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Connecting the Dots with Causal Attitude Network (CAN): A Psychological Network Approach to Populist Attitudes, Nativism, Conspiracy Mentality and Threat Appraisals

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ABSTRACT

This methodological paper uses a new conceptualization of attitudes, the Causal Attitude Network (CAN) model, to investigate populism and nativism. The CAN model conceptualizes attitudes as a complex system of interrelated factors and captures different attitude components' interplay and mutual dependence. Drawing on two previously collected, representative datasets (N_1 = 8046, N_2 = 2030) from 15 European countries, we estimated the networks structure of populist attitudes (PA), nativism, conspiracy mentality, threat appraisals, and demographics. Besides confirmatory factor analyses (CFA) and exploratory factor analyses (EFA), our general procedure included the estimation of *Mixed Graphical Models* (MGMs) with *LASSO Regularization* and the *Extended Bayesian Information Criterion* (EBIC), before we analyzed our network models with the *Walktrap* algorithm and *Network Comparison Test* (NCT). A cluster analysis based on different algorithms (*hierarchical, clara, pam*) divided the countries into two clusters, while the main difference between them was how the networks related to perceiving politicians as corrupt elites. To gain a deeper understanding of the PA scale, we investigated it from a network perspective. We found that the PA network of Turkey (a hybrid case of religious-conservative and nationalist-authoritarian) differed the most from all other countries under investigation.

KEYWORDS
Appraisal theory; attitudes; causal attitude network; conspiracy mentality; emotion; nativism; populism; psychometrics; threat

Introduction

In the course of the last decades, populism has been on the rise across Europe. Populist parties, such as the *AfD* in Germany, the *Front National* in France, the *PVV* in the Netherlands, *Syriza* in Greece, and *Podemos* in Spain, have gained momenta across Europe (e.g., Inglehart & Norris, 2016; Nagan & Manausa, 2018). One crucial factor explaining the success of these populist parties is the populist attitudes (PA) held by citizens (Van Hauwaert & van Kessel, 2018). In recent years, scholars have investigated how PA relate to socio-demographic variables (e.g., Goodhart, 2017; Inglehart & Norris, 2016), behavioral outcomes (e.g., Akkerman et al., 2017; Hawkins et al., 2020), conspiracy beliefs (e.g., Castanho Silva et al., 2017; Hameleers, 2021; Van Prooijen, 2018), and emotions (Abadi, Bertlich, et al., 2024; Huguet-Cabot et al., 2021).

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Recently, a new conceptualization of attitudes has been introduced to the attitudes literature, the Causal Attitude Network (CAN) model. The CAN model conceptualizes attitudes as a complex system of causally connected beliefs, feelings, and behaviors toward an attitude object. These complex systems are modeled using empirical network models. Thereby, the CAN model captures the interrelatedness of different attitude components and points out that these interrelations convey important information. CAN is a type of psychometric network analysis and allows us to derive a realistic conceptualization of attitudes (Borsboom et al., 2021; Dalege et al., 2016).

To the best of our knowledge, this is the first methodological paper to apply this novel model to our measures, namely populism, nativism, threat appraisals and conspiracy mentality (see also Abadi, van Prooijen, et al., 2024). Thereby, we aim to introduce a new methodology to computational social science research, gain a deeper understanding, and add to the existing literature.

Conceptualizing populism

There is an ongoing debate surrounding the conceptualization of populism (Hawkins et al., 2020; Rooduijn, 2019). It pertains to whether it is a political strategy with charismatic leadership (Weyland, 2001), a set of economic policies that aim to redistribute wealth (Acemoglu et al., 2013), or an ideology (Mudde, 2004; Stanley, 2008). Although conceptualizations differ, many scholars agree that populism is inherently connected to the struggle of "the people" against "the elites" or, more generally, "the enemies of the people." The enemies of the people can be financial elites (left-wing populism; Bonansinga, 2022) or minorities, immigrants, and political elites (right-wing populism; Mudde & Rovira Kaltwasser, 2018; Rodrik, 2020; Rooduijn, 2019).

Depending on how populist leaders frame the conflict between "the people" and the enemies of the people, populism can take on different forms: In *cultural populism*, "the people" are people native to a nation-state, while non-native people and elites are perceived as enemies. In *socioeconomic populism*, "the people" are hard-working working-class people, while big corporations and alleged representatives of the capitalistic system are seen as "the enemies." And in *anti-establishment populism*, "the people" are all those who are not the established political elites, which is perceived as the enemy of the people (Kyle & Gultchin, 2018).

Our research uses the *ideational* approach to investigate populism, which enjoys growing support as it allows the investigation from both the supply side (e.g., populist actors and parties) and the demand side (populist attitudes) of populism (Hawkins et al., 2020). Within this approach, populism is defined as a limited set of ideas about society. These ideas are that 1) the "pure people" are a homogeneous and moral group (*people-centrism*), 2) the "corrupt elites" are immoral and opposed to the people (*anti-elitism*), and 3) the world is divided into antagonistic and homogeneous groups and this perception of groups being either inherently good or evil is called a *Manichean outlook*. Following this definition, populism occurs when all three elements are present (Hawkins et al., 2020; Mudde & Rovira Kaltwasser, 2018).

Socio-demographic profile

The first research into the profiles of people holding PA originated from the political radicalization literature. It assumed that older white men (in comparison to younger people, ethnic minorities, and women) with lower socioeconomic status were more prone to hold higher levels of PA (Goodhart, 2017; Inglehart & Norris, 2016). However, populism scholars criticized this idea for applying rather to right-wing PA, but not to PA in general (Mudde & Rovira Kaltwasser, 2018; Rovira Kaltwasser & Van Hauwaert, 2020). The broader populism literature has shown that left-wing populism is more prevalent among younger, higher-educated people living in urban areas. In comparison, right-wing populism tends to be more prominent among men with lower socioeconomic status (Arzheimer, 2009; Fukuoka, 2020; Ramiro & Gomez, 2017; Rodríguez-Teruel et al., 2016). In line with these differences, cross-country studies on PA show no uniform populist socio-demographic profile (Rooduijn, 2017).

Left- and right-wing populism

As mentioned above, populism consists of three core ideas attached to other ideologies, such as socialism or nationalism. Therefore, we also find left-wing and right-wing populism, meaning populist ideas connected to ideologies from the political right or left (Akkerman et al., 2014; Mudde, 2007; Vasilopoulos & Jost, 2020). Depending on the ideologies populism is attached to, the understanding of its core ideas might differ. For example, the conceptualization of "the people" can be inclusionary for left-wing populism (i.e., minority and majority members can be part of "the people") or exclusionary for right-wing populism (i.e., only a specific group of people, for example, majority members, can be part of "the people"; Vasilopoulos & Jost, 2020). Another difference between right-wing populism and left-wing populism is their relation to collective narcissism. Collective narcissism is the belief that the own ingroup is exceptional and deserves special privileges, but others do not recognize this special status (Golec De Zavala et al., 2009; Golec de Zavala et al., 2019). Collective narcissism is related to right-wing populism because they share a narrow and divisive definition of who is part of the ingroup (here: "the people"). For example, some right-wing populist actors emphasize that outgroup members (e.g., non-populist politicians, immigrants, LGBTQ+ members) threaten the deserved privileges of the pure and moral ingroup (Golec de Zavala et al., 2019; Mols & Jetten, 2016). These differences could cause populism to relate differently to other constructs, such as nativism.

Conceptualizing nativism

One ideology that is often combined with populism is nativism (Betz, 2017; Heiss & Matthes, 2020; Mudde, 2007, 2012; Rooduijn et al., 2021). Nativism can be understood as "an ideology which holds a country should be inhabited exclusively by members of the native group ('the nation') and that nonnative elements (persons and ideas) are fundamentally threatening to the homogeneous nation-state" (Mudde, 2007, p. 19). Moreover, it is argued that nativism (and not populism) is the ultimate core feature of the populist radical right ideology (Mudde, 2007, p. 26).

The main difference between populism and nativism is the "us" versus "them" dichotomy; nativism considers racial and cultural natives as "ingroups," while racial and cultural others are described as "outgroups" (e.g., Newth, 2021). Populism differentiates between the "pure people" versus the "corrupt elites" (Mudde, 2004, p. 543).

Nativism focuses on the idea that people being native to a country believe to have more rights to be treated fairly, and to receive priority treatments when living in the country of birth (Hochschild, 2018). Indeed, one prominent argument of five European populist radical right parties (Ivaldi & Mazzoleni, 2020), is that economic prosperity of the heartland should be defended against the elites and immigrants. Natives should protect their economic interests, because their ancestors built the country (Betz, 2017; Heiss & Matthes, 2020; Hochschild, 2018; Mudde, 2012), while "foreigners" and elites behaving "foreign" are considered a threat to the native nation (see Kešić & Duyvendak, 2019).

In previous populism research, populism and nativism have been conceptualized together (Hameleers et al., 2017), but more recent scholars call for a distinction of the phenomena (Abadi, Bertlich, et al., 2024; De Cleen & Speed, 2020; Rooduijn, 2019; Rooduijn et al., 2021). In comparison to some definition of populism, which makes a vertical distinction between the "pure people" and the "corrupt elites," nativism captures a horizontal distinction between the "pure people" and the so-called "dangerous others" (Rooduijn, 2019). It becomes apparent that nativism and populism share the perception of a good ingroup and an evil outgroup, but they can differ in what the outgroup entails. Thus, it is not surprising that nativism and populism are often intertwined. Especially right-wing populism often appears together with nativism (Mudde, 2007).

Threat and appraisal theory of emotion

Scholars studying intergroup threat have emphasized the importance of conceptualizing and measuring threat as *perceived* threat. This idea aligns with appraisal theories of emotion, which suggest that it is the subjective experience rather than the objective features of an event that are crucial for an emotion to occur (see Roseman, 1984, Roseman, 2013; Scherer et al., 2001). Appraisals are quick, and often subconscious, evaluations of an event, based on one's concerns, goals or desires. They can thus be conceived of as mediators between a stimulus and an emotion, the stimulus being the remote cause of the emotion, and the appraisal the proximate cause (Moors, 2013; Moors et al., 2013; Roseman & Smith, 2001; Scherer et al., 2001).

Both populist and nativist attitudes are related to intergroup perceptions. Based on the Intergroup Threat Theory (Stephan et al., 2009), outgroups can be perceived (i.e., appraised) as threatening. Two general types of intergroup threat have been distinguished in the literature (Stephan, 2014; Stephan & Stephan, 2000; Stephan et al., 2015): *realistic threats* (threats to the ingroup's power, financial resources, or well-being) and *symbolic threats* (threats to the ingroup's system of values, cultural identity, or way of life). Both types of threat can be considered as a social status threat, where people perceive their ingroup as threatened by actions of the outgroup (Branscombe et al., 1999), while often these different threats co-exist.

The literature shows that these intergroup threat perceptions are essential in shaping intergroup relations (Rios et al., 2018). Attitudes regarding the outgroup are more negative when realistic and symbolic threats are perceived as high (Rios et al., 2018). This means that people with more elevated levels of perceived threat should also have stronger PA (Abadi, van Prooijen, et al., 2024).

Conspiracy mentality

Another phenomenon related to PA is conspiracy mentality (Castanho Silva et al., 2017; Erisen et al., 2021; Van Prooijen, 2018) which describes the general tendency to believe in conspiracy theories (Bruder et al., 2013). Conspiracy beliefs are explanatory beliefs that assume that some actors meet in secret to pursue a fundamentally evil goal (Van Prooijen & Douglas, 2018). These beliefs are used to explain complex societal phenomena, such as the COVID-19 pandemic, in a simple and deterministic way. Manichean narratives are used within these theories, in which fundamentally evil actors are fighting against fundamentally good opponents (Erisen et al., 2021; Oliver & Wood, 2014). Thus, the Manichean outlook is shared by both conspiracy mentality and PA. Recent studies have shown that there is indeed a positive relationship between conspiracy mentality and PA (Castanho Silva et al., 2017; Erisen et al., 2021).

Country differences

One limitation of most research on PA is that many studies are single-country studies using Western European populations. However, it is crucial to take into account country differences. For example, cross-country studies on socio-demographic profiles of populist citizens have shown that the profile of such citizens differs across world regions and political profiles (Rooduijn, 2017; Rovira Kaltwasser & Van Hauwaert, 2020). Similarly, a cross-sectional study on PA in the aftermath of the Great Recession (2007–2009) showed that demographic and socioeconomic correlates of PA are different across European countries (Rico & Anduiza, 2017). They found that lower education was positively related to PA in Italy and Sweden, but not in Germany, the UK, Switzerland, Spain, Poland, Greece, and France. Moreover, being unemployed had a positive relationship with PA in Greece and Italy, while in Germany and Poland, the relationship was negative. For other countries (Sweden, the UK, Switzerland, Spain, France), unemployment was not related to PA. These studies show the importance of applying a cross-national perspective to PA research.

Latent variable models

Most research reviewed so far has in common that it models PA using latent variables. Latent variable models assume that a shared and unobservable latent variable causes the level of observable indicators. Following this idea, correlations between indicators are spurious due to the shared dependence on the latent variable. This shared dependency also implies that the different attitude components align perfectly (Borsboom, 2008; Borsboom et al., 2003). However, these assumptions seem implausible in the context of attitudes. Indicators of attitudes, namely different attitude components, likely influence each other (Dalege et al., 2016). For example, if a person judges a politician to be corrupt, this likely influences the person's judgment that politicians should listen to the people's will (i.e., the interrelatedness of attitude components). The Causal Attitude Network (CAN) model overcomes these shortcomings and captures this interrelatedness and inconsistencies of different attitude components (Dalege et al., 2016).

The Causal Attitude Network (CAN) model

Instead of using latent variable modeling, the CAN model uses empirical network models to capture attitudes. In such network models, the relations between observed variables are thought to stem from logical and causal connections between these variables (Cramer et al., 2010; Dalege et al., 2016). In this network, the relationships between the variables do not stem from an underlying common cause, the latent variable. Instead, the observable variables themselves are part of the attitude construct, and all observable variables and their interaction form the attitude construct (Cramer et al., 2010; Dalege et al., 2016).

In the CAN model, attitudes are evaluative reactions and their interactions in a network. These evaluative reactions are feelings, beliefs, or behaviors toward an attitude object. The evaluative reactions are represented as nodes, and the relationships between evaluative reactions are represented as edges. The edges represent partial correlations between two nodes. More specifically, they represent the relationship between two variables while controlling for all other variables in the network. The relationships between nodes can differ in their polarity (positive or negative) and in their strength. We displayed two examples of a simplified network in Figure 1.

Networks and elements within the network can have different features. First, networks can differ in their global connectivity. Global connectivity refers to the strength and the number of connections within a network. Higher connectivity represents a stronger attitude (Dalege et al., 2016, 2019). Higher connected networks are also more resistant to change. However, if a node in a highly connected network changes, it has a bigger impact on the rest of the network than a node within a less connected network (Dalege et al., 2016). Figure 1 shows an example of a weakly and a highly connected network, where the latter shows more and stronger edges.

Second, nodes can differ in their centrality within the network. Here, centrality represents the structural importance of a node in the network. One centrality measure that scholars have found

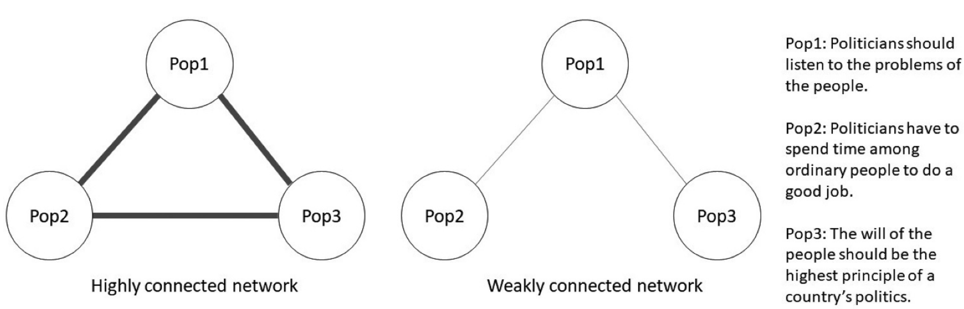


Figure 1. Example networks for populist attitudes.

suitable for psychological networks is *strength* (Bringmann et al., 2019). This centrality measure captures the number of connected nodes while accounting for the edge weights between the nodes (Bringmann et al., 2019; Opsahl et al., 2010). In the weakly connected network of Figure 1, for example, the node *Pop1* is more central than the node *Pop2*, because it is connected to more edges and connects other nodes. The more central a node in a network, the more difficult it is to change. However, changing a more central node has a greater effect on the rest of the network (Dalege et al., 2016; Zwicker et al., 2020).

The current research

We used the CAN model to explore PA, nativism, conspiracy mentality, realistic and symbolic threat, and key demographics. Using the data from two previously collected datasets of cross-sectional survey studies, we aimed to answer the following research questions (RQs):

RQ1: How does the network structure of populist attitudes, nativism, threat, conspiracy mentality, and demographics look like?

It is possible that the relationship between the variables of the network change depending on the strength of the PA. For example, the relationship between conspiracy mentality and threat perception could be stronger for people scoring high in PA, which could lead to a higher connected network (Dalege et al., 2019).

RQ2: How does the empirical network of nativism, threat, and conspiracy mentality differ for individuals scoring high and low in PA?

Additionally, as discussed earlier, it is possible that the meaning and core ideas of PA change across the political spectrum. Therefore, the relationships with nativism and conspiracy mentality might change as well, depending on the political spectrum.

RQ3: How does the network of PA differ for left- and right-wing PA?

And lastly, the relationships between the concepts under investigation may differ across countries.

RQ4: How does the network of PA differ between countries?

Methods

Operationalization

We used previously collected data from two cross-sectional survey studies (Abadi et al., 2023; Abadi, Bertlich, et al., 2024; Abadi, Duyvendak, et al., 2024). Study 1 was conducted in August 2019 and Study 2 was conducted in April 2020. The data were collected via *Qualtrics XM*, and participants were recruited with the help of the opt-in online panel *Cint*, a global research platform with a heterogeneous pool of respondents. Both datasets were already cleaned and anonymized, and missing data were removed.

Participants

Study 1 included participants from 15 European countries,[1] with roughly 500 participants per country. The country samples were representative for age, gender, and geographical region using quotas based on the latest UN census data. The inclusion criterion was that respondents needed to have lived in their current country of residence for at least ten years. Additionally, we removed participants who chose the gender response "other" (N = 13), because the number of responses was too low to use them as a category in the network analysis. Based on these criteria, the total sample size was N = 8046 participants.

In study 2, participants were recruited from four different countries (Germany, The Netherlands, Spain, and the United Kingdom), with approximately 500 participants per country. Again, country samples were representative for age, gender, and geographical region, based on UN-census data. People who did not pass an attention check item and who responded with "other" to the gender item (N = 1) were excluded from the sample. This led to a total sample size of N = 2030 participants.

Previous simulation studies have shown that for a moderately sized network of 25–30 nodes, a sample size of 500 is sufficient (Epskamp, 2016; Van Borkulo et al., 2014). Therefore, we could assume sufficient power for our analyses.

Measures

Unless mentioned otherwise, participants responded to items on a 7-point Likert scale, ranging from 1 (*strongly agree*) to 7 (*strongly disagree*). We report the internal consistency of the scales in the form of Cronbach's alpha (α) to indicate the reliability of the scales. However, these scores are not relevant for our psychometric network analyses as internal consistency measures do not allow us to determine whether items remain unidimensional within multidimensional models, while it is the structural consistency method that indicates whether scales are unidimensional and internally consistent (Christensen et al., 2020). More information on items included in the original studies can be found in the corresponding papers (Abadi et al., 2023; Abadi, Bertlich, et al., 2024).

Populist attitudes

PA were measured using a 9-item scale measuring the dimensions *people-centrism, anti-elitism*, and *Manichean outlook* (Castanho Silva et al., 2018). In Study 1, three items measured each dimension of PA. In Study 2, only two items measured the dimensions anti-elitism and Manichean outlook. Therefore, the PA scale in Study 2 consisted of seven instead of nine items. The scale has a good construct validity, and previous studies show a good internal consistency (Castanho Silva et al., 2018, 2020). However, the inner consistency for this scale in our studies was poor (Cronbach's α_{Study1} = 0.44, α_{Study2} = 0.53). Details on the internal consistencies are displayed in Tables A4 and A5 (see Appendix A).

Nativism

One previous attempt to measure nativism includes the *Ipsos Nativism Scale* (Young, 2016; Zhao, 2019), by using five items from the *World Values Survey* (WVS) and the *General Social Survey* (GSS). The scale captures anti-immigrant perceptions, in which foreigners are described as taking away jobs and social services from "native" populations and weakening the economy as a result. We found these items too constrictive for our research as they did not cover further important topics, such as housing market, identity, culture and values. Therefore, we used items developed by Abadi, Bertlich, et al. (2024) to measure nativism, in which participants indicated how much they agreed with three different statements representing nativist attitudes, such as "The political elites have failed to protect our cultural identity," "People who are born in [country name] should be given priority over immigrants in the employment and housing market" and "People who have immigrated to [country name] should adjust to our habits, values and traditions here and give up their own culture." The internal consistency of the nativism scale was good in both studies (Cronbach's α_{Study1} = .7, α_{Study2} = .77).

Realistic and symbolic threat

The items used to measure realistic and symbolic threat were based on Stephan et al. (2009), with four items measuring realistic threat (e.g., "I am anxious about what the future will bring."), and four items measuring symbolic threat (e.g., "The immigration of people from many other countries is a threat to my values"). The scales have been used in a variety of studies, where they showed good internal consistency (Cronbach's α between.70 and.93) and good face- and construct validity (Riek et al., 2006; Stephan et al., 1999). The internal consistency in our data was poor (Cronbach's α_{Study1} = .55, α_{Study2} = .56).

Conspiracy mentality

To measure the tendency to believe in conspiracy theories, we used the *Conspiracy Mentality Questionnaire* (Bruder et al., 2013). Participants were asked how much they agreed with five different items, such as "I think that government agencies closely monitor all citizens." The scale has a good construct validity, as well as a satisfactory test-retest reliability and inner consistency (Bruder et al., 2013). The internal consistency in our data was good (Cronbach's α_{Study1} = .81, α_{Study2} = .82).

Subjective social status

To capture the subjective social status of respondents, the *MacArthur Scale of Subjective Social Status* was used (Adler et al., 2000). It depicts the social status as an ascending ladder, ranging from rung 1 to rung 10, with the latter being the highest status. Participants can respond by choosing the rung that best represents their perceived social status (1–10).

Demographics

Participants indicated their gender, age, religion, highest achieved education, and employment status. Additionally, in Study 2 only, participants indicated their political orientation on a left-right spectrum, ranging from −5 (*left-wing*) to +5 (*right-wing).*

Results

As a first step, we recoded some of the demographic items (see Appendix A). There were no missing data in the dataset, and multivariate normality did not hold (all p <.001 for Mardia's test of skewness and kurtosis; Mardia, 1970; Zhao, 2019).

The general procedure to investigate the network structures was the following: We estimated undirected network models using the statistical software *R* (R Development Core Team, 2016). Because we intended to investigate continuous and ordinal data, we used the package *mgm* to estimated *Mixed Graphical Models* (MGMs) with *LASSO Regularization* and the *Extended Bayesian Information Criterion* (EBIC; Chen & Chen, 2008; Haslbeck & Waldorp, 2020; Tibshirani, 1996). First, we estimated the network models and centrality indices. For all our estimated models, we tested the accuracy and stability using bootstrapping. Then, we used the *Walktrap* algorithm (Pons & Latapy, 2006) to analyze the different communities existing in the data. To increase the robustness of the community analysis, we used a recent approach (Chambon et al., 2022).[2] We visualized the results using the *qgraph* package (Epskamp et al., 2012). Next, we compared networks using the *Network Comparison Test* (NCT; Van Borkulo et al., 2016) to determine whether networks differ in their network structure, global strength, and edge invariance. For the confirmatory factor analyses (CFA) reported below, we used robust maximum likelihood estimation to account for non-normality.

Jointly estimated network of populist attitudes (RQ1)

Study 1

To answer RQ1, we estimated the network structure and centrality indices of the network consisting of PA, nativism, conspiracy mentality, realistic and symbolic threat, and demographics using data from

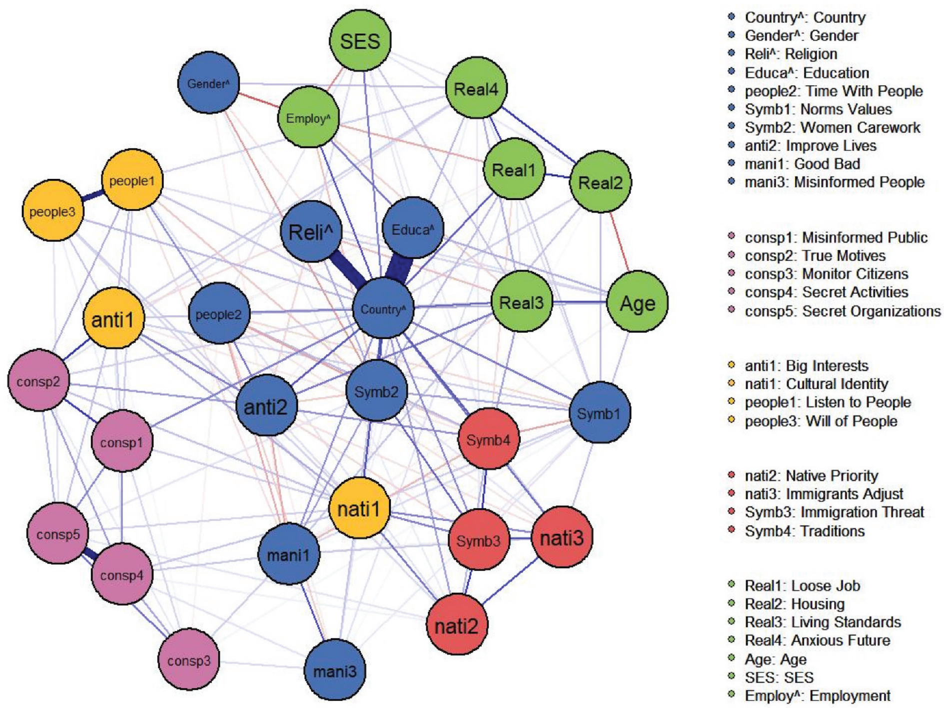


Figure 2. The estimated network of populist attitudes and related constructs in study 1.

all countries. To compare the data from both studies, we only included the variables included in both studies. We displayed the resulting weighted, undirected graph in Figure 2. The different colors of the nodes indicate different communities within the network. The communities represent highly interconnected nodes.

Five different communities emerged from the data. We call the first the *demographic-populist* cluster because it consists of demographic variables, such as country, gender, religion, education, symbolic threat items, and multiple populist attitudes items. We call the second cluster the *conspiracy mentality cluster* because it consists of all conspiracy mentality items. We call the third cluster the *anti-elitist and people-centrist* cluster because it consists of those items. We call the fourth cluster *exclusionist cluster* because it consists of anti-immigrant symbolic threat items and nativist items. And the last cluster we call *socioeconomic cluster* because it consists of all realistic threat items and indicators of socioeconomic status.

The strongest edges in the overall network were the following: First, there was a strong relationship between country and education as well as between country and religion. This means the country of residence was associated with being religious or not and the highest level of education. However, we tested the robustness of these relationships using Chi-square tests and found that effect sizes were low to medium (see Table B1 in Appendix B). This indicates that the estimation method we used might have overestimated the relationships between the categorical variables. Second, there was a strong positive relationship between two people-centrism variables ("Politicians should listen to the people" and "The will of the people should be the highest principle of politics") and between two conspiracy mentality items ("Events are often the result of secret activities" and "There are secret organizations that greatly influence political decisions"). The strongest edges between a populist and a non-populist item existed between the anti-elitism item "The government is run by a few big interests looking out for themselves" and the conspiracy mentality item "Politicians do usually not tell us the true motives for their decisions." Both items capture an anti-elitist sentiment toward politicians.

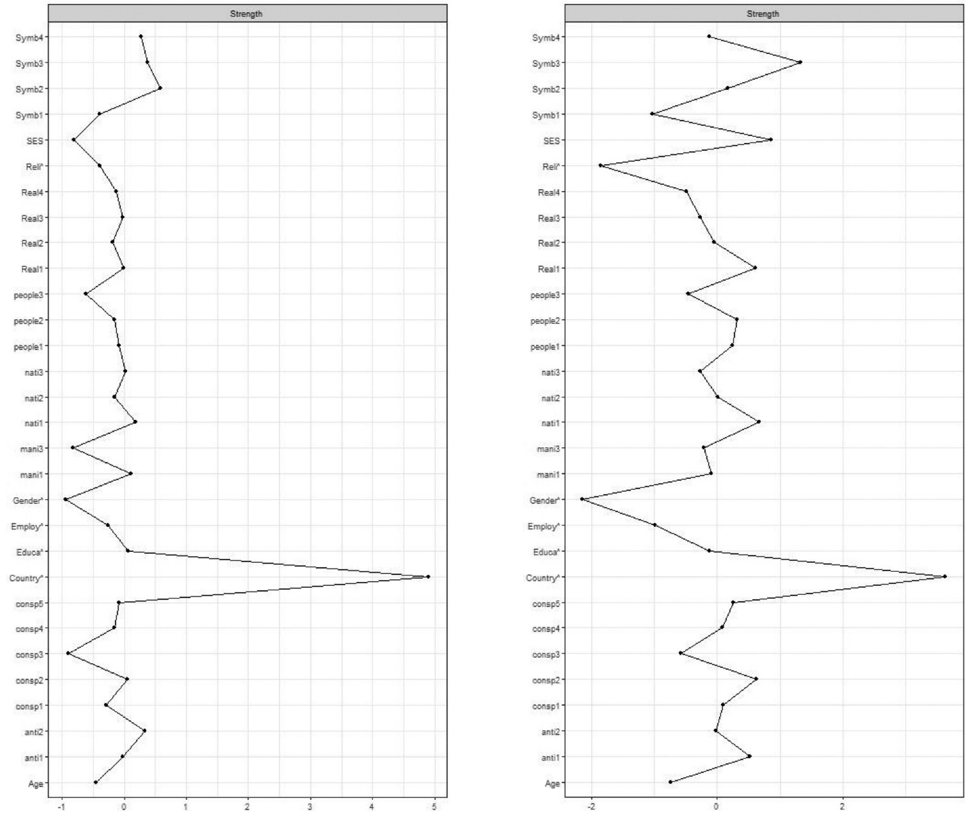


Figure 3. Network centrality indices for study 1 (left) and study 2 (right)

We used the package *qgraph* (Epskamp et al., 2012) to calculate the strength centrality of the nodes in the network. The results are displayed in Figure 3. The node country is remarkably stronger than all other variables in the network. This means that the variable country had the most connections to other variables in the network. Additionally, this means that the relationships between the nodes should differ for the respective countries. The next most central nodes were one symbolic threat item (addressing women's role in the household) and one anti-elitist item ("Government officials use their power to try to improve people's lives"). Generally, the findings indicate that the countries in which data were collected play a major role in the networks, although this might have been partly caused by the estimation method used. Therefore, individual country-level networks are likely to shed more light on the network structure of PA.

Study 2

We repeated the same analysis for the dataset in Study 2. The estimated weighted network graph can be found in Figure 4. Again, the different communities are displayed by the colors of the nodes. In comparison to Study 1, there were more network clusters in Study 2.

The first *conspiracy mentality cluster* included all conspiracy mentality items. The second *people-centrism cluster* included all people-centrality items. The third and fourth clusters consisted of individual items only, namely "The government is pretty much run by a few big interests looking out for themselves" and "The norms and values that I find important are not as important in the UK." The fifth *Manichean cluster* consists of both Manichean outlook items and the recoded anti-elitist item "Government officials use their power to try to improve people's lives." The sixth *nativism cluster* consists of all nativism items and two symbolic threat

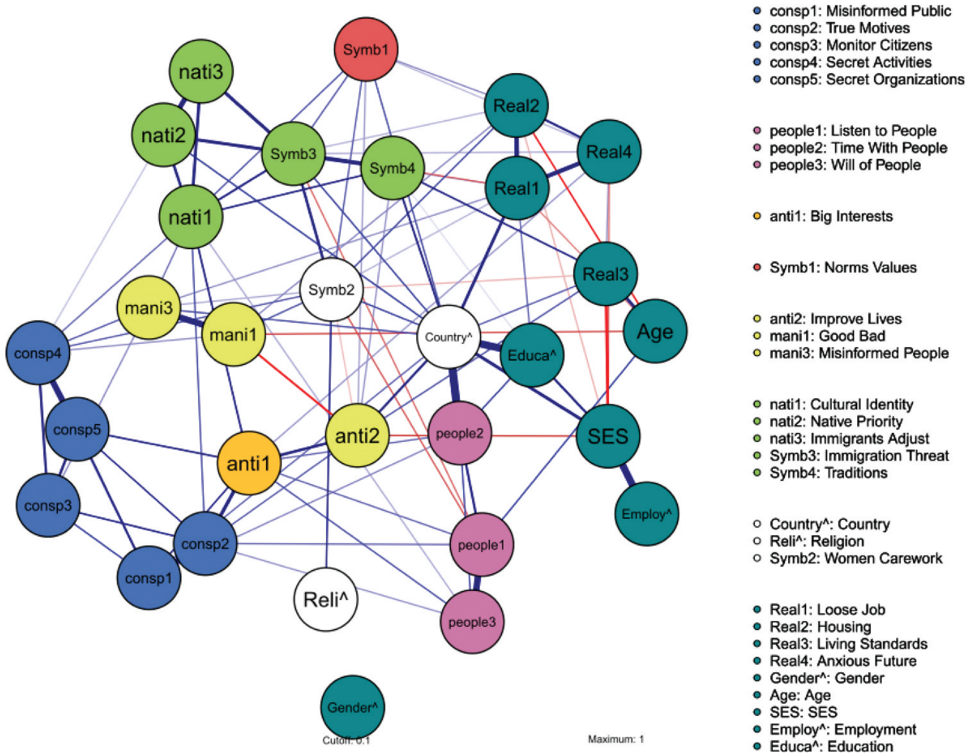


Figure 4. The estimated network of populist attitudes and related constructs in study 2.

items that addressed immigration and native traditions. The seventh *culture cluster* consisted of country, religion, and the symbolic threat item measuring whether women should be responsible for the household. And the last *socioeconomic cluster* consists of a variety of variables capturing the socioeconomic status of individuals as well as realistic threat items. To summarize, Study 1 and Study 2 have similar socioeconomic clusters and conspiracy mentality clusters, while they differ in their clusters for nativism, symbolic threat, and most populist attitudes items. In Study 1, most of these items form a common cluster, whereas in Study 2, they form multiple smaller clusters.

As in Study 1, the strongest edges of the overall network were between some of the demographic variables. Specifically, country had a strong and positive association with education and people-centrism ("Politicians don't have to spend time among ordinary people to do a good job," recoded), and (perceived) subjective social status was strongly associated with employment. Again, Chi-square tests showed that the effect size of the relationship between the categorical variables was medium to low (see tables in Appendix B). This could indicate that the strong relationships between the categorical variables might have been an artifact of the estimation method used.

The strongest edges relating to the PA nodes were, as mentioned above, the country variables for one of the people-centrism items, as well as a strong connection between both Manichean outlook items. Also similar to Study 1, Study 2′s most central node was country. This network's other central nodes were symbolic threat (immigration poses a threat to one's values) and socioeconomic status. We displayed the corresponding network centrality indices in Figure 3.

Additionally, we tested whether the two networks from Study 1 and Study 2 differed significantly from each other using the NCT. The correlation of the two weighted adjacency matrices was high (r = 0.73, df = 433, p < .001). However, the global network invariance test indicated that the two networks differed significantly (p <.01). This is not surprising because the NCT picks up slight differences in the networks with large sample sizes. The network's global strength did not differ (p = .69), and several edges differed significantly from each other (see Table B1 in Appendix B).

In summary, the analysis indicates that the country in which the data were collected had a central influence on the network. Additionally, we found that the communities in Study 1 and Study 2 differed, and that Study 2 had more communities than Study 1. This aligns with the global network invariance test results, which showed that the networks in Study 1 and Study 2 differed significantly from each other.

High vs. Low populist attitudes (RQ2)

To investigate whether the networks of people with high vs. low PA differ, we originally planned to use the PA scale to separate participants into having high vs. low PA. To test the validity of the PA scale, we conducted a confirmatory factor analysis (CFA). In study 1, the CFA showed that the model did not fit well (X^2 [22, N = 8059] = 1398.86, $p < .01$, RMSEA = 0.088, CFI = 0.871, GFI = 0.962, TLI = 0.788). We conducted a CFA for all countries separately, revealing that the model fit was unacceptable for many countries (see Table C1 in Appendix C). Using modification indices and dropping worst indicators did not improve the country-level model fit sufficiently. An exploratory factor analysis (EFA) showed strong differences in the factor structures of the PA scale across countries (see Table C2 – C16 in Appendix C). This indicates that the CFA model did not fit our data well. We decided not to use the items as a latent variable because the factor structure indicated no comparable scale (for more details on this analysis see Appendix C).

Instead, we decided to investigate the PA and nativism scales from a network perspective. We first estimated country networks which included the PA and nativism items. We chose to include nativism into the network to see whether it plays a central role in PA in different countries. Because these networks included continuous data only, we estimated them using Gaussian Graphical Models (e.g., Epskamp, Waldorp et al., 2018) and the package *bootnet* (Epskamp, Borsboom et al., 2018). Again, we applied a *LASSO Regularization* and used the EBIC to select the best model, and we used spearman correlations to account for the quasi-continuous data. The resulting network graphs, including their communities and the centrality indices, are displayed in Figures D1 – D19. The graphs show that the community structure of the networks differs strongly across the countries. This means that the items of the PA scale had different relationships across the countries.

To compare the different country networks, we used the NCT and compared the networks of all 15 countries to each other, resulting in 105 comparisons. To account for the multiple comparisons, we intended to use the Bonferroni correction (Westfall et al., 1997), which corrects the alpha level considered significant by the number of comparisons done. As we compared every country network to 14 other networks, the alpha value was adjusted to 0.05/14 = 0.0036. Due to computation limitations, we could only estimate the NCT using 100 iterations. This resulted in the NCT only indicating whether networks differ on an alpha level of.01. Therefore, for this test, we considered all alpha levels smaller than.01 as significant.

Again, we correlated the edge weight matrices of the networks with each other (for correlation results see Table D1 in Appendix D). Most country networks correlated highly and significantly with each other. The only exceptions were the correlations between Hungary and Italy (r = .27, p = .028), Hungary and France (r = .35, p = .004), Italy and Poland (r = .30, p = .014), Italy and Turkey (r = .25, p = .044), France and Turkey (r = .25, p = .042), and Denmark and Turkey (r = .30, p = .015). The NCT showed that out of 105 comparisons, 57 networks differed significantly from each other on an alpha level of.01. The country networks that differed the most from other countries were Italy, France, Denmark, and Turkey. Turkey differed from all countries but Lithuania, whereas Italy, Denmark, France differed from all countries but each other (for NCT results see Table D2 in Appendix D).

As a next step, we investigated whether the populist attitudes country networks can be clustered into groups. Similar to Verschoor et al. (2020), we applied *k-means* clustering to the edge weight matrices of the country networks. This way, countries with similar edge weight matrices are clustered together. To choose the amount of clusters k, we used the gap statistic. The gap statistic balances the trade-off between explaining the variance in the data and overfitting the data (Tibshirani et al., 2001). We performed the cluster algorithms via the R packages *cluster* (Maechler et al., 2021) and *factoextra* (Kassambara & Mundt, 2020). The gap statistic using *k-means* clustering indicated a one-factor solution. To test the robustness of the cluster analysis, we repeated this analysis with other cluster algorithms (*hierarchical, pam*, and *clara* clustering) and another criterion to choose the cluster, namely the within sum of squares. When using the gap-statistic, all cluster algorithms point to a one-cluster solution. However, if we use the within sum of squares approach, all cluster algorithms point to a 2-cluster solution. As we already know that the networks differ, we are particularly interested in a multiple cluster solution. Clustering the country networks into two clusters produced the following results: the first cluster consists of France, Italy, and Denmark, while the second cluster consists of all remaining countries. These results align with the NCT tests.

To test the robustness of our cluster analysis, we investigated whether the *networktree* algorithm would partition the country networks into the same groups of countries as found in the cluster analysis. This algorithm allows us to test whether the country variables can be used to significantly partition the network into different sub-networks (Jones et al., 2020). And indeed, the algorithm partitions our countries into the same two groups as the cluster analysis. The *networktree* algorithm also shows how these two clusters of countries differ when all of the remaining countries within the clusters are used to jointly estimate a network. The network estimated using all countries from cluster one and the jointly estimated network of cluster two are displayed in Figure 5. The main differences between the networks are the following: First, in cluster one, the edge between two anti-elitist items ("Government officials use their power to try to improve people's lives" and "Quite a few of the people running the government are crooked") are negative, whereas the same edge is positive in cluster two. Second, the same holds for the political corruption item ("Quite a few of the people running the government are crooked") and another anti-elitist item ("The government is pretty much run by a few big interests looking out for themselves"). And third, the edge between the political corruption item and one nativism item ("The political elites have failed to protect our cultural identity") is absent in

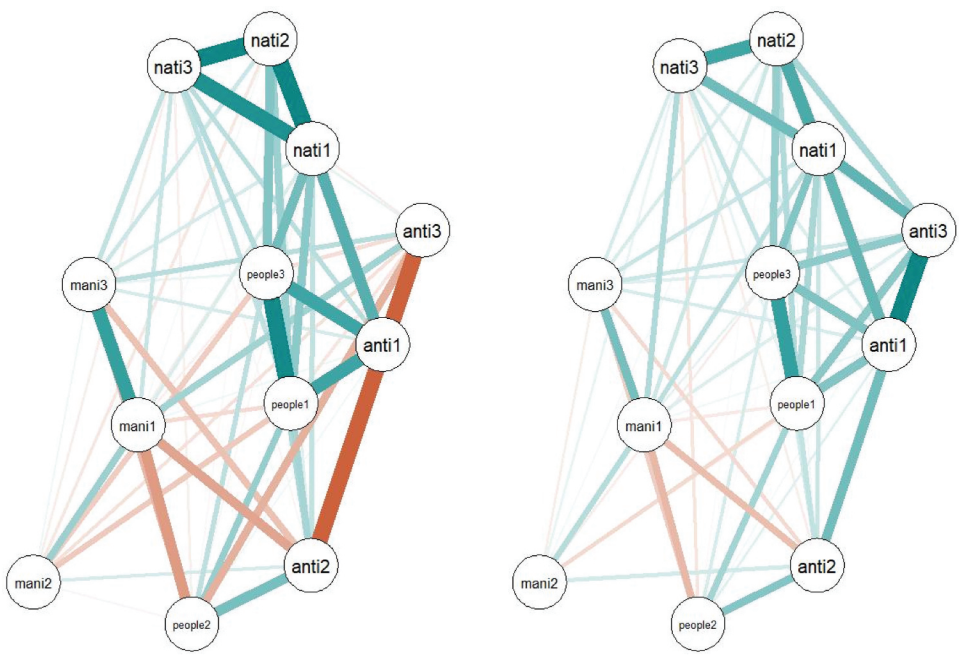


Figure 5. Jointly estimated network of cluster one (left) and cluster two (right) for populist attitudes and nativism.

cluster one and positive in cluster two. These results point out that for Denmark, France, and Italy, the political corruption item has a reversed relationship to all other items and thus might capture something different. We reviewed its original translations into Danish, French, and Italian to investigate the political corruption item further. And indeed, these translations slightly differed in their exact wording from the English version, which could explain why the items load differently in the clusters.

Overall, we did not find the PA factor structure proposed in previous literature (Castanho Silva et al., 2018, 2020). The factor structure of the items differed across countries, and we could not find a meaningful explanation. Therefore, we decided to skip the question of whether the high vs. low populist attitudes networks differ. Instead, we decided to investigate the scale from a network perspective. We found that many country networks differed significantly from each other and that the items build different communities across the countries. Cluster analysis indicated that two clusters represent the country networks the best, with Italy, Denmark, and France as one cluster and all other countries as a second cluster. These results again highlight the importance of country differences in the data.

Left- vs. Right-wing populist attitudes (RQ3)

Study 1

To investigate whether the networks of citizens with left- vs. right-wing PA differ, we used nativism as a proxy for political orientation. First, we tested the fit of the CFA for the nativism scale. The CFA with one factor and three indicators was just identified with a degree of freedom of zero. We inspected the factor loadings, which were all positive and greater than 0.57, and Cronbach's alpha was acceptable (α = .69). Additionally, we tested whether the factor structure for nativism was acceptable for every individual country. The CFA model did not converge for Hungary, which we excluded from the dataset for this analysis. This means that for all countries but Hungary, the CFA was acceptable.

For the remaining countries, we tested whether the scale's factor structure is comparable across countries using measurement invariance testing (Milfont & Fischer, 2010). For most countries, partial strong invariance did not hold. Only for five countries (Germany, UK, Italy, France, Spain), the nativism scale showed partial strong invariance (χ^2 [12, N = 2935] = 11.69, p =.47, RMSEA < 0.01 0.065, CFI = 1.0, TLI = 1.0, GFI = 1.0). However, as the number of comparable countries was low, we decided to investigate RQ3 for each country separately. Or, to put it differently, instead of testing whether having high vs. low nativist attitudes affects the overall network, we investigated whether it influenced each country network.

We used a median split to separate participants into having high vs. low nativist attitudes because this allowed us to have a sufficient sample size in both sub-samples. For every country, we estimated two network models as described above, one for participants high, one for participants low on nativist attitudes. Then, we correlated the weighted adjacency matrices to see whether they correlate (see Table E1 in Appendix E). In the next step, we conducted the NCT for participants high vs. low on nativist attitudes for every country. Again, we considered an alpha level of p <.01 as significant. The analysis showed that having high (in comparison to low) nativist attitudes did not affect the attitude networks (all p > .02, see Table E2 in Appendix E).

Study 2

Analogous to the analysis in Study 1, we first tested the fit of the CFA in every individual country. For all countries, the factor loadings of the nativism scale were above.5, and the inner consistency was above.69. Therefore, the fit was acceptable. As a next step, we again used a median split to separate participants in every country into having high vs. low nativist attitudes. We estimated two networks for people high vs. low on nativism for all four countries in the dataset. Next, we analyzed the correlation of the adjacency matrices (for the results, see Table E3 in Appendix E) and compared

Table 1. Zero-Order correlations between nativism and political spectrum per country.

Country	r	df	p
Germany	.39	522	<.001
Spain	.3	494	<.001
Netherlands	.32	501	<.001
UK	.33	506	<.001

Higher values indicate stronger nativist attitudes and a stronger orientation toward the political right.

them using the NCT. As in Study 1, the networks did not differ significantly for participants high vs. low on nativism (all $p > .1$, see Table E4 in in Appendix E).

Additionally, we also tested whether nativism was indeed a good indicator for the political spectrum. Therefore, we ran a correlation analysis between the three nativism items and the political spectrum variable for each country. The correlations were low but significant (see Table 1). As nativism was not a perfect indicator for the political spectrum, in Study 2, we also investigated whether people from the political left and right differed significantly in their networks using the political spectrum variable.

First, we used the political spectrum variable to code whether people identified as left-wing, center, or right-wing. Then, we used the *networktree* algorithm to test whether the political spectrum variable could be used to significantly partition the country networks of Germany, Netherlands, UK, and Spain into sub-networks. We used the *networktree* approach because this allowed us to include participants who responded to be in the political center, too, while not having to a priori assign if the political center is summarized with the left-wing or right-wing participants. The results indicated that the networks did not differ significantly for people on the political left- or right. Altogether, neither having high (vs. low) nativist attitudes nor political orientation significantly influenced the country network in Study 1 and 2.

Country differences and similarities (RQ4)

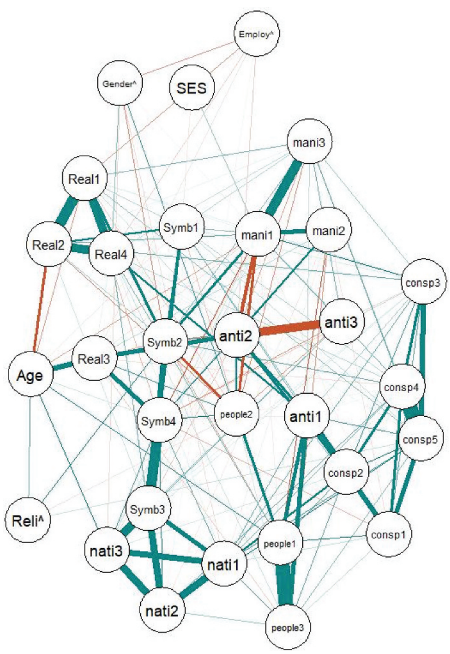
In contrast to RQ1, in which we estimated the network for PA networks jointly for all countries, for RQ4, we estimated all country networks separately. We estimated individual country networks for PA, nativism, conspiracy mentality, threat, and demographics and displayed them (including their communities and centrality indices) in Figures F1 – F19. The graphs show that the networks differ in their global network connectivity and their communities. Interestingly, in all countries but Bosnia, the perception of immigration as a threat is the most central node in the network. In all these countries, this threat perception has the strongest influence on the other variables of the networks.

Next, we performed a correlation test of the weighted adjacency matrices of the country networks. The results are displayed in Table F1 (see Appendix F). All networks correlated significantly with each other. The lowest correlations were between Denmark and Turkey ($r = .37$), Italy and Turkey ($r = .40$) and the Netherlands and Turkey ($r = .40$), and the highest correlations existed between Hungary and Poland ($r = .84$), Czechia and Slovakia ($r = .82$), and the UK and Hungary ($r = .82$). Then, we used the NCT with an adjusted alpha level of <.01 to see whether the country networks differed significantly from one another. We summarized the full results for the NCT in Table F2 (see Appendix F). The countries that differ the most from other countries are Italy and the Netherlands. Italy differs from every country but France and Spain, and the Netherlands differs from every country but France and Bosnia.

As a next step, we conducted a cluster analysis parallel to the one described for RQ2. We used *k-means* clustering and the gap-statistic to find whether we can cluster our country networks into different groups that are similar to each other. The gap-statistic for the *k-means* cluster algorithm was highest for a one-cluster solution. To test the robustness of this result, we repeated the cluster analysis with different clustering methods and different criteria as described above. All clustering algorithms (*k-means, hierarchical, clara, pam*) using the gap-statistic pointed to a one-cluster solution. The *hierarchical, clara*, and *pam* clustering algorithms with the within sum of squares statistic pointed to a two-cluster solution. Using *k-means* clustering and the within sum of squares statistic pointed to a three-cluster solution. Considering that the NCT showed differences between the networks, we were particularly interested in the multiple-clusters solution. Using *hierarchical* clustering with two clusters produced the following results: cluster one consists of the Netherlands, Italy, France, and Denmark, and cluster two consists of Germany, UK, Czechia, Hungary, Poland, Slovakia, Lithuania, Turkey, Spain, Greece, and Bosnia.

To test the robustness of our cluster analysis, we again investigated whether the *networktree* algorithm would partition our networks into the same country clusters as the cluster analysis. And indeed, the first partitioning that the algorithm performs is separating the countries of cluster one from countries of cluster two. Figure 6 displays the two resulting networks of the clusters. The most significant differences between the two networks are the following: Like the previous results, the relationship between the political corruption item and the other anti-elitism items differ in their polarity. Additionally, in cluster one, the political corruption item does not have a relationship to a conspiracy mentality item, whereas, in cluster two, there is a positive relationship between these items. This again points out that the political corruption items seem to capture something other than populism in cluster one. Another difference between the two networks is that in cluster one, there is a positive relationship between the people-centrism item "Politicians should always listen closely to the problems of the people" and the anti-elitist item "The government is pretty much run by a few big interests looking out for themselves." Contrarily, in cluster two, these two items are not related. Putting it differently, in cluster one, people who have a stronger people-centrist attitude are also more likely to have stronger anti-elitist attitudes, which is not the case for participants of cluster two.

To sum up, the analysis showed significant differences in the communities, overall networks, and global network strengths of the country networks. The cluster analysis was somewhat ambiguous and indicated a one- or two-cluster solution. The two-cluster solution suggested that Italy, Denmark, and



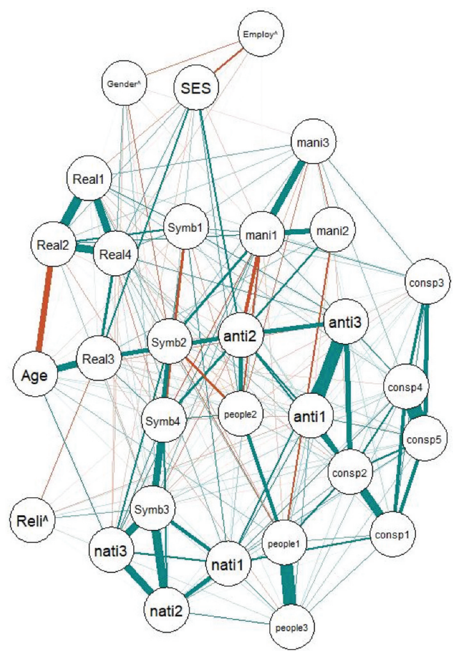


Figure 6. Estimated networks of cluster one (left) and cluster two (right) for populist attitudes and related constructs.

France form one cluster, while the remaining countries form another one. A political corruption item likely drove the cluster formation.

Discussion

The goal of this methodological study was to apply a novel conceptualization of attitudes to populism and nativism research. Thereby, we aimed to investigate populist attitudes (PA) from a new perspective, inspire new theorizing on PA, and add to the existing literature. To do so, we uncovered the network structure of PA, nativism, symbolic and realistic threat, conspiracy mentality, and important demographics (RQ1). Then, we tested whether the factor structure of the PA scale used here held for all countries under investigation (RQ2). Next, we investigated whether nativist attitudes and political orientation play a role in the network structure mentioned above (RQ3). And lastly, we analyzed differences in the country networks of PA and clustered them based on these differences and similarities (RQ4).

When investigating the network structure of PA for RQ1, we found that the country variable was the most influential in the networks of both Study 1 and 2. This aligned with our other findings that showed the importance of the country variable on the results. We were unable to replicate the community structure of Study 1 in Study 2, and the general network structure of the two studies differed significantly. This is not surprising because the data of Study 2 were collected at the beginning of the COVID-19 pandemic. In April 2020, governments all over Europe enforced strict new policies to react to the global pandemic. The crisis led to increased discontent with governments (Neumayer et al., 2021), conspiracy theories around the origin of the coronavirus emerged (Imhoff & Lamberty, 2020), and xenophobia and racism, especially toward Asian people, increased (Gover et al., 2020; Liu et al., 2020). These societal changes may have influenced the relationship between the variables under investigation, presenting a plausible cause for the observed difference between the networks of Study 1 and 2. In both studies the most central nodes were country, symbolic threat (immigration poses a threat to one's values) and socioeconomic status.

To address RQ2, we intended to use the PA scale to separate participants into having either low or high PA. Contrarily to the literature, we could not to replicate the factor structure of the PA scale proposed by Castanho Silva et al. (2018). Additionally, we could not create measurement invariance for the countries in both studies, which means that the countries are not comparable regarding the PA scale (Van de Schoot et al., 2012). This is interesting, as this scale was developed specifically for cross-country usage and validated on a diverse set of countries. However, this finding aligns with previous literature showing that cross-country comparisons are often difficult. For example, Rovira Kaltwasser and Van Hauwaert (2020) mentioned that creating measurement invariance is a problem within their populism studies. Similarly, recent research points out that failing to create measurement invariance could also signify that contextual and cultural differences influence the construct under investigation (Davidov et al., 2018). One explanation for the inability to reproduce the factor structure proposed in the literature is the quality of the data collected. However, this is unlikely, as the quality of data used in the present research fulfills higher standards than the data used by the authors of the validation study, with the only expectation that our Study 1 did not include an attention check item. The data used in this research were representative of age, gender, and geographical region and consisted of at least 450 participants per country. In comparison, the data collected by Castanho Silva et al. (2018) were collected via student samples, Amazon Mechanical Turk, and CrowdFlower, and consisted of 200–300 participants per country. Using student samples and these platforms to recruit participants generally produces less generalizable samples than representative samples (Cheung et al., 2017; McCredie & Morey, 2019).

Another explanation for these findings is that a latent variable does not ideally model PA. It may imply that there is no such thing as a "common cause" (PA) that influences our measurement instrument (the PA scale) to show the strength of the underlying cause. Instead, this could indicate that empirical networks are better suited to model causally linked attitude components. Empirical networks allow contextual factors to influence the network structure and explain differences between the countries. Considering the political corruption item, which was negatively associated with the other anti-elitist items in Italy, Denmark, and France, it is possible that, within these countries, populist discourses are less strongly concerning political corruption. In these countries, political actors who are part of the government might even dominate the discourses around political corruption. In this case, the political corruption item is expected to be more strongly and more positively associated with items that we did not capture in the studies at hand – items that address attitudes toward corrupt politicians not part of the government. However, one should bear in mind that the translation differences could have caused the political corruption item to behave differently in Italy, Denmark, and France. Further studies investigating PA and attitudes toward other political actors are necessary to test this idea.

To gain a deeper understanding of the PA scale, we investigated it from a network perspective. We found that the PA network of Turkey differed the most from all other countries under investigation. This is not surprising as Turkey is a special case in our sample as it is the only country characterized as a hybrid case of religious-conservative and nationalist-authoritarian (i.e., non-democratic; Karaveli, 2016), governed by the far-right, Islamist-populist leader Recep Tayyip Erdogan, since 2002 (Solomon, 2019). Moreover, since 2016, Turkey has undergone a process of de-democratization and experienced a rise of competitive authoritarianism, which refers to a state in which formal institutions of democracy exist, while incumbents yet have unfair advantages over the opposition (Esen & Gumuscu, 2016). This makes it difficult for Erdogan to authentically criticize a "corrupt political elite" within the country, as it would be typical for populist actors. Instead, in his rhetoric he continuously uses conspiracy theories to depict himself as a protector of Turkish interests against "evil foreign forces." These evil forces can be Western powers (e.g., the EU and USA) and specific or unspecific international interest groups (e.g., the alleged secret Jewish control over the global economy). Using conspiracy theories, Erdogan has shifted the meaning of "the evil elites" from the politicians in his government to a diverse set of evil foreign enemies to himself (Balta et al., 2021; Saglam, 2020; Yilmaz & Shipoli, 2021). Because of the difference in anti-elitist notions, people with strong PA are more likely to show their anti-elitism not toward the Turkish government but toward foreign political actors framed as evil or corrupt. The measures we used in this research are unable to capture this difference, which could be why the network of Turkey might differ from the rest of the countries. This is in line with recent research demonstrating that common PA scales fail to capture populism in countries where populists are in power (Jungkunz et al., 2021).

Cluster analysis showed that the PA networks could be clustered into two groups: one consisting of Italy, France, and Denmark, the other one consisting of the remaining countries. One political corruption item was the main driver of the cluster analysis results. This could have been caused by the translation mistakes that we mentioned above. In France, Italy, and Denmark, the item's wording was slightly different from the original English version, which might have caused the item to behave differently. Previous studies demonstrated the importance of proper translation of scales and the effects on the measure's validity (Bontempo, 1993; Hambleton & Kanjee, 1993).

Another explanation could be that this item is not a good measure for PA for these countries. This result is somewhat in line with Polk et al. (2017), who investigated calls for anti-corruption and anti-elitist notions across 268 political parties from all EU countries plus Switzerland, Norway, and Turkey. They found that calls for reducing corruption were stronger related to levels of corruption within a country than with anti-elitist attitudes. In line with this, individual-level perceived corruption is strongly correlated with objective indicators of corruption and the electoral system of countries (Pellegata & Memoli, 2018; Transparency International, 2020). Putting it differently, it might be that the political corruption item in Italy, France, and Denmark is less indicative of anti-elitism and more indicative of political corruption and the corruptibility of the electoral system. This would also explain why the political corruption item does not relate to conspiracy mentality.

We did not find evidence that the strength of nativist attitudes and political orientations significantly influenced the network structure of PA, threat, conspiracy mentality, and demographics (RQ3).

This finding is surprising, as previous research suggests that right- and left-wing populism differs regarding the socio-demographic profile of its supporters, its relationship to nativism, to personality, and its emotional underpinning (Arzheimer, 2009; Mudde, 2007; Ramiro & Gomez, 2017; Rodríguez-Teruel et al., 2016; Salmela & von Scheve, 2017; Vasilopoulos & Jost, 2020). Similarly, we would have expected people with strong nativist attitudes to differ on the aforementioned constructs and threat perception (Davidov et al., 2020).

One explanation for this null finding could be that the networks only differ for people on the political extreme (very left/very right) and people who have very strong (vs. very weak) nativist attitudes. Unfortunately, we could not test this because of the low sample size for people on the political extreme. Another explanation for our null finding could be that the sample size was too small for RQ3.

Lastly, we investigated how the network of PA, nativism, threat, and demographics differed across countries (RQ4). Remarkably, for all countries but Bosnia, we found that perceiving immigration as a threat was the most central and, therefore, the most influential in the networks. This is in line with previous research showing that right-wing populist actors often portray immigrants as a realistic and symbolic threat, and that symbolic threat, in particular, fuel anti-immigrant attitudes (Matthes & Schmuck, 2017). For the populist attitudes network, influencing this symbolic threat item has the strongest effect on the rest of the network. This makes this item particularly interesting for prevention programs aiming to decrease PA. Experimental studies are necessary to test whether influencing this item has a significant effect on the rest of the network.

Furthermore, the cluster analysis for RQ4 indicated that the Netherlands, Italy, Denmark, and France build one cluster, and all other countries build a second cluster. These results are in line with the cluster analysis for RQ2. As mentioned above, one political corruption item was the main driver for these results. In addition, the political corruption item mentioned above was related to conspiracy mentality item for all countries but Italy, Denmark, France, and the Netherlands. These results could indicate that this item captured something different from the other two anti-elitism items, as previous research would suggest a positive relationship between conspiracy mentality and populism (Castanho Silva et al., 2017; Erisen et al., 2021; Hameleers et al., 2021; Van Prooijen, 2018).

Another difference between the two clusters of RQ4 was the positive relationship between one anti-elitist item and one people-centrism item in cluster one. As mentioned above, this positive relationship could indicate that in the countries of cluster one, people-centrist and anti-elitist attitudes are more aligned with each other. More research on the relationship between people-centrism and anti-elitism across Europe is needed to falsify this possible explanation.

Limitations and future research

Few minor limitations should be considered when interpreting the results of our methodological paper at hand: 1.) Consortium partners, instead of professional translators, (back-)translated the items into all languages other than English. This could introduce bias into the scales, making it more difficult to control whether translation problems caused differences in the results. 2.) Our sample size to investigate the difference among people with diverse political orientations and various levels of nativist attitudes might have been too low to detect meaningful differences in the networks. 3.) For the empirical network of PA to be as meaningful as possible, it is necessary to include all concepts relevant to populism into the network analysis. We could not include them in our methodological paper because we relied on previously collected data.

Future studies should consider these minor limitations and investigate PA from a network perspective when considering further factors relevant to populism. Additionally, it would be fascinating to include behavioral variables into the network of PA, such as voting for populist parties, to see which nodes are most influential for a relevant behavior. And lastly, future research could investigate the development and change of PA over time from a network perspective. This would be especially interesting in times of a continuous crisis, such as the COVID-19 pandemic.

Conclusion

This methodological paper aimed to use a new conceptualization of attitudes, the Causal Attitude Network (CAN) model, to investigate populist attitudes (PA), nativism, threat and conspiracy mentality. In line with this aim, we found that countries differed in their network structure of PA, pointed out possible reasons for difference and similarities, and showed that nativism and political orientation did not play a role in the populist attitudes networks. Additionally, we identified promising nodes for future studies interested in social-psychological interventions for PA, and added to the existing literature on attitudes. And lastly, we pointed out future research directions, such as investigating how voting for populist parties connects to other variables in a populist attitudes network.

Notes

1. Bosnia-Herzegovina, Czech Republic, Denmark, France, Germany, Greece, Hungary, Italy, Lithuania, the Netherlands, Poland, Slovakia, Spain, Turkey, and the United Kingdom
2. More details on the robust community detection method can be found in the study by Chambon et al. (2022).

Disclosure statement

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Data availability statement

Based on the GDPR agreements of the H2020 project, the datasets are only available to consortium partners until published in a data journal (see Abadi et al., 2023; Abadi, Duyvendak, et al., 2024). Requests to review the datasets can be directed to the corresponding author.

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