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Toward a Formalized Account of Attitudes:
The Causal Attitude Network (CAN) Model

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This article introduces the Causal Attitude Network (CAN) model, which conceptualizes attitudes as networks consisting of evaluative reactions and interactions between these reactions. Relevant evaluative reactions include beliefs, feelings, and behaviors toward the attitude object. Interactions between these reactions arise through direct causal influences (e.g., the belief that snakes are dangerous causes fear of snakes) and mechanisms that support evaluative consistency between related contents of evaluative reactions (e.g., people tend to align their belief that snakes are useful with their belief that snakes help maintain ecological balance). In the CAN model, the structure of attitude networks conforms to a small-world structure: evaluative reactions that are similar to each other form tight clusters, which are connected by a sparser set of "shortcuts" between them. We argue that the CAN model provides a realistic formalized measurement model of attitudes and therefore fills a crucial gap in the attitude literature. Furthermore, the CAN model provides testable predictions for the structure of attitudes and how they develop, remain stable, and change over time. Attitude strength is conceptualized in terms of the connectivity of attitude networks and we show that this provides a parsimonious account of the differences between strong and weak attitudes. We discuss the CAN model in relation to possible extensions, implication for the assessment of attitudes, and possibilities for further study.

Keywords: network models, attitudes, tripartite model, connectionism, small-world

The attitude concept continues to occupy a central role in the social sciences. Not only are attitudes a core topic in social psychology; they also play an important role in economics and the political sciences (e.g., Latané & Nowak, 1994). While research on attitudes has spawned a vast literature, it has been argued that the theoretical integration of empirical findings is still limited (e.g., Monroe & Read, 2008). In particular, a realistic formalized theoretical framework is lacking that can be directly related to empirical data through statistical estimation and fitting techniques. In the

current article, we put forward such a formalized measurement model of attitudes, and argue that this model shows promise in integrating our understanding of the structural and dynamical properties of attitudes.

Any formal measurement model of attitudes needs to fulfill two basic properties. First, it must address how multiple responses on an attitude questionnaire relate to the attitude construct. Second, it must provide an explanation of the correlations among these multiple responses. Historically the most influential model of attitudes that fulfills these two basic properties has been the tripartite model of attitudes. In this model, attitudes are assumed to consist of cognitive, affective, and behavioral components (e.g., Bagozzi, Tybout, Craig, & Sternthal, 1979; Breckler, 1984; Eagly & Chaiken, 1993; Fishbein & Ajzen, 1975; Rosenberg, Hovland, McGuire, Abelson, & Brehm, 1960). Formalized accounts of the tripartite model assume that attitudes act as latent variables that cause these three components, which in turn cause specific responses to attitude questions. Due to a number of problems discussed below this view of attitudes has fallen out of vogue (e.g., Fazio & Olson, 2003a; Zanna & Rempel, 1988). However, no dominant alternative formalized measurement model of attitudes has yet replaced it. To fill this gap, the present article presents a

formalized measurement model of attitudes based around network theoretical principles.

In evaluating the tripartite model's contributions to attitude research, it is important to distinguish between how the model *describes* and *explains* attitude structure. In the descriptive sense, the tripartite model represents the basic correlational structure of responses to attitude questions: Different responses to the same attitude object are substantively interrelated. However, in the explanatory sense, the tripartite model is limited because it explains the correlations among responses to attitude questions in terms of the shared influence of a small number of latent variables. As discussed below, it is our view that such latent variable models do not offer plausible representations of the structure of attitudes in relation to formation and dynamics.

Recently developed connectionist models of attitudes, on the other hand, may better capture the dynamics of attitude formation and change (Monroe & Read, 2008; van Overwalle & Siebler, 2005). In these connectionist models, human cognition is simulated with a network of several interrelated nodes. These models provide plausible mechanistic explanations of how attitudes form and change as a result of the interplay between evaluative reactions that concern the attitude object. However, a weakness of current connectionist models of attitudes is that they are separated from the dominant statistical approaches used in the analysis of attitude data, and their relevance to empirical phenomena is thus indirect. For instance, while connectionist models are suited to address the inherent complexity of attitudes, currently implemented models rely solely on simulated data (e.g., Monroe & Read, 2008). Therefore, their description of attitudinal processes tends to be at the metaphorical level. Thus, while the tripartite model can be fitted to empirical data but relies on a substantively implausible model of attitudes, current connectionist models of attitudes provide a plausible account of attitude formation and change but cannot be fitted to empirical data.

Here we propose a new network model of attitudes that can address both the above concerns: the Causal Attitude Network (CAN) model. This model conceptualizes attitudes as networks that consist of evaluative reactions and interactions between these reactions. Relevant reactions include beliefs, feelings, and behaviors toward an attitude object. Interactions between these reactions arise through direct causal influences (e.g., the belief that snakes are dangerous *causes* fear of snakes) and mechanisms that support evaluative consistency between related contents of evaluative reactions (e.g., people tend to align their belief that snakes are useful with their belief that snakes help maintain ecological balance). In the CAN model, the structure of attitude networks is held to conform to a small-world structure (e.g., Watts & Strogatz, 1998): Evaluative reactions that are similar to each other form tight clusters, which are connected by a sparser set of "shortcuts" between them. Importantly, the CAN model allows for the application of *empirical* network models (i.e., models in which observed variables are treated as causally related nodes in a network; Schmittmann et al., 2013; van der Maas et al., 2006). Such models can be fitted to actual data, but can also deal with complex systems (Barabási, 2011) such as attitudes, and thus combine the explanatory power of connectionist approaches with empirical analyses of attitude structure. This combination allows us to derive a realistic psychometric conceptualization of attitudes.

The outline of this article is as follows. First, we discuss the current lack of formalized measurement models in the attitude literature. Second, we combine the notion of cognitive consistency, recent connectionist modeling of attitudes (Monroe & Read, 2008) and recent advancements in applying network theory in psychology (e.g., Cramer, Waldorp, van der Maas, & Borsboom, 2010; for excellent discussions of the relevance of network analysis to the social sciences in general and psychology in particular see Borgatti, Mehra, Brass, & Labianca, 2009; Westaby, Pfaff, & Redding, 2014) to derive a set of requirements for a realistic formalized measurement model of attitudes. Third, based on these requirements we develop the CAN model and discuss the proposed small-world structure of attitudes that underlies it. Fourth, we discuss the CAN model's perspective on attitude formation and structure, attitude stability and change, and attitude strength. Fifth, we discuss possible extensions of the CAN model, the model's implications for the assessment of attitudes, and some possible avenues for further study of the CAN model.

The Need for a Formalized Measurement Model of Attitudes

Attitude research was one of the first fields in psychology in which researchers developed and tested formalized measurement models (e.g., Bagozzi, 1981; Bagozzi & Burnkrant, 1979; Breckler, 1984). These models rested on the tripartite model of attitudes, which, as we noted, holds that attitudes consist of affective, behavioral, and cognitive components (e.g., Eagly & Chaiken, 1993; Fishbein & Ajzen, 1975; Rosenberg et al., 1960) and treated the components as unobservable common causes of observable variables (i.e., reflective latent variables). This conceptualization of attitudes, however, has been criticized for not being able to integrate inconsistencies between attitude and behavior, as the model assumes that behavior is part of the attitude (e.g., Cacioppo, Petty, & Green, 1989; Fazio & Olson, 2003a; Tesser & Shaffer, 1990; Zanna & Rempel, 1988). Based principally on this shortcoming, the formalized account of the tripartite model has largely fallen out of vogue despite the lack of an acceptable formalized measurement model to replace it.

Due to this omission, currently there is no satisfactory explanation for a pervasive finding across the attitude field: attitude items display a positive manifold (i.e., attitude items of the same valence are substantively positively related and attitude items of different valence are substantively negatively related; Bagozzi & Burnkrant, 1979; Bagozzi et al., 1979; Breckler, 1984; Conner, Godin, Sheeran, & Germain, 2013; Haddock, Zanna, & Esses, 1993; Kothandapani, 1971; Ostrom, 1969; van den Berg, Manstead, van der Pligt, & Wigboldus, 2005). This positive manifold is reflected in the findings that: (a) items, which assess the same component, are highly interrelated (e.g., judging snakes as dangerous, ugly); and (b) the fitted latent variables representing the components are substantively interrelated (e.g., beliefs and feelings toward snakes).

The formalized account of the tripartite model appeared to provide a parsimonious explanation of the interrelations of items and variables assessing the same component—such items are related because they depend on the same underlying component. However, adding to the former discussed critique of the tripartite model, this explanation is likely to be incorrect because it rests on

two assumptions of latent variable modeling that are improbable in the context of attitudes. First, items, or indicators, must be *locally independent* and second, items must be *exchangeable* (e.g., Bollen, 1989; Borsboom, 2008; Borsboom, Mellenbergh, & van Heerden, 2003; Cramer et al., 2010; Jöreskog, 1971).

Local independence refers to the assumption that indicators, which measure the same latent variable, have no direct causal influence on each other (e.g., two thermometers are independent when temperature is held constant; Borsboom, 2008). In the context of attitudes, this assumption is unrealistic, as it would mean that there are no interactions between evaluative reactions. As discussed later, this assumption is at odds with the notion of cognitive consistency and with the basic mechanisms of recent connectionist models of attitudes.

Exchangeability of indicators refers to the assumption that adding indicators to a questionnaire only increases reliability but does not add substantial information (e.g., adding thermometers to a perfect thermometer is superfluous; Bollen & Lennox, 1991). If a value of a person on any one of the observed indicators were measured perfectly without any error (i.e., the true score), this value would exhaustively characterize that person's position on the latent variable; thus, as soon as the true score on any one indicator is known, the other indicators cannot add independent information. In other words, the relations between true indicator scores are deterministic: The reflective latent variable model can in fact be derived from the assumption that all true indicator scores are perfectly correlated (Jöreskog, 1971). In the context of attitudes, this would mean that if a given evaluative reaction (e.g., a given belief toward a presidential candidate) truly changes (i.e., change caused by the underlying latent variable), the other evaluative reactions, which belong to the same attitude component (e.g., all other beliefs toward the presidential candidate), have to change the exact same amount. All other variation is attributed to random error. In our view, such an account of attitudes is much too restrictive and not in accordance with views that emphasize internal inconsistencies within attitudes (e.g., Newby-Clark, McGregor, & Zanna, 2002; Thompson, Zanna, & Griffin, 1995; van Harreveld, van der Pligt, & de Liver, 2009).

If one is to reject the idea that beliefs, feelings, and behaviors regarding an attitude object reflect underlying attitude components, the question arises as to how such evaluative reactions relate to the attitude concept. The currently prevalent view holds that beliefs, feelings, and behaviors represent different classes of channels through which attitudes are formed (e.g., Zanna & Rempel, 1988).[1] As Fabrigar, MacDonald, and Wegener (2005, p. 82) state:

> . . . the contemporary view holds that an attitude is an entity distinguishable from the classes of affect, behavior, and cognition. An attitude, therefore, does not consist of these elements, but is instead a general evaluative summary of the information derived from these bases (Cacioppo et al., 1989; Crites, Fabrigar, & Petty, 1994; Zanna & Rempel, 1988).

This perspective on attitudes also forms the basis for Fazio's (1995, 2007) influential account of attitudes, in which attitudes are defined as associations between an attitude object and a summary evaluation. According to Fazio (1995, 2007), this summary evaluation is derived from cognitive, affective, and/or behavioral information.

Conversely, the view that attitudes are *causes* of cognition, affect, and behavior can also be found in current theorizing. This view is, for example, expressed by Eagly and Chaiken (2007), who state that "Attitude is . . . a tendency or latent property of the person that gives rise to judgments as well as to many other types of responses such as emotions and overt behaviors" (p. 586).

To summarize, current theorizing on the relation between evaluative reactions and attitudes holds that attitudes can be formed by cognition, affect, and behavior and that attitudes in turn also influence cognition, affect, and behavior. A formal model of attitudes should thus integrate this bidirectional influence between the components of attitudes and the attitude itself. Such a model should furthermore integrate the pervasive finding that evaluative reactions are generally substantively positively interrelated (e.g., Bagozzi & Burnkrant, 1979; Breckler, 1984; Conner et al., 2013; Haddock et al., 1993; Kothandapani, 1971; Ostrom, 1969; van den Berg et al., 2005).

From Cognitive Consistency to Network Models

In this section, we discuss the notion of cognitive consistency and use this notion to derive a formalized measurement model of attitudes. In contrast to the formalized conceptualization of the tripartite model of attitudes, which assumes that correlations between evaluative reactions are spurious, we propose that the correlations between evaluative reactions are meaningful because they stem from direct interactions between the evaluative reactions. Through these interactions the attitude construct is formed.

The notion of cognitive consistency plays a central role in both classic and contemporary theorizing in social psychology (Gawronski, 2012; Gawronski & Strack, 2012). Both Heider's balance theory (1946, 1958) and Festinger's (1957) cognitive dissonance theory make the assumption that humans have a basic need for consistency between their cognitions. Consistency theories also extend to the notion that feelings and beliefs should also be at least somewhat consistent (i.e., affective-cognitive consistency; Rosenberg et al., 1960) and that people are motivated to reduce inconsistencies within their attitudes (e.g., van Harreveld et al., 2009). Consistency theories thus assume that evaluative reactions have a tendency to align with each other.

Recently, the mechanism of parallel constraint satisfaction was used to implement a formalized conceptualization of cognitive consistency in a connectionist model of attitudes (Monroe & Read, 2008). Parallel constraint satisfaction in the context of attitudes holds that beliefs impose constraints on other beliefs. For example, if two beliefs are positively connected and one of the beliefs becomes activated, the other belief is likely to become activated as well. On the other hand, if two beliefs are negatively connected and one belief becomes activated, activation of the other belief is subsequently inhibited. Whenever the attitude object is activated in working memory, the associated beliefs self-organize in such a way that the constraints are more and more satisfied (i.e., become

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[1] This view on attitudes is more related to formative factor models, in which the indicators cause the construct (e.g., Bollen & Lennox, 1991). We refrain from discussing such models in detail, because formative factor models do not make any assumptions on the correlational pattern between the measurements (e.g., Schmittmann et al., 2013) and are therefore of limited use as measurement models.

more consistent). The system thus strives for an optimized representation of the attitude object.

Using simulation studies, it was shown that the model built on the mechanism of constraint satisfaction can account for several well-known empirical findings on attitudes (e.g., thought-induced attitude polarization, systematic vs. heuristic processing, implicit attitude processes; Monroe & Read, 2008). In addition to the insights from cognitive consistency theories, parallel constraint satisfaction further establishes that the need for consistency is a driving factor in attitude formation and change (see also Holyoak & Simon, 1999; Simon & Holyoak, 2002; Simon, Krawczyk, & Holyoak, 2004; Shultz & Lepper, 1996; Simon, Snow, & Read, 2004).

To derive a measurement model of attitudes that integrates the above-discussed notions of consistency and optimization, we use *empirical* network models that have recently been applied to research on clinical disorders and personality (Borsboom & Cramer, 2013; Cramer et al., 2012; Cramer et al., 2010). In empirical network models, relations between observed variables are not assumed to reflect an underlying factor as, for example, general intelligence, major depression, or in the current discussion, an attitude (Borsboom, 2008; Cramer et al., 2010; van der Maas et al., 2006). Rather, relations between variables are assumed to stem from a network of causally related variables. The relation between, for example, judging snakes as dangerous and as ugly arises through a direct causal connection between the judgments in order to make the attitude more consistent.

A network is a system of such interrelated variables. Some of these variables are directly connected and others only indirectly connected through other variables. While judging snakes as ugly is probably directly related to judging snakes as dangerous, judging snakes as ugly might cause fear of snakes only through also judging snakes as dangerous. As long as the variables in a network are all connected at least indirectly, information can flow from one variable to all other variables in a network. The variables in the network thus all align to some extent (i.e., they become correlated), so that the variables can be regarded as parts of the same system.[2]

A fundamental difference between latent variable models and empirical network models concerns the causal power of observable variables. In latent variable models, observable variables have virtually no causal power, as all causation flows from the latent variable to the observable variables. Empirical network models allow for more causal power of observable variables. From a network perspective, observable variables are not merely indicators of a psychological construct—the construct is isomorphic to the observable variables and their causal connections. From this perspective, the attitude construct is isomorphic to evaluative reactions toward a given attitude object and the interactions among those evaluative reactions (i.e., the whole network of the evaluative reactions and the interactions between these reactions represents the attitude construct). It then follows that observable variables are part of the construct and therefore can influence the construct (i.e., the whole system of the causally connected variables) and the construct can also influence the observable variables. For example, judging a snake as dangerous influences the system of the attitude toward snakes through its causal connections to the other evaluative reactions but is also influenced by the system of the attitude through these causal connections. Judging

snakes as dangerous can thus both (to some extent) be a cause of a negative attitude toward snakes and also a result or expression of a negative attitude.

Network models are furthermore equally well suited to explain interrelations between observable variables as latent variable models are. Several simulations that aimed to explain the positive manifold of intelligence subtests with a network model showed that networks can shape data that resembles different factor analytic findings (van der Maas et al., 2006).

By combining insights from cognitive consistency theories, connectionist models of attitudes and empirical network models, we derive two main requirements for a measurement model of attitudes. First, correlations between evaluative reactions stem from pairwise interactions between the reactions and, second, these interactions are aimed at optimization of the consistency of the evaluative reactions. These two requirements are readily fulfilled by the recently proposed application of the Ising model (Ising, 1925) to psychological data (Epskamp, Maris, Waldorp, & Borsboom, in press; van Borkulo et al., 2014). The Ising model belongs to the class of Markov Random Field models used in network analysis and constitutes the Markov Random Field for binary data (Kindermann & Snell, 1980). Originating in statistical physics, the Ising model has been applied in several research areas. The interested reader is referred to Epskamp et al. (in press) for a thorough discussion of the Ising model.

In the Ising model, nodes can be of two states (-1, 1; Kindermann & Snell, 1980). These nodes can represent all kinds of objects that can be in two states (van Borkulo et al., 2014). For example, dipoles of a magnet that are either in "spin up" or "spin down," neurons that either fire or not fire, psychopathological symptoms that are either present or absent, or evaluative reactions that are endorsed or that are not endorsed. Each node in a network is connected to a given number of neighboring nodes and these connections can be either positive or negative. If the connection between two nodes is positive then two neighboring nodes will be pressured to assume the same state and if the connection is negative then the two nodes will be pressured to assume the opposite states. The connections can also vary in strength. Because of the connections between the nodes, the first requirement of a measurement model of attitudes—pairwise interactions between evaluative reactions—is fulfilled.

The second requirement of a measurement model of attitudes— optimization of consistency—is fulfilled by the axiom of the Ising model that the system strives to reduce energy expenditure. In a given Ising model, configurations of the system that cost a lot of energy to maintain are less likely than configurations that cost less energy. Inconsistent attitudes therefore cause much energy expenditure and the system will strive to reduce this inconsistency. Given two positively connected nodes, the configurations in which both nodes are either positive ($+1$, $+1$) or negative (-1, -1) are thus more likely than the configurations in which the nodes are not

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[2] One might object that alignment of variables suggests some exchangeability between the variables. To the extent that they share variance, this objection is correct. However, variables seldom perfectly align and are therefore also not completely exchangeable in terms of shared variance. Furthermore, even if two variables perfectly align for some time, this does not exclude the possibility that they are influenced by different factors at other times.

aligned [(+1, −1), (−1, +1)], as the latter configuration costs more energy to maintain. The extent to which the unaligned configurations cause energy expenditure depends on the strength of the connection between the nodes.

To summarize, the Ising model represents a promising conceptualization of attitudes as this conceptualization readily integrates both interactions between evaluative reactions and the need to maximize cognitive consistency. In the next section, we present the specifics of the Causal Attitude Network (CAN) that implements this conceptualization.

The Causal Attitude Network (CAN) Model

In the CAN model, attitudes are conceptualized as networks of interacting evaluative reactions (e.g., feelings, beliefs, and behaviors toward an attitude object) and the dynamics of the networks conform to the Ising model. Evaluative reactions are represented as *nodes* in the networks and causal influences between these reactions are represented as *edges* (i.e., links between the nodes). Edges can represent either excitatory or inhibitory influence and can have varying weights (i.e., the causal influence between evaluative reactions varies). Attitude networks strive for an optimized consistent representation of the attitude object to reduce energy expenditure. To acquire a consistent state, evaluative reactions of the same valence generally have excitatory influence between them and evaluative reactions of different valence generally have inhibitory influence between them.

However, as individuals are also motivated to hold at least somewhat accurate attitudes (e.g., Chaiken, Liberman, & Eagly, 1989; Petty & Cacioppo, 1986), optimization is bound by the motivation to have an accurate attitude. While striving only for consistency would lead to perfectly aligned evaluative reactions, striving only for accuracy can, in some instances, lead to completely unaligned evaluative reactions. To deal with this trade-off between optimization of consistency and accuracy, attitude networks are proposed to show clustering (i.e., different sets of evaluative reactions are highly interconnected). Clustering allows for energy reduction within clusters (e.g., all evaluative reactions toward a person that pertain to the dimension of warmth are highly aligned) but also allows for accuracy by having unaligned or even misaligned clusters that do not cost much energy (e.g., the evaluative reactions that pertain to the dimension of warmth are not highly aligned to the evaluative reactions that pertain to the dimension of competence).

The trade-off between optimization of consistency and accuracy is somewhat reminiscent of the trade-off between effort and accuracy in decision-making (e.g., Payne, Bettman, & Johnson, 1988, 1993). Noteworthy from the line of research on the trade-off between effort and accuracy is that in many scenarios decision-strategies that do not require much effort (e.g., heuristics) fare equally well or even better than decision-strategies that require much effort (e.g., Payne et al., 1988; Gigerenzer, Todd, & the ABC Research Group, 1999). This might indicate that also in the case of attitudes, a representation that optimizes the trade-off between consistency and accuracy might be the most adaptive representation.

Attitude Formation and Structure

From the perspective of the CAN model, attitudes start out with one or just a few specific evaluative reactions. These first reactions then serve as a model for the person to predict which other characteristics the attitude object might have. This is in accordance with the free-energy principle, which holds that humans need to make inferences from learned information to derive predictions (Friston, 2009; Friston, Daunizeau, Kilner, & Kiebel, 2010). Then, also in line with the free-energy principle, information is sought that conforms to this prediction (see also Hart et al., 2009 for a meta-analysis that indicates that individuals generally prefer information that supports their attitudes). Evaluative reactions therefore cause readiness of other evaluative reactions. However, this readiness is not deterministic as it is also possible that no confirming information is found. Such a situation is likely to arise when individuals are highly motivated to be accurate, which lowers their preference for information that supports their attitudes (Hart et al., 2009).

As individuals are motivated to make correct inferences, it is likely that the strength of the readiness depends on the similarity of the reactions because correct inferences are more likely to be made for similar evaluative reactions. For example, two judgments that pertain to the dimension of warmth (e.g., friendly and sincere) would cause more readiness of each other than two judgments that pertain to different dimensions (e.g., friendly and competent; cf. Fiske, Cuddy, Glick, & Xu, 2002). Reactions from different attitudinal components are also generally less similar than reactions from the same component and are therefore also generally less closely connected. Another factor that makes it more likely that an evaluative reaction causes readiness for another evaluative reaction is that the evaluations share the same valence because evaluations of differing valence can behave relatively independent of each other (Cacioppo & Berntson, 1994). Connecting this line of reasoning to research on the development of networks, a recent study showed that nodes that make new connections are more likely to connect to similar nodes than to less similar nodes (e.g., a U.S. web page is more likely to connect to another U.S. web page than to a Russian web page; Papadopoulos, Kitsak, Serrano, Boguñá, & Krioukov, 2012).

Another factor of importance in the attachment of new nodes to the network is the popularity of the nodes (i.e., how many connections a node already has; Barabási & Albert, 1999). This means that nodes are more likely to connect to nodes that already have many connections (a phenomenon known as preferential attachment). In the case of attitudes, this would mean that evaluative reactions that already have many connections are more likely to lead to the activation of additional evaluative reactions. The proposed mechanism behind this effect is that evaluative reactions that are strongly connected already have proven to be predictive in the *past*, which makes such evaluative reactions more likely to cause readiness of other evaluative reactions in the *present*.

Let us illustrate how attitude networks might take shape using the example of someone, say Bob, developing a positive attitude toward Barack Obama during the American presidential election campaign of 2008. First, Bob formed the impression of Obama being an honest person. Quickly after forming this initial simple impression, Bob also formed similar judgments about Obama, such as judging him as a moral person who cares about people like Bob. The formed judgments hold each other in check, so that none of these judgments can readily change without inflicting some change on the other judgments. This already constitutes a small network, see Figure 1a.

After Bob has thought a bit more about Obama, he also extended his judgment to other dimensions and came to the conclusion that Obama is also intelligent and competent and that he will probably be a good leader. These judgments form a new cluster but are also
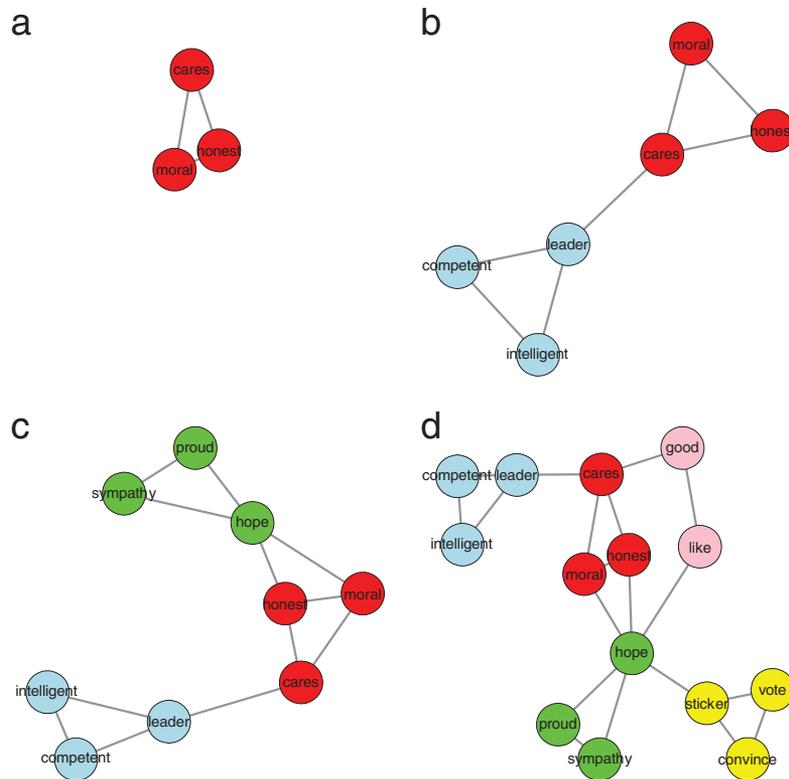
Figure 1. Hypothetical attitude network at four points in time (a–d). Nodes represent evaluative reactions and edges represent causal influence between the evaluative reactions. Note that for reasons of simplification, all edges represent excitatory influence and all edges have the same strength. The layouts of these graphs are based on the Fruchterman-Rheingold algorithm (Fruchterman & Reingold, 1991), which places closely connected nodes near each other. As all networks shown in this article, this network was created using the R-package qgraph (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). See the online article for the color version of this figure.

to some extent linked to the other judgments through the connection between judging Obama as a good leader and judging him to care about people like Bob, as Bob thinks that this is a crucial aspect of being a good leader. The attitude network has thus grown and now consists of two *clusters* (i.e., set of nodes that are highly interconnected), which are connected by a *shortcut*, see Figure 1b. The reason that this edge represents a shortcut is that removing this edge would substantially decrease the global connectivity (i.e., average connectivity of each node with all other nodes; West, 1996) of Bob's attitude network (Watts, 1999). In the current example, removing the edge between judging Obama as caring and judging Obama to be a good leader would result in Bob's attitude network no longer being fully connected.

At some point, Bob also had evaluative reactions of a more affective nature toward Obama. Because he judged Obama as honest and moral, he also started to feel hopeful toward Obama and this in turn caused him to feel proudness and sympathy toward him (see Figure 1c). Again, these different affective reactions cannot change without exerting some pressure to change on the other affective reactions. Furthermore, Bob's feeling of hope toward Obama and his judgments that Obama is honest and moral are closely connected, so that when one of these evaluative reac-

tions increases or decreases, the other reactions will also more readily increase or decrease.

Due to his already very positive attitude, Bob also started to convince other people to vote for Obama, he placed a sticker on his car saying "Vote Obama" and, of course, at the election he voted for Obama. From the more specific evaluative reactions toward Obama, more general evaluations subsequently emerged. For example, Bob would state that he likes Obama and that he generally sees him as a good person. These new clusters attached to the evaluative reactions of judging Obama as caring and feeling hopeful toward Obama due to the popularity (i.e., number of connections) of these evaluative reactions (see Figure 1d).

As the above example illustrates, attitude networks are expected to show a structure with high clustering, in which these clusters are connected through shortcuts. Through these shortcuts, attitude networks have high global *connectivity* (i.e., all nodes on average are closely connected to each other). The combination of high clustering and high connectivity is known as a small-world structure (Albert & Barabási, 2002; Watts & Strogatz, 1998). The formalized definition of small-world networks holds that such networks have a higher clustering than a random graph (i.e., network in which the nodes are randomly connected) but about the

same connectivity as a random graph. For example, the network shown in Figure 1d has a clustering index almost three times as high ($C = .59$) as the clustering index of a corresponding random graph ($C = .21$) but only a slightly higher average shortest path length ($L = 2.74$) than the corresponding random graph ($L = 2.33$), implying slightly lower connectivity. For all network-based calculations in this article, we used either the R-package qgraph (Epskamp et al., 2012) or the R-package igraph (Csárdi & Nepusz, 2006).

The small-world structure has been observed for several networks from distinct areas of research. For example, small-world structures have been found for the power grid of the western United States; collaboration between film actors; neural networks of worms (Watts & Strogatz, 1998), monkeys (e.g., Stephan et al., 2000), and humans (e.g., Achard, Salvador, Whitcher, Suckling, & Bullmore, 2006); human language (Ferrer-i-Cancho & Solé, 2001); and symptoms of psychological disorders (Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011).

To provide a first test of the hypothesis that attitude networks have a small-world structure, we used the American National Election Study (ANES) of 1984 (see the Appendix for a detailed description of the data set). In the ANES of 1984, evaluative reactions toward the presidential candidates were assessed in a nationwide random sample of 2,257 participants. Participants were asked whether or not they attributed several positive characteristics to each candidate (e.g., whether the candidate is a decent, intelligent or a moral person) and whether they had ever had positive or negative feelings toward each candidate (e.g., feelings of hope or anger). We used the participants' responses toward these evaluative reactions to estimate attitude networks for the attitudes toward each presidential candidate.[3]

To estimate attitude networks, we used the eLasso-procedure, which is designed to find the optimal Ising model for a set of data by regressing each variable on all other variables (van Borkulo et al., 2014). The regression function is subjected to regularization to control the size of the statistical problem (see Friedman, Hastie, & Tibshirani, 2008; Tibshirani, 1996). For each node, the set of edges that displays the best fit to the data is selected based on the fit of the regression functions according to the Extended Bayesian Information Criterion (Chen & Chen, 2008). Weights of the edges are then based on the regression parameters in the selected neighborhood functions (van Borkulo et al., 2014).[4]

We then calculated the small-world index for the unweighted networks (Humphries & Gurney, 2008). A small-world index higher than one indicates that the network has a small-world structure. To test whether the small-world index was significantly higher than one, we calculated confidence intervals using 1,000 Monte-Carlo simulations of random graphs (Humphries & Gurney, 2008).

The estimated networks are shown in Figure 2. The network of the attitude toward Ronald Reagan had a small-world index of 1.16 and the upper limit of the 99.9% confidence interval for the corresponding random graphs was 1.13 ($C_{attitude\ network} = .62$, $L_{attitude\ network} = 1.47$, $C_{random\ network} = .53$, $L_{random\ network} = 1.47$). The network of the attitude toward Walter Mondale had a small-world index of 1.25 and the upper limit of the 99.9% confidence interval for the corresponding random graphs was 1.19 ($C_{attitude\ network} = .57$, $L_{attitude\ network} = 1.55$, $C_{random\ network} = .46$, $L_{random\ network} = 1.54$). Both networks thus had a small-world

structure. Apart from the global structure, it can also be seen that similar evaluative reactions are more closely connected than dissimilar evaluative reactions. For example, both positive and negative feelings form distinct clusters (see Figure 2). Also, judgments that pertain more to the warmth-dimension (e.g., the candidate is fair, cares about people and is compassionate) and judgments that pertain to the competence-dimension (e.g., the candidate is intelligent, knowledgeable, and hardworking) are each closely connected to each other.

To summarize, the CAN model holds that evaluative reactions cause readiness of related evaluative reactions to the same attitude object and through this process attitude networks take shape. Similar evaluative reactions tend to cluster and these clusters are connected by shortcuts, which give rise to the small-world network structure of attitudes. Having discussed the formation and structure of attitude networks we now turn to the implications of the CAN model for change and stability in formed attitudes.

Attitude Stability and Change

After an attitude network has formed, the CAN model suggests that different evaluative reactions tend to hold each other in check. While in the formation phase of an attitude, the influence of evaluative reactions on other evaluative reactions is unidirectional, evaluative reactions in formed attitude networks probably have bidirectional influence on each other. The reason for this is that an evaluative reaction B that was activated by another evaluative reaction A will also cause further readiness in evaluative reaction A. As an example let us return to Bob's attitude network. After having formed the judgment that Obama cares for people like Bob *because* he earlier judged Obama to be honest, judging Obama as caring also serves as a model of how honest Obama is. So, if Bob observes an incident that strengthens his judgment of Obama as caring, his judgment of Obama being honest will also strengthen to some extent.

While we have discussed attitude formation and the behavior of formed attitudes in isolation, the distinction between these two phases of attitudes will not be that clear-cut in reality. New nodes

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[3] The reason that we analyzed the ANES of 1984 instead of any other ANES is that the number of assessed evaluative reactions was the largest in the ANES of 1984. As the evaluative reactions are represented as nodes, the size of the network (i.e., number of nodes) depends on the number of assessed evaluative reactions. As the small-world index linearly increases with the size of the network in small-world networks (Dunne, Williams, & Martinez, 2002; Humphries & Gurney, 2008), the power to detect a small-world structure is higher for the ANES of 1984 than for any other ANES. Note, however, that the size of the estimated networks based on the ANES of 1984 is still relatively small.

[4] Note that also other methods than the eLasso-procedure can be used to estimate networks from psychometric data (e.g., Costantini et al., 2015). Two common practices involve estimating edges by using zero-order correlations or using partial correlation between any given pair of the nodes in the network while controlling for all other nodes (e.g., Cramer et al., 2013; Cramer et al., 2010). The eLasso-procedure, however, has clear advantages compared with these procedures. First, the eLasso-procedure provides an estimation of the causal structure underlying the data, which zero-order correlations do not. Second, the eLasso-procedure produces less false positives than does using partial correlations (Costantini et al., 2015). The reason for that is that the eLasso-procedure uses regularization, which reduces the number of false positives. In fact, simulation studies have shown that the eLasso-procedure has very high specificity (van Borkulo et al., 2014).
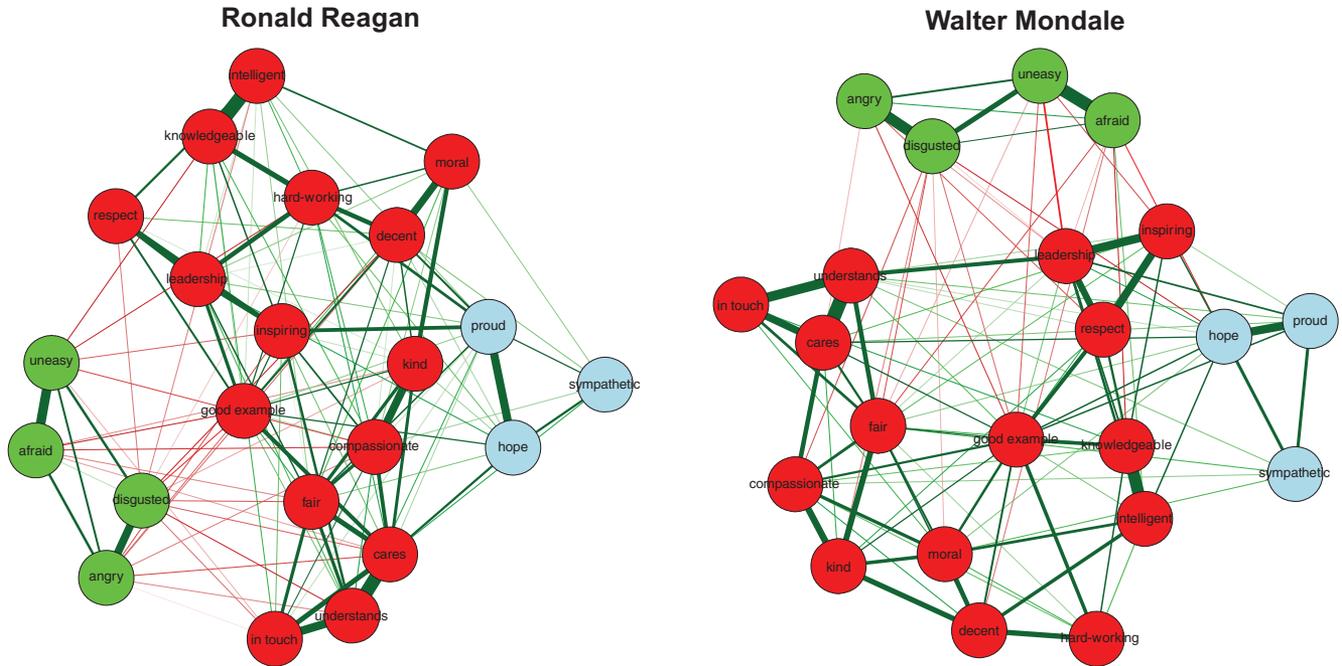
Ronald Reagan

Walter Mondale

Figure 2. Estimated attitude networks toward the two main candidates in the U.S. presidential election in 1984. Red (gray) nodes represent positive judgments, blue (light gray) nodes represent positive feelings, and green (dark gray) nodes represent negative feelings (see the Appendix for the complete wording of the items). Green (solid) edges indicate excitatory influence between the nodes and red (dashed) edges indicate inhibitory influence between the nodes. Thicker edges represent higher weights of the edges. The same algorithm as for Figure 1 was used for the layout of these graphs. See the online article for the color version of this figure.

and new connections will probably be formed continuously and the extent of this likely depends on how often a person interacts in some way with the attitude object. We discuss this point further in the section on the relation between attitude strength and network connectivity.

Apart from implications for attitude stability, conceptualizing attitudes as networks also has implications for attitude change. The most straightforward implication of conceptualizing attitudes as networks for attitude change is that attitudes can be changed via a plethora of different processes as each node in the attitude network can serve as a gateway to instigate change in the network. Looking back at Figure 1d, change in the network could, for example, be instigated by cognitive dissonance (e.g., Bob did not vote for Obama because of minor situational constraints and because of this a more negative evaluation spread through the network; cf., Festinger, 1957), evaluative conditioning (e.g., pairing Obama with images related to hope through which an even more positive evaluation spread through the network; cf., De Houwer, Thomas, & Baeyens, 2001; Jones, Olson, & Fazio, 2010) or by presenting arguments (e.g., a friend convinces Bob that Obama is not so competent after all from which again a more negative evaluation spread through the network).

Whether the state of the targeted evaluative reaction changes (e.g., from +1 to −1), however, is a function of not only the strength of external pressure but also of the state of the neighboring nodes and the strength of the links between the targeted node and the neighboring nodes. If a single node changes to a state that

is incongruent to its links with neighboring nodes, the energy expenditure of the system rises. The amount of energy expenditure of a given configuration is calculated using the Hamiltonian function $H(\chi)$:

$$H(\chi) = -\sum_i \tau_i \chi_i - \sum_{i,j} \omega_{i,j} \chi_i \chi_j, \qquad (1)$$

where τ_i is the threshold of any given evaluative reaction χ_i and represents the disposition of the given evaluative reaction to be endorsed (1) or not endorsed (−1). A threshold higher than 0 indicates that the probability of the given evaluative reaction to be endorsed is higher (given the absence of any influence of neighboring evaluative reactions) than the probability that the evaluative reaction is not endorsed. Conversely, a threshold lower than 0 indicates that the probability of the given evaluative reaction to be endorsed is lower than the probability that the evaluative reaction is not endorsed.

$\omega_{i,j}$ is the weight of the interaction between χ_i and its neighboring evaluative reaction χ_j. A weight higher than 0 indicates that that the interaction between two evaluative reactions is positive (e.g., if one evaluative reaction is endorsed, the probability that the other evaluative reaction is endorsed heightens). Conversely, a weight lower than 0 indicates that that the interaction between two evaluative reactions is negative (e.g., if one evaluative reaction is endorsed, the probability that the other evaluative reaction is endorsed lowers).

The probability of a given configuration can be calculated with the following equation:

$$Pr(X = \chi) = \frac{1}{z}\exp(-H(\chi)), \qquad (2)$$

where Z is the normalizing constant that guarantees that the probabilities sum to 1 and is given by:

$$Z = \sum_{\chi}\exp(-H(\chi)) \qquad (3)$$

To acquire a consistent state, weights between the evaluative reactions of the same valence (e.g., honest and fair) have to be positive and weights between evaluative reactions of different valence have to be negative (e.g., honest and mean). The strength of the weights is a function of the amount of interaction with the attitude object (Monroe & Read, 2008) and the similarity of the evaluative reactions.

The CAN model holds that the threshold depends on several factors, implying that evaluative reactions differ in their disposition to be endorsed. While a high threshold indicates that a given evaluative reaction has a disposition to be endorsed, a low threshold indicates that a given evaluative reaction has a disposition to be not endorsed (see Equation 1). First, some evaluative reactions are likely to have inherently higher thresholds than other evaluative reactions. For example, some emotions are experienced more frequently (e.g., joy, anger) than others (e.g., euphoria, contempt; Schimmack & Diener, 1997) and are therefore likely to have higher thresholds. Second, thresholds of different persons probably also vary. For example, persons differ in their disposition to adopt negative or positive attitudes (Eschleman, Bowling, & Judge, 2015; Hepler & Albarracín, 2013). Third, whether one has endorsed (not endorsed) an evaluative reaction in the past will probably also heighten (lower) the threshold of this evaluative reaction in the future, implying that the evaluative reaction is more likely to be endorsed (not endorsed) in the future. This postulate is based on the finding that rehearsal of attitudes results in the strengthening of attitudes (e.g., Fazio, 1995). Fourth, external persuasion attempts might also affect the threshold of a given evaluative reaction. One route to change an attitude would thus be to change the threshold of evaluative reactions.

Let us return to Bob to illustrate how an attitude network would be affected if the threshold of an evaluative reaction were to change as a result of a persuasion attempt. For simplification, we will only look at the cluster of the evaluative reactions that Obama is competent, intelligent, and a good leader. Let us assume that the thresholds before the persuasion attempt were all equal to .3 and that the weights between all evaluative reactions were all equal to .5. These represent moderately high thresholds and weights (using uniform weights and thresholds is a simplification, as these parameters are likely to vary in real attitude networks, a point we address later).

The persuasion attempt on Bob's attitude was directed at the evaluative reaction that Obama is competent and the attempt was quite strong. Because of this, Bob's threshold of judging Obama as honest dropped to −.3. We can now calculate the energy that each of the configurations will cost and how probable each configuration is. As can be seen in Table 1, the configuration in which all three evaluative reactions are endorsed, is the most likely configuration. The most likely scenario for this illustration is thus that, while the persuasion attempt was quite strong, Bob will still think of Obama as competent. This illustrates our point that the success

Table 1

All Possible Configurations of the Evaluative Reactions Competent, Good Leadership, and Intelligent and Their Associated Energies and Probabilities

Competent	Good leader	Intelligent	$H(\chi)$	$Pr(X = \chi)$
−1	−1	−1	−1.2	.24
1	−1	−1	1.4	.02
−1	1	−1	.2	.06
1	1	−1	.8	.03
−1	−1	1	.2	.06
1	−1	1	.8	.03
−1	1	1	−.4	.11
1	1	1	−1.8	.44

Note. Competent has a threshold of −.3 and good leader and intelligent have thresholds of .3, respectively. All weights between the evaluative reactions are equal to .5.

of a persuasion attempt not only depends on the strength of the persuasion attempt but also on the parameters of the attitude network. It is also important to note that it is more probable that evaluative reactions will become uniformly negative after the persuasion attempt, than that the judgment of Obama as competent will change in isolation. This leads to a testable prediction of the CAN model: If one evaluative reaction changes and this change persists, other evaluative reactions are also likely to change.

Changes in the threshold of a given node can be interpreted as rather subtle attitude change. Such changes can, for example, arise if arguments are presented that make one doubt one's current evaluation. However, there might also be situations, in which one not only doubts one's current evaluation but discards it completely. Such attitude change could be modeled by fixing one of the nodes to a given state. This would be the case if, for example, Bob were to receive information which would make it impossible to remain viewing Obama as competent. In this event, only the configurations in which judging Obama as competent is not endorsed feed into Equation 3. As a result, the configuration in which none of the positive evaluative reactions are endorsed becomes the most likely scenario.

While up to this point we have discussed how attitude change takes place in a network, in which all nodes are uniformly connected to each other, nodes in real attitude networks will differ in their connectivity. This can be seen in both the hypothetical attitude network of Bob and the estimated networks of the ANES data. How a given node is connected in the network will influence whether and how change in this node will spread to other nodes. Connecting attitude change to the small-world structure of attitudes, the first important implication of network structure for attitude change is the existence of clusters within the network. As can be seen in Figure 2, negative feelings toward the presidential candidates form rather distinct clusters in both attitude networks. If a node in this cluster were to be changed, this change would mostly spread to other nodes in this cluster.

If the different clusters in an attitude network were not strongly connected, configurations of the network, in which clusters do not align to the same evaluation, would cost rather low energy. Because of this, even an attitude network consisting of clusters that are not aligned to each other can be relatively stable. Even misaligned clusters might cause low energy when the weights between

the clusters are lower than the inconsistent thresholds of the different clusters. For example, if both negative feelings and positive beliefs in the attitude network toward Ronald Reagan had highly positive thresholds and the (negative) weights between the clusters were low, having both negative feelings and positive beliefs toward Ronald Reagan would not cause much energy expenditure.

Apart from belonging to different clusters, nodes can also differ in their *centrality*. Centrality refers to the structural importance of a given node in the network and three of the most popular centrality measures are *betweenness*, *degree*, and *closeness* (Freeman, 1978; Opsahl, Agneessens, & Skvoretz, 2010). Betweenness refers to how often a node lies in the shortest path between two other nodes. The shortest path between two nodes is defined as the shortest distance it takes to "travel" between two nodes over the edges in the network. The distance is a function of both the number and strength of the edges that lie between two nodes.

Betweenness can be linked to the notion of clustering, as nodes that connect different clusters will generally have high betweenness. If change affects one cluster of the attitude network, whether the change will spread through the whole network depends on the behavior of the nodes that connect this cluster to other parts of the network. In the network of the attitude toward Ronald Reagan, the node with the highest betweenness is the evaluative reaction of whether he sets a good example. As can be seen in Figure 2, this node is rather closely connected to the negative affect cluster. Thus, whether change in the negative affect cluster would spread through the network would depend on whether you change your mind that Ronald Reagan sets a good example.

Degree is a function of the number of neighbors a given node has and of the weights of the edges between the given node and its neighbors (Freeman, 1978). Degree thus refers to how strongly a given node is *directly* connected to all other nodes in the network. Closeness is the inverse of the shortest path length between a given node and all other nodes in the network and thus refers to how strongly a given node is both *directly and indirectly* connected to all other nodes in the network.

While a node with high degree and/or high closeness is very unlikely to change independent of change in the whole network and vice versa, a node with low degree and low closeness can change rather independently of the other nodes in the network. Therefore, it will be more difficult to change nodes with high degree and/or high closeness than nodes with low degree and low closeness. If change, however, takes place, it will be more consequential if it takes place in a node with high degree and/or closeness than when it takes place in a node with low degree and low closeness. For example, the evaluative reaction with both the highest degree and highest closeness in the network of the attitude toward Ronald Reagan is the judgment of whether he cares about people like oneself. It is thus likely that it would be very difficult to change this judgment but that change in this judgment would affect the attitude network to a large extent.

To summarize, different routes of attitude change can be integrated in the CAN model. First, subtle attitude change can be modeled by decreasing or increasing the threshold of a given node and drastic attitude change can be modeled by fixing a given node to a given state. Attitude change will also depend on the position of the targeted evaluative reaction in the attitude network. Change of an evaluative reaction will first spread to evaluative reactions that belong to the same cluster and the extent to which an attitude network will be affected by change in a single evaluative reaction will depend on the centrality of the evaluative reaction. While highly central evaluative reactions will be likely to resist change, their change will also be more consequential than change in an evaluative reaction that is not central.

Attitude Strength

Strong attitudes are defined by their stability, resistance to change, and impact on behavior and information-processing (Krosnick & Petty, 1995; Visser, Bizer, & Krosnick, 2006). Apart from these *key features* of attitude strength, several other *attributes* have been identified that are related to attitude strength, such as extremity (Abelson, 1995), elaboration (Petty, Haugtvedt, & Smith, 1995), and importance (Boninger, Krosnick, Berent, & Fabrigar, 1995). In this section, we show that the CAN model integrates the key features of attitude strength into a single framework. Specifically, in the CAN model, the *global connectivity* (i.e., average shortest path length; West, 1996) of an attitude network can be regarded as a mathematically formalized conceptualization of attitude strength. We first discuss how the global connectivity of a network affects the dynamics of a network and link these differing dynamics to the key features of attitude strength. Then we discuss some empirical support for the proposition that attitude strength and connectivity of attitude networks are related, after which we discuss how connectivity of attitude networks relates to the other attributes related to attitude strength.

As we already hinted at in our discussion of attitude change, stability and resistance to change of a given node in a network depends on how strongly this node is connected to other nodes in the network. By extending this argumentation to the whole network, it follows that nodes in a highly connected network are more stable and resistant than nodes in a weakly connected network and that because of this the whole network can be regarded as more stable and resistant (Kindermann & Snell, 1980; van Borkulo et al., 2014). Note that for these dynamics to occur, the assumption is made that the weights are organized in a way that not much conflicting influence is present (e.g., connections between evaluative reactions of the same valence are mostly excitatory).

To illustrate that highly connected attitude networks are more stable than weakly connected attitude networks, let us return to the example of Bob's judgments that Obama is competent, intelligent, and a good leader. To compare the dynamics of these judgments in a highly connected network to the dynamics in a weakly connected network, we can set the weights between the nodes to 1 (representing a highly connected network) or .1 (representing a weakly connected network). To first focus on stability without external pressure, the thresholds were all set to .3. As can be seen in Table 2, the probability that all judgments are positive is much higher in the highly connected network than in the weakly connected network. These probabilities can be interpreted as the likelihood that we would observe a given configuration if we measure a person's attitude at a given point in time. So, if we were to measure attitudes of a group of individuals who have a highly connected attitude network at two points in time, we would find a higher correlation between their attitude scores than were we to measure a group of individuals who have a weakly connected network, which mirrors

Table 2
Configurations of Three Evaluative Reactions (Competent, Good Leader, Intelligent) and Associated Probabilities With Either Congruent or Incongruent Thresholds and Either Low or High Weights

	$Pr(X = \chi)$			
	$\tau_i = \{.3, .3, .3\}$		$\tau_i = \{-.3, .3, .3\}$	
Configuration	$\omega_{ij} = \{.1, .1, .1\}$	$\omega_{ij} = \{1, 1, 1\}$	$\omega_{ij} = \{.1, .1, .1\}$	$\omega_{ij} = \{1, 1, 1\}$
$(-1, -1, -1)$	.06	.14	.11	.33
$(1, -1, -1)$	.07	.00	.04	.00
$(-1, 1, -1)$	.07	.00	.13	.01
$(1, 1, -1)$	.13	.01	.07	.01
$(-1, -1, 1)$	.07	.00	.13	.01
$(1, -1, 1)$	.13	.01	.07	.01
$(-1, 1, 1)$	.13	.01	.24	.02
$(1, 1, 1)$	.35	.83	.20	.61

how attitude stability is assessed in the attitude strength literature (e.g., Bassili, 1996; Prislin, 1996).

To illustrate that highly connected attitude networks are also more resistant than weakly connected attitude networks, we return to our example, in which persuasion was targeted at Bob's evaluative reaction that Obama is competent. Again, we set the threshold of this evaluative reaction to −.3 and calculate the probability of what would happen in a highly connected network (all weights equal to 1) and in a weakly connected network (all weights equal to .1). Based on the probabilities shown in Table 2, the chance that the targeted evaluative reaction will change is higher for the weakly connected network than for the highly connected network. The chance that the sum score of the three evaluative reactions will reflect a less positive evaluation is also higher for the weakly connected network than for the highly connected network.[5] The probability that the targeted evaluative reaction will become negative is .62 and the expected mean evaluation of the three evaluative reactions is .12 for the weakly connected network compared with .38 and .28 for the highly connected network. Highly connected attitude networks are thus more likely to resist persuasion attempts than weakly connected networks, which fits what is known about the resistance of strong versus weak attitudes to persuasion attempts (e.g., Bassili, 1996; Visser & Krosnick, 1998).

Impact of attitude on behavior in the attitude strength literature is generally assessed by measuring individuals' attitude at a given point in time and then predicting a related behavior at a later point in time (e.g., Fazio & Williams, 1986; Holland, Verplanken, & van Knippenberg, 2002). There are two reasons to expect attitudes with highly connected networks to be more predictive of behavior than weakly connected networks. First, due to the stability and resistance of highly connected networks, it is more likely that the attitude will be the same at the time it is measured and at the time the behavior is executed.

Second, as we can see in Table 2, evaluative reactions in highly connected attitude networks are more likely than evaluative reactions in weakly connected attitude networks to align to each other. An aligned attitude network is likely to be more informative for a decision on whether a related behavior should be executed or not. For example, it would be easier for Bob to decide to vote for Obama if he thinks that Obama is competent, a good leader, and intelligent than when he only thinks that Obama is competent and

intelligent but not really a good leader. In the latter case, Bob would probably base his decision on other factors (e.g., which of the candidates his friends prefer), which would make his attitude less predictive of his voting behavior. Furthermore, it is possible that the salience of evaluative reactions differs between situations (cf., Sparks, Conner, James, Shepherd, & Povey, 2001). If Bob's evaluative reactions differed in their endorsement, it might be that at the time his attitude is assessed, mostly negative evaluative reactions are salient. By the time he executes the behavior, other evaluative reactions that are mostly positive might be salient. In such a case, his measured attitude would have low predictive value.

The impact of strong attitudes on information processing refers to the power of strong attitudes in directing attention and influencing the way in which incoming information is integrated (e.g., Fazio & Williams, 1986; Houston & Fazio, 1989; Roskos-Ewoldsen & Fazio, 1992). The connectivity of an attitude network influences the way in which incoming information is integrated, because evaluative reactions that are not aligned to each other cost more energy in a highly connected attitude network than in a weakly connected attitude network. There is thus more pressure to fit incoming information to one's evaluative reactions in a highly connected network than in a weakly connected network. This pressure might also lead to heightened attention to attitude objects in order to detect "attacks" on the attitude network at an early stage.

As we have shown, the key features of attitude strength follow from conceptualizing strong attitudes as highly connected networks. From this reasoning, the hypothesis follows that strong attitudes correspond to highly connected networks. Indeed, this is exactly what we found in a study focusing on attitudes toward presidential candidates in the American presidential elections from 1980–2012 (Dalege, Borsboom, van Harreveld, & van der Maas,

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[5] In the CAN model, the unweighted sum score of the evaluative reactions can be used as a measure of the overall state of the network. A possibility for a more sophisticated calculation for the overall state of the network might be to weigh the evaluative reactions by their closeness centrality, as evaluative reactions with a high closeness hold more information about the other evaluative reactions than evaluative reactions with low closeness.

2015). In this study, we first assigned participants into three strength groups based on whether the participants were interested in presidential campaigns (interest in an attitude object is known to be a reliable indicator of attitude strength; Krosnick, Boninger, Chuang, Berent, & Carnot, 1993). We then checked whether these groups differed in their attitude's stability, extremity, and impact on behavior. All of the attributes differed between the groups in the expected direction, so that the high attitude strength group had attitudes with the highest stability, extremity and impact on behavior.

We then estimated networks for each attitude strength group for the attitudes toward the Democratic and Republican candidate at each election and compared the global connectivity of the attitude networks, giving us a total of 18 sets of attitude networks of groups with either low, moderate, or high strength. Confirming the hypothesis that strong attitudes correspond to highly connected networks, we found that the groups' networks differed robustly and strongly in their global connectivity. In every set of attitude networks, the network of the strong attitude group had a higher connectivity than average and in all but one set, the network of the weak attitude group had a lower connectivity than average.

Thus, the conceptualization of strong attitudes as highly connected networks directly implies that strong attitudes are stable and resistant. By adding a few simple assumptions, the other two key features of attitude strength—impact on behavior and information processing—can also be integrated in the current framework. Furthermore, initial empirical results show that attitude strength and connectivity of attitude networks are indeed strongly and robustly related. The question then arises of how attributes that are related to attitude strength relate to the connectivity of attitude networks.

In their review on attitude strength-related attributes, Visser, Bizer, and Krosnick (2006) identified elaboration (Petty et al., 1995), importance (Boninger, Krosnick, Berent, & Fabrigar, 1995), knowledge (Wood, Rhodes, & Biek, 1995), accessibility (Fazio, Jackson, Dunton, & Williams, 1995), certainty (Gross, Holtz, & Miller, 1995), ambivalence (Thompson et al., 1995), structural consistency (Chaiken, Pomerantz, & Giner-Sorolla, 1995), extremity (Abelson, 1995), and intensity (Cantril, 1946) as the most prominent attributes related to attitude strength. It is our view that these attributes can be roughly grouped into three clusters in relation to connectivity of attitude networks: attributes that are determinants of heightened connectivity, attributes that are consequences of connectivity, and attributes that moderate the consequences of connectivity.

Elaboration is probably a direct cause of connectivity. Building on the proposition of connectionist models of attitudes that evaluative reactions self-organize when the attitude object is activated in working memory (Monroe & Read, 2008) and the principle that humans are motivated to decrease free-energy (e.g., Friston, 2009), it follows that connections between evaluative reactions will become stronger when a person elaborates on his or her attitude. The same holds for determinants of attitude importance. Three key determinants of attitude importance are self-interest, social identification and value relevance (Boninger, Krosnick, & Berent, 1995). Self-interest refers to the extent that one perceives that a given attitude has influence on one's life, social identification refers to whether an attitude is relevant to groups a person identifies with, and value relevance refers to how strongly an attitude

is linked to a person's value. What these three determinants of attitude importance have in common is that they all make it likely that an attitude will play a large role in a person's life. The attitude object therefore is frequently activated in working memory. This is, for example, illustrated by the finding that individuals often think about attitudes that are important to them (Herzog, 1993; Krosnick et al., 1993). It thus follows that determinants of attitude importance are also likely to determine connectivity of attitude networks.

Knowledge on the attitude object can rather be seen as an amplifier of attitude strength than as being directly related to attitude strength—the effects of attitude strength are more pronounced when there is a large amount of knowledge (e.g., a strong attitude in combination with much knowledge is very resistant to change; Wood et al., 1995). In the CAN model, large amounts of knowledge about an attitude object could best be modeled by having a network with many nodes, as it is likely that an individual with much knowledge about an attitude object will also have many different evaluative reactions. Knowledge about an attitude object would thus affect the size of the attitude network but not necessarily the connectivity of the attitude network. The size of a network was shown to amplify the effect of connectivity on network dynamics (Cramer et al., 2013) leading to the hypothesis that attitude networks that are both highly connected and consist of many different evaluative reactions will correspond to stronger attitudes. This is in line with the idea that knowledge amplifies the effects of attitude strength (Wood et al., 1995).

In our view, accessibility, certainty, structural consistency, intensity, and extremity are all likely to be caused by connectivity. Accessibility refers to how fast a person can judge whether a given attitude object is positive or negative (e.g., Fazio & Williams, 1986). We would argue that it is easier to judge an attitude object as either positive or negative if one has an attitude that consists of aligned evaluative reactions (which is more likely in a highly connected attitude network) than when the attitude consists of unaligned evaluative reactions (which is more likely in a weakly connected attitude network). This reasoning is supported by the finding that judging an attitude object, to which an individual holds an ambivalent attitude, takes longer than judging an attitude object, to which an individual holds an univalent attitude (Bargh, Chaiken, Govender, & Pratto, 1992; van Harreveld, van der Pligt, de Vries, Wenneker, & Verhue, 2004).

Attitude certainty can be divided into the constructs attitude clarity and attitude correctness (Petrocelli, Tormala, & Rucker, 2007). Attitude clarity refers to how certain a person is what his or her attitude actually is and attitude correctness refers to how convinced a person is that his or her attitude is valid. It is our view that attitude clarity rather than attitude correctness can be directly linked to the connectivity of attitude networks. First, having an aligned attitude network will probably make it more likely that a person is certain about his or her attitude. Second, both attitude clarity and connectivity of attitude networks are likely to be higher when one has frequently interacted with the attitude object. This could also explain why some ambivalent attitudes are held with certainty. This would be the case if, for example, one has received much conflicting information regarding an attitude object and the strongly connected attitude network was not able to settle in a state, in which the evaluative reactions are aligned. We will return

to this point in more detail when we discuss the relation between ambivalence and connectivity of attitude networks.

Structural consistency refers to attitudes being evaluative-affective consistent, evaluative-cognitive consistent and affective-cognitive consistent (Chaiken et al., 1995). Affective-cognitive consistency directly follows from an attitude network being highly connected because the affective and cognitive nodes are likely to align. Also, having an attitude network, in which all (or most) of the evaluative reactions are aligned, makes it likely that both feelings and beliefs will be consistent with one's general evaluation (i.e., evaluating an attitude object as positive or negative overall).

Intensity refers to how strongly an attitude object elicits emotional reactions (Visser et al., 2006). As emotional reactions represent nodes in an attitude network, strong emotional reactions are expected in attitudes with highly connected networks. Returning to Bob's attitude toward Obama, Bob will have strong positive emotional reactions toward Obama when his attitude network is highly connected as these reactions are pressured to align to the overall positivity of the attitude network. In a weakly connected network, his emotional reactions can vary more freely, so that weaker emotional reactions are expected.

Finally, extremity follows directly from high connectivity. As can be seen in Table 2, in highly connected attitude networks it is virtually impossible that the sum score of the evaluative reactions takes a moderate value. This finding also links the CAN model to the catastrophe model of attitudes (Flay, 1978; Latané & Nowak, 1994; Zeeman, 1976), which holds that attitude importance determines whether attitudes act like categories (i.e., attitudes are only stable in discrete states of positive or negative evaluations) or dimensions (i.e., attitudes can take any place on the dimension ranging from positive to negative): Important attitudes act more like categories and unimportant attitudes act more like dimensions. Studies that focused on political attitudes provided support for this hypothesis (Latané & Nowak, 1994; Liu & Latané, 1998; van der Maas, Kolstein, & van der Pligt, 2003). It is our view that important attitudes or more generally, strong attitudes, act as categories because strong attitudes correspond to highly connected networks.

Linking attitude strength to the connectivity of attitude networks can also shed more light on the consequences of ambivalence. In relation to attitude strength, ambivalence is a puzzling phenomenon because, on the one hand, ambivalent attitudes are weak predictors of behavior (Armitage & Conner, 2000; Conner & Sparks, 2002), and on the other hand, have high impact on information processing (Jonas, Diehl, & Bromer, 1997; Nordgren, van Harreveld, & van der Pligt, 2006). High impact on information processing of ambivalent attitudes was mostly found in the context of felt ambivalence (i.e., ambivalence that causes discomfort; e.g., van Harreveld, Rutjens, Rotteveel, Nordgren, & van der Pligt, 2009; van Harreveld, van der Pligt et al., 2009). In our view, felt ambivalence is likely to arise in highly connected networks with unaligned evaluative reactions because highly connected networks are in an unstable state when the nodes are not aligned (Cramer et al., 2013). This proposition can explain why ambivalent attitudes are less predictive of behavior while they do influence information processing. Due to the high connectivity, motivation arises to process information in a way that resolves the unstable state of ambivalence (cf., Nordgren et al., 2006; van Harreveld, Nohlen, & Schneider, 2015; van Harreveld, van der Pligt et al., 2009) but

because the evaluative reactions are not aligned yet, the impact on behavior is low.

To summarize, conceptualizing strong attitude as highly connected networks provides a framework in which the key features of attitude strength—stability, resistance, and impact on behavior and information processing—as well as attributes related to attitude strength, such as importance, elaboration and extremity can be integrated. Furthermore, this conceptualization sheds more light on the underlying process of the catastrophe model of attitudes and can explain why ambivalent attitudes can be regarded as both weak and strong.

Discussion

In the present article, we introduced the Causal Attitude Network (CAN) model as a formalized measurement model of attitudes. In this model, attitudes are conceptualized as networks of interacting evaluative reactions (e.g., beliefs, feelings, and behaviors toward an attitude object). Interactions arise through direct causal connections and mechanisms that support evaluative consistency. Attitude networks are driven by the trade-off between optimization (i.e., consistency between evaluative reactions) and accuracy. This trade-off results in a small-world structure, in which evaluative reactions, that are similar to each other, tend to cluster. Conceptualizing attitudes as networks provides testable hypotheses for attitude change (e.g., change in an evaluative reaction will foremost affect the cluster it belongs to) and a parsimonious explanation for the differences between strong and weak attitudes by conceptualizing attitude strength as connectivity of attitude networks. Initial empirical tests of the CAN model support both the proposed small-world structure of attitude networks and the hypothesis that strong attitudes correspond to highly connected attitude networks.

Extensions of the CAN Model

The CAN model as presented in this article can only deal with binary data but items are often assessed on nominal or continuous scales in the attitude literature. A natural extension of the model therefore would be to allow for nominal or continuous data. Such extensions are relatively straightforward as there are both Markov Random Field models available for nominal data (Potts model; Wu, 1982) and continuous data (Gaussian Random Field; Lauritzen, 1996) and their application to psychometric data is currently under development (Epskamp et al., in press; van Borkulo et al., 2014).

In our view, whether evaluative reactions are binary, categorical, or continuous variables is a challenging question for research in itself and we would urge attitude researchers to use models developed to test the underlying distribution of evaluative reactions (e.g., De Boeck, Wilson, & Acton, 2005). Connectivity of the attitude network might provide a tentative answer of whether evaluative reactions represent dimensions or categories. As we discussed in the section on attitude strength, highly connected attitude networks behave more like categories and weakly connected attitude networks behave more like dimensions. It is likely that the overall behavior of the attitude network also extends to the behavior of the evaluative reactions, so that evaluative reactions in a highly connected network behave more like categories and

evaluative reactions in a weakly connected network behave more like dimensions.

Another possible extension of the CAN model would be to use time-series data to estimate individual attitude networks. The measurement model that we developed in this article is only suited to cross-sectional data but related approaches can be used to model time-series data (Bringmann et al., 2013). While estimating networks on cross-sectional data provides useful information on the general structure of the attitude networks in the population, modeling individual attitude networks on time-series data provides a powerful tool to detect individual differences in attitude structure. Several studies indicate that individuals differ in their attitude structure (e.g., Huskinson & Haddock, 2004; van der Pligt, de Vries, Manstead, & van Harreveld, 2000; van der Pligt & de Vries, 1998; van Harreveld, van der Pligt, de Vries, & Andreas, 2000) but statistical tools to model such differences have, as yet, been lacking. It is our view that network analysis can fill this gap.

A related possibility to extend the CAN model would be to model the sizes of the attitude networks of different individuals. It is likely that individuals will differ in how many evaluative reactions they have toward an attitude object and that therefore their attitude networks consist of different numbers of nodes. As we have argued here, the size of the network has implications for the dynamics of the network. To measure, however, how many evaluative reactions an individual has toward an attitude object new approaches to the assessment of attitudes have to be developed.

The Challenge to Assess Attitude Networks

Devising attitude questionnaires that are tailored to the theoretical background of the CAN model in some instances contrasts markedly with devising attitude questionnaires from a latent variable perspective. For example, developing questionnaires that can be used to asses virtually all attitudes is reasonable from a latent variable perspective (cf., Crites et al., 1994), as items in the questionnaires are simply indicators, but it is not necessarily reasonable from a network perspective. There is no a priori reason to assume that every attitude network consists of the same nodes. It is, for example, very likely that some emotions are often experienced toward some attitude objects (e.g., anger toward presidential candidates), while they are virtually never experienced toward other attitude objects (e.g., anger toward a detergent brand).

Another implication of the CAN model for the assessment of attitudes that differs from the implications of latent variable models is that researchers should strive to measure all relevant evaluative reactions because otherwise the danger arises that one measures not the whole attitude network but only parts of it. As evaluative reactions in the CAN model represent autonomous causal entities, omissions of relevant evaluative reactions would decrease the validity of the model (in contrast to only decreasing reliability in latent variable models).

To construct attitude questionnaires from a network perspective, a theory-driven approach to questionnaire construction instead of an empirically driven approach should be adopted (see Borsboom, Mellenbergh, & van Heerden, 2004). A challenge in the construction of such attitude questionnaires becomes to assess all relevant evaluative reactions in the attitude network. This approach shifts the focus of attitude questionnaire construction from striving for internal consistency to striving for assessing attitudes comprehen-

sively. As nodes in attitude networks represent autonomous entities, they might in some instances correlate only weakly—internal consistency and validity of the attitude questionnaire might therefore be incompatible in some instances. It is therefore our view that estimating reliability of the whole attitude questionnaire is of limited value—it is, however, possible to assess each evaluative reaction with several indicators. In this case, reliability can be estimated to investigate whether the different questions tapping one evaluative reaction are likely to indeed measure a single entity. One way to go about constructing comprehensive attitude questionnaires might be to assess, in an open-ended questionnaire, which evaluative reactions are most common for the attitude object of interest.

After having constructed a comprehensive attitude questionnaire, the next challenge is to assess whether individuals differ in the number of evaluative reactions they have. As we already discussed here, it is likely that individuals with more knowledge of the attitude object have larger attitude networks. Furthermore, elaboration is also likely to increase the number of evaluative reactions one has (cf., Tesser & Leone, 1977; Wood et al., 1995).

Assessing whether an evaluative reaction represents a relevant node in an individual's attitude network might be possible by measuring how long it takes a participant to respond to an item. An item that reflects a relevant node in an individuals' attitude network should be judged faster than an item that does not, because subjectively important attitudinal beliefs are judged faster (van Harreveld et al., 2000) and accessible attitudes are more easily retrieved from memory (Fazio & Williams, 1986).

Another possibility to distinguish between irrelevant and relevant nodes might be to assess the salience or importance of a given belief (e.g., Ajzen, 1991; van der Pligt et al., 2000). The more salient or important a given belief, the more likely it would be that this belief represents a relevant node in the attitude network. Using this technique to distinguish between relevant and irrelevant nodes would be relatively straightforward, as instruments to assess the importance of a given belief have already been developed (e.g., van der Pligt et al., 2000).

The distinction between irrelevant or nonexistent nodes and relevant nodes bears some resemblance to the distinction between attitudes and nonattitudes (Converse, 1970), which was further developed by Fazio, Sanbonmatsu, Powell, and Kardes (1986). They argued that the distinction between attitudes and nonattitudes should be seen as a continuum rather than a dichotomy. From a network perspective, attitude networks that consist of only few nodes that are only weakly connected lie more at the nonattitude end of the continuum and attitude networks that consist of several nodes that are strongly connected lie more at the attitude end of the continuum.

Another issue in the assessment of attitude networks concerns the boundary specification problem in network analysis (Laumann, Marsden, & Prensky, 1989). The boundary specification problem refers to the difficulty of deciding which entities form part of the network. In attitude networks, it is for example, difficult to decide whether the attitude toward a presidential candidate and the attitude toward the candidate's party represent two distinct networks or one large network. There are, however, algorithms available that detect so-called community structures in the data (e.g., Clauset, Newman, & Moore, 2004; Girvan & Newman, 2002; Newman, 2004, 2006; Newman & Girvan, 2004). A community structure

refers to nodes that are highly interconnected and that only share weak connections with other community structures. A possible solution to the former example might thus be to assess both evaluative reactions toward the presidential candidate and her party and then apply an algorithm to detect community structures in the data. Based on this, one could then investigate whether the two attitudes represent two distinct networks or one large network.

A problematic aspect of applying community algorithms to detect the boundaries of attitude networks is that researchers have to assess a large set of items if they want to assess each variable that might be closely connected to the attitude network. Especially, if researchers want to focus on individual attitude networks, the set of items can quickly become too large to assess them frequently. However, this issue is less problematic for cross-sectional research. It would be possible to administer an extensive questionnaire with the most important variables that might be related to the attitude network to a group of individuals. Assessing the boundaries of attitude networks therefore currently needs to be done at the group level instead of at the individual level.

Future Study of the CAN Model

We now turn to some possible avenues for future study of the CAN model. Related to the implications on assessment of attitude networks, a possibility for future study would be to model responses on implicit measurements of attitudes with the CAN model. The currently most prominent reaction time (RT) based measure of attitudes, the Implicit Association Test (IAT; Greenwald, McGhee, & Schwartz, 1998), however, is not suited to investigate attitudes from a network perspective, as it is not possible to analyze single items in this measure. Adopted variants of the Affect Misattribution Procedure (AMP; Payne, Cheng, Govorun, & Stewart, 2005), on the other hand, can be used to measure specific evaluative reactions (stereotype misperception task; Krieglmeyer & Sherman, 2012; emotion misattribution procedure; Rohr, Degner, & Wentura, 2015). However, different theoretical viewpoints on responses toward implicit measures of attitudes have different implications for which nodes should be measured with implicit measures. Two influential models of implicit measures of attitudes are the Motivation and Opportunity as Determinants of behavior (MODE) model (Fazio, 1990; Fazio & Olson, 2003b) and the Associative-Propositional Evaluation (APE) model (Gawronski & Bodenhausen, 2006, 2007, 2011).

From the perspective of the MODE model, implicit measures of attitudes are regarded as more "pure" estimates of attitudes because they limit the opportunity to conceal the attitude (Fazio & Olson, 2003b). A central postulate of the MODE model regarding the relation between implicit and explicit measures of attitudes holds that the different measures show high correspondence when the attitude object is a socially nonsensitive issue (e.g., attitudes toward presidential candidates) and low correspondence when the attitude object is a socially sensitive issue (e.g., prejudice). From the perspective of the MODE model, evaluative reactions toward sensitive issues should thus be measured using implicit measurements. Measuring evaluative reactions toward nonsensitive issues, on the other hand, would not require the use of implicit measurements.

From the perspective of the APE model, responses on implicit measures of attitudes represent affective 'gut' reactions and responses on explicit measures of attitudes represent deliberative judgments that are propositional in nature (Gawronski & Bodenhausen, 2006). What follows from this postulate is that implicit measures would be better suited to measure evaluative reactions that represent feelings toward an attitude object and explicit measures would be better suited to measure beliefs toward an attitude object. To acquire a complete picture of an attitude network, researchers thus would have to use combinations of implicit and explicit measures.

We emphasize that arguments against conceptualizing attitudes as latent variables also pertain to models focusing on attitudes assessed with implicit measures. In our view, implicit measures of attitudes do not acknowledge the inherent complexity of attitudes as these measures treat attitudes as unidimensional continua, which is clearly expressed by how attitudes are assessed with implicit measures: in the four most used implicit procedures to assess attitudes (Nosek, Hawkins, & Frazier, 2011)—IAT, AMP, Go/No-Go Association Task (Nosek & Banaji, 2001), and evaluative priming procedures (Fazio et al., 1995)—attitudes are reduced to a single score, which presupposes them to be unidimensional. As we have shown in this article, however, a conceptualization of attitudes that instead treats attitudes as complex systems has many advantages over treating attitudes as unidimensional continua. Developing implicit measures of attitudes from a network perspective is thus likely to further the understanding of attitudes to a greater extent than imposing the (untested) assumption that attitudes are unidimensional.

As we argued in this article, the CAN model also aids the progress of integrating connectionist models of attitudes with empirical research on attitudes. We showed that the basic tenet of connectionist models of attitudes—attitudes are conceived as a product of a network of interrelated nodes—is also a realistic conceptualization of empirical data on attitudes. A next step in integrating connectionist models with empirical data would be to use empirically estimated attitude networks as input for data simulation (see van Borkulo, Borsboom, Nivard, & Cramer, 2011 for an example of how an empirically estimated network can be used for data simulation in Netlogo; Wilensky, 1999). The advantage of using empirically estimated attitude networks as input for data simulation is that the connection strengths between the network nodes are no longer based on arbitrary choices, but can be grounded in empirical data. In addition, while the CAN model can be used as a tool for data simulation, it can also produce empirical predictions on the dynamic behavior of estimated attitude networks.

We already discussed two central empirical predictions of the CAN model in the context of persuasion: (a) changes in a given evaluative reaction will foremost affect closely connected evaluative reactions, and (b) successful persuasion directed at highly central evaluative nodes is more likely to result in a fundamental change in the attitude network. A related prediction holds that evaluative reactions with high closeness have the highest impact on decisions. This prediction flows from the notion that evaluative reactions with high closeness are the most influential nodes in a network. While evaluative reactions with high closeness are not necessarily the nodes that are directly related to the decision, they can still have a profound influence on the decision through their influence on the other evaluative reactions in the network.

While persuasion research might benefit from investigating closeness of nodes, research on ambivalence might benefit from investigating the connectivity of attitude networks. The connectivity of attitude networks is particularly relevant to the distinction between potential and felt ambivalence (e.g., Newby-Clark et al., 2002). Potential ambivalence refers to ambivalent evaluations and felt ambivalence refers to psychological discomfort resulting from potential ambivalence. Some factors that influence whether potential ambivalence results in felt ambivalence have been identified. For example, simultaneous accessibility of ambivalent evaluations heightens discomfort resulting from ambivalence (Newby-Clark et al., 2002) and ambivalent attitudes that are relevant for decision-making are likely to cause aversive feelings (van Harreveld, Rutjens et al., 2009; van Harreveld, van der Pligt et al., 2009). A general framework to integrate these different findings, however, has not yet been proposed. The CAN model might provide such a framework.

To see this, it is important to consider the notion of *attractor states*. Attractor states refer to states that a dynamical system is driven to (Alligood, Sauer, Yorke, & Crawford, 1997). Which attractor states exist in an attitude network likely depends on the connectivity of the network. Attitude networks that are highly connected probably display only two attractor states (positive or negative) because the strong connections between the nodes force all nodes to align to the same state. In a weakly connected network, several attractor states are likely to exist, as only some nodes have to settle in the same state.[6]

The drive of the attitude network to settle in an attractor state might reflect aversive feelings caused by ambivalence. Highly connected attitude networks would thus be more likely to cause aversive feelings in the light of ambivalence than weakly connected attitude networks. This is because highly connected networks must settle in one of only two attractor states, while weakly connected networks can settle in one of several attractor states. Factors that heighten the probability of felt ambivalence might thus be integrated by proposing that they cause stronger connectivity in attitude networks.

Another research area, in which network analysis and the CAN model in particular might provide new insights, is research on the development of attitudes over time. This area has received somewhat limited attention and the CAN model might aid progress in this area as network analysis is well suited to model developmental changes (Bringmann et al., 2013). A central postulate of the CAN model is that attitude networks grow (i.e., new evaluative reactions attach to older evaluative reactions). This growth might depend on how often an individual elaborates on the attitude (Monroe & Read, 2008). As we already discussed here, the CAN model predicts that the structure of attitude growth will be driven by the similarity and popularity of evaluative reactions.

Another issue in research on attitudes that might benefit from investigating attitudes from the perspective of the CAN model is the question of to what extent attitudes are formed through environmental factors and genetic factors, and how these factors interact in the shaping of attitudes. While studies investigating influences on attitudes generally have focused on environmental influences (e.g., persuasion), genetic influences on attitudes have also been observed (Eaves, Eysenck, & Martin, 1989; Olson, Vernon, Harris, & Jang, 2001; Tesser, 1993).

Research on personality has shown that different genes influence different nodes in a network to a different extent (Cramer et al., 2012) and it is likely that a similar pattern exists for nodes in attitude networks. For example, fearful reactions to attitude objects might have a stronger genetic basis than other nodes in attitude networks because conservative attitudes were shown to be predicted by individual differences in arousal in response to threatening stimuli (Oxley et al., 2008), which in turn are predicted by amygdala activation (e.g., Larson et al., 2006), while amygdala activation was found to have a genetic basis (e.g., Hariri et al., 2002). A possible mechanism of how a conservative attitude network might develop is that an individual, who is genetically predisposed to fearful reactions, reacts fearfully to threats to social order and therefore is more vulnerable to persuasion attempts that promote that political decisions foremost must guarantee safety to social order. Network analysis would aid in identifying such processes.

Conclusion

In this article we introduced the CAN model and argued that (a) the Ising model provides a psychometrically realistic formalization of attitudes, (b) attitude networks conform to a small-world structure, and (c) network connectivity provides a mathematically formalized conceptualization of attitude strength. The CAN model shows promise in integrating existing findings, which are hitherto disparate, and in furthering the development of new insights in several areas of attitude research. For these reasons, the CAN model is likely to make significant contributions to the integration of different areas of attitude research, and to further new insights into the complex concept of attitude.

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[6] This point is also illustrated in the section on attitude strength. As can be seen in Table 2, configurations of the attitude network, in which not all evaluative reactions are aligned, are more probable in weakly connected networks than in highly connected networks.

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Appendix

Description of the ANES 1984 Data Set

Evaluative Reactions

Sixteen evaluative reactions toward the presidential candidates tapping beliefs and seven evaluative reactions tapping feelings were assessed. For items tapping beliefs, participants were asked: "In your opinion, does the phrase 'he . . .' describe *the candidate*?" The beliefs that completed the items were "is moral," "is knowledgeable," "is inspiring," "would provide strong leadership," "is hard-working," "is decent," "is compassionate," "commands respect," "is intelligent," "is kind," "sets a good example," "really cares about people like you," "understands people like you," "is fair," "is in touch with ordinary people," and "is religious." We excluded the item focusing on whether the participants believed that the candidates were religious because this belief is ambiguous in relation to valence. Items were assessed on a 4-point scale, with answer options 4 = *extremely well*, 3 = *quite well*, 2 = *not too well*, 1 = *not well at all*. As the eLasso-procedure only allows dichotomous data (van Borkulo et al., 2014), we scored Options 3 and 4 as 1 and Option 1 and 2 as 0.

For items tapping feelings, participants were asked: "Has *the candidate*—because of the kind of person he is or because of something he has done, ever made you feel: . . .?" The feelings that completed the items were "angry," "hopeful," "afraid of him," "proud," "disgusted," "sympathetic toward him," and "uneasy." These items were assessed dichotomously, with the answer options 1 = "Yes" and 0 = "No".

Missing Data

Some participants had missing data on at least one of the evaluative reactions because they responded "Don't know." We deleted missing data casewise, which led to the final sample of 1,877 participants for the analysis on the attitude toward Ronald Reagan and 1,628 participants for the analysis on the attitude toward Walter Mondale. To check the robustness of our results, we also imputed missing values with randomly assigning 0 or 1, when a participant had missing values. The results of this analysis mirrored the results reported here.