Perspectives on Psychological Science
1–10

DOI: 10.1177/17456916231185776
www.psychologicalscience.org/PPS

A Network Approach to Investigate the Dynamics of Individual and Collective Beliefs: Advances and Applications of the BENDING Model

Madalina Vlasceanu[1], Ari M. Dyckovsky[2], and Alin Coman[2,3]
[1]Department of Psychology, New York University; [2]Department of Psychology, Princeton University; and [3]School of Public and International Affairs, Princeton University

Abstract
Changing entrenched beliefs to alter people's behavior and increase societal welfare has been at the forefront of behavioral-science research, but with limited success. Here, we propose a new framework of characterizing beliefs as a multidimensional system of interdependent mental representations across three cognitive structures (e.g., beliefs, evidence, and perceived norms) that are dynamically influenced by complex informational landscapes: the BENDING (Beliefs, Evidence, Norms, Dynamic Information Networked Graphs) model. This account of individual and collective beliefs helps explain beliefs' resilience to interventions and suggests that a promising avenue for increasing the effectiveness of misinformation-reduction efforts might involve graph-based representations of communities' belief systems. This framework also opens new avenues for future research with meaningful implications for some of the most critical challenges facing modern society, from the climate crisis to pandemic preparedness.

Keywords
collective beliefs, mental representation, social cognition, thinking/reasoning/judgment

Beliefs have long been hypothesized to affect behavior (Ajzen, 1991; Hochbaum, 1958). A large body of empirical research shows an association between these two constructs (Sulat et al., 2018; for a more nuanced view, see Bechler et al., 2021). For example, beliefs about tuberculosis predict voluntary chest X-rays (Hochbaum, 1958), religious beliefs associate with crime rates (Shariff & Rhemtulla, 2012), and beliefs about intelligence correlate with learning success (Mangels et al., 2006). More recent work also found that a manipulation aimed at changing politically charged beliefs led to change in donations to political causes (Vlasceanu et al., 2023).

Researchers have built on this extensive literature, and interventions to alter beliefs have proliferated in recent years (Farkas & Schou, 2019). Large-scale studies took aim at significant problems of today, from misinformation and conspiracy theories (Lewandowsky et al., 2012) to discrimination toward women in workplaces (Chang et al., 2019) to polarization in American society (Voelkel et al., 2023). For all their strengths, these promising efforts reveal significant limits of belief interventions. As an example, Voelkel and colleagues (2023) tested 25 interventions to reduce political animosity between liberals and conservatives in the United States. Compared with a control group, a large majority of these interventions were significantly more effective at reducing partisan animosity immediately after the treatments were administered. However, after a 2-week delay, the impact of these interventions diminished drastically. Similar limitations of belief-based interventions were observed in field experiments that tested the impact of an online diversity training on promoting equality in an organizational setting (Chang et al., 2019). The positive effect of this intervention on behavior emerged only for employees whose attitudes were supportive of gender equality before the online training.

Corresponding Author:
Alin Coman, Department of Psychology, Princeton University
Email: acoman@princeton.edu

In this article, we propose that beliefs are resilient to change because they are (a) embedded in a multidimensional, self-sustaining system of mental representations and (b) shaped and reinforced continuously by the social interactions people have in their communities. Simple and brief interventions aimed at changing beliefs are therefore unlikely to be successful in the long term (Rodriguez et al., 2016). This is for at least two reasons. First, belief systems—by virtue of the relational nature of the belief elements they contain—exhibit homeostasis. Previous work has convincingly modeled these system-level forces as solutions to constraint satisfaction (Monroe & Read, 2008) or energy-minimization (Dalege et al., 2016) problems. And second, following these brief interventions, people often return to their previous informational environments. This involves frequent exposure to situations that are likely to evoke their long-held beliefs (Brugnoli et al., 2019), such as consumption of mass media and social media that offer a ready-made defense of their preexisting views (Broockman & Kalla, 2022), and interactions within tight-knit communities that are likely to further reinforce their belief systems (Frenkel et al., 2020).

Acknowledging the complex ecosystem that people's beliefs are grounded in and supported by should not deter programmatic efforts to counter beliefs that can scientifically prove to be egregiously false. Well-established research has shown that beliefs can be a gateway to behavior (Van der Linden, 2021). The key to advancing more successful interventions, we claim, is a more sophisticated mapping of beliefs as mental constructs embedded in complex systems at both individual and collective levels (Botvinik-Nezer et al., 2023; Dalege et al., 2016; Rodriguez et al., 2016). This mapping has the potential to guide the design of effective belief-based interventions. In what follows, we provide a framework that could be used to map people's beliefs. Building on this framework, we suggest ways to design interventions aimed at changing people's beliefs and behaviors.

Belief Systems as Multidimensional Cognitive Structures: Beliefs, Evidence, Norms Dynamic Information Networked Graphs

The psychological construct of "belief," broadly defined as the mental acceptance of the truth of a statement (Ajzen & Fishbein, 1975; Eagly & Chaiken, 1998; Shermer, 2012), has sparked the interest of scientists for at least a century (e.g., Lund, 1925). More recently, this interest has reemerged across the social sciences, with burgeoning developments in philosophy (Schwitzgebel, 2011), social psychology (Rutjens & Brandt, 2019), behavioral economics (Minton & Kahle, 2013), environmental science (Sherman et al., 2022), sociology (Boutyline & Vaisey, 2017), and computational modeling (Brandt & Sleegers, 2021). Capitalizing on this emerging body of work, we propose a theoretical framework for studying beliefs: the BENDING (Beliefs, Evidence, Norms Dynamic Information Networked Graphs) model (Fig. 1). This framework has the potential to facilitate a more systematic investigation of belief systems, incorporating not only within-individuals dynamics (Vlasceanu & Coman, 2018) but also between-individuals social influence (Vlasceanu et al., 2020; Vlasceanu et al., 2021b).

We define belief systems as dynamical systems of interrelated mental representations specific to each individual that can give rise to concrete behavioral signatures. Several research groups have made meaningful advances in understanding the dynamics of these belief systems. Some have conceptualized attitudes as networks that consist of beliefs, feelings, and emotions toward an attitudinal object (causal-attitude network; Dalege et al., 2016), whereas others have modeled belief systems as interconnected attitudes and values (Turner-Zwinkels & Brandt, 2022). We complement these approaches by conceiving belief systems as interrelated networks of belief elements composed of evidence, beliefs, and perceived norms (see Fig. 1). These levels and the characteristics of the different constructs are not exhaustive. Rather, they are provided as examples of dimensions on which these constructs may vary. We chose to focus on these specific examples given recent empirical developments showing how beliefs can be changed by leveraging these constructs (Vlasceanu, 2021). We encourage researchers to consider additional dimensions that might be relevant to the particular contexts in which they study belief systems. In what follows, we describe the different levels of the framework and discuss features we believe are important to consider in any endeavor aimed at measuring—and intervening on—belief systems.

The "evidence" consists of factual pieces of information that an individual uses to either support or oppose a given set of beliefs. An example of such evidence is "Burning fossil fuels emits over 40 billion tons of carbon dioxide each year." If people have a mental representation of this piece of evidence, they could use it to support their belief that burning fossil fuels dramatically affects climate change. The pieces of evidence in this framework are characterized by several important features. Here, we briefly consider their accuracy, but other features could be measured as well, such as mode of acquisition and level of activation. Accuracy captures the distance between the subjective evidence the person

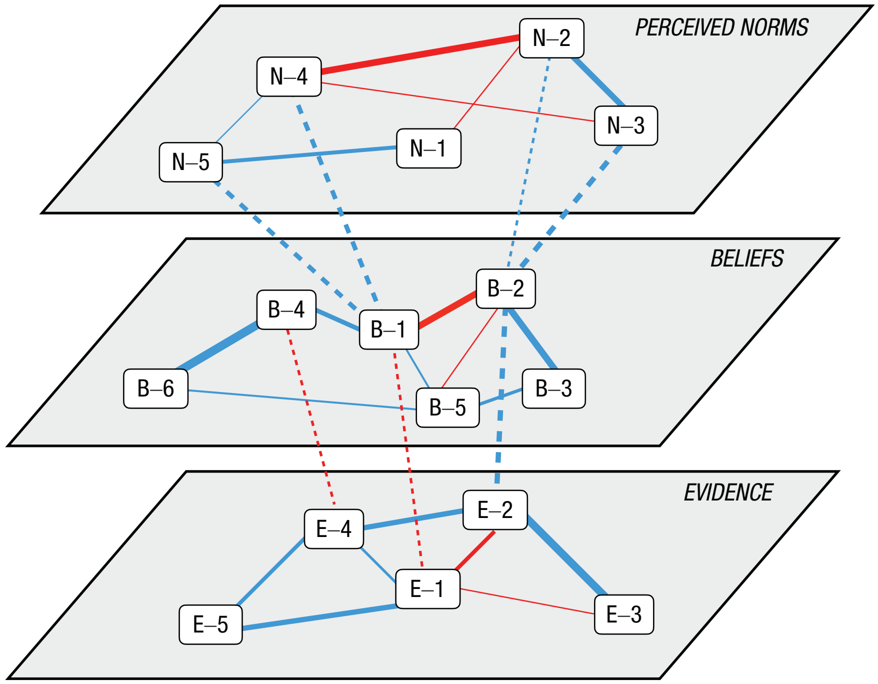

Fig. 1. An illustration of a belief-systems approach that conceptualizes belief elements as multidimensional cognitive structures with three levels: evidence, beliefs, and perceived social norms. The connection among the different cognitive units represents a relation of proximity, as evaluated by the individual believer. Line thickness indicates strength of relation (thicker implies stronger relations). Line color indicates compatibility (red = incompatible; blue = compatible). Line continuity indicates the level at which a relation occurs (uninterrupted: within-level relation; interrupted: cross-level relation).

holds and the objective scientific truth of the statement. Although in some cases this deviation is nominal (e.g., true/false), it can also be continuous in nature. For instance, the fossil-fuel evidence that the person holds deviates from scientific evidence by 10 billion tons. In fact, scientists have estimated that the actual quantity is closer to 30 billion tons of carbon dioxide (World Nuclear Association, 2022).

"Beliefs" are more complex than evidence given the conviction with which they are held and the identity component they contain (Jervis, 2006). The identity component involves a self-relevant dimension of one's belief system by which one's beliefs could be subjectively evaluated as more or less central to one's sense of self (Connors & Halligan, 2015). An example of a belief is "Human activities are causing a climate crisis." For a believer in climate change, this belief would likely be evaluated as relatively central to one's identity. At this level, features such as belief strength and accessibility play an essential role in forming, maintaining, and updating beliefs (Brinol & Petty, 2009; Ozubko & Fugelsang, 2011; Swann et al., 1988). For example, beliefs vary in the strength of endorsement on a continuum such that different beliefs can be endorsed or opposed to different degrees (Wyer & Albarracín, 2005). One could strongly believe that "climate change is human-made," whereas someone else could just moderately endorse the belief and easily update it upon encountering opposing views. Beliefs also vary in their cognitive accessibility. That is, given a certain contextual configuration, one could selectively activate beliefs to serve the current goals of the cognitive system (Taylor & Fiske, 1978). This model accounts for the capacity of a belief system to sustain inconsistent beliefs by resolving inconsistencies only when cognitive dissonance is triggered by two inconsistent beliefs becoming simultaneously accessible (McGuire, 1960; Rosen & Wyer, 1972).

The third level of the proposed belief framework consists of "perceived norms," or informal rules of behavior that individuals are sensitive to because they believe others follow them, think they should be followed, and are willing to sanction others who deviate (Bicchieri et al., 2011; Miller & Prentice, 2016; Paluck et al., 2016). An example of such a social norm is "Over 97% of scientists agree that human activities are causing a climate crisis." Social norms have been long theorized to influence people's beliefs (Festinger, 1954). Just as in the case of evidence, these perceived norms are characterized by a degree of accuracy. A person's subjective estimation of the proportion of people in a community that endorses or opposes a belief can deviate from the actual objective measurement. This discrepancy has been documented across the social sciences and is evident in phenomena such as pluralistic ignorance (O'Gorman, 1986), false consensus (Ross et al., 1977), and false polarization (Fernbach & Van Boven, 2022). For example, even though polls have revealed that two-thirds of Americans support climate-mitigation policy, when they are asked to estimate the level of support at a national level, American participants think that only one-third is in favor of such legislation (Sparkman et al., 2021).

The proposed framework has two main aims: (a) to guide novel research questions into the organizing principles of belief systems and (b) to increase the efficiency of belief-based interventions in real-world circumstances. Before we offer recommendations in these directions, we provide empirical evidence for the validity of the framework and discuss how these individual belief systems are shaped by the interactions people have in their social networks.

Empirical Support for the BENDING Model

Does altering evidence affect beliefs?

The evidence that people use to support their beliefs is often scientifically inaccurate. Given this deviation, one could attempt to affect individuals' beliefs by correcting the inaccurate evidence they hold. Recent work supporting this conjecture has found that triggering large prediction errors about pieces of evidence supporting or refuting beliefs might be a powerful strategy for changing beliefs (Vlasceanu et al., 2021a). As part of the paradigm, participants first evaluated the believability of a set of statements (e.g., "All cities in the US experience more extremely hot days compared to 50 years ago."). Then, they either made predictions about evidence associated with the statements (e.g., "What percentage of US cities experience more extremely hot days compared to 50 years ago?") and received feedback (i.e., "73%") or were presented with just the evidence (i.e., "Compared to 50 years ago, 73% of cities in the US experience more extremely hot days"). Finally, participants reevaluated the believability of the initial statements. The results showed that triggering large prediction errors leads to a larger magnitude of belief update than simply being presented with the evidence (Vlasceanu et al., 2021a). Several other studies have documented that correcting the inaccurate evidence that people use to support their beliefs affects their beliefs in domains ranging from sex trafficking (Porter et al., 2018) to climate change (Ranney & Clark, 2016).

Does making social norms salient affect beliefs?

A burgeoning literature provides evidence that making social norms salient can be used as a strategy for changing beliefs. In one such study, participants first rated the accuracy of a set of statements (e.g., "Supporting climate policy is one of the most effective ways of curbing the climate crisis."), after which they were provided with relevant evidence, either normative (e.g., a Twitter post stating "Studies show that supporting climate policy is one of the most effective ways of curbing the climate crisis" was constructed to appear as having thousands of likes and retweets) or nonnormative (e.g., the same Twitter post was manipulated to appear as having only a few likes and retweets). Finally, participants rated the accuracy of the initial set of statements again. The results showed that participants changed their beliefs more in line with the evidence when the evidence was portrayed as normative compared with when the evidence was portrayed as nonnormative, pointing to the meaningful influence social norms have on health beliefs (Vlasceanu & Coman, 2022). In agreement with these results, other studies have documented the impact of social norms on people's beliefs both in classical work on the consequences of misperceiving norms (Prentice & Miller, 1993) and in more recent investigations on norm perceptions using virality metrics of social media posts (Kim, 2018).

Are the elements of belief systems networked?

If one asks people to indicate whether their beliefs are related to one another, a connected structure emerges (Brandt & Sleegers, 2021). But are these self-reported relations of any consequence or just transitory side effects of task demands? To provide a test for the consequential nature of this mapping, one could investigate whether changing one belief results in specific changes in related but not unrelated beliefs. Recent research has found that selectively exposing participants to beliefs can make those beliefs more prominent in the cognitive system. This prominence—manifested as increased recall of the beliefs that received selective practice—resulted in increased believability of these statements (i.e., the illusory-truth effect; Fazio et al., 2015; Hasher et al., 1977). At the same time, this exposure resulted in decreased believability of beliefs that were part of the same category with the practiced beliefs but no change in believability for beliefs that were not part of the same category (Vlasceanu & Coman, 2018).

Note that the degree of connectivity among the different elements in the belief system does not involve objective estimates but, rather, rely on measuring a believer's subjective estimation. This subjective estimation could involve both the degree of similarity among the different constructs and their compatibility. For example, evidence regarding fossil fuels is more similar in topic to evidence regarding energy efficiency than to evidence regarding vaccination benefits. Moreover, these constructs can be compatible or incompatible with each other. At a perceived-norm level, a registered Republican could be aware that "a majority of Republicans think climate change is a threat," while at a belief level, the same person could believe "that climate change is not a threat." The two constructs in this case would exhibit a high degree of incompatibility (Van Boven et al., 2018). Measuring the different types of relations among the elements of belief systems has the potential to reveal not only how they are connected but also what pathways one could target for belief change, as will be made clear in a subsequent section.

Are belief systems malleable?

Even though we proposed that the connectivity of the different elements of a belief system involves more than transitory relations, it does not mean that these relations are rigid and unchangeable. The flexibility of belief systems is revealed in a range of situations: from simply making salient inconsistencies known to the believer (Rosen & Wyer, 1972) to cataclysmic events that completely reshape one's core beliefs (Falsetti et al., 2003). Some of the most compelling evidence of belief-system flexibility comes from experiments that involve networks of interacting participants (Macy et al., 2019). In one such study, Republicans and Democrats were first asked to indicate their political affiliation and were then randomly assigned to 10 different "worlds." Participants had access to information that was circulating in only their designated world. At this time, they were asked to indicate their agreement with a list of 20 political and cultural opinion statements. Participants in some of these worlds could see which party (Republican or Democrat) was more likely to agree with an item, whereas participants in other worlds answered the questions without being given information about which party is more likely to endorse a statement. Finally, participants' agreements with the statements were used to update the relative support coming from each party that was presented to the other participants in the world. The main result of this study is that some beliefs that ended up being widely endorsed by Republicans in one "world" became widely endorsed by Democrats in another "world," and thus establishing that the belief systems emerging out of the interactions among individuals are relatively unpredictable (Macy et al., 2019).

In sum, we claim that these belief systems exhibit constraints and homeostatic forces that make them relatively stable while at the same time being dynamic and changeable under certain circumstances. A mapping that expands measurement of a belief system in the domain of evidence and perceived norms would likely reveal the nature of the system's stability and the pressure points that could be targeted to guide belief and behavior change.

Belief Systems Are Shaped by Social Interactions

One reason why belief-based interventions might not be as impactful as expected is that belief systems are constantly reinforced by the communities that the individual belongs to. Consistent with this claim, an extensive literature in psychology has established that an individual's cognition is shaped by social interactions, for example, through informational influence (Bicchieri & Dimant, 2022; Deutsch & Gerard, 1955; Smith & Semin, 2007). Interactions that take place in small groups (Vlasceanu & Coman, 2022) or larger social networks (Christakis & Fowler, 2009; Vlasceanu et al., 2021b) constitute the main engine for the formation of collective beliefs. Therefore, if people are interested in increasing the efficiency of belief-based interventions, they must understand both how collective beliefs are formed in communities and how to measure collective-belief systems.

"Collective beliefs" has been broadly defined as the joint commitment of a group to accept a statement as true (Friedkin et al., 2016; Gilbert, 1994). Using a social-interactionist approach, we similarly define "collective beliefs" as individual beliefs shared by members of a community that bear on the collective identity of that community. This definition raises two considerations when measuring collective beliefs. First, what constitutes a shared belief? For example, an initial assessment of whether a set of beliefs is shared by the members of a community can be performed by computing the degree of synchronization or alignment between the different individuals within a community (Coman et al., 2016; Vlasceanu et al., 2020). This computation assesses the degree to which different beliefs are endorsed in common by community members and opposed in common by community members. For instance, recent work showed how conversational interactions lead to increased synchronization in social networks by increasing community members' believability of beliefs held in common

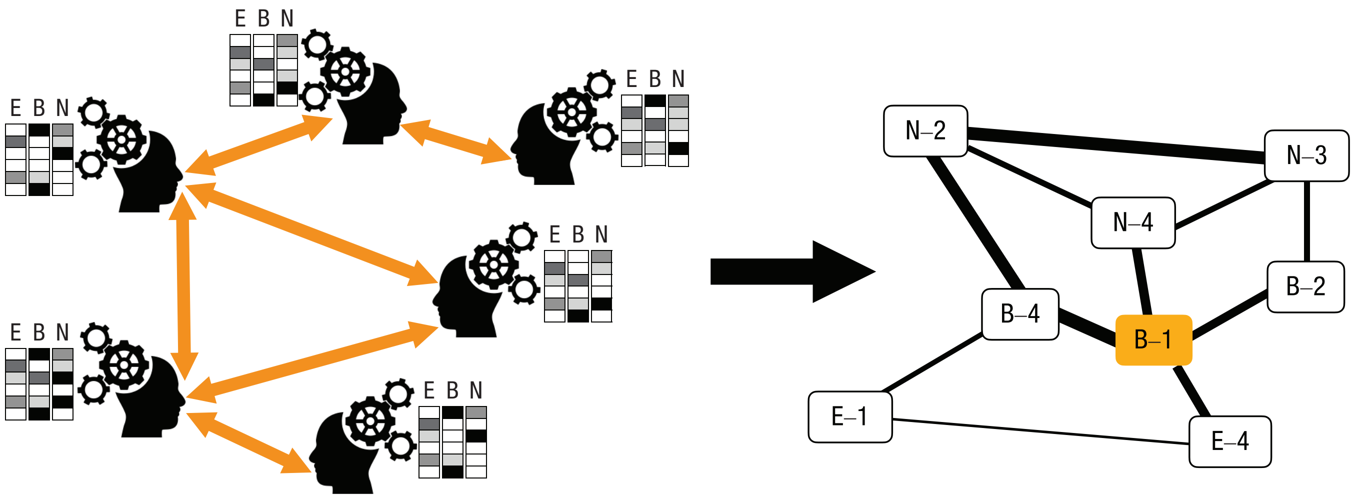

Fig. 2. An illustration of the mapping of a community's belief system. (Left) A social network of individuals who interact with one another (represented as bidirectional arrows) and update their evidence (E), beliefs (B), and perceived norms (N). The degree of activation of each one of these constructs is captured by the shades of gray associated with each person's belief system elements. (Right) A graphical representation of the collective beliefs of the community, computed as a function of the proportion of participants who endorse any two constructs in common. The thickness of the link indicates the proportion of the community members that holds the two belief elements in common. Note that the social-influence dynamics that occur on the left panel will shape the aggregated belief system on the right panel, making links thicker (i.e., endorsed by more people in common) or thinner (i.e., endorsed by fewer people in common).

and by decreasing the believability of beliefs opposed in common (Vlasceanu et al., 2020). In addition to this quantitative assessment of sharedness, we propose that an essential feature of a shared belief is individuals' understanding of the social consensus regarding a given belief—in other words, recognizing that the belief is widely endorsed by one's affinity groups.

The second consideration of a collective belief lies in the belief's centrality to the group's identity. The centrality feature can be quantified as the degree to which a belief is idiosyncratically held by a group compared with other groups or with the general population. For example, the belief that immigrants "hurt the country and make it a worse place to live" is a collective belief of Republicans in the United States, given that this belief is held by 59% of Republicans but only 21% of Democrats (*Fox Poll*, 2022). However, the belief that "eating carrots makes eyesight sharper" is not a collective belief according to our definition because it is not preferentially endorsed by members of a community (Vlasceanu et al., 2021b). This criterion of collective beliefs aligns with social-identity theory (Tajfel & Turner, 2004) and with the identity-based model of political belief (Van Bavel & Pereira, 2018).

Applications: Targeted Interventions in Communities

Conceptualizing collective beliefs using the framework introduced here has the potential to (a) facilitate a more systematic investigation of belief systems and (b) increase the impact of belief interventions that could lead to meaningful and stable behavior change. In what follows, we elaborate on how interventions could capitalize on the framework we propose in this article.

First, one could measure the degree to which individuals endorse certain beliefs in a particular domain (Brandt, 2022). Individuals could also be asked to provide an assessment of the evidence that supports/opposes the beliefs they hold and the perceived norms associated with these beliefs. Vectors could be created to capture each participant's belief system with either binary values that indicate the presence or absence of a belief (evidence and perceived norm) in the individuals' belief systems or continuous values to capture the strength of their endorsement. These vectors could be aggregated into matrices that contain the vectors of multiple participants that make a particular community (i.e., a participant-by-item matrix). Transforming this matrix from a two-mode network (i.e., a participant-by-item matrix) into a one-mode network (i.e., item-by-item matrix) would capture the number of community members that hold two belief elements in common. A graph-based representation of such a belief-system network (see Fig. 2) would not only provide a visual representation of the belief units that are more central to a community's belief system but also highlight certain pathways that could be used for intervention purposes.

For example, the belief that "climate change is due to natural causes" (B1 in Fig. 2) could be a central belief in some communities. Furthermore, it could be simultaneously endorsed by multiple individuals in the community along with the "evidence" that "periods of global warming occurred in the past, even before humans were roaming the planet" (E4 in Fig. 2). The perceived norm that "most Americans have changed their minds that climate change is human-made, during the last 10 years" might also be endorsed collectively by the community (N4 in Fig. 2) and be connected with B1. Being able to model these connections in the community's belief-system network provides an entry point for interventions. Such interventions could involve focusing on the subset of participants in the community who endorse the inaccurate belief elements in common. This could be done by both attempting to understand the social-influence processes that facilitated the shared endorsement of these beliefs (e.g., highly connected nodes who spread false beliefs) and by targeting these specific individuals with well-established interventions to reduce the dissemination of inaccurate beliefs through the network. Attempting to change a community's widely endorsed (and inaccurate) belief that "climate change is due to natural causes" could become a more tractable problem once its connectivity in the community's collective belief system is understood. This approach still requires empirical evidence in the form of controlled experiments that test these interventions against other available strategies. But the infrastructure, methodology, and analytical techniques to allow for such empirical tests are already in place (Vlasceanu et al., 2018).

Conclusion

Changing entrenched beliefs to alter people's behaviors and increase societal welfare has been at the forefront of a growing body of interdisciplinary research. Here, we propose a new framework of conceptualizing individual and collective beliefs as a multidimensional system of mental representations across three cognitive structures (e.g., evidence, beliefs, and perceived norms) that are continuously influenced by complex informational landscapes. This account of collective beliefs helps explain beliefs' long-term resilience to behavioral interventions and suggests that a promising avenue for increasing the effectiveness of misinformation campaigns should involve the graph-based mapping of communities' belief systems: the BENDING model. This mapping can be used to identify the network connections that could be targeted as part of community-wide interventions.

This approach meaningfully advances the field by suggesting that to change individuals' beliefs in consequential and long-lasting ways, a more efficient strategy than the current status quo involves collective-level targeting of belief systems. This targeting strategy builds on the premise that people's beliefs are shaped and continuously reinforced by social interactions. Therefore, interventions scaffolded onto a community's belief system will be more efficient than those targeted at individuals in isolation. Beliefs that are inaccurate and central to the community's belief system could be corrected with strategies that consider their connectivity in the community's belief system. The alternative, targeting beliefs simply based on their level of endorsement in the population, which involves just a proportion of people who endorse a particular belief, is likely suboptimal. Experiments involving both controlled lab experiments and randomized controlled trials in the field should test this conjecture.

Given their novelty, network-based approaches aimed at understanding and intervening on belief systems are in need of meaningful development. First, different measurement approaches (e.g., causal-attitude network, BENDING model) might benefit from comparative evaluations to establish their descriptive and predictive usefulness for different contexts. Note that these models make different predictions about which pathways might be more efficiently targeted to change a community's behavioral responses. Second, programmatic investigations should be undertaken to establish which connectivity features of the belief system should be targeted for intervention. For instance, focusing on the central nodes of the belief system first could be more meaningful but could also result in unintended backfire effects or targetting highly connected nodes in the community's belief system as opposed to sparsely connected nodes could be differentially impactful for changing their beliefs. Finally, but maybe most important, the ethical dimension of intervening on belief systems should be front and center. Various actors might be interested in the social engineering of a community's beliefs, from corporations to governments. Regulations and transparency around belief-system interventions should be made clear to the targeted communities, and their well-being should constitute the main priority.

The approach proposed here has already opened new avenues for future research an will likely be used to tackle some of the most critical challenges facing modern society, from climate-change mitigation to pandemic preparedness. For instance, how do efficacy beliefs around pro-environmental behaviors or pandemic preparedness interact with perceived normativity of adoption and support for environmental policies? What are the optimal paths of intervening to stimulate climate action or preventive pandemic behaviors across different political and cultural communities? Using the new network approaches to belief systems, we claim, will get researchers closer to answering these questions and, thus, making an impact in the world.

Transparency

Action Editor: Henrik Olsson
Editor: Interim Editorial Panel
Declaration of Conflicting Interests
The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Ajzen, I., & Fishbein, M. (1975). A Bayesian analysis of attribution processes. *Psychological Bulletin*, *82*(2), 261–277.

Bechler, C. J., Tormala, Z. L., & Rucker, D. D. (2021). The attitude–behavior relationship revisited. *Psychological Science*, *32*(8), 1285–1297.

Bicchieri, C., & Dimant, E. (2022). Nudging with care: The risks and benefits of social information. *Public Choice*, *191*(3–4), 443–464.

Bicchieri, C., Muldoon, R., & Sontuoso, A. (2011). Social norms. In E. N. Zalta (Ed.), *The Stanford encyclopedia of philosophy*. https://plato.stanford.edu/entries/social-norms/

Botvinik-Nezer, R., Jones, M., & Wager, T. D. (2023). A belief systems analysis of fraud beliefs following the 2020 US election. *Nature Human Behaviour*. https://doi.org/10.1038/s41562-023-01570-4

Boutyline, A., & Vaisey, S. (2017). Belief network analysis: A relational approach to understanding the structure of attitudes. *American Journal of Sociology*, *122*(5), 1371–1447.

Brandt, M. J. (2022). Measuring the belief system of a person. *Journal of Personality and Social Psychology*, *123*, 830–853.

Brandt, M. J., & Sleegers, W. W. (2021). Evaluating belief system networks as a theory of political belief system dynamics. *Personality and Social Psychology Review*, *25*(2), 159–185.

Brinol, P., & Petty, R. E. (2009). Source factors in persuasion: A self-validation approach. *European Review of Social Psychology*, *20*(1), 49–96.

Broockman, D., & Kalla, J. (2022). *Consuming cross-cutting media causes learning and moderates attitudes: A field experiment with Fox News viewers*. OSF. https://doi.org/10.31219/osf.io/jrw26

Brugnoli, E., Cinelli, M., Quattrociocchi, W., & Scala, A. (2019). Recursive patterns in online echo chambers. *Scientific Reports*, *9*(1), Article 20118. https://doi.org/10.1038/s41598-019-56191-7

Chang, E. H., Milkman, K. L., Gromet, D. M., Rebele, R. W., Massey, C., Duckworth, A. L., & Grant, A. M. (2019). The mixed effects of online diversity training. *Proceedings of the National Academy of Sciences, USA*, *116*, 7778–7783. https://doi.org/10.1073/pnas.1816076116

Christakis, N. A., & Fowler, J. H. (2009). *Connected: The surprising power of our social networks and how they shape our lives*. Little, Brown Spark.

Coman, A., Momennejad, I., Drach, R. D., & Geana, A. (2016). Mnemonic convergence in social networks: The emergent properties of cognition at a collective level. *Proceedings of the National Academy of Sciences, USA*, *113*(29), 8171–8176.

Connors, M. H., & Halligan, P. W. (2015). A cognitive account of belief: A tentative road map. *Frontiers in Psychology*, *5*, Article 1588. https://doi.org/10.3389/fpsyg.2014.01588

Dalege, J., Borsboom, D., Van Harreveld, F., Van den Berg, H., Conner, M., & Van der Maas, H. L. (2016). Toward a formalized account of attitudes: The Causal Attitude Network (CAN) model. *Psychological Review*, *123*(1), 2–22. https://doi.org/10.1037/a0039802

Deutsch, M., & Gerard, H. B. (1955). A study of normative and informational social influences upon individual judgment. *The Journal of Abnormal and Social Psychology*, *51*(3), 629–636.

Eagly, A., & Chaiken, S. (1998). Attitude structure and function. In D. T. Gilbert, S. T. Fiske, & G. Lindzey (Eds.), *The Handbook of social psychology* (Vol. 1, 4th ed., pp. 269–322). McGraw-Hill.

Falsetti, S. A., Resick, P. A., & Davis, J. L. (2003). Changes in religious beliefs following trauma. *Journal of Traumatic Stress*, *16*(4), 391–398.

Farkas, J., & Schou, J. (2019). *Post-truth, fake news and democracy: Mapping the politics of falsehood*. Routledge.

Fazio, L. K., Brashier, N. M., Payne, B. K., & Marsh, E. J. (2015). Knowledge does not protect against illusory truth. *Journal of Experimental Psychology: General*, *144*(5), 993–1002.

Fernbach, P. M., & Van Boven, L. (2022). False polarization: Cognitive mechanisms and potential solutions. *Current Opinion in Psychology*, *43*, 1–6.

Festinger, L. (1954). A theory of social comparison processes. *Human Relations*, *7*(2), 117–140.

Fox Poll. (2022). https://static.foxnews.com/foxnews.com/content/uploads/2022/05/Fox_April-28-May-1-2022_Complete_National_Cross-Tabs_May-4-Release.pdf

Frenkel, S., Alba, D., & Zhong, R. (2020, March 8). Surge of virus misinformation stumps Facebook and Twitter. *The New York Times*. https://www.nytimes.com/2020/03/08/technology/coronavirus-misinformation-social-media.html

Friedkin, N. E., Proskurnikov, A. V., Tempo, R., & Parsegov, S. E. (2016). Network science on belief system dynamics under logic constraints. *Science*, *354*(6310), 321–326.

Gilbert, M. (1994). Remarks on collective belief. In F. Schmitt (Ed.), *Socializing epistemology: The social dimension of knowledge* (pp. 235–256). Rowman & Littlefield.

Hasher, L., Goldstein, D., & Toppino, T. (1977). Frequency and the conference of referential validity. *Journal of Verbal Learning and Verbal Behavior*, *16*(1), 107–112.

Hochbaum, G. M. (1958). *Public participation in medical screening programs: A socio-psychological study* (No. 572). U.S. Department of Health, Education, and Welfare, Public Health Service, Bureau of State Services, Division of Special Health Services, Tuberculosis Program.

Jervis, R. (2006). Understanding beliefs. *Political Psychology*, *27*(5), 641–663.

Kim, J. W. (2018). Rumor has it: The effects of virality metrics on rumor believability and transmission on Twitter. *New Media & Society*, *20*(12), 4807–4825.

Lewandowsky, S., Ecker, U. K., Seifert, C. M., Schwarz, N., & Cook, J. (2012). Misinformation and its correction:

Continued influence and successful debiasing. *Psychological Science in the Public Interest*, *13*(3), 106–131.

Lund, F. H. (1925). The psychology of belief. *The Journal of Abnormal and Social Psychology*, *20*(1), 63–81, 174–195.

Macy, M., Deri, S., Ruch, A., & Tong, N. (2019). Opinion cascades and the unpredictability of partisan polarization. *Science Advances*, *5*(8), Article 0754. https://doi.org/10.1126/sciadv.aax0754

Mangels, J. A., Butterfield, B., Lamb, J., Good, C., & Dweck, C. S. (2006). Why do beliefs about intelligence influence learning success? A social cognitive neuroscience model. *Social Cognitive and Affective Neuroscience*, *1*(2), 75–86.

McGuire, W. J. (1960). Direct and indirect persuasive effects of dissonance-producing messages. *The Journal of Abnormal and Social Psychology*, *60*(3), 354–358.

Miller, D. T., & Prentice, D. A. (2016). Changing norms to change behavior. *Annual Review of Psychology*, *67*, 339–361.

Minton, E. A., & Kahle, L. R. (2013). *Belief systems, religion, and behavioral economics: Marketing in multicultural environments*. Business Expert Press.

Monroe, B. M., & Read, S. J. (2008). A general connectionist model of attitude structure and change: The ACS (Attitudes as Constraint Satisfaction) model. *Psychological Review*, *115*(3), 733–759.

O'Gorman, H. (1986). The discovery of pluralistic ignorance: An ironic lesson. *Journal of the History of the Behavioral Sciences*, *22*(4), 333–347.

Ozubko, J. D., & Fugelsang, J. (2011). Remembering makes evidence compelling: Retrieval from memory can give rise to the illusion of truth. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *37*(1), 270–276.

Paluck, E. L., Shepherd, H., & Aronow, P. (2016). Changing climates of conflict: A social network experiment in 56 schools. *Proceedings of the National Academy of Sciences*, *113*(3), 566–571.

Porter, E., Wood, T., & Kirby, D. (2018). Sex trafficking, Russian infiltration, birth certificates, and pedophilia: A survey experiment correcting fake news. *Journal of Experimental Political Science*, *5*(2), 159–164.

Prentice, D. A., & Miller, D. T. (1993). Pluralistic ignorance and alcohol use on campus: Some consequences of misperceiving the social norm. *Journal of Personality and Social Psychology*, *64*(2), 243–256.

Ranney, M. A., & Clark, D. (2016). Climate change conceptual change: Scientific information can transform attitudes. *Topics in Cognitive Science*, *8*(1), 49–75.

Rodriguez, N., Bollen, J., & Ahn, Y. Y. (2016). Collective dynamics of belief evolution under cognitive coherence and social conformity. *PLOS ONE*, *11*(11), Article e0165910. https://doi.org/10.1371/journal.pone.0165910

Rosen, N. A., & Wyer, R. S. (1972). Some further evidence for the "Socratic effect" using a subjective probability model of cognitive organization. *Journal of Personality and Social Psychology*, *24*(3), 420–424.

Ross, L., Greene, D., & House, P. (1977). The false consensus effect: An egocentric bias in social perception and attribution processes. *Journal of Experimental Social Psychology*, *13*(3), 279–301.

Rutjens, B. T., & Brandt, M. J. (Eds.). (2019). *Belief systems and the perception of reality*. Routledge.

Schwitzgebel, E. (2011). Belief. In S. Bernecker & D. Pritchard (Eds.), *The Routledge companion to epistemology* (pp. 40–50). Routledge.

Shariff, A. F., & Rhemtulla, M. (2012). Divergent effects of beliefs in heaven and hell on national crime rates. *PLOS ONE*, *7*(6), Article e39048. https://doi.org/10.1371/journal.pone.0039048

Sherman, D. K., Updegraff, J. A., Handy, M. S., Eom, K., & Kim, H. S. (2022). Beliefs and social norms as precursors of environmental support: The joint influence of collectivism and socioeconomic status. *Personality and Social Psychology Bulletin*, *48*(3), 463–477.

Shermer, M. (2012). *The believing brain: From ghosts and gods to politics and conspiracies–How we construct beliefs and reinforce them as truths*. St. Martin's Griffin.

Smith, E. R., & Semin, G. R. (2007). Situated social cognition. *Current Directions in Psychological Science*, *16*(3), 132–135.

Sparkman, G., Attari, S. Z., & Weber, E. U. (2021). Moderating spillover: Focusing on personal sustainable behavior rarely hinders and can boost climate policy support. *Energy Research & Social Science*, *78*, 102150.

Sparkman, G., Geiger, N., & Weber, E. U. (2022). Americans experience a false social reality by underestimating popular climate policy support by nearly half. *Nature Communications*, *13*(1), Article 4779. https://doi.org/10.1038/s41467-022-32412

Sulat, J. S., Prabandari, Y. S., Sanusi, R., Hapsari, E. D., & Santoso, B. (2018). The validity of health belief model variables in predicting behavioral change: A scoping review. *Health Education*, *118*, 499–512.

Swann, W. B., Pelham, B. W., & Chidester, T. R. (1988). Change through paradox: Using self-verification to alter beliefs. *Journal of Personality and Social Psychology*, *54*(2), 268–273.

Tajfel, H., & Turner, J. C. (2004). The social identity theory of intergroup behavior. Key readings in social psychology. In J. T. Jost & J. Sidanius (Eds.), *Political psychology: Key readings in social psychology* (pp. 276–293). Psychology Press.

Taylor, S. E., & Fiske, S. T. (1978). Salience, attention, and attribution: Top of the head phenomena. *Advances in Experimental Social Psychology*, *11*, 249–288.

Turner-Zwinkels, F. M., & Brandt, M. J. (2022). Belief system networks can be used to predict where to expect dynamic constraint. *Journal of Experimental Social Psychology*, *100*, Article 104279. https://doi.org/10.3389/fpls.2022.970410

Van Bavel, J. J., & Pereira, A. (2018). The partisan brain: An identity-based model of political belief. *Trends in Cognitive Sciences*, *22*(3), 213–224.

Van Boven, L., Ehret, P. J., & Sherman, D. K. (2018). Psychological barriers to bipartisan public support for climate policy. *Perspectives on Psychological Science*, *13*(4), 492–507.

Van der Linden, S. (2021). The Gateway Belief Model (GBM): A review and research agenda for communicating the scientific consensus on climate change. *Current Opinion in Psychology*, *42*, 7–12.

Vlasceanu, M. (2021). *Cognitive processes shaping individual and collective belief systems* [Unpublished doctoral dissertation]. Princeton University.

Vlasceanu, M., & Coman, A. (2018). Mnemonic accessibility affects statement believability: The effect of listening to others selectively practicing beliefs. *Cognition*, *180*, 238–245.

Vlasceanu, M., & Coman, A. (2022). The impact of social norms on health-related belief update. *Applied Psychology: Health and Wellbeing*, *14*(2), 453–464.

Vlasceanu, M., Enz, K., & Coman, A. (2018). Cognition in a social context: A social-interactionist approach to emergent phenomena. *Current Directions in Psychological Science*, *27*(5), 369–377.

Vlasceanu, M., McMahon, C., Van Bavel, J. J., & Coman, A. (2023). Political and nonpolitical belief change elicits behavioral change. *Journal of Experimental Psychology: Applied*. Advance online publication. https://doi.org/10.1037/xap0000455

Vlasceanu, M., Morais, M. J., & Coman, A. (2021a). The effect of prediction error on belief update across the political spectrum. *Psychological Science*, *32*(6), 916–933.

Vlasceanu, M., Morais, M. J., & Coman, A. (2021b). Network structure impacts the synchronization of collective beliefs. *Journal of Cognition and Culture*, *21*(5), 431–448.

Vlasceanu, M., Morais, M. J., Duker, A., & Coman, A. (2020). The synchronization of collective beliefs: From dyadic interactions to network convergence. *Journal of Experimental Psychology: Applied*, *26*(3), 453–464.

Voelkel J. G., Stagnaro, M. N., Chu, J., Pink, S. L., Mernyk, J. S., Redekopp, C., Ghezae, I., Cashman, M., Adjodah, D., Allen, L., Allis, V., Baleria, G., Ballantyne, N., Van Bavel, J. J., Blunden, H., Braley, A., Bryan, C., Celniker, J., Cikara, M., . . . Willer, R. (2023). *Megastudy identifying effective interventions to strengthen Americans' democratic attitudes*. Center for Open Science. https://www.strengtheningdemocracychallenge.org/paper

World Nuclear Association. (2022). *Carbon dioxide emissions from electricity*. https://www.world-nuclear.org/information-library/energy-and-the-environment/carbon-dioxide-emissions-from-electricity.aspx#:~:text=Worldwide%20emissions%20of%20carbon%20dioxide,2%20and%20other%20greenhouse%20gases

Wyer, R. S., & Albarracín, D. (2005). Belief formation, organization, and change: Cognitive and motivational influences. In D. Albarracín, B. T. Johnson, & M. P. Zanna (Eds.), *The handbook of attitudes* (pp. 273–322). Erlbaum.