothesis 7:* When applied to predicting future voluntary turnover, the psychometric network model will outperform a corresponding structural equation model.

No research to date has directly tested the idea that network models can identify those items most associated with change in other items, nor compared the efficacy of each to predicting future outcomes. Thus, confirming this hypothesis would add substantial weight to the CAN model's predictive utility along psychometric network models more generally.

Method

Here, we give brief overviews of the samples and measures utilized to test hypotheses, summarized in Table 3, which also reports basic demographics and reliability statistics. A more detailed version of the Methods can be found in Appendix B. Sample 1a (a subset of Sample 1b) and Sample 2 were used to address Hypotheses 1a and 1b. Sample 1a consisted of 499 persons with greater than 1 year of job tenure (taken from Sample 1b), whereas Sample 2 consists of persons specifically recruited for having less than one year of job tenure. Both Sample 1 and Sample 2 participants were recruited via Amazon Mechanical Turk.[6] Each sample was administered the 70-item JDI subscale of Work, Pay, Promotion, Coworker, Supervisor, and Job in General (JIG) subscales (Lake et al., 2010), as well as the 36-item JSS (Spector, 1985). The JSS was divided into a set of items reliably categorized by raters into 22 items representing symbolic features of the job (i.e., nature of the job, supervisor, coworkers, working conditions, communication, and two items from the rewards scale) and 14 items representing instrumental features of the job (i.e., pay, promotions, benefits, and two items from the rewards scale). Details on the classification of items for the JDI and JSS as either symbolic or instrumental are discussed in the Detailed Methods in Appendix B. Hypotheses 2–5 were tested using Sample 1b—559 Mechanical Turk respondents—and Sample 3 comprised 1,485 persons in the 2009 JDI norming sample. In each sample, the JDI was used to address these hypotheses. Research Question 1 was addressed using Sample 3. Finally, Hypotheses 6 and 7 were tested using the Health and Retirement Survey (HRS) dataset, which contained 15 items relevant to job satisfaction that were broken into two factors with seven and eight items, respectively, based on exploratory factor analyses. The HRS job satisfaction items were administered to the same set of persons in 2006 and 2010, and another set of persons in both 2008 and 2012, creating samples 4a1 (2006 → 2010; $N = 1{,}242$) and 4a2 (2008 → 2012; $N = 843$); these samples were used to address Hypothesis 6. A different subset of the HRS dataset was also used to address Hypothesis 7. Every other year from 2008 to 2014, the HRS recorded turnover data. This turnover data corresponds to job satisfaction data collected from the same persons two years prior. We coded this turnover variable into a dichotomous variable to reflect voluntary turnover (coded as 1) and all else (coded as 0; see Appendix B). Hypothesis 7 was addressed using the job satisfaction data from one year to predict voluntary turnover in the following measurement occasion, creating four subsamples: 4b1 (2006 → 2008; $N = 513$), 4b2 (2008 → 2010; $N = 525$), 4b3 (2010 → 2012; $N = 599$), and 4b4 (2012 → 2014; $N = 498$). To address Hypothesis 2b, the JDI and JSS items were coded by 12 and nine raters, respectively, as either being cognitively laden versus affectively laden with ICCs of .74 and .93, respectively (see Table 3). For consistency in presentation, the HRS items were coded in the same way by nine raters with ICC = .68 (see Table 4).

All network analyses were conducted using the R (R Core Team, 2015) package *qgraph* (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). Example code for the JIG scale is included in Appendix C. Additionally, the correlation matrices for all data used here are included in the online supplemental materials. All confirmatory factor models and structural equation models were estimated using the *lavaan* package and implemented maximum likelihood estimation. To address the predictability of networks in Hypothesis 7, the *mgm* package (Haslbeck & Waldorp, 2018b) was utilized to evaluate variance explained in future voluntary turnover by the network (see Appendix B).

Results

Hypothesis 1

Using the JDI networks acquired from Samples 1 and 2 to address Hypothesis 1a—that evaluation networks of more instrumental aspects of the job (i.e., pay and promotion) would generally show higher connectivity than those for more symbolic aspects of the job (i.e., the work itself, coworkers, and supervisor)—and Hypothesis 1b—that whereas the connectivity of evaluation networks regarding more instrumental aspects of the job would show no change with higher job tenure, networks for more symbolic aspects would show increased connectivity with higher job tenure—we first estimated the shortest path lengths (SPLs) for each of the five facet scales within each group (i.e., this with and without one or more years of tenure). Estimation of the SPLs was conducted using Dijkstra's (1959) algorithm as implemented with the *qgraph* package in R. This algorithm finds the shortest paths between a given pair of nodes and then averages them, resulting in a $k \times k$ matrix of shortest path lengths, where k is a node. Using these SPLs as an outcome variable, we conducted independent-samples and paired-samples t tests to address these two hypotheses, respectively. All p values reported are two-tailed and Bonferroni-corrected for the number of comparisons made. Consistent with Hypothesis 1a, we found that the networks for more instrumental aspects of the job generally showed significantly higher connectivity (i.e., lower SPLs), $M = 9.11$, $SD = 4.44$, compared with more symbolic facets, $M = 14.60$, $SD = 5.76$,

[6] Institutional review for these data were collected under the University of Georgia Institutional Review Board, with identification code STUDY00004232 and title "Job Satisfaction Across Levels of Job Tenure"; all other data were considered archival data and therefore were exempt from review.

Table 3
Summary Information for Samples Used

Sample	*N*	*M* age	% Male	% White	Description	Hypotheses	Measures (# of items; α)
1a	499	37.4	40.1%	84.3%	Workers from Sample 1 with 1 year or greater of job tenure	H1a & H1b	JDI: Work (18; .92), Pay (9; .92), Promotion (9; .80), Supervisor (18; .87), Coworkers (18; .90), JIG (18; .93). JSS: Symbolic (22; .92), Instrumental (14; .92)
1b	559	37.7	39.1%	83.8%	Mturk workers (general sample)	H2a, H2b, H3, H4, & H5	JDI: Work (18; .92), Pay (9; .91), Promotion (9; .79), Supervisor (18; .89), Coworkers (18; .92), JIG (18; .94). JSS: Symbolic (22; .92), Instrumental (14; .93)
2	499	32.5	47.7%	79.4%	Workers from Sample 1 with 1 year or less of job tenure	H1a & H1b	JDI: Work (18; .91), Pay (9; .90), Promotion (9; .80), Supervisor (18; .86), Coworkers (18; .89), JIG (18; .93). JSS: Symbolic (22; .92), Instrumental (14; .92)
3	1,485	40.7	57.7%	80.0%	Job Descriptive Index Working Group Normative Sample	H2a, H2b, H3, H4, H5, & RQ1	JDI: Work (18; .90), Pay (9; .87), Promotion (9; .91), Supervisor (18; .92), Coworkers (18; .92), JIG (18; .72). Intention to Quit: (1; .66 [Spearman-Brown]; .61 Squared Factor Loading)
4a1	1,242	48.8	44.7%	86.3%	HRS dataset; 2006 → 2010	H6a, H6b, & H6c	HRS JS Factor 1 (2006): (7; .78), HRS JS Factor 2 (2006): (8; .71), HRS JS Factor 1 (2010): (7; .81), HRS JS Factor 2 (2010): (8; .76)
4a2	843	49.7	40.8%	68.7%	HRS dataset; 2008 → 2012	H6a, H6b, & H6c	HRS JS Factor 1 (2008): (7; .80), HRS JS Factor 2 (2008): (8; .71), HRS JS Factor 1 (2012): (7; .81), HRS JS Factor 2 (2012): (8; .79)
4b1	513	37.8	55.2%	70.3%	HRS dataset; 2006 → 2010	H7	HRS JS Factor 1: (7; .79), HRS JS Factor 2: (8; .77)
4b2	525	38.9	45.8%	64.2%	HRS dataset; 2008 → 2012	H7	HRS JS Factor 1: (7; .81), HRS JS Factor 2: (8; .70)
4b3	599	42.1	56.3%	57.8%	HRS dataset; 2006 → 2010	H7	HRS JS Factor 1: (7; .79), HRS JS Factor 2: (8; .74)
4b4	498	40.7	64.8%	69.3%	HRS dataset; 2008 → 2012	H7	HRS JS Factor 1: (7; .81), HRS JS Factor 2: (8; .78)

Note. JDI = Job Descriptive Index; JSS = Job Satisfaction Survey; HRS = Health and Retirement Survey; JS = Job Satisfaction. See Appendix B for more detailed information on samples used.

$t(1060) = 10.79$, $p < .001$, $d = 1.07$.[7,8] Consistent with Hypothesis 1b, for the more symbolic aspects of the job we found no significant difference in connectivity, $t(71) = -2.21$, $p = .093$, between the group with less than one year of tenure, $M = 8.75$, $SD = 3.85$, versus the group with one year or more tenure, $M = 9.46$, $SD = 4.94$. However, as predicted, there was a significant difference in connectivity, $t(458) = 3.15$, $p = .004$, $d = .12$, such that the group with less than one year of tenure had lower connectivity, $M = 14.95$, $SD = 5.97$, compared with the group with one year or more tenure, $M = 14.25$, $SD = 5.44$, although it is notable the effect size is small for this comparison.

We tested the same hypotheses using the JSS networks acquired from the same two samples. Due to the small number of items for all JSS subscales, we combined these scales into two categories—(a) instrumental (i.e., pay, promotions, benefits, two items from the rewards scale) and (b) symbolic (i.e., working conditions, supervisor, coworkers, nature of the job, communication, two items from the rewards scale)—and compared these two networks for the two tenure groups using the same strategy as for the JDI. First, the independent-samples *t* test confirmed Hypothesis 1a, $t(362) = 11.16$, $p < .001$, $d = 1.17$, showing that the network for more instrumental aspects showed generally higher connectivity, $M = 11.61$, $SD = 5.02$, compared with the network for the more symbolic aspects of the job, $M = 18.62$, $SD = 6.79$. Regarding Hypothesis 1b, for the more instrumental aspects of the job, the paired-samples *t* test showed no significant difference, $t(90) = -1.31$, $p = .581$, between the group with lower, $M = 11.37$, $SD =$

[7] To ensure that this comparison was not influenced by the differing sizes of the networks for the instrumental (pay and promotions, both nine-node networks) and symbolic (work itself, coworker, supervisor, all 18-node networks), we also conducted these analyses by estimating a network that combines the pay and promotions scale to form an 18-node network; results were almost identical as for the analyses presented here.

[8] One reviewer noted possible confusion over how the *df* of the independent samples *t*-test is equal to 1,060. For each $k \times k$ matrix of SPLs, where k is the number of nodes (or items), there are $[(k \times k)/2] - (k/2)$ unique subdiagonal elements in the matrix. Because two samples taking the same scale were used, there are twice that many SPLs used for each scale. So, for an 18-item scale there are $2 \times ([(18 \times 18)/2] - [18/2]) = 306$ unique SPLs, and for a nine-item scale there are $2 \times ([(9 \times 9)/2] - [9/2]) = 72$ unique SPLs. There are three 18-item scales and two nine-item scales in the JDI, leading to $3 \times 306 + 2 \times 72 = 1{,}062$ unique SPLs. Of course for an independent samples *t* test $df = N - 2$, or $1{,}062 - 2 = 1{,}060$. For the paired-samples *t* tests that follow, the *df* are 71 for the test involving the two nine-item scales, thus $2 \times ([(9 \times 9)/2] - [9/2]) = 72$, and $df = N - 1 = 71$, and for the three 18-item scales, $3 \times ([(18 \times 18)/2] - [18/2]) = 459$, and $df = N - 1 = 458$.

Table 4
Statistical Indicators of Network Structure for the JIG, JDI Subscales, JSS, and MSQ in the Sample With Less Than One Year Tenure

Scale and sample	Facet	Small World Index (*SW*)	Clustering (*C*)	95% CI for clustering in random network (C_{rand})	Average length (*L*)	95% CI for average length in random network (L_{rand})
Job Descriptive Index (Sample 2; *N* = 499)	Job in general	**1.05**	**.69**	[.64, .67]	1.37	[1.37, 1.37]
	Coworkers	**1.05**	**.71**	[.66, .68]	1.33	[1.33, 1.33]
	Pay	1.00	.85	[.84, .85]	1.14	[1.14, 1.14]
	Promotion	1.02	.73	[.69, .73]	1.25	[1.25, 1.25]
	Supervisor	**1.06**	**.66**	[.61, .64]	1.36	[1.36, 1.36]
	Work	**1.09**	**.68**	[.60, .64]	1.42	[1.42, 1.42]
Job Satisfaction Survey (Sample 2; *N* = 499)	Symbolic	**1.08**	**.52**	[.45, .50]	1.53	[1.53, 1.54]
	Instrumental	1.03	.66	[.62, .66]	1.35	[1.35, 1.35]

Note. JIG = Job in General; JDI = Job Descriptive Index; JSS = Job Satisfaction Survey; Numbers in boldface indicate that they are significantly higher than in a random graph.

4.63, versus higher tenure, $M = 11.86$, $SD = 5.36$. For the more symbolic aspects of the job, the paired-samples *t* test showed the predicted difference, $t(90) = 2.21$, $p = .086$, $d = 1.14$, such that the network in the group with lower tenure showed lower connectivity, $M = 19.36$, $SD = 7.52$, than the group with higher tenure, $M = 11.87$, $SD = 5.37$. Although this *p* value is only close to significant, the large *d*-value is considered evidence for the prediction. Thus, the results for both the JDI and JSS confirm Hypotheses 1a and 1b. As one reviewer pointed out, there is a possibility that—because of violation of independence—the *p* values reported for these analyses may be artificially low; the reviewer also pointed out that this is unlikely to be problematic because of the large effect sizes.

Hypothesis 2

Hypothesis 2a predicted that items would cluster together based on their (positive or negative) valence. To address this hypothesis, we examined networks from Sample 1b ($N = 559$), which included responses to the JDI and JSS, and Sample 3 ($N = 1,485$), which included only the JDI scales. Figures 2 and 3 show JDI attitude networks for symbolic and instrumental job features, respectively, and Figure 4 shows symbolic and instrumental attitude networks for the JSS. Valence-based clustering was clear for more symbolic attitude objects. As seen in Figures 2 and 4, items with negative valence are situated at one end of the network graph, whereas items with positive valence fall on the opposite side. The trend was less clear for the instrumental attitude objects, lending partial support to Hypothesis 2a, suggesting that only symbolic attitude object networks cluster based on their valence.

Hypothesis 2b predicted that for symbolic attitude networks, items would cluster together based on whether their content was more cognitively laden or affectively laden within the valence-based clusters. Given that the JIG network showed only two cognitively laden items of differing valence, we focus on the other scales. Examining Figures 2 and 4, we see that this pattern generally describes the networks for symbolic attitude objects, such that within valence clusters cognitively and affectively laden cluster together with other items in their respective category. On the other hand, in the pay subscale (see Figure 3) and the network for instrumental job features in the JSS (see Figure 4), there is no clear clustering according to whether the item is cognitively- or affectively laden. In general, little systematic clustering appeared for instrumental attitude objects, supporting Hypothesis 2b.

Hypothesis 3

To examine Hypothesis 3—that attitude networks for more symbolic features of the job would show a small-world structure, whereas networks for more instrumental attitude objects would not—we first examined the same networks used to address Hypothesis 2. As can be seen in Table 5, Hypothesis 3 was supported in two samples for the JDI and in one sample for the JSS, with the exception of the JDI supervisor subscale, which showed small-world structure in Sample 3 ($N = 1,485$) but not in Sample 1b ($N = 559$). This comports with the findings regarding Hypothesis 2b, as the lack of clear clusters in instrumental attitude networks indicates that these networks do not have small-world structure. Importantly, these networks are highly connected but do not show smaller, more independent clusters that are found in the attitude networks for more symbolic features of the job. In addition to these samples, we sought to ensure this pattern would replicate for the JDI and JSS networks in Sample 2, which included only those respondents with less than one year of job tenure. As shown in Table 6, the JDI and JSS networks all showed small-worldness for more symbolic job features but not for more instrumental features. Thus, apart from the supervisor subscale in Sample 1b, Hypothesis 3 was fully supported.[9]

In response to one review comment, we attempted a variety of more complex factor models to determine whether they could provide similar structural information in multiple data sets, including modeling a CFA with a higher-order factor, exploratory analyses on each individual scale with more complex structures based on various liberal factor retention indices (e.g., BIC, Velicer MAP, parallel analysis, Very Simple Structure statistics), but we found

[9] To further ensure that the results of tests for Hypothesis 3 were not driven by differences between instrumental and symbolic attitude networks in their respective number of nodes, we also examined eight-node attitude networks for the highly symbolic attitude objects of Santa Claus and George Washington compared with the highly instrumental networks of the Tools/Resources Provided at Your Workplace and the Automotive Vehicle persons own. Results confirmed the expected small-worldness for symbolic attitude objects but not for the more instrumental objects. Results are discussed in Appendix D.

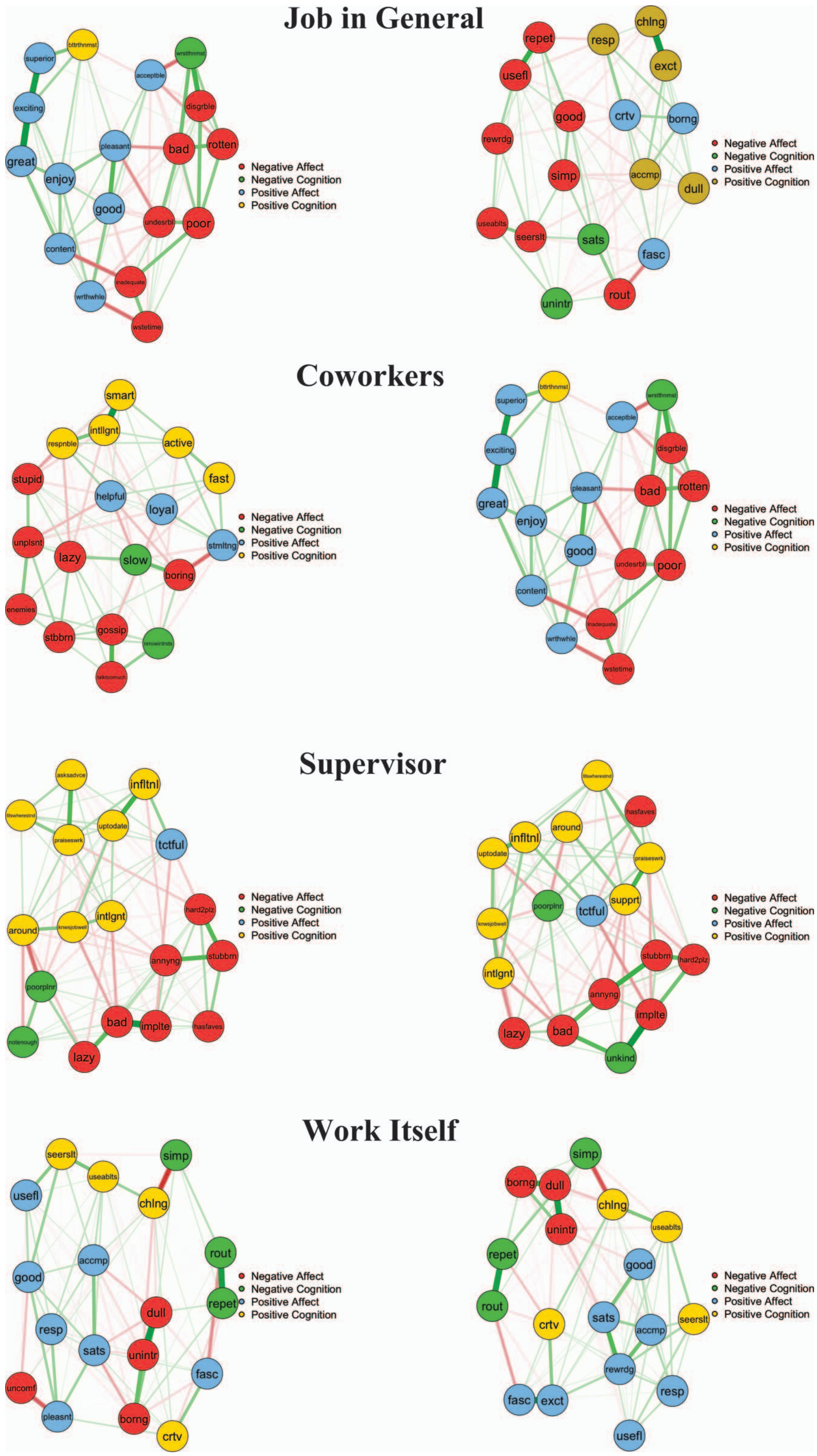

Figure 2. Networks for Job Descriptive Index scales regarding symbolic job features in Sample 1b (left; $N = 559$) and Sample 3 (right; $N = 1{,}485$). Green (solid) lines represent positive ties; red (dashed) lines represent negative ties. See the online article for the color version of this figure.

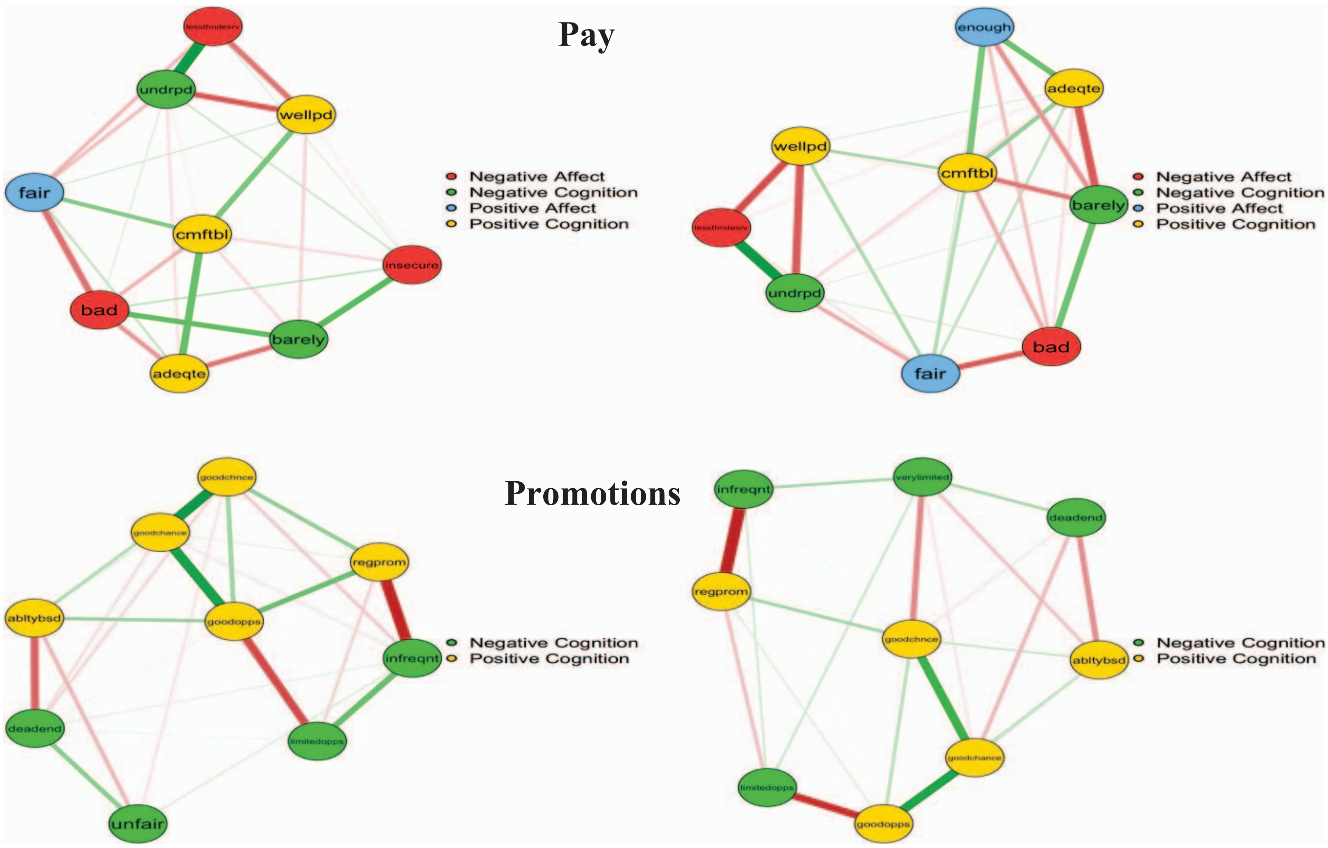

Figure 3. Networks for Job Descriptive Index scales regarding instrumental job features in Sample 1b (left; $N = 559$) and Sample 3 (right; $N = 1{,}485$). Green (solid) lines represent positive ties; red (dashed) lines represent negative ties. See the online article for the color version of this figure.

that they did not appear to be able to replicate any structural properties provided by network models. Thus, it appears that getting rid of the latent variable is indeed required to gain the information provided by network models.

Hypotheses 4 and 5

To test Hypothesis 4—that closeness and strength centrality of nodes would be better predicted by the characteristics of those nodes (i.e., valence, cognitive vs. affective evaluations)—and Hypothesis 5—that more affective evaluations would be more central to attitude networks for symbolic attitude objects, but not for more instrumental attitude object networks—we calculated these three measures of node centrality for the attitude networks shown in Figures 2 through 4. To avoid highly unbalanced cell sizes, we analyzed data regarding instrumental job features separately from data regarding symbolic features. For these two data sets, we conducted a multivariate ANOVA using two predictive factors: (a) the valence of the item, and (b) whether the item was more cognitively versus affectively laden. In all analyses, we controlled for differences in the sizes of the estimated networks.

First, results showed no significant multivariate or univariate tests for instrumental attitude objects. For symbolic attitude objects, multivariate tests suggested measures of centrality are generally driven by whether the item is cognitively- or affectively laden, $F(3, 159) = 3.69$, $p = .013$, $\eta^2 = .07$. All other primary factors and their interactions were nonsignificant. Inspection of univariate tests showed that—consistent with Hypothesis 4—the only significant effect was for the factors' relation to strength centrality, $F(4, 161) = 10.33$, $p = .001$, $\eta^2 = .06$. Consistent with Hypothesis 5, this effect was such that more affectively laden items showed higher strength centrality, $M = .18$, $SD = .99$, than more cognitively laden items, $M = -.29$, $SD = .96$. The effect was marginally significant for closeness centrality, $F(4, 161) = 3.58$, $p = .060$, $\eta^2 = .02$, but was nonsignificant for betweenness centrality, $F(4, 161) = 2.34$, $p = .128$. This confirms the hypothesis that strength centrality would emerge as more important centrality measures in attitude networks, consistent with Borgatti (2005).

Research Question 1

Our research question involved an exploration of the evaluations that were most likely to affect change throughout the network. Due to our finding that strength centrality was most associated with the psychological aspects of evaluative reactions, we focus on that measure. Thus, using Sample 3, we examined those items with highest strength centrality (see Table 7). Specifically, we considered those with a standardized $C_D^{\omega}(i) > 1$ as being considerably

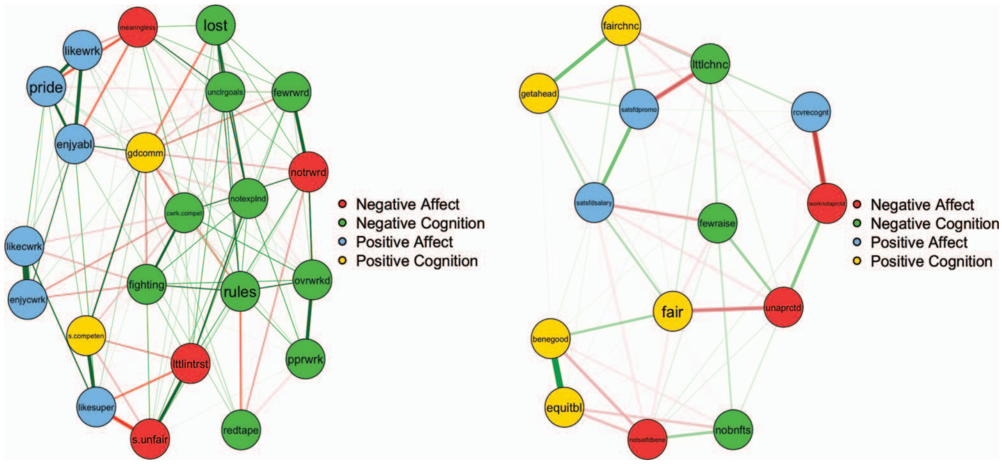

Figure 4. Networks for the Job Satisfaction Scales regarding symbolic (left) and instrumental (right) features of the job in Sample 1b ($N = 559$). Green (solid) lines represent positive ties; red (dashed) lines represent negative ties. See the online article for the color version of this figure.

high in strength centrality. First, we consider the attitude networks for the more symbolic features of the job. For the JIG scale the most central items were *bad*, $C_D^{\omega}(i) = 2.05$, and *enjoyable*, $C_D^{\omega}(i) = 1.30$, both affective evaluations. Regarding the coworkers subscale, the items highest in centrality were the evaluations of coworkers as *intelligent*, $C_D^{\omega}(i) = 1.75$ – a cognitive evaluation—and *rude*, $C_D^{\omega}(i) = 1.62$—an affective evaluation. The most central evaluations toward one's supervisor were *supportive*—a cognitive evaluation—and *annoying*, $C_D^{\omega}(i) = 1.63$, and *impolite*, $C_D^{\omega}(i) = 1.51$—both affective evaluations. For the work itself subscale, the items highest in centrality were *dull*, $C_D^{\omega}(i) = 1.70$, *rewarding*, $C_D^{\omega}(i) = 1.59$, and *satisfying*, $C_D^{\omega}(i) = 1.25$, all affective evaluations. Regarding instrumental features of the job, the pay subscale showed the items *comfortable*, $C_D^{\omega}(i) = 1.26$, and *underpaid*, $C_D^{\omega}(i) = 1.23$, were highest in centrality, both cognitive evaluations. For the promotions subscale, the items highest in centrality were the items *good opportunities for promotion*, $C_D^{\omega}(i) = 1.45$, and *good chance for promotion*, $C_D^{\omega}(i) = 1.18$, both cognitive evaluations.

To further explore Research Question 1, we estimated the JIG and five JDI subscales' networks, adding in the ITQ item *I intend to leave this company soon*. The addition of this item resulted in essentially the same networks for all subscales. The values for all three indices and confidence intervals discussed above (i.e., ω, *C*, and *L*) were within .02 compared with the values in the original networks, and centrality estimates were correlated .98. Here we focus on the work itself and promotions subscales to illustrate the difference between how change can be affected in a small-world versus a more random network.

As can be seen in Figure 5, for the JIG, although the items *inadequate*, *content*, and *ideal* cluster most closely to ITQ, impacting one or all of these sentiments is not as efficient as affecting

Table 5
Items in the Full Job Descriptive Network With Highest Standardized Strength Centrality in Sample 3 (N = 1,485)

Scale	Node label	Item content	Cognitive/Affective	Valence	Centrality
Supervisor	implte	Impolite	Affective	Negative	1.07
JIG	poor	Poor	Affective	Negative	1.13
JIG	exciting	Exciting	Affective	Positive	1.15
Coworkers	lazy	Lazy	Affective	Negative	1.16
Work itself	sats	Satisfying	Affective	Positive	1.17
Promotion	goodchance	Good chance for promotion	Cognitive	Positive	1.19
Work itself	exct	Exciting	Affective	Positive	1.23
JIG	good	Good	Affective	Positive	1.29
Supervisor	annyng	Annoying	Affective	Negative	1.33
JIG	ideal	Ideal	Affective	Positive	1.44
Coworkers	intllgnt	Intelligent	Cognitive	Positive	1.53
Promotion	goodopps	Good opportunities for promotion	Cognitive	Positive	1.60
Work itself	dull	Dull	Affective	Negative	1.72
JIG	bad	Bad	Affective	Negative	1.95
Work itself	rewrdg	Rewarding	Affective	Positive	1.98
Supervisor	supprt	Supportive	Cognitive	Positive	2.17
JIG	enjoy	Enjoyable	Affective	Positive	2.21

Note. JIG = Job in General.

Table 6
Item Content, Node Label, and Classification of Items in the Health and Retirement Survey Data

Item	Node label	Cognitive/ Affective	Valence
I am satisfied with my job.	sat	Affective	Positive
My job is physically demanding.	phy	Cognitive	Negative
I receive the recognition I deserve for my work	rcg	Affective	Positive
My salary is adequate	slr	Cognitive	Positive
My job promotion prospects are poor.	prm	Cognitive	Negative
My job security is poor.	scr	Cognitive	Negative
I am under constant time pressure due to a heavy workload.	prs	Cognitive	Negative
I have very little freedom to decide how I do my work.	fre	Cognitive	Negative
I have the opportunity to develop new skills.	dvl	Cognitive	Positive
I receive adequate support in difficult situations.	spp	Cognitive	Positive
At work, I feel I have control over what happens in most situations.	cnt	Affective	Positive
Considering the things I have to do at work, I have to work very fast.	fst	Cognitive	Negative
I often feel bothered or upset in my work.	bth	Affective	Negative
In my work I am free from conflicting demands that others make.	dmn	Cognitive	Positive
The demands of my job interfere with my personal life.	int	Affective	Negative

change to highly central items such as *bad* and *enjoyable*. Changing the sentiment that the job is *enjoyable* would theoretically activate a chain reaction that would ripple through the network, affecting change in all three of the evaluations clustering more closely to the ITQ item—the system would need to change to reduce the energy needed to maintain the system of evaluations. By affecting change in how *enjoyable* employees view their job, a number of evaluations would theoretically be brought to bear in a combinatorial fashion on the intention to quit. Affecting the most central items at once would be ideal and would send a much stronger ripple—perhaps a wave—through the network to change the intention to quit. However, in the promotions network (see Figure 6), affecting change in ITQ through the most central item *good opportunities* would in theory not carry the same advantage as in the networks that take on small-world structure. Rather, the theoretically most efficient change occurs via the *dead-end job* pathway and other evaluations with relatively short distances from the behavioral intention; in other words, changing a small number of evaluations will not lead to change rippling through the network that lacks a small-world structure.

Finally, we also explored the full network of the JDI scale. Although in some cases it will be most interesting to examine a unidimensional measure with psychometric network analysis to uncover the nature of the structure of an attitude toward a particular attitude object, it can also be interesting to examine networks based on a multidimensional measure. For example, in practical applications, organizational leaders may want to know which items among *all* subscale items are most central to employees' intentions to quit in determining specific, actionable takeaways that can more quickly influence changed. Notably, in multidimensional measures, it will not be surprising to find significant small-worldness. Indeed, the network in Figure 7 has a small-world index of 1.77 (C = .39, 95% CI [.20, .21]; L = 1.93, 95% CI [1.93, 1.93]), much higher than those for the unidimensional networks. This phenomenon is attributable to the clustering that occurs due to different scale dimensions. Figure 7a shows the network with color-coding of nodes reflecting the various subscales of the JDI, whereas Figure 7b shows the same network with color-coding reflecting the distinction between cognitively and affectively laden items and their valences.

As can be seen in Figure 7a, the items clearly cluster based on subscale in the full network, which is unsurprising. Much of the information contained in this graph is consistent with—and could be surmised—from a structural equation model.[10] For example, the JIG and work itself scales cluster most closely together of all subscale items, and their corresponding interfactor correlation is .73, whereas the promotion and coworkers subscales do not cluster close together, and have a relatively low interfactor correlation of .24. Similarly, the JIG items cluster—on average—most closely to ITQ, reflecting the high structural equation coefficient of $-.39$, $z = -9.01$, $p < .001$, whereas the coworkers subscale items do not, reflecting the nonsignificant coefficient of .04, $z = 1.36$, $p = .174$. Additionally in Figure 7b, we see that a similar type of clustering is observed for the valence and cognition-affect distinction within these subscale clusters, which would lead to similar conclusions as from analyses of individual scales. Thus, much of this information is generally redundant with that covered in previous sections, or similar to the information gained from a structural equation model.

The true added value of examining the full JDI network is to examine—within the *full* network—which items are most central, and thus would affect the ITQ. This allows for conclusions about the general evaluations (regardless of subscale) that are central to the job satisfaction network. Table 4 shows those items in the full network with strength centrality greater than 1.0. As can be seen, there is some overlap with the findings of individual networks discussed above. For example, the JIG items *enjoyable* and *bad*, as well as the work itself items *dull* and *rewarding* are both highly central. Further, 13 of the 17 items highest in centrality are affective items. However, some unique insights can be gained. For example, none of the pay subscale items are high in centrality, despite its significant relation to ITQ in the structural equation model of $-.12$, $z = -4.30$, $p < .001$, whereas the coworkers subscale items *intelligent* and *lazy* were both highly central, despite the null relation to ITQ in the structural model of .04, $z = 1.36$, $p = .174$. Further, despite the work itself and supervisor

[10] The structural equation model showed $\chi^2(3, 630) = 18{,}424.98$; RMSEA of .052 and SRMSR of .058.

Table 7
Statistical Indicators of Network Structure for the JIG, JDI Subscales, and JSS

Scale and sample	Facet	Small World Index (*SW*)	Clustering (*C*)	95% CI for clustering in random network (C_{rand})	Average length (*L*)	95% CI for average length in random network (L_{rand})
Job Descriptive Index (Sample 3; *N* = 1,485)	Job in general	**1.12**	**.69**	[.60, .65]	1.36	[1.35, 1.36]
	Coworkers	**1.03**	**.73**	[.68, .71]	1.30	[1.30, 1.30]
	Pay	1.00	.86	[.85, .87]	1.14	[1.14, 1.14]
	Promotion	1.02	.80	[.77, .80]	1.22	[1.22, 1.22]
	Supervisor	**1.04**	**.75**	[.70, .73]	1.29	[1.29, 1.29]
	Work	**1.05**	**.71**	[.65, .69]	1.36	[1.35, 1.36]
Job Descriptive Index (Sample 1b; *N* = 559)	Job in general	**1.22**	**.67**	[.52, .56]	1.46	[1.46, 1.46]
	Coworkers	**1.04**	**.64**	[.60, .63]	1.37	[1.37, 1.37]
	Pay	1.01	.79	[.75, .79]	1.22	[1.22, 1.22]
	Promotion	1.01	.72	[.77, .80]	1.22	[1.22, 1.22]
	Supervisor	1.03	.68	[.65, .68]	1.33	[1.33, 1.33]
	Work	**1.07**	**.63**	[.57, .61]	1.40	[1.40, 1.40]
Job Satisfaction Survey (Sample 1b; *N* = 559)	Symbolic	**1.13**	**.56**	[.48, .52]	1.51	[1.51, 1.51]
	Instrumental	1.01	.59	[.55, .60]	1.37	[1.37, 1.37]

Note. JIG = Job in General; JDI = Job Descriptive Index; JSS = Job Satisfaction Survey. Numbers in boldface indicate that they are significantly higher than in a random graph.

subscales showing the smallest relations in the structural equation model, $\beta = -.08$, $z = -2.27$, $p = .023$, and $\beta = -.09$, $z = -3.16$, $p = .002$, their items are among the most highly central to the attitude network, and thus the most likely to affect change in the network.

Another interesting pattern is that the affective evaluations most central to the network appear to take paths through the cognitive evaluations, and then through another affective evaluation to arrive at a path to behavioral intentions (ITQ). For example, the most central item *enjoyable* (from the JIG scale; affectively laden item) has a very strong path to the item *better than most* (JIG scale; cognitively laden item), which has a direct link to the item *content* (JIG scale; affectively laden item), which in turn connects to the ITQ item. This item, *enjoyable* also has a direct link to the *content* item. Thus, making the work itself more enjoyable should lead to a belief that the job is better than most jobs, leading to a feeling of contentment, thus reducing the intention to quit. Notably, most highly central affective reactions have a path to ITQ through cognitive evaluations, and then through another affective evaluation, consistent with ideas regarding cognitive-affective consistency (Rosenberg, 1968).

Further examination of the full JDI network shows assortativity in the types of nodes that connect one scale to another. For example, the pay and work itself subscales are most highly connected via the connection between the items *bad* (pay) and *fascinating* (work itself) as well as the items *barely live on income* (pay) and *routine* (work itself). These pairs are alike in that they are affective and cognitive reactions, respectively. That is, clusters in the network communicate with one another via similar types of evaluations with regard to the cognitive-affective distinction. A final interesting feature of the full network of the JDI is that the evaluative reactions in the graph that connect one cluster (i.e., subscales) to another show *assortative mixing* (Newman, 2002). This is a special case of assortativity wherein nodes that are high in strength centrality will connect to other clusters via nodes that are also high in strength centrality. For example, the most central item in the network is the affective evaluation of *enjoyable* in the JIG scale is highly connected to other highly central, positive affective evaluations such as *rewarding* and *ideal*.

Hypothesis 6

To test Hypothesis 6a, that those items with high centrality would be able to identify those items whose change is most predictive of change in other items, we utilized Samples 4a1–4a2 from the HRS dataset. In this dataset, repeated measures are only available to predict 2010 job satisfaction items from 2006 job satisfaction items (i.e., 2006 → 2010), and to predict 2012 job satisfaction items from 2008 (i.e., 2008 → 2012). Thus, we narrowed the sample down to those persons with complete data in 2006 and 2010, resulting in *N* = 1,264 (i.e., Sample 4a1), and a nonoverlapping subset of persons with complete data in 2008 and 2012, *N* = 843 (i.e., Sample 4a2).

First, we estimated the job satisfaction networks in each year: 2006 (*N* = 1,264), 2008 (*N* = 843), 2010 (*N* = 1,264), and 2012 (*N* = 843; see Figure 8). Table 8 shows that the network in each year could be considered a small world network. Centrality statistics were also calculated for each year. Notably, strength centrality was the most stable from year to year, with between-year correlations ranging from .89 to .95, whereas closeness and betweenness showed lower between-year correlations, ranging from .21 to .81, and .15 to .82, respectively. As noted by one reviewer, this may indicate that strength centrality is the most reliable metric, and therefore is also the most predictive, and we agree with this assessment.

Next, we sought to determine whether the items identified as high in centrality were also those whose change was most predictive of change in other items. To test this idea, we calculated residualized change scores by regressing each 2010 job satisfaction item onto its 2006 counterpart (i.e., 2006 → 2010), and each 2012 job satisfaction item onto its 2008 counterpart (2008 → 2012). We then built a structural equation model in which the residualized change of a given item (e.g., residualized change in the item *satisfied* from 2006 to 2010) is an observed predictor of

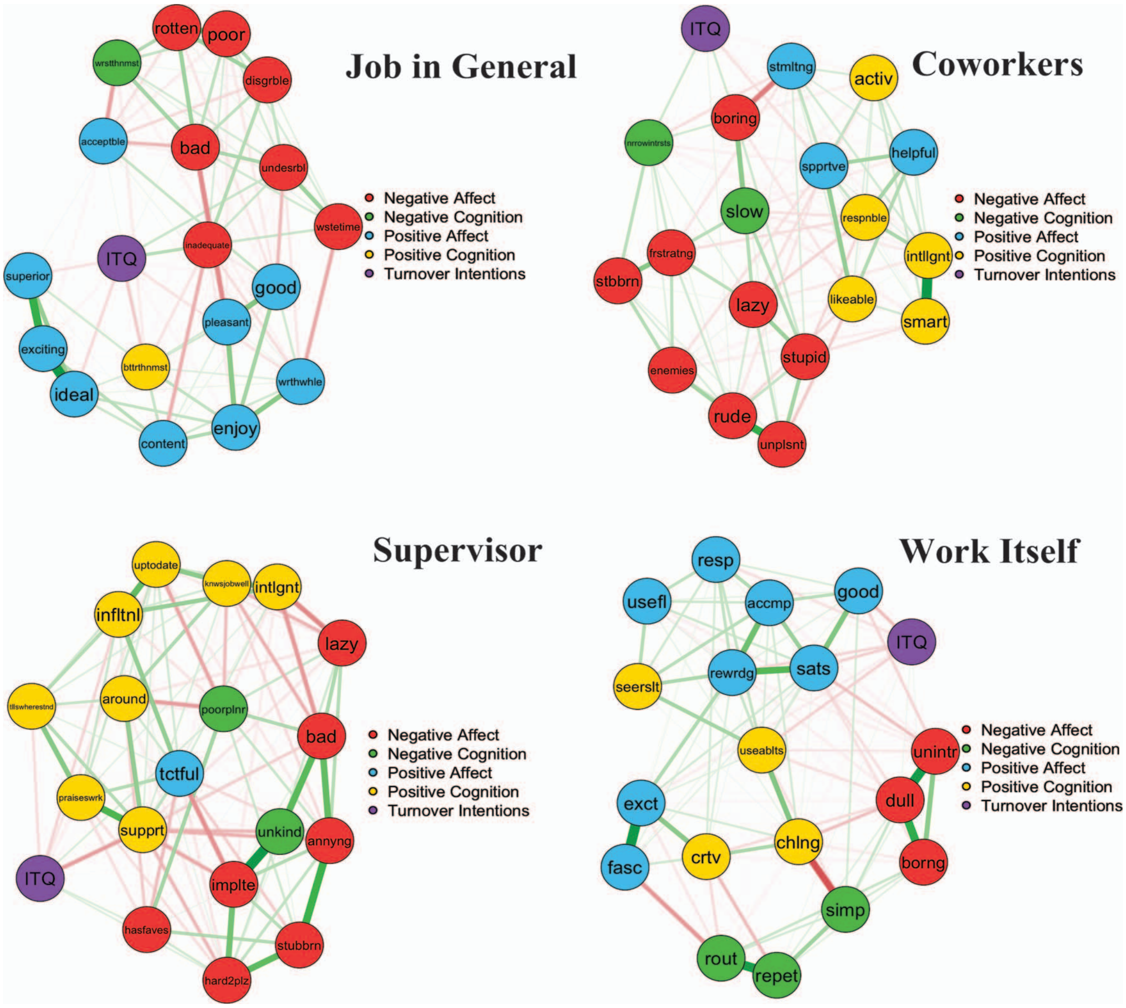

Figure 5. Job Descriptive Index (JDI) subscale networks that show small-world structure, including the Intention to Quit item. Green (solid) lines represent positive ties; red (dashed) lines represent negative ties. See the online article for the color version of this figure.

two latent variables reflecting the dimensionality of the HRS job satisfaction items whose indicators are the residualized change in all other items. Thus, 15 SEM_{RC} models were estimated for 2006 → 2010 and 15 SEM_{RC} models were estimated for 2008 → 2010. We then calculated R^2_{RC} (i.e., the sum of R^2 for the two latent factors) for each model.

To directly test Hypothesis 6a, we examined the correlations between items' centrality estimates in 2006 and the R^2_{RC} in the 2006 → 2010 structural model, and the correlations between items' centrality estimates in 2008 and the R^2_{RC} in the 2008 → 2012 structural model (see Table 9). For 2006 centrality estimates, strength centrality correlated $r = .85$, $p < .001$, with R^2_{RC} in the 2006 → 2010 structural model. For 2008 centrality estimates, strength centrality correlated $r = .78$, $p < .001$, with the R^2_{RC} in the 2008 → 2012 structural model. This confirms Hypothesis 6a, suggesting that strength centrality can indeed be used to determine which items' change will best predict change in other items.

To test Hypothesis 6b—that strength centrality would outperform other centrality measures in predicting R^2_{RC}—we estimated two hierarchical regressions. In Step 1, we entered either betweenness centrality or closeness centrality as a predictor of t R^2_{RC} (using both 2006 → 2010 and 2008 → 12 data). In Step 2, we added strength centrality as a predictor. Consistent with Hypothesis 6b, strength centrality showed incremental variance explained above and beyond both betweenness, $\Delta F(1, 28) = 17.29$, $p < .001$, $\Delta R^2 = .18$, and closeness centrality, $\Delta F(1, 28) = 11.47$, $p = .002$, $\Delta R^2 = .13$, suggesting strength centrality is the best of these centrality measures at identifying those items that are most influential in the network.

To test Hypothesis 6c—that strength centrality would outperform standard CFA factor loadings in predicting R^2_{RC}—in Step 1 of a hierarchical regression, we regressed the R^2_{RC} for both 2006 → 2010 and 2008 → 2012 onto the CFA factor loadings from 2006 and 2008, and in Step 2, we added the strength centrality estimates as a predictor. Results of Step 1 showed that factor loadings were able to predict variance explained by residualized change scores, $F(1, 28) = 31.49$, $p < .001$, $R^2 = .53$, $\beta = .81$. Confirming Hypothesis 6c, adding centrality to the model significantly in-

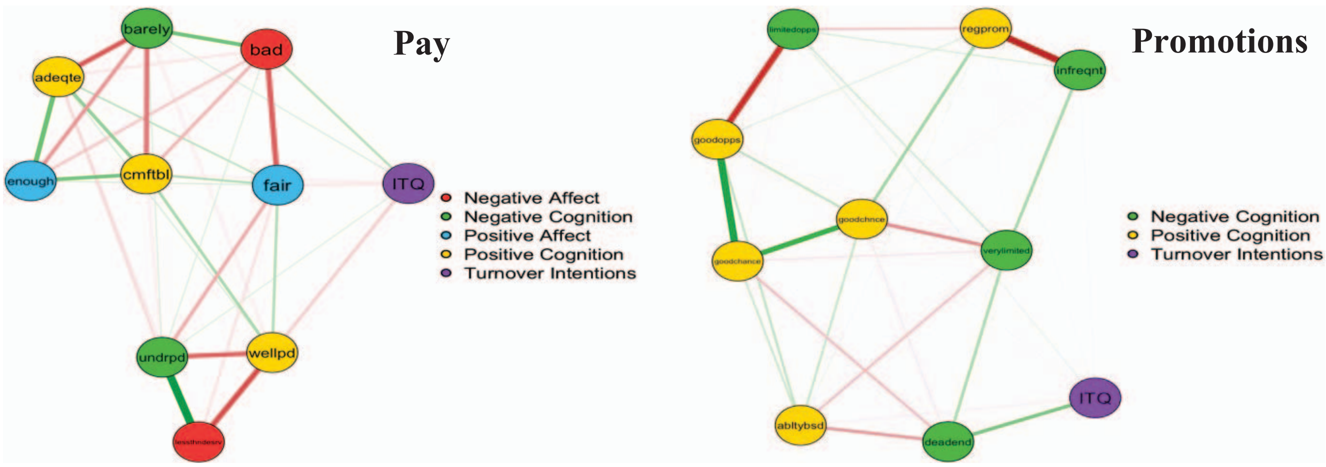

Figure 6. Job Descriptive Index (JDI) subscale networks that do not show small-world structure including the Intention to Quit item. Green (solid) lines represent positive ties; red (dashed) lines represent negative ties. See the online article for the color version of this figure.

creased variance explained $\Delta F(1, 28) = 14.01$, $p < .001$, $\Delta R^2 = .16$. Notably, in Step 2, only strength centrality was a significant predictor of R^2_{RC}, explaining 68% of the variance, and the CFA factor loadings were no longer a significant predictor, suggesting any power of the CFA loadings to predict centrality is redundant with—and better predicted by—strength centrality.[11]

Hypothesis 7

To test our final hypothesis—that the CAN psychometric network model would better predict future voluntary turnover—we utilized Sample 4b from the HRS dataset. First, we estimated the psychometric networks of the job satisfaction items only (i.e., not including the voluntary turnover item) for each year (2006, 2008, 2010, and 2012; see Figure 9) to ensure that the networks represented small worlds even in the reduced sample (due to availability of turnover data). As shown in Table 8, all networks constituted small worlds, and showed similar properties as those in their larger-*N* correspondents in Sample 4a.

Next, we used the *mgm* package (Haslbeck & Waldorp, 2018b) to estimate these same networks including the future voluntary turnover item (i.e., 2006 → 2008, 2008 → 2010, 2010 → 2012, and 2012 → 2014), which was treated as categorical (see Figure 10). Additionally, we estimated a corresponding structural equation model in which the two latent job satisfaction factors were predictors of future voluntary turnover; the outcome was treated as categorical. Finally, we calculated the $\mathcal{A}_{\mathrm{norm}}$ statistic for these two models, which is an effect size metric for categorical predictions that tells how much greater prediction is gained by the model information above and beyond the base rate of turnover (see Appendix B). Table 10 shows these models' $\mathcal{A}_{\mathrm{norm}}$ and corresponding fit statistics. As can be seen, with the exception of the 2008 → 2010 model, in which neither the network model nor SEM was able to predict voluntary turnover, the network model generally was capable of making more correct predictions than the SEM. This generally support Hypothesis 7, which stated that network models should better predict future outcomes compared with a SEM.

Notably, a potential reason that job satisfaction was unrelated to turnover for 2008 → 2010 could be attributable to high unemployment in 2010. Based on theoretical work by Muchinsky and Morrow (1980), Carsten and Spector (1987) found that the correlation between job satisfaction and turnover was stronger in times of low unemployment. Indeed, examination of the Bureau of Labor Statistics seasonally adjusted unemployment data shows that unemployment rates for 2010 ranged from 9.3 to 9.8%, which was high compared with 2008 (4.9% to 7.3%), 2012 (7.7% to 8.3%), and 2014 (5.6% to 6.7%; https://data.bls.gov/timeseries/LNS14000000).

As one reviewer pointed out, a potential explanation for the superiority of prediction in the network model is that it is overparameterized, and thus can explain the data in which it is estimated but would not cross-validate to other data sets. However, as we show in Appendix E, when the psychometric network model is estimated on 80% of the data and then applied to the remaining 20% for cross-validation, predictability is still relatively high. In fact, in most cases the network model does as well or better in prediction for the cross-validated dataset as the SEM was capable of predicting turnover for the dataset in which it was estimated. Thus, overparameterization does not appear to be the reason for greater prediction of the network model.

Discussion

A comprehensive understanding of job attitudes is paramount to the science and practice of applied psychology. In this article, we detailed an exciting new theoretical model—the CAN model (Dalege et al., 2016)—and harnessed its power to zoom in closer on the network structure of job satisfaction. Further, we contrib-

[11] Given the chance for replication, we also tested Hypothesis 5 using the 2006 and 2008 data used to test Hypotheses 6–8. We found in a 2 × 2 ANOVA that affect-laden items were significantly more central, $M = .57$, $SD = .73$, than cognitively-laden items, $M = -.27$, $SD = .98$, $F(1, 26) = 4.95$, $p = .019$, $\eta^2 = .19$. The valence of items had no significant main effect, and there was no significant interaction.

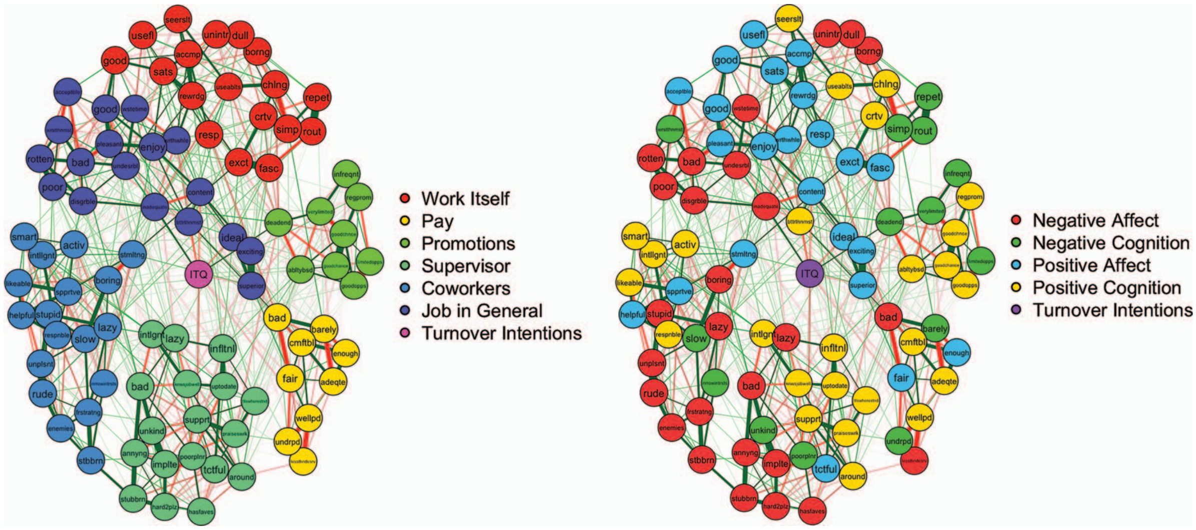

Figure 7. Full Job Descriptive Index (JDI) networks color-coded reflect subscale (left) and to reflect differing valence and reflection of cognition versus affect (right). Green (solid) lines represent positive ties; red (dashed) lines represent negative ties. See the online article for the color version of this figure.

uted to this emerging literature by making new distinctions drawn from attitude theory and network theory alike. In fact, perhaps the most compelling feature of CAN is its connection to network theory and analysis, lending itself to the generation of hypotheses that follow from its tenets. The ubiquity of networks has grown continually in many scientific fields including biology, physics, chemistry, economics, sociology, and psychology; this generality implies the possibility of a fruitful interdisciplinary exchange, in which findings regarding networks in one field can serve the function of generating new ideas and hypotheses in others. Below we discuss the findings and limitations of the current study, moving on to consider the practical applications of the CAN approach to attitudes in organizational settings. Finally, we discuss future directions for researchers interested in applying network-theoretic models to the study of job attitudes.

Findings of the Current Study

The CAN approach to understanding attitudes holds promise for both research and practice in application to important job attitudes, such as job satisfaction. In our investigation, we showed that the instrumental-symbolic distinction between attitude objects (Katz, 1960)—which has been applied in the literature on organizational attraction (Carter & Highhouse, 2014; Highhouse, Brooks, & Gregarus, 2009; Highhouse, Thornbury, & Little, 2007; Lievens & Highhouse, 2003)—is observable in job satisfaction networks. First, we showed that whereas evaluations toward more instrumental job features (e.g., pay and promotions)—which generally require more cognitive evaluations—are highly connected, stable networks that form a single cluster, whereas symbolic attitude objects (e.g., work itself, supervisor) are less directly observable and rely on a balance of cognitive and affective evaluations that increase in connectivity with exposure to the attitude object (operationalized here as job tenure) which is consistent with perspectives on how attitude strength increases (Howe & Krosnick, 2017).

Further, we showed that networks regarding more symbolic attitude networks form relatively independent clusters based on the cognitive-affective distinction and their valences. Due to these properties, more symbolic attitude networks showed a small-world

Table 8
Statistical Indicators of Network Structure for the HRS job Satisfaction Items in Each Survey Year

Sample	Year	*N*	Small World Index (*SW*)	Clustering (*C*)	95% CI for clustering in random network (C_{rand})	Average length (*L*)	95% CI for average length in random network (L_{rand})
Sample 4a	2006	1,264	**1.05**	**.72**	[.67, .70]	1.30	[1.30, 1.30]
	2008	843	**1.06**	**.68**	[.61, .63]	1.38	[1.38, 1.38]
	2010	1,264	**1.05**	**.64**	[.58, .63]	1.35	[1.35, 1.35]
	2010	843	**1.18**	**.59**	[.46, .53]	1.47	[1.46, 1.48]
Sample 4b	2006	513	**1.06**	**.67**	[.61, .65]	1.36	[1.36, 1.36]
	2008	526	**1.07**	**.61**	[.54, .60]	1.39	[1.39, 1.39]
	2010	599	**1.09**	**.63**	[.55, .61]	1.42	[1.42, 1.42]
	2012	498	**1.39**	**.66**	[.41, .50]	1.57	[1.51, 1.52]

Note. HRS = Health and Retirement Survey. Numbers in boldface indicate that they are significantly higher than in a random graph. For Sample 4a, the 2006 and 2008 networks are used in the primary analyses to make predictions about which items' change would predict other items' changes in 2010 and 2012, respectively. Thus, the 2010 and 2012 networks are not utilized from primary analyses, but are shown here for the sake of complete reporting.

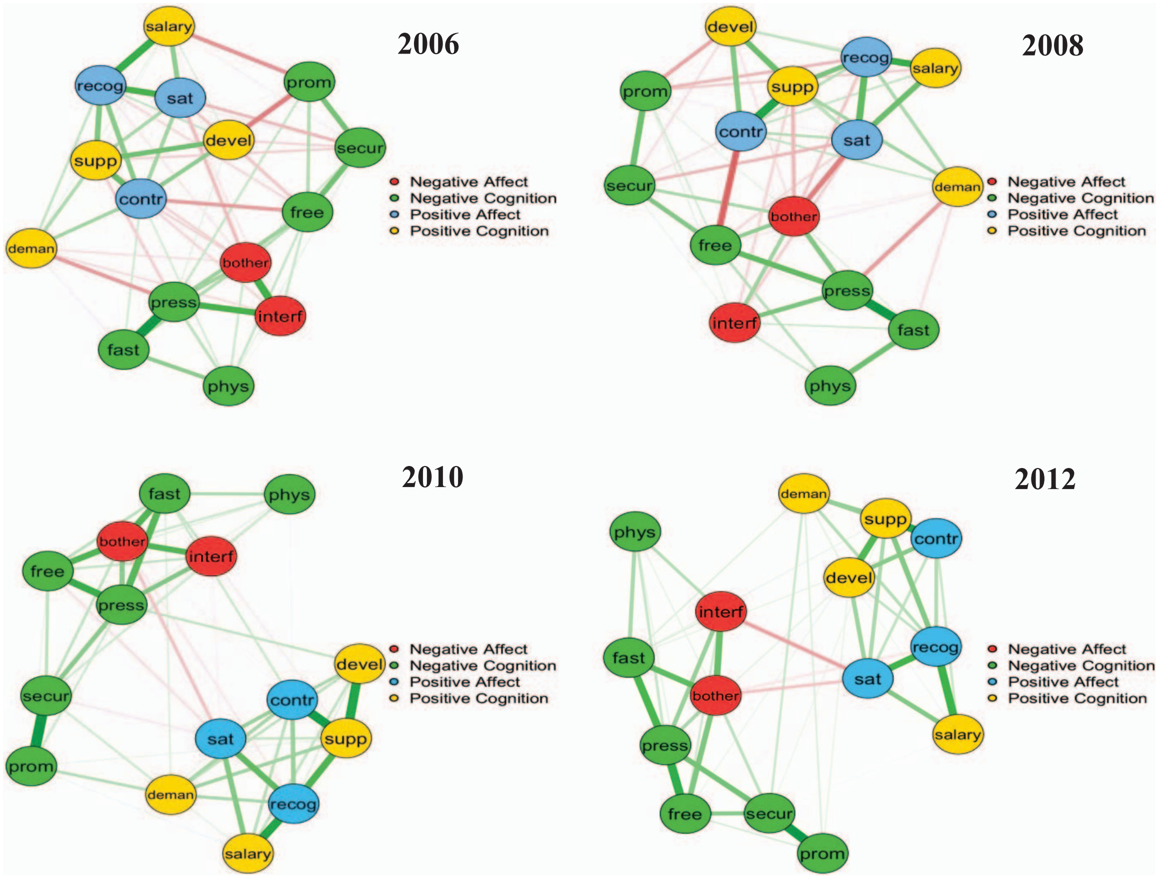

Figure 8. Attitude networks for the Health and Retirement Survey (HRS) job satisfaction items in 2006, 2008, 2010, and 2012 in Sample 4a. Green (solid) lines represent positive ties; red (dashed) lines represent negative ties. See the online article for the color version of this figure.

structure, consistent with Dalege et al. (2016), who examined only symbolic attitude objects (i.e., political candidates). The current study contributes to this literature by showing that more instrumental objects do not conform to this structure. One implication of this finding for attitude change is that changes in any given evaluation in an instrumental attitude object network would theoretically have a similar impact as affecting other evaluations. Thus, instrumental networks are unlikely to provide more information than latent variable models, which would suggest that change in evaluations occurs—in theory—by impacting the latent variable underlying the responses. Further, it implies that attitude change will be difficult for these tightly connected, single-cluster instrumental networks, whereas in more loosely connected, multicluster small-world network structures the change in the network based on a change to a single evaluation is proportional, a disproportionate amount of change in one node is needed to affect change throughout a tightly connected network (Cramer et al., 2016). Upon reflection, this result is sensible; changes in attitudes toward for example, pay should require an *actual* change in the pay they receive. On the other hand, change in networks regarding symbolic objects should be proportional to changes in nodes, and most effective when the most central nodes are targeted.

Another contribution to the literature is the finding that strength centrality may be a better measure of centrality for understanding the evaluations affecting change in attitude networks than those of betweenness and closeness centrality. We relied on theoretical work regarding network flow (Borgatti, 2005) to make the case that strength centrality would be more important. Thus, we postulated and tested the idea that strength centrality would be more accurately predicted by psychological features of the network—namely the cognitive-affective and valence distinctions of evaluations—than betweenness. Indeed, we found that only strength centrality was significantly related to the cognitive-affective distinction in symbolic attitude networks, but no effect for valence. Further confirming the idea that attitude networks regarding more instrumental attitude objects will not have better candidates for affecting change in the attitude network as the cognitive-affective distinction did not predict differences in strength centrality for these networks. Future research should further test this idea and question whether different types of attitude networks might benefit from comparing different measures of centrality. For example, though we rely on a parallel between change in attitude networks to Borgatti's ideas about interpersonal attitude transmission, personality change may result from a different process.

Another important contribution of this article was the finding that affectively laden items may generally the best candidates for influencing other evaluations in the attitude network (i.e., highest in strength centrality). This would suggest that job satisfaction

Table 9
Items' Centrality, Variance Explained for Structural Models of Change, and Loadings From Standard CFA by Year in Sample 4b

Item ID	R^2_{RC} 2006 → 2010	2006 strength centrality	2006 CFA λ	R^2_{RC} 2008 → 2012	2008 strength centrality	2008 CFA λ
sat	.29	.54	.66	.35	**1.08**	.67
phy	.13	−1.83	.29	.09	−2.00	.25
rcg	.46	**1.08**	.71	.40	**1.26**	.71
slr	.25	−.71	.53	.19	−.56	.54
prm	.16	−.77	.40	.25	−.75	.43
scr	.24	−.49	.47	.42	−.52	.50
prs	.52	**1.70**	.62	.63	**.88**	.58
fre	.44	.61	.60	.47	.73	.65
dvl	.35	−.12	.52	.39	−.13	.58
spp	.58	**1.02**	.67	.58	.84	.68
cnt	.47	**.85**	.63	.48	**.94**	.69
fst	.38	−.71	.42	.37	−.52	.41
bth	.46	.66	.64	.35	.81	.67
dmn	.24	−1.24	.40	.25	−1.19	.42
int	.26	−.59	.55	.18	−.90	.46

Note. Values in boldface indicate the four most central items as indexed by strength centrality.

change begins on an emotional level rather than a cognitive level and is consistent with the affective primacy hypothesis (Cervellon & Dube, 2002; Huskinson & Haddock, 2006), which states that the activation of cognitive evaluations of the attitude object are temporally preceded by emotional reactions (see Crano & Prislin, 2006). This indicates that attitude change may begin with affective change, whereas cognitions are a mechanism through which affective evaluations are transmitted to one another to result in changes in behavioral intentions. Indeed, this would be consistent with Judge and Kammeyer-Mueller's (2012) observation that "higher-level cognition relies on evaluative input in the form of emotion" (p. 345). This does not seem to be the case for more instrumental attitude object networks, which did not show a direct link between cognitive evaluations and behavioral intention to quit in this study.

We believe it important to mention another interesting finding: in all networks involving the ITQ item, the behavioral intention node is on the outskirts of the attitude network (and in the case of the full network is on the outskirts of all subclusters). This is particularly interesting due to claims that the EBICglasso procedure utilized here (for continuous Gaussian data; see Dalege et al., 2016; Dalege, Borsboom, van Harreveld, & van der Maas, 2017) is capable of providing an estimate of the (mutually) causal structure among evaluations. Thus, whereas latent variable models (both exploratory and confirmatory) force causal structure onto data, the procedures utilized here attempt to find the causal structure which can then be evaluated post hoc for rationality. Additionally, this model does away with many of the philosophically troubling problems of invoking the latent variable to explain interrelations between items (see Schmittmann et al., 2013), instead focusing on the mutual causality between observable variables as the explanation for the structure of evaluations.

Finally, we utilized longitudinal data to more directly test two basic claims about CAN and network models more generally: that when considering the mutually causal structure from cross-sectional data we can (a) determine those attitude object evaluations whose change will most likely affect change in the rest of the attitude evaluation network and (b) better predict future outcomes. Indeed, regarding (a), we found that items' centrality estimates uncovered in cross-sectional data were highly correlated with the degree to which—in longitudinal data—change in an item was most predictive of change in other items, consistent with the findings of Dalege, Borsboom, van Harreveld, Waldorp, and van der Maas (2017), who found a high correlation between centrality measures on political attitude items and voting decisions. Further, we showed that strength centrality may be the better centrality estimate in this determination compared with betweenness and closeness centrality, as well as factor loadings from a standard CFA. This finding is compelling in making the case for use of psychometric network models in practice to identify particular feelings and thoughts to be targeted in interventions aimed at increasing job satisfaction. Regarding point (b), we indeed found that the psychometric network model was better able to predict future voluntary turnover compared with a SEM in three of four data sets, and that in in two of those three the difference in classification accuracy was quite large. This should be seen as a promising finding for the CAN and psychometric networks in general, and is the first study known to the authors to make direct comparisons between network models and SEMs. Future studies should seek to examine other predictor variables and/or a larger variety of outcomes using longitudinal data. In general, we believe these findings suggest that applied psychology could benefit by giving more attention to the theories of inferred causation based on counterfactuals that are being utilized in many other applications (see Pearl, 2009). We must, however, be careful in making causal inferences.

Limitations and Future Directions

Of course, this study has some notable limitations. First, we used preexisting, popular measures of job satisfaction and relied on raters to assign items to reflect the cognitive-affective distinction, requiring us to take these measures as they are. Future work could look to build measures that are more balanced in the distribution of cognitions and affect. However, as we noted, we do believe that for certain attitude objects it will be difficult to do so, as more instrumental features mainly appear to involve cognitively laden judgments rather than affective reactions. Moreover, some of these

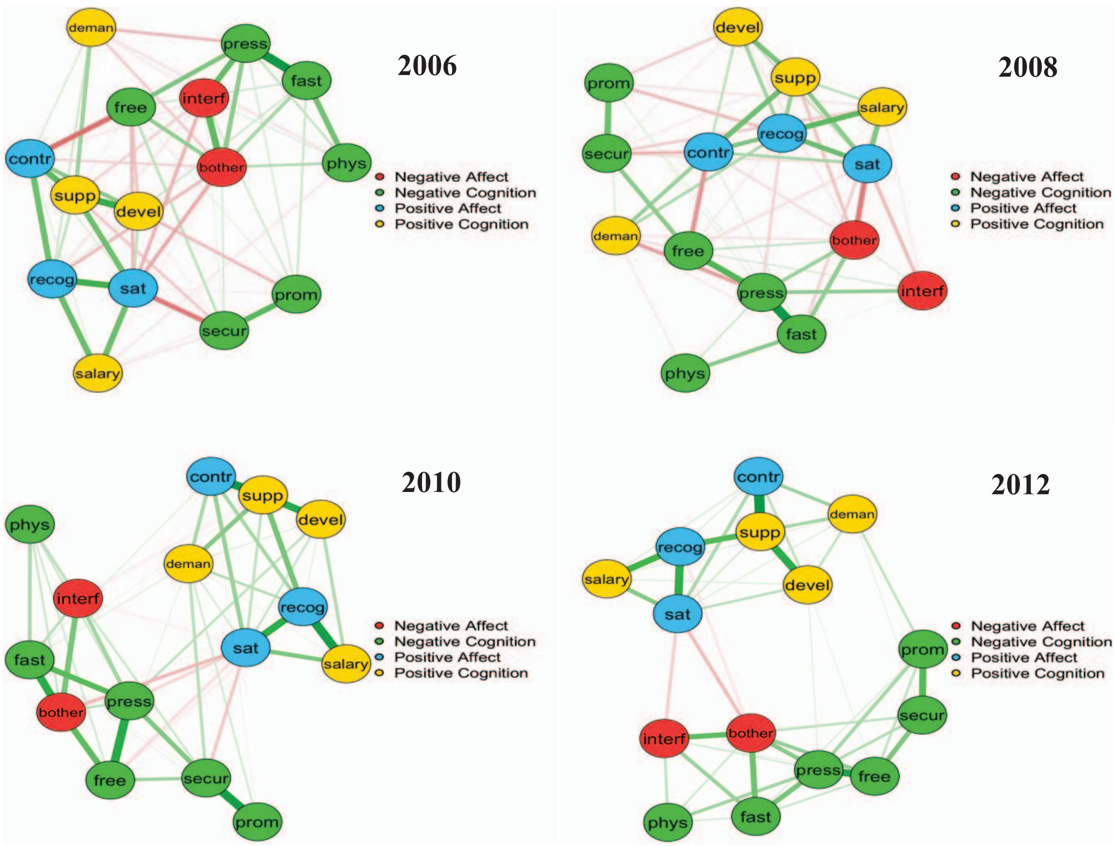

Figure 9. Attitude networks for the Health and Retirement Survey (HRS) job satisfaction items in 2006, 2008, 2010, and 2012 in Sample 4b. Green (solid) lines represent positive ties; red (dashed) lines represent negative ties. See the online article for the color version of this figure.

measures (e.g., the work itself subscale) were well-balanced in this regard. Additionally, although we examined those evaluations that are likely to lead to change in the networks, such findings should be confirmed with interventions targeted more generally at the attitude versus those that rely on centrality information to target specific nodes. A third limitation is that in this article we focused only on job satisfaction (other than those in Appendix D) to limit our discussion to its particular theoretical and practical underpinnings. However, future research should seek to examine something similar to the study by Joseph, Newman, and Hulin (2010) who examined many job attitudes—this could further explicate the core of these variables and their potentially complex interrelations. Finally, on the more statistical side, many of the job satisfaction network *SW* values for unidimensional measures of facet satisfaction were only slightly above the criteria for small-worldness, though this is consistent with past studies utilizing psychometric data (e.g., Dalege et al., 2016). Studies are greatly needed to determine a clearer interpretation of *SW* values in psychometric data, which are likely to be weaker than in some other systems that are more perfectly observed. Additionally, the connections and differences between network models and factor and structural equation models should be further explored, and further verification of the greater predictive accuracy of network models is needed, particularly using longitudinal data. It should be noted that care needs to be taken in separating the *theoretical* language of causality inherent to these models (e.g., see Pearl, 2009) from *practical* conclusions of causality, particularly in cross-sectional data.

In addition to studying the structure of attitudes statically, one can also apply these methods to experience sampling studies, which is beyond the scope of the present investigation. Whereas the CAN model is applied to cross-sectional, static data, the use of repeated measures data submitted to various multilevel, time-lagged vector autoregressions allows for greater confidence in the estimation of causal structure, resulting in directed graphs that depict edges with either uni- or bidirectional ties, rather than relying on the concept of mutual causal reinforcement. This type of exploration could lead to major developments in our understanding of attitude formation and change in organizational attitudes. Such investigations will require intensive data collections wherein respondents are surveyed multiple times per day over many days. So far, the application of network approaches to longitudinal data approach has been applied successfully to understand the etiology of psychopathology (see Bringmann et al., 2013). The interested reader is referred to the Psychosystems Group (http://psychosystems.org/) in Amsterdam that has spearheaded the majority of the work discussed here.

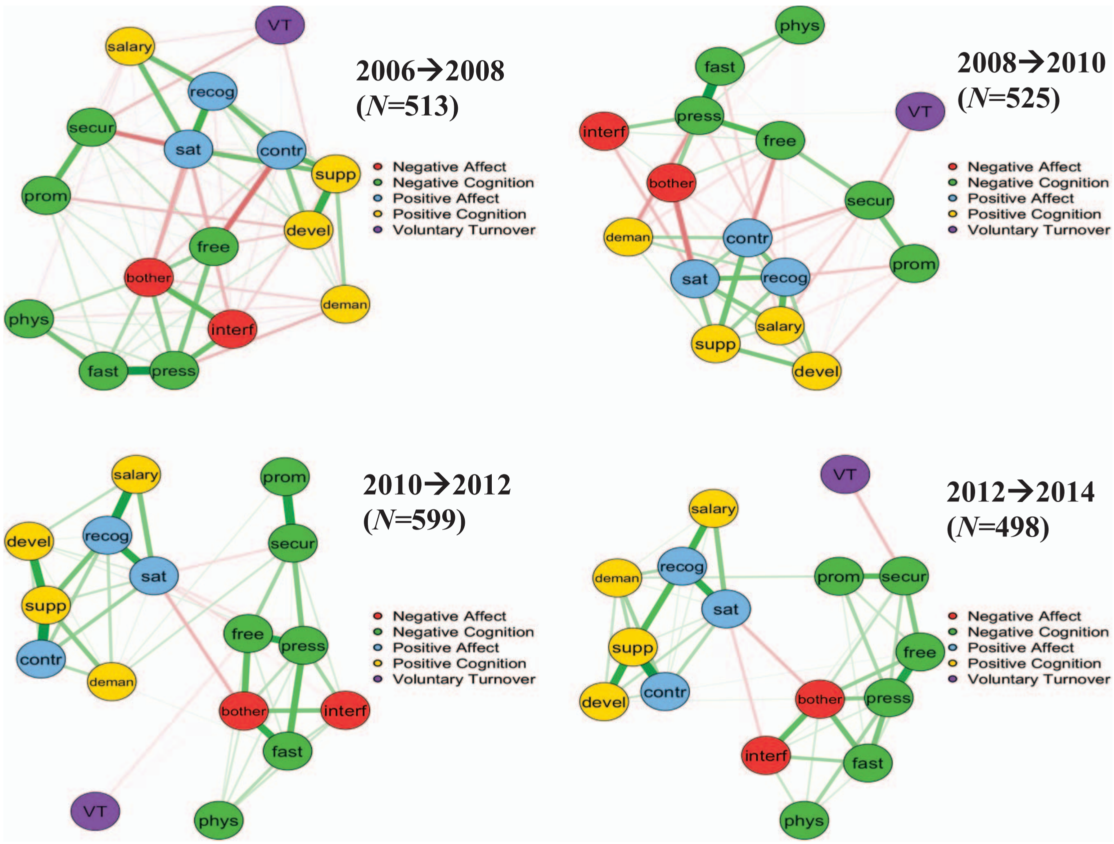

Figure 10. Attitude networks for the Health and Retirement Survey (HRS) job satisfaction items and future voluntary turnover in Sample 4b. Green (solid) lines represent positive ties; red (dashed) lines represent negative ties. See the online article for the color version of this figure.

Practical Implications

Although we have mostly discussed the CAN model at length from an attitude-theoretic perspective, it has some interesting implications for practitioners involved with organizational surveys. First, by understanding the connectivity and structure (e.g., small world or not), it will be easier to determine which attitudes can be changed more easily than others. Second, if they *do* show a small-world structure, an understanding the centrality of particular attitude object evaluations can be leveraged to effectively change the network of evaluations. For example, we showed that instrumental features of the job have high connectivity, and thus are dense networks that crystallize quickly (i.e., do not change with job tenure). Whereas attitudes toward more symbolic features of the job can be changed by targeting specific evaluations, those more instrumental features are unlikely to change by such ap-

Table 10
Comparison of Predictive Efficacy of the Psychometric Network and Structural Equation Models for Predicting Future Voluntary Turnover

	2006 → 2008		2008 → 2010		2010 → 2012		2012 → 2014	
Measure	PNM	SEM	PNM	SEM	PNM	SEM	PNM	SEM
$\mathcal{A}_{\text{norm}}$	.121	.000	.000	.000	.147	.000	.150	.100
χ^2	65.76	291.46	62.36	217.60	78.92	471.83	74.87	345.40
df	63	102	71	102	78	120	53	120
RMSEA	.01	.06	.00	.05	.00	.08	.00	.07
CFI	1.00	.96	1.00	.97	1.00	.90	1.00	.91
TLI	1.00	.95	1.00	.97	1.00	.88	1.00	.89
SRMR	.02	.07	.03	.06	.02	.07	.03	.07
N	513	513	526	526	599	599	498	498

Note. PNM = Psychometric network model; SEM = Structural equation model; 2006 → 2008 indicates 2006 job satisfaction items were used to predict 2008 voluntary turnover, and so on.

proaches. In other words, if an attitude network does not constitute a small-world, there is not as clear a path to change. In fact, it may be that for tightly connected, non-small-world networks, the entire attitude object has to change (e.g., increasing pay, providing more opportunities for promotion), whereas specific evaluations (e.g., making the job feel more enjoyable) can be manipulated to affect change throughout the network. Thus, the network-theoretic view of attitude structures allows for realistic assessment of both the ability of an intervention to change attitudes, and—if a small-world structure—the paths through which change may occur. Indeed, our study shows that identifying those evaluations whose change best predicts changes in other evaluations is possible. Further, our studies' corroboration with the literature on affective primacy would suggest that centrality statistics offer a powerful means through which we can identify how to best change attitudes.

Second, we showed that the network approach can better predict future outcomes compared with a SEM approach. This is because of the focus of the network model on the inferred causal structure, in which counterfactuals are leveraged to estimate the path through which outcomes are affected. For example, we can see in Figure 10 that the central affective evaluation of whether one receives sufficient recognition would lead directly and indirectly to change in several nodes that connect directly to voluntary turnover. Thus, we might expect that increasing recognition for work completed would lead to better cognitive evaluations of salary, which is directly connected to voluntary turnover, and more of a general feeling of satisfaction with the job, which connects to turnover through the cognitive evaluation of job security. On the other hand, latent variable models would leave us with little to work with, only that we should increase satisfaction with the job. Increasing recognition, on the other hand is more actionable through simple means such as offering public rewards, "employee of the month" program, employee awards ceremonies, and so on. Thus, in the words of Pearl (2009), we can use the estimated causal structure in networks as "oracles for intervention" (p. 22).

In addition to the technical/theoretical benefits involved in the CAN model, there is a somewhat superficial, but nonetheless critical, benefit of providing an intuitive visualization of survey results. Indeed, gaining buy-in and increasing understanding of major partners in organizations is always a key ingredient to successful change in organizations. We believe that the graphics-oriented approach to the CAN model, along with the many available metaphorical avenues one can travel to explain these graphs (items as persons in a social network, electrical circuits, etc.) allow for a refreshingly intuitive approach to communicating survey results and rationale for organizational interventions intended to change attitudes.

Conclusions

In this paper, we have demonstrated the exciting potential of the CAN model (Dalege et al., 2016) for application to applied psychology and the constructs that are central to our science. The model's logical merits are strong and represent a major move toward a more comprehensive account of the structure and operation of attitudes. We also showed that the theory and its corresponding network-analytic framework offer promise for understanding the formation, structure, and dynamics of constructs in applied psychology. We believe work in this area will prove to be highly influential in the years to come.

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(*Appendices follow*)

Appendix A

The Connection Between CAN and Latent Variable Theory

As detailed above, the CAN approach to understanding attitudes has many advantages over traditional latent variable approaches. At the same time, however, the approach is also surprisingly consistent with latent variable models. The major difference is that whereas latent variable models view patterns of evaluative reactions to attitude objects to be the outcome of an overarching hidden variable, the CAN approach views attitude evaluations as emerging from the interactions of the evaluations themselves, with each evaluation directly and indirectly affecting other evaluations. The similarity and major difference can be seen by comparing their fundamental equations. In the latent variable item response theory (IRT) partial credit model, the probability of a particular response pattern can be stated:

$$P(X = x) = \prod_i P(X_i = x_i) = \prod_i \frac{\exp(\theta_p - \tau_i)}{1 + \exp(\theta_p - \tau_i)}. \quad \text{(A1)}$$

Notably, here the threshold (i.e., difficulty or extremity) of the item influences how likely an item is to be endorsed by a respondent; to the extent that person p has a latent attitude, θ_p, higher than the threshold of the item they will be likely to endorse a given item; the probability of the pattern as a whole is simply the product of these probabilities across all items. Both account for the fact that some items are more likely than others to be endorsed when controlling for other factors through the threshold parameter. However, whereas IRT views the probability of patterns as influenced by a latent variable, the CAN model replaces the latent attitude with the interactions among attitude object evaluations themselves:

$$P(X = x) = \frac{\exp\left(-\sum_i \tau_i X_i - \sum_{ij} \omega_{ij} X_i X_j\right)}{\sum_X \left[\exp\left(-\sum_i \tau_i X_i - \sum_{ij} \omega_{ij} X_i X_j\right)\right]}. \quad \text{(A2)}$$

In other words, no magical latent variable is necessary to explain why someone reacts a particular way to an attitude object; one need look no further than how the respondent reacts to *other* evaluative stimuli. Notably, one could envision the latent variable as actually being nothing more than that: a representation of how one reacts to other evaluative stimuli and the interactions between those stimuli. For a more detailed, technical discussion see Epskamp, Maris, Waldorp, and Borsboom (in press).

Appendix B

Detailed Methods

Samples 1 and 2: Tenure Comparison

Two samples were collected online through Amazon Mechanical Turk: Sample 1a includes participants with one year of tenure or greater, and Sample 2 includes participants with less than one year of tenure. To be eligible to participate, individuals had to be living in the United States, 18 years or older, and holding a full-time job. The first wave of data collection targeted individuals at all levels of job tenure, and resulted in 559 working adults. The average age of participants was 37.7 years, with 39.1% males and 83.8% Caucasians. However, within the first wave, only 60 people had less than one year of job tenure and therefore, a second wave of data collection was needed to create equivalent samples of new employees (i.e., <1 year tenure) and more tenured employees (i.e., ≥ 1 year tenure). Thus, the 60 participants with less than one year of job tenure were deleted from the first wave of data collection and the remaining participants with one year or more of job tenure constituted Sample 1a (≥ 1 year tenure; $n = 499$). For analyses that do not compare employees with differing tenure levels, all participants originally surveyed in the first wave of data collection are used, which we refer to as Sample 1b ($n = 559$). The second data collection targeted new employees and resulted in 508 working individuals with less than one year of job tenure. The 60 individuals having less than one year of job tenure from the first wave of data collection were added to this sample yielding a total of 568 participants with less than one year of job tenure. However, to equate the sample sizes of the more tenured employee sample and the new employee sample, the 69 individuals with the greatest job tenure were deleted from this sample resulting in Sample 2 (<1 year tenure; $n = 499$). Participants in Sample 2 had a mean age of 32.5 years, with 47.7% males and 79.4% Caucasians.

Sample 1 and 2 Measures

Job descriptive index scales. The job descriptive index (JDI; Smith et al., 1969) was used to measure the faceted features of the job. The JDI consists of five subscales, including satisfaction with: work in general (<1 year tenure, $\alpha = .91$; ≥ 1 year tenure, $\alpha = .92$), pay (<1 year tenure, $\alpha = .90$; ≥ 1 year tenure, $\alpha = .91$) promotion (<1 year tenure, $\alpha = .80$; ≥ 1 year tenure, $\alpha = .79$), supervisor (<1 year tenure, $\alpha = .86$; ≥ 1 year tenure, $\alpha = .89$), and coworkers (<1 year tenure, $\alpha = .89$; ≥ 1 year tenure, $\alpha = .92$). The number of items in the JDI scales were 18, 9, 9, 18, and

(*Appendices continue*)

18, respectively. Global job satisfaction was measured using the 18-item job in general scale (JIG; < 1 year tenure, $\alpha = .93$; ≥ 1 year tenure, $\alpha = .94$; Ironson, Smith, Brannick, Gibson, & Paul, 1989) scale. All items in the JIG and JDI are short words or phrases, such as *Boring* or *Good*. Participants respond to each item using: *Yes* if it describes their work, *No* if it does not describe their work, or *?* if they were unsure or could not decide. The responses are assigned values of 3 for *Yes*, 1 for *?*, and 0 for *No*. Consistent with prior research, these value assignments reflect the finding that the *?* response option is more negatively weighted than a typical neutral response (see Carter, Dalal, Lake, Lin, & Zickar, 2011; Hanisch, 1992). Regarding the symbolic-instrumental distinction, we assumed that the JIG, as well as coworkers, supervisor, and the work itself subscales regarded symbolic attitude objects, whereas pay and promotions subscales represented instrumental attitude objects.

Job satisfaction scale. Respondents in Samples 1 and 2 also were administered the 36-item job satisfaction survey (JSS; Spector, 1985) The JSS consists of 9 four-item subscales, which were categorized by the authors into 22 items representing symbolic features of the job (i.e., nature of the job, supervisor, coworkers, working conditions, communication, and two items from the rewards scale; <1 year tenure, $\alpha = .92$; ≥ 1 year tenure, $\alpha = .92$) and 14 items representing instrumental features of the job (i.e., pay, promotions, benefits, and two items from the rewards scale; <1 year tenure, $\alpha = .92$; ≥ 1 year tenure, $\alpha = .93$). Participants responded to items such as "I feel I am being paid a fair amount for the work I do" for the Pay (i.e., instrumental) scale on a Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

Sample 3: Intentions to Quit

Data for Sample 3 were collected in 2009 through online panels by the JDI office at Bowling Green State University. Individuals must have been living in the United States, 18 years or older, and working at least 35 hr per week to meet eligibility requirements. The final Sample 3 resulted in 1,485 working adults, which previous research has analyzed, providing support that the sample is representative of national norms (Lake et al., 2010). The average age of participants in Sample 3 was 40.7 years, with 57.7% males and 80% Caucasian.

Sample 3 Measures

Job descriptive index scales. Global job satisfaction was measured using the 18-item job in general ($\alpha = .72$; JIG; Ironson et al., 1989) scale. Satisfaction with the faceted features of the job was measured with the Job descriptive index (JDI; Smith et al., 1969). The JDI consists of 5 subscales, including satisfaction with: work in general ($\alpha = .90$), pay ($\alpha = .87$), promotion ($\alpha = .91$), supervisor ($\alpha = .92$), and coworkers ($\alpha = .92$). See above for scoring protocol.

Turnover intentions. Turnover intentions were measured with the Intention of Turnover Questionnaire (ITQ) item "I intend to leave this organization before too long" which is rated on a 7-point Likert-type scale (1 = *low turnover intentions*, 7 = *high turnover intentions*). The Cronbach's alpha obtained by combining this item with seven other items with similar wording (e.g., "I plan to leave this organization in 6 months") was .93. Using this reliability estimate, the single-item reliability can be estimated using the Spearman-Brown formula, and was determined to be .66. Similarly, the estimated reliability from its squared factor loading (i.e., .78) was .61.

Sample 4: Predicting Change in Attitudes and Voluntary Turnover

Data for Sample 4 are derived from the 2006, 2008, 2010, 2012, and 2014 Health and Retirement Study (HRS) data, which is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan. Job satisfaction items responses from 2006, 2008, 2010, and 2012 were utilized, and turnover data from 2008, 2010, 2012, and 2014 were utilized. Two subsamples were utilized for various reasons pertaining to the nature of the data and hypotheses being addressed, which we explain below. To maintain consistency between all analyses using this sample, all missing data were omitted. Notably, this is due to the requirement of the *mgm* package (Haslbeck & Waldorp, 2018b), which does not allow for missing data.

Sample 4a. To address Hypotheses 6–8, we required repeated measures of job satisfaction items to determine how well change in each given item response could predict change in all other item responses. Two nonoverlapping subsets of Sample 4a had repeated measures data. Those persons administered job satisfaction items in 2006 were also administered the same items in 2010, creating the subset we refer to here as 2006 $\rightarrow$ 2010, N = 1,242, and another subset was administered the job satisfaction items in 2008 and 2012, which we refer to as 2008 $\rightarrow$ 2012, N = 843.

Sample 4a measures. The 15 job satisfaction items administered in the HRS (see Table 5) in years 2006, 2008, 2010, and 2012 were utilized. Examination of parallel analysis and the Velicer MAP based on exploratory factor analyses in the *psych* package (Revelle, 2018) for each year of data suggested the presence of two factors, with only one exception—in the 2010 data, three factors were suggested by parallel analysis but the Velicer MAP still suggested two factors. Confirmatory factor models were also fit to these data, which suggested reasonable model-data fit, with RMSEAs ranging from .071 to .081 and SRMSR from .061 to .075. These two factors represented a positive and negative valence factors, with intercorrelations ranging from $-.65$ to $-.73$. Coefficient alpha for scales based on these two factors ranged from .71 to 83.

(*Appendices continue*)

To test Hypotheses 6 through 8, we calculated residualized change scores for each item in each repeated measures subset (i.e., 2006 → 2010 and 2008 → 2012) by regressing the item from the more recent year onto the same item from the previous measurement (e.g., regressing the *satisfied* item in 2010 onto its respective 2006 scores).

Using these residualized change scores, we fit a series of structural equation models in which an item's residualized change score predicts two latent factors that represent the common residualized change among all items (other than the predictor) within each factor. We refer to these models here as $\mathrm{SEM}_{\mathrm{RC}}$ (i.e., SEMs of residualized change). The latent factors were the same as those using the standard item scores discussed in the paragraph above, corresponding to items with positive and negative valence. The utility of using the change in each item as a predictor of these latent factors was indexed by the sum of the variance explained (i.e., R^2) in each of the two factors, which we refer this sum as R^2_{RC}. These models are discussed in more detail in the Results section.

Sample 4b. To address Hypothesis 7, we retained data facilitating the prediction of turnover in the subsequent measurement occasion. We refer to these subsets as—for example—2006 → 2008 for the data subset in which both job satisfaction item responses in 2006 and voluntary turnover data in 2008 were available. The subsets utilized here are: (a) 2006 → 2008, $N = 513$; (b) 2008 → 2010, $N = 525$; (c) 2010 → 2012, $N = 599$; and (d) 2012 → 2014, $N = 498$.

Sample 4b measures. The same 15 items for job satisfaction as in Sample 4a were used in Sample 4b. Examination of parallel analysis and the Velicer MAP based on exploratory factor analyses in the *psych* package (Revelle, 2018) showed an identical pattern of results as in Sample 4a (see above). Coefficient alphas for scales based on these two factors ranged from .70 to .81. In examining CFAs, RMSEAs ranged from .071 to .085, and SRMSRs from .063 to .072. The 15 job satisfaction items for these years were used to compare how well the network model could predict subsequent voluntary turnover.

In 2008, 2010, 2012, and 2014, participants were asked why they left their employer. We coded the following option as indicating voluntary turnover (i.e., coded as 1): (a) BETTER JOB (start own business; go to school/get more training; make more money; work in family business; go into military); (b) QUIT (bored/burned out; didn't like job/wanted a change; problems with supervisor/coworkers; lack of pay/work hours/promotion/benefits/help; dispute with employer; sexual harassment; couldn't do work anymore; poor/dangerous working conditions; too stressful); and (c) RETIRED. All other options were coded as 0. In 2008, 2010, 2012, and 2014, the percentage of respondents reporting voluntary turnover were 56.3%, 37.3%, 45.6%, and 49.6%, respectively.

Classification of Cognitive and Affective Items

The grouping of items based on positive and negative-valence evaluations and cognitively- and affectively-laden groups was determined utilizing ratings from subject matter experts who were unaware of the hypotheses being tested, and coded the items as being affectively laden versus cognitively laden. For the JDI, 12 experts rated the items, and showed sufficient interrater agreement (ICC = .74). For the JSS nine expert raters were used, showing high interrater agreement (ICC = .93). For the HRS items, nine experts were used, showing sufficient agreement (ICC = .68). Using these ratings, items were assigned to the category most frequently chosen. Four of the JDI items required further investigation, as they resulted in a tie between affectively laden and cognitively laden. Therefore, ratings from three graduate students, who were also unaware of the hypotheses, were used to arrive at a final classification for these items. For the JDI, 63.9% of items in symbolic scales were affectively laden items. The rest were classified as cognitively laden. On the other hand, for instrumental objects, 22.2% of the items were classified as affectively laden, and the rest as cognitively laden. For the JSS, a more even balance was found such that 45.5% of the symbolic object items were classified as affectively laden, and 42% of the instrumental object items were classified as affectively laden. For the HRS items, 33% of items were classified as affectively laden, and the rest as cognitively lade.

(*Appendices continue*)

Analyses

All network analyses were conducted using the R (R Core Team, 2015) package *qgraph* (Epskamp et al., 2012). Example code for the JIG scale is included in Appendix C. Additionally, the correlation matrices for all data used here are included online supplemental materials. The model estimated is a sparse undirected Gaussian graphical model with *lasso* regularization (i.e., *GLasso*; see Friedman, Hastie, & Tibshirani, 2008) and is conducted using the *glasso* package (Friedman, Hastiee, & Tibshirani, 2014). This estimation procedure is somewhat similar to maximum-likelihood factor analysis in that it attempts to minimize the difference between the inverse of the observed covariance matrix (i.e., the precision matrix) and a predicted matrix based on weights estimating the interacting influence between nodes (i.e., evaluative reactions or evaluations). What differentiates this method from factor analysis is the exclusion of the latent variable as the mechanism that explains the interrelations between observable variables. Instead, the interactions between nodes in the network are used to explain the relations among nodes in the network, drawing on theories of causality based on Markov random fields and theories of inferred causation (see Pearl, 2009). This is done operationally by conducting regressions of each variable onto all other variables utilizing a tuning parameter that makes the size of the problem more manageable. The extended Bayesian information criterion (EBIC; see Chen & Chen, 2008) was utilized to detect the maxima for the likelihood of all regression models estimated via the EBICglasso command; these results are utilized as inputs for edge weights in the final network. Thus, the weights quantifying the interactions between nodes, ω_{ij}, can be thought of similarly to partial correlations between nodes controlling for their relations with all other nodes. However, it is notable that the EBICglasso method is more advantageous than using partial correlations, as they are more reflective of the mutual causality of observed indicators on other indicators. Using these weights, the various statistics detailed previously can be calculated including the small-world index, ω, and centrality statistics. All graph layouts were determined using the "Spring" function in 'qgraph' which implements the Fruchterman-Reingold (Fruchterman & Reingold, 1991) algorithm. This algorithm is used to produce graphs that best characterize these complex models in two-dimensional space.

All confirmatory factor models and structural equation models were estimated using the *lavaan* package and implemented maximum likelihood estimation. To address the predictability of networks in Hypothesis 7, the *mgm* package (Haslbeck & Waldorp, 2018b) was utilized to evaluate variance explained in future voluntary turnover by the network. Variance explained both in a network with one binary variable (voluntary turnover) and in structural equation models with a binary outcome was operationalized using the $\mathcal{A}_{\text{norm}}$ metric described by Haslbeck and Waldorp (2018a) to provide a common metric for comparing the two models' performance in prediction. This metric is intended as an alternative to R^2, which is not easily estimable given categorical data. Normalized accuracy in the binary case is indexed by comparing the proportion of correct classifications of the model, $\mathcal{A} = \frac{\sum_{i=1}^{n} \mathbb{I}(y_i - \hat{y}_i)}{n}$, where y_i is the observed binary response, $y_i \hat{y}_i$ is the predicted classification of the binary outcome, and $\mathbb{I}$ is an indicator of the event where the observed response is equal to the predicted response. The frequency of correct classification, $\mathcal{A}$, is then compared with the marginal probabilities of the response, p_1 (i.e., the probability of observing a response of '1') or p_0, whichever is greater. This comparison is the normalized accuracy, expressed as

$$\mathcal{A}_{norm} = \frac{\mathcal{A} - max\{p_0, p_1\}}{1 - max\{p_0, p_1\}}. \tag{4}$$

This statistic tells us how much greater our classification accuracy over and above the null model (i.e., a model whose predictions are based only on model intercepts).

(*Appendices continue*)

Appendix C

Example ‘qgraph’ Code for the Work Itself Scale

```
#################################################################
##################General Information###############################
#################################################################

#Data are from the BGSU JDI norming data set of 2009
#Figures of graph can look different because this article used graph Version 1.3.2

#####see http://psychosystems.org/network-model-selection-using-qgraph-1-3-10/for more
information

#################################################################
###############################Load the data#######################
#################################################################

#First save the .csv data file in your working directory

JDIW2009<- read.csv("/Documents/JDIW.csv") #Read in the dataset

#################################################################
#########################Setting up data for graphing##################
#################################################################

colnames(JDIW2009, do.NULL = TRUE) #Reads you the column names so you can verify that this
is what you want your nodes to be named

jdiw<-colnames(JDIW2009, do.NULL = TRUE) #Name the nodes based on their column names

library(qgraph)

JDIWCors<-cor_auto(JDIW2009, detectOrdinal = FALSE) #Create correlation matrix

JDIWC<-EBICglasso(JDIWCors, n = 1485) #Create Gaussian graphical model using graphical lasso
based on extended BIC criterium

jdiwgroups <-structure(list(negativefeel = c(4,15,16), negativejudge = c(2,12,13),
positivefeel = c(3,5,6,9), positivejudge = c(1,7,8,10,11,14,17,18), itq = c(19)), .Names =
c("Negative Affect","Negative Cognition," "Positive Affect", "Positive Cognition", "Turnover
Intentions")) #Create graph structure; telling R how many groups and which columns/nodes
belong to which groups.

#################################################################
###########################Graphing the objects######################
#################################################################

JDIWCGraph<-qgraph(JDIWC, layout = "spring", vsize = 6, esize = 5, labels = jdiw, label
.cex = 4, groups = jdiwgroups) #Graphing the network. Spring indicates fructerman-reingold
algorithm. vsize indicates the size of the node. esize indicates the size of the largest
edge. label.cex indicates the scale of the label size of the nodes.

#################################################################
############################Pulling Network statistics##################
#################################################################

smallworldness(JDIWCGraph) #Pull the small world index
centrality(JDIWCGraph) #Get the centrality statistics
```

(*Appendices continue*)

Appendix D

Analysis of Additional Attitude Measures

Table D1
Statistical Indicators of Network Structure for Additional Symbolic and Instrumental Attitude Objects

Scale	Small World Index (ω)	Clustering (C)	95% CI for clustering in random network (C_{rand})	Average length (L)	95% CI for average length in random network (L_{rand})
Symbolic					
Santa Claus	**1.21**	**.66**	[.45, .50]	1.39	[1.39, 1.43]
George Washington	**1.09**	**.74**	[.61, .70]	1.42	[1.36, 1.39]
Instrumental					
Tools and resources	1.00	.84	[.84, .84]	1.14	[1.14, 1.14]
Vehicle	1.03	.81	[.75, .81]	1.21	[1.21, 1.21]

Note. $N = 559$. Numbers in boldface indicate that they are significantly higher than in a random graph.

To ensure that (a) we were correct in our hypothesis that attitude networks regarding instrumental attitude objects would not show small-worldness whereas networks regarding symbolic attitude objects would, and (b) that the number of nodes did not fully drive the findings confirming hypotheses in Samples 1, 2, and 3, in the JDI and JSS, we also collected data in Sample 1b ($N = 559$) on a variety of attitude objects.

First, we sought extremes with regard to the instrumental-symbolic distinction. For the instrumental attitude objects, we chose attitudes toward (a) the tools and resources provided by the person's workplace (8 items; α = .88), and (b) the automotive vehicle the person owns (8 items; α = .75). For symbolic attitude objects, we chose attitudes toward (a) Santa Claus (8 items; α = .74), and (b) George Washington (8 items; α = .72). As can be seen, the highest small-worldness index was for Santa Claus, $SW = 1.21$. The George Washington attitude network also showed significant small-worldness of 1.09, though weaker than the Santa Claus network. This is a sensible result considering that Santa Claus—as typically conceived—is a mythical figure, whereas George Washington is a long-deceased iconic figure. Both are highly symbolic and attitudes toward these figures are likely to serve self-expressive, social identity functions. On the other hand, significant small-worldness was not found for either of the instrumental attitude objects (see Table D1).

As can be seen in Figure D1, the attitude networks for the symbolic figures form distinct clusters that are sufficiently independent of another, with relatively moderate clustering and longer path lengths (i.e., lower connectivity) compared with the networks for instrumental attitude objects shown in Figure D2. These results are highly consistent with those found in our primary analyses. Although the network for automotive vehicle appears to approach small-worldness, this is likely due to the fact that—for some people—their automobile serves a self-expressive function. Future research should consider whether attitude networks persons endorsing the view that such objects inform their identity.

(*Appendices continue*)

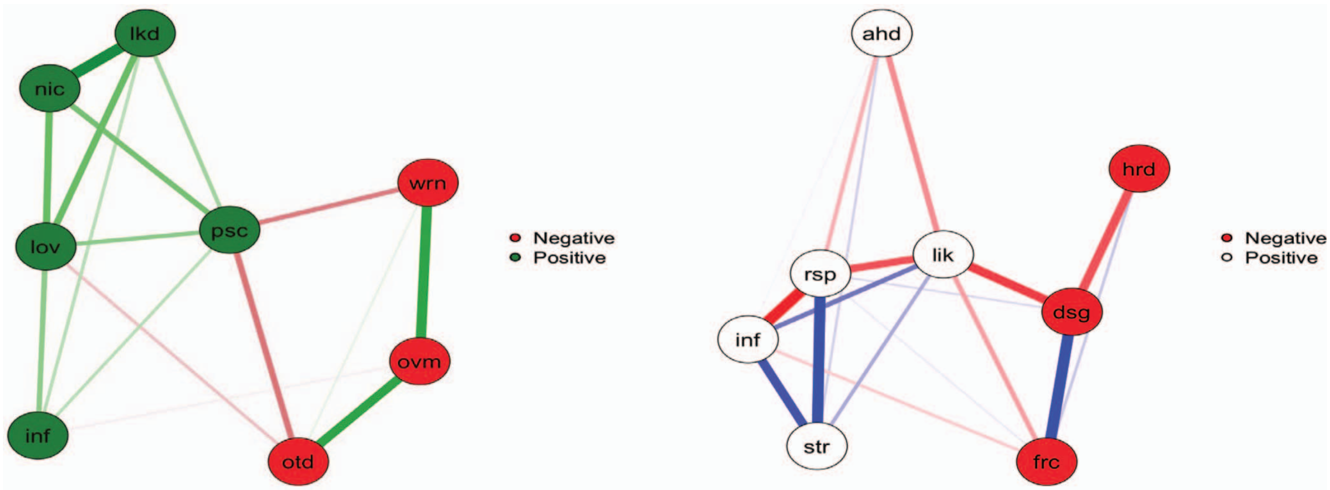

Figure D1. Attitude networks for symbolic attitude objects Santa Claus (left) and George Washington (right). See the online article for the color version of this figure.

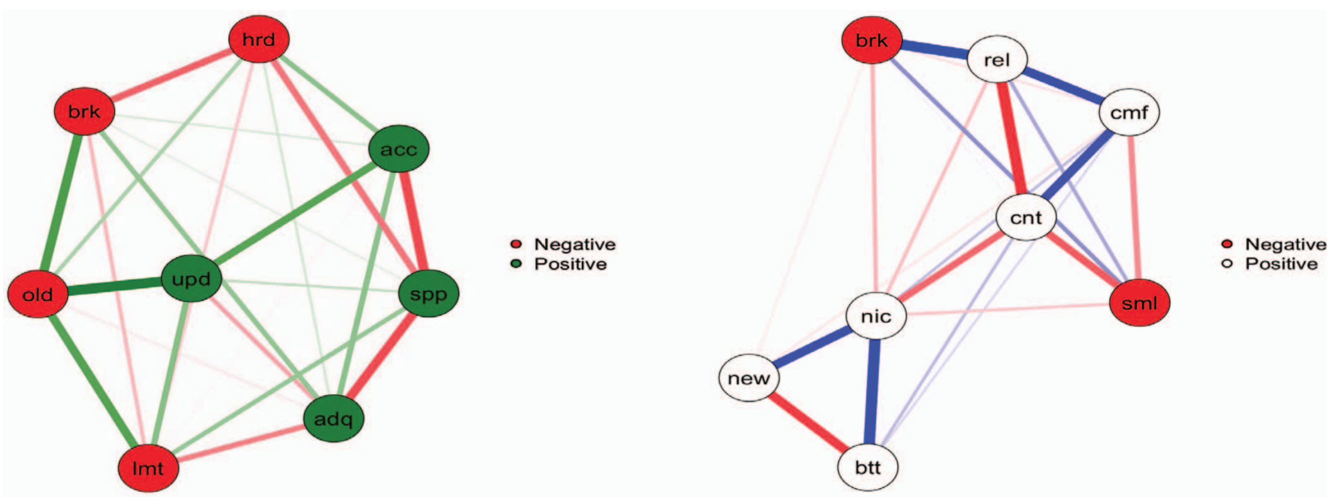

Figure D2. Attitude networks for instrumental attitude objects: tools/resources provided by work (left) and automotive vehicle (right). See the online article for the color version of this figure.

(*Appendices continue*)

Appendix E

Cross-Validation of Network and SEMs

Table E1
Predictability ($\mathcal{A}_{norm}$) in Training and Cross-Validation Datasets Predicting Voluntary Turnover

Data	2006 → 2008	2008 → 2010	2010 → 2012	2012 → 2014
Training data (80%)	.040	.000	.115	.099
Cross-validation data (20%)	.106	.000	.073	.073

In the analysis of the predictability of turnover, one reasonable concern raised by a reviewer was that the network model may only have an advantage owing to overparameterization. Indeed, the psychometric network model has many more. Indeed, the SEM has much higher *df* than its corresponding network model. This is a cause for concern, because it may be that although the model can do well at predicting turnover within the dataset upon which it was trained, it may not show such predictive efficacy in new data sets. To test this idea, we estimated—for each of the four analyses (2006 → 2008, 2008 → 2010, 2010 → 2012, and 2012 → 2014)—the prediction networks, first on 80% of the data (chosen randomly), which was utilized as the training dataset. Next, we utilized these parameter estimates to calculate how well these parameters were able to predict turnover in the remaining 20% of the dataset (i.e., the cross-validation dataset). We found that the psychometric network model still showed impressive cross-validation. Table E1 shows $\mathcal{A}_{\mathrm{norm}}$ for both the training and cross-validation data sets. Notably, for all analyses, the cross-validation $\mathcal{A}_{\mathrm{norm}}$ for the network model was higher than the $\mathcal{A}_{\mathrm{norm}}$ for the original SEM analyses (i.e., the psychometric network model performed better on a new dataset than the SEM for the dataset in which it was estimated).

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