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The Structure and Correlates of Societal Threat Perceptions: A Network Approach

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Supplementary Materials: Code, Data, Preregistration [see Index of Supplementary Materials]

Abstract

Societal threats such as climate change, economic crises, and wars shape citizens' political attitudes and behaviors. Yet, the structure of threat perceptions and their socio-demographic and ideological correlates remain underexplored. Using a six-wave Dutch survey (*N* = 685) and a network approach, we uncover the complexity of societal threat perceptions. First, we show that societal threat perceptions vary in their interconnectedness, with security threats, such as crime, threats related to asylum seekers, and the war in Ukraine emerging as central nodes. Second, ideology, age, and education are the most relevant variables linked to societal threat perceptions. Third, we replicate the levels and structure of societal threat perceptions over time, highlighting the robustness of our conclusions. Our study's results indicate that societal threat perceptions form a complex network that replicates over one year. We outline an agenda for the next generation of theorizing on the structure, correlates and stability of societal threat perceptions.

Keywords

societal threat perceptions, threat-politics link, network analysis, complex systems, ideology, news consumption, panel data

Highlights

- Societal threats such as climate change, economic crises, and wars shape citizens' political attitudes and behaviors, yet, the structure of threat perceptions and their socio-demographic and ideological correlates remain underexplored.
- First, using a six-wave Dutch survey ($N = 685$) and a network approach, we show that societal threat perceptions vary in their interconnectedness, with security threats as crime, the war in Ukraine, and asylum seekers emerging as central nodes.
- Second, ideology, age, and education are the most relevant variables linked to societal threat perceptions.
- Third, we replicate the structure of societal threat perceptions over time, highlighting the robustness of our conclusions.

Societal threat perceptions—i.e., the feelings and perceptions that something aversive is going to happen (Brandt & Bakker, 2022)—are high among citizens (World Economic Forum, 2025) and can have far-reaching consequences. For example, societal threat perceptions can be mobilizing drivers of positive societal change, but also contribute to averse outcomes, such as support for undemocratic politics (Asbrock & Fritsche, 2013; Shepherd et al., 2018). Various studies have investigated the causes, consequences, and correlates of societal threat perceptions (e.g., Bisbee & Honig, 2022; Cassario & Brandt, 2024; Godefroidt et al., 2019; Holman et al., 2022). Research predominantly conceptualizes societal threat perceptions as one or more latent dimensions (e.g., Eadeh & Chang, 2020; Hibbing et al., 2014; Kahn et al., 2022; Onraet et al., 2013). Inspired by the complex systems literature, a recent line of research conceptualizes political attitudes as networks (e.g., Brandt, 2020; Dalege et al., 2016; Fishman & Davis, 2022). Applying this approach to societal threat perceptions gives us the opportunity to comprehensively consider interrelations between a) different societal threat perceptions, and b) societal threat perceptions and their correlates, in a complex system. In this paper, we conceptualize societal threat perceptions as networks, and deepen and broaden the threat-politics literature in three ways.

First, research on societal threat perceptions predominantly analyzes perceptions of individual threats, disregarding the relations between them (e.g., Eadeh & Chang, 2020; Onraet et al., 2013; Thórisdóttir & Jost, 2011). A network approach allows for identifying which societal threat perceptions are most central in our sample and may thus be the most “important” to the system of societal threat perceptions in the population (Brandt, 2020). A benefit of this approach lies in obtaining a better understanding of the belief system and the relations among the components within it, which provides a theoretical basis for developing more specific accounts of the dynamics of societal threat perceptions.

Second, research on the correlates of societal threat perceptions isolates the direct associations between specific threats and specific constructs, such as ideology. This limits the possibility to theorize about more complex relationships between threats and other constructs that are part of a belief system (Eadeh & Chang, 2020; Jost et al., 2007). Indeed, as Chambon, Dalege, Waldorp et al. (2022, p. 234) explain, "understanding the whole system, and the mutual dependence of its elements, provides more insight than only understanding its individual elements". Here, we utilize a network approach to societal threat perceptions to study the associations between different societal threat perceptions and a range of correlates such as ideology, ideological extremity, age, gender, education, interest in politics and consumption of different news media. Mapping these relationships provides a new perspective on the ongoing debate on the threat-politics link (Godefroidt et al., 2019; Hibbing et al., 2014), and extends the existing literature towards thus far under-explored correlates that may shape or be shaped by societal threat perceptions (Andersen et al., 2024; Kesberg et al., 2022).

Third, previous research has largely disregarded to what extent societal threat perceptions and the associations between them replicate over time. Utilizing our panel data, we assess the replicability of threat perceptions and their network structure over a one-year period. Doing so contributes to the robustness of our conclusions and informs further theory building about the stability of societal threats, and more broadly, the stability of belief systems in political psychology.

We address the gaps in the literature with theoretically-motivated, preregistered research questions and analyses. The first preregistered research question is: How are societal threat perceptions structured? Our study addresses this question by taking a network approach to societal threat perceptions. Previously, societal threat perceptions have been studied following a latent variable approach, whereby threat perceptions are ascribed to a single underlying threat sensitivity trait (e.g., Hibbing et al., 2014; Jost, 2017), or threats are grouped into two or more latent dimensions (Kahn et al., 2022), for instance, cultural and economic threats (e.g., Lucassen & Lubbers, 2012), or internal and external threats (e.g., Onraet et al., 2013). However, the latent variable approach employed in the literature does not suffice if we want to theorize about and test the position and relevance of different societal threat perceptions within a threat perception network. Such information on the network structure of societal threat perceptions allows us to assess which threats are the most central—and thus relevant—in the network of societal threat perceptions. These insights advance both theorizing and empirical research on societal threat perceptions.

Our study's second contribution is embedding societal threat perceptions in a broader network that contains political ideology variables, socio-demographic background variables, and news consumption variables. To this aim, we answer the second preregistered research question of this paper: To what extent do political ideology, news consumption, and demographic variables correlate with societal threat perceptions? The network approach allows us to study the centrality of all nodes, as well as exploring specific edges between nodes. Centrality provides indications regarding which correlates of societal threat perceptions are the most relevant for explaining variation in societal threat perceptions. This informs future theoretical developments on the embedding of societal threat in a broader net of concepts, and offers suggestions for potential interventions, as changes in the most central nodes are most likely to "spread" to the rest of the network (Chambon, Dalege, Waldorp et al., 2022). When it comes to the edges between nodes, answering our second research question provides a novel perspective on ongoing theoretical debates and future theorizing about the links between societal threat perceptions and their correlates. Starting with ideology, there are three perspectives on the associations between societal threat perceptions and ideology (Arceneaux et al., 2025). First, the "ideological asymmetry perspective" (e.g., Hibbing et al., 2014) puts forward that those on the political right, compared to those on the left, are more threatened by their environment and report higher levels of perceived societal threats, regardless of the exact nature of the threat. According to this perspective, threat perceptions should be positively associated with right-wing ideology in a network model. Second, the "threat ownership" perspective (e.g., Eadeh & Chang, 2020; Godefroidt et al., 2019) argues that people's perceptions of a threat "match" their ideology when there is an ideology that is seen as "owning" the threat. For instance, right-wing ideology is positively associated with the threat of crime, while left-wing ideology is positively associated with the threat of climate change (Brandt & Sleegers, 2021). According to this perspective, perceptions of threats that are more heavily emphasized by politically right (resp. left) parties should be more associated with right-wing (resp. left-wing) ideology. Third, the "rigidity-of-the-extremes" perspective (e.g., Brandt et al., 2014; Zmigrod et al., 2019) poses that those on the ideological extremes are most receptive to threats. Accordingly, threat perceptions should be positively associated with political extremism. We compare these three competing expectations on the threat-politics link in a network that models the interrelations between societal threat perceptions and ideological variables.

Considering socio-demographic variables, earlier work has only studied the association between single threats and socio-demographic variables. For instance, previous studies found higher climate threat perceptions among women, more highly educated people, and older people (Hornsey & Pearson, 2024), higher levels of security threats among older people (Poushter & Huang, 2020), and higher levels of threat by crime, inflation, and climate change among more politically interested people (Smith, 2022). Moving towards a perspective that considers the associations of multiple threats and correlates at once, recent work by Kesberg et al. (2022) suggests that individuals' age, gender, and education (among other socio-demographic variables) predict the structure of their threat perception network. However, Kesberg et al. (2022) rely upon proxies, as opposed to direct measures of societal threat perceptions. Addressing this gap, we extend the literature beyond associations of single threats and socio-demographics by adding socio-demographic variables into an extended network of direct societal threat perception measures.

Turning to our final group of correlates, previous work demonstrates that the news people consume plays a significant role in shaping citizens' issue awareness and perceptions (Djerf-Pierre & Shehata, 2017; Lecheler et al., 2015). News consumption habits can shape worries about societal issues (Iwanowska et al., 2023; Woods, 2011). People who consume more news are, for instance, more anxious about climate change, and people who consume more alternative news are more anxious about crimes (Andersen et al., 2024). Yet, previous studies do not analyze extensive sets of societal threats, and do not identify consumption at the outlet level. We address this critical gap.

Finally, the third and fourth preregistered research questions of this paper are: *Are societal threat perceptions stable over time?* and *Are associations between societal threat perceptions stable over time?* As our study's third contribution, we address these questions by assessing the stability of societal threat perception scores over time, and replicating the structure of the societal threat perception network over time. Threats come and go in society (World Economic Forum, 2025), but the literature on threat perceptions has not addressed the temporal stability of societal threat perceptions (Brandt & Bakker, 2022). Answering these two research questions informs theory building about the causes and consequences of societal threat perceptions. If societal threat perceptions and their structure do not replicate over time, this indicates that short-term influences, such as those coming from (social) media, political elites, and one's social circle, may have profound effects on the perception and structure of societal threats. Short-term fluctuations would also indicate that societal threat perceptions could have short-lived and immediate consequences on political attitudes and behaviors. Yet, if societal threat perceptions and their structure replicate over time, scholars will need to theorize about and conceptualize societal threat perceptions as more stable beliefs influenced by structural factors (e.g., socialization) and other bottom-up factors, such as core values and personality traits (Bakker & Lelkes, 2022). The consequences of societal threat perceptions for, for instance, political attitudes and behavior, would, in this case, also be more structural and long-term.

Method

Network Methodology

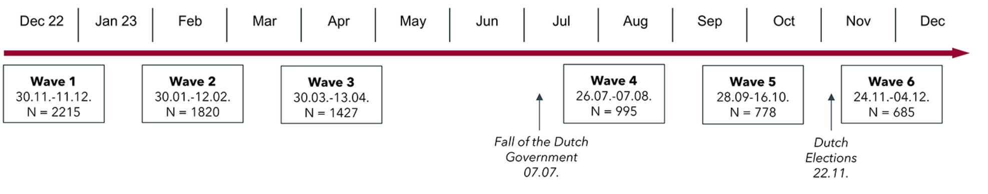
We follow a network approach and refer to variables as nodes and to the associations between them as edges. All networks estimated in the present research are Gaussian Graphical Models (Epskamp & Fried, 2018). The links (edges) between nodes in Gaussian Graphical Models are weighted—as visually indicated by their thickness—, undirected, and represent partial correlations between two nodes given all other nodes in the network (Epskamp et al., 2018). As such, they range between -1 and 1. For each preregistered research question, we briefly explain the preregistered modeling strategy in the results section, but refer to the pre-analysis plan (see Bomm et al., 2024b) and the Appendices D–F for details.

Research Design

We rely on a six-wave panel study collected in the Netherlands in a politically dynamic period between December 2022 and December 2023 that spans the sudden fall of the Dutch government in July 2023, and cabinet elections in November 2023. Figure 1 shows the data collection start and end dates and sample sizes per wave[1]. The study was approved by the Ethics Review Board of our university.

Figure 1

Timeline of Data Collection Waves and Relevant Societal Events



Note. Timeline spans December 2022–December 2023. Sample sizes refer to the number of participants who completed the respective and all previous waves and met all of the preregistered attention and speed criteria.

Transparency and Openness

The sample size was determined by the team collecting this omnibus study. We use all available data (Lakens, 2022) and did not conduct an a priori power analysis. Our sample size (*N* = 685 for all analyses in the main text) is in line with other studies using similar network methodology (e.g., Belvederi Murri et al., 2020; Chambon, Dalege, Elberse et al., 2022).

Network analysis involves a large number of analytic choices. Within the network modeling literature, preregistration is seen as “a helpful tool, limiting researchers’ degrees of freedom in obtaining desired results” and “ensures that researchers cannot cherry-pick particular estimation methods or network inference metrics after the fact to support their hypotheses” (Fried et al., 2022, p. 148). Therefore, we chose to preregister our research questions and analysis strategy. We opted for a split-wave approach. We used the first three waves to inform the most appropriate analytic strategy (e.g., specific

1) The full survey, in Dutch, can be found on the OSF page of the omnibus project: https://osf.io/vwngm/overview

regularization and fitting procedures). After preregistration of our research questions and analysis-strategy, we obtained access to wave 4-6. Here we present the results of the preregistered research questions tested with the preregistered modeling strategy. We deviate from our preregistration in only one case: We adjusted the equivalence bounds for the test of research question 3, as we mistakenly preregistered this as .1, which is too conservative compared to the more commonly used cut-off of .5 (Lakens, 2016), see Appendix F.

The raw data, code, and pre-analysis plan belonging to this paper can be found on our project's OSF-page (see Bomm et al., 2024b). Data were analyzed using R, Version 4.3.1 (R Core Team, 2023), using the tidyverse (Wickham et al., 2019) for basic coding. Specific packages for each research question are cited in the results section. We report all manipulations, measures, and exclusions in this study.

Sample

The panel company I&O Research recruited a sample of Dutch respondents with quotas for gender, age, education, and region. Participants signed informed consent before accessing the questionnaire. Of the original $N = 2215$ participants in Wave 1, $N = 685$ completed all 6 waves. Equivalence tests show that participants who completed all six waves and participants who dropped out at any point of data collection do not meaningfully differ in their societal threat perceptions, ideology, and news consumption (see Appendix A). The final sample was diverse and comprised of 55.7% men, 44.3% women, and 0.14% individuals who indicated their gender as “other”, with a mean sample age of $M_{Age} = 55.16$ ($SD_{Age} = 15.76$) years. 54.2% of participants had completed higher general secondary education or a higher education.

Variables

Societal threat perceptions were measured with the question “To what extent do you feel threatened by the following topics?”, for the following twelve issues, presented in randomized order, rated on a 1–7 Likert scale from “1 - Not at all threatened” to “7 - Very highly threatened”: crime, climate change, the influx of asylum seekers, inflation, energy costs, war in Ukraine, the nitrogen problem[2], the housing shortage, increasing contrasts between groups in society (polarization), the inhumane reception of asylum seekers, the labour shortage, and Covid-19.

Our selection of threats meets two relevant criteria. First, the selected threats cover a broad range of overlapping groups commonly examined in research on societal threat.

2) The nitrogen problem refers to the long-standing issue of excessive nitrogen emissions in the Netherlands, resulting in harmful nitrogen deposition that negatively affects both nature and public health (Ministry of General Affairs, 2023). The Dutch government has implemented measures to reduce nitrogen deposition that prompted debates and farmer protests, making the issue politically and socially contested (NOS, 2022).

We cover economic threats (inflation, energy costs; Brandt et al., 2021), security threats (crime, influx of asylum seekers, war in Ukraine; Brandt et al., 2021; Federico & Malka, 2018; Stevens & Vaughan-Williams, 2016), environmental threats (climate change, nitrogen problem; Fritsche et al., 2012; Smith & Kim, 2026), and threats to social cohesion (polarization; Feldman, 2003; Onraet et al., 2013). Second, the selected threats include threats associated with both right-wing ideology (influx of asylum seekers, crime; Jost, 2017) and left-wing ideology (e.g., climate change; Smith & Kim, 2026), as well as issues without a clearly established ideological alignment (e.g., the housing shortage and the labour shortage).

We list the items used to measure the other analyzed variables in Table 1. We report descriptive statistics on societal threat perceptions, ideology, and news consumption in Appendix B.

Table 1

Overview of the Variables, Including Item Wording, Response Scale and Missing Values, and Waves Measured

Item	Item wording	Response scale and missing values	Waves
Political Ideology			
Left-Right	"In politics, people sometimes talk about "left" and "right". Where would you place yourself? Display your position using a scale from 0 to 10, where 0 means "left" and 10 "right". Which number best describes your position?"	11-point semantic differential scale (0 = Left; 10 = Right); Recoded to missing values: "11 (I don't know)"; "12 (I don't want to say)"	1–6
Extremity Left-Right	*Constructed by folding Left-Right variable at half point*	Recoded to missing values: "11 (I don't know)"; "12 (I don't want to say)"	1–6
Progressive-Conservative[a]	"In politics, people sometimes talk about "conservative" and "progressive". Where would you place yourself ? Display your position using a scale from 0 to 10, where 0 means "conservative" and 10 "progressive". Which number best describes your position?	11-point semantic differential scale (0 = Conservative, 10 = Progressive); Recoded to missing values: "11 (I don't know)"; "12 (I don't want to say)	1
Extremity Progressive-Conservative	*Constructed by folding Progressive-Conservative variable at half point*	Recoded to missing values: "11 (I don't know)"; "12 (I don't want to say)"	1

Item	Item wording	Response scale and missing values	Waves
News Consumption[b]	"How many days in a typical week do you watch / read / use the following television programs / printed newspapers / websites or apps for the news?" Measured for: NOS; RTL; Hart van Nederland (HvNL); EenVandaag; EditieNL; de Telegraaf; de Volkskrant; Algemeen Dagblad (AD); NU.nl	8 response options, ranging from "0 days" to "7 days". Missing values if participants never consume news through outlet's domain	1
Socio-demographics and Political Interest			1
Age	"What is your date of birth?"	Recoded to age in years	1
Gender[c]	"What is you gender?"	Options "Man", "Woman", "Other"; "Other" was recoded to missing values[d]	1
Education	"What is the highest education you followed?"	7 ordered categories; recoded to missing values: "I don't know / I don't want to say"	1
Political Interest	"How interested are you in politics?"	11-point Likert scale (0 = Not interested at all; 10 = Very interested); No missing values (forced response)	1

[a]We reversed the variable conservative-progressive ideology, so that its poling matches the variable left-right ideology. [b]We preregistered the selection of the news consumption measures for our network based on previous exploration. The construction of the news consumption measures is detailed in Appendix C. [c]In the RQ2 network model, we treat gender identification (categorical) as a continuous variable (1 = male; 2 = female). [d]One person indicated their gender as "Other", and was excluded from data analysis

Results

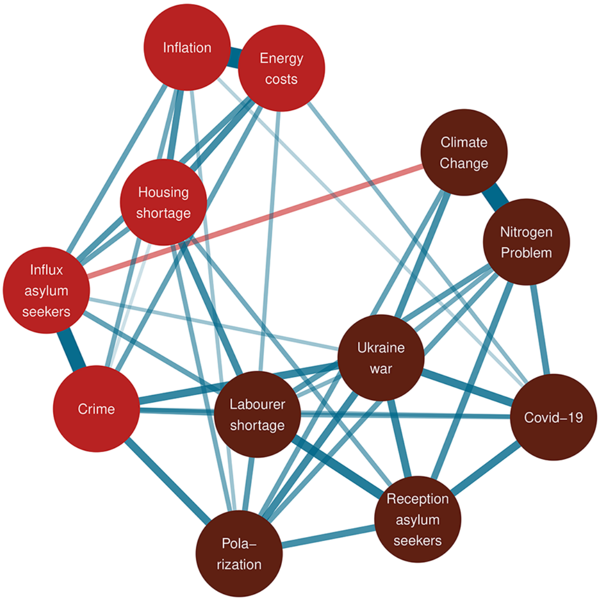
The Structure of Societal Threat Perceptions

To investigate how societal threat perceptions are structured (RQ1), we performed Exploratory Graph Analyses (EGA) with the EGAnet package (Golino & Epskamp, 2017). Exploratory Graph Analyses (EGAs) study both the network structure and dimensionality of nodes in a network. The EGA first creates a network model, after which an iterative algorithm categorizes all of the network's nodes into clusters (i.e., dimensions). The algorithm aims to obtain sparse clusters, within which the nodes are densely connected through partial correlation edges (Golino & Epskamp, 2017). See Appendix D.1 for details on the EGA procedure.

Figure 2 depicts the network resulting from the EGA on aggregated societal threat perceptions based on person means across Waves 4–6.[3] As suspected in our pre-analysis plan, we found three (modestly strong) interrelations between pairs of threats in the EGA on person means across Waves 4–6, and the single-wave EGAs, namely: the influx of asylum seekers and crime ($w_{wave4-6}$ = .44), inflation and energy costs ($w_{wave4-6}$ = .66), and climate change and the nitrogen problem ($w_{wave4-6}$ = .56). Other nodes – i.e., societal threat perceptions – in the network were also related through edges, but less strongly than these three pairs. As suspected, the nodes in each of the three pairs were grouped in the same cluster, respectively, by the EGA, consistent with the strong edges between them.

Figure 2

EGA of Societal Threat Perceptions on Aggregated Person Means Across Waves 4–6



Note. Preregistered Exploratory Graph Analysis over aggregated person means using waves 4–6, created with the GLASSO modelling strategy and the Walktrap algorithm (Golino & Epskamp, 2017). The edges between nodes represent partial correlations and depict their strength (i.e., edge weight). The stronger an edge, the thicker and more opaque its depiction. Blue edges indicate positive, red edges indicate negative partial correlations.

3) We present separate EGA plots for Waves 4, 5, 6, and person means across Wave 1–6 in Appendix D.2.

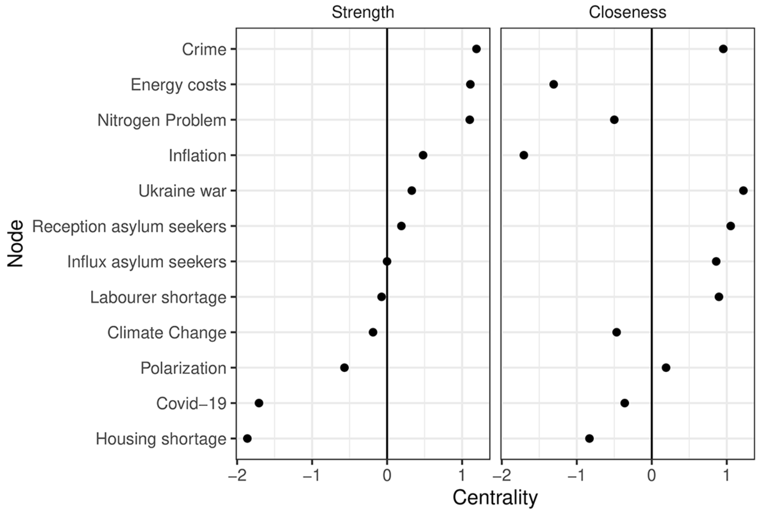
However, preregistered and exploratory analyses indicate that the clustering solution is inconsistent and not stable. Regarding the consistency of the clustering, the way the nodes are grouped into clusters differs between the individual data collection waves and the full sample, see Appendix D.2. Regarding the stability, the bootstrapped exploratory graph analysis (Christensen & Golino, 2021), which formally evaluates the stability of the obtained EGA results by comparing them to a sampling distribution of bootstrapped EGA results based on the same data, indicates that the clusters are unstable, see Appendix D.3 for details. We interpret this as an indication that categorizing our set of societal threat perceptions into dimensions may not be the most appropriate way to model them. While some threats are consistently closely associated with each other, we conclude that we do not obtain distinct clusters—i.e., dimensions—of societal threat perceptions on this data.

Next, we calculated the centrality indices strength and closeness of the different threats with the qgraph package (Epskamp et al., 2012) for the nodes in the societal threat perception network. Strength is the sum of the absolute edge values connected to a given node. Strength expresses the extent to which a node is interrelated to its neighbors in the network (Brandt et al., 2019; Dalege et al., 2017). Closeness is the inverse of the sum of the shortest path lengths between a given node and all other nodes in the network and represents how “quickly” a node’s influence can get from one node to the rest of the nodes in the network (Dalege et al., 2017). Closeness thus represents a node’s potential influence on the network as a whole (Brandt et al., 2019). Both centrality indices for the network were stable enough to interpret; see the stability assessment of the centrality indices in Appendix D.4.

Figure 3 plots the strength (left-hand panel) and closeness which we z-standardized to facilitate interpretation. The most central nodes in terms of strength were crime (1.19), energy costs (1.11), and the nitrogen problem (1.10). The extent to which individuals perceive crime, energy costs, and the nitrogen problem as threatening is thus the most strongly associated with the extent to which they perceive other societal issues as threatening. When it comes to closeness, the most central nodes in terms of closeness were the war in Ukraine (1.22), the reception of asylum seekers (1.05), and crime (.95). This means that the war in Ukraine, the reception of asylum seekers, and crime are the threat perceptions that have the most influence on the threat perception system as a whole. Together, crime stands out as being highly central both in terms of strength and closeness, indicating that a change in crime threat perceptions may have a sizable impact on the entire threat perception network.

Figure 3

Centrality Indices Strength and Closeness of the Network Model of Twelve Societal Threats



Note. Centrality indices strength and closeness (both *z*-standardized), ordered by strength. Node strength is the sum of a node's absolute edge weights and indicates how well a node is directly connected to others. Node closeness is the inverse of the sum of the shortest path lengths between a given node and all other nodes in the network and represents how "quickly" a node's influence can get from one node to the rest of the nodes in the network.

To summarize, our network of societal threat perceptions is structured by varying degrees of interrelations, and some threats are more central than others to this network. The threat of crime, as well as other threats, like the war in Ukraine and the reception of asylum seekers stand out as being relatively central in the network, while other threats like Covid-19, the housing shortage and polarization are less central.

Societal Threat Perceptions in a Broader Network With Ideology, Socio-Demographics, Political Interest, and News Consumption

To investigate the associations between societal threat perceptions and ideology, the socio-demographic background and political interest, and news consumption (RQ2), we created a network model with the stepwise model search selection technique with the ggmModSelect algorithm from the bootnet package (Epskamp et al., 2018).[4] The

4) Note that all variables are continuous. Education as an ordinal variable is the exception, yet we treat it as a continuous variable from 1 (lowest level of education) to 7 (highest level of education). This should not affect the network model performance, as education has over five levels (e.g., Johal & Rhemtulla, 2023).

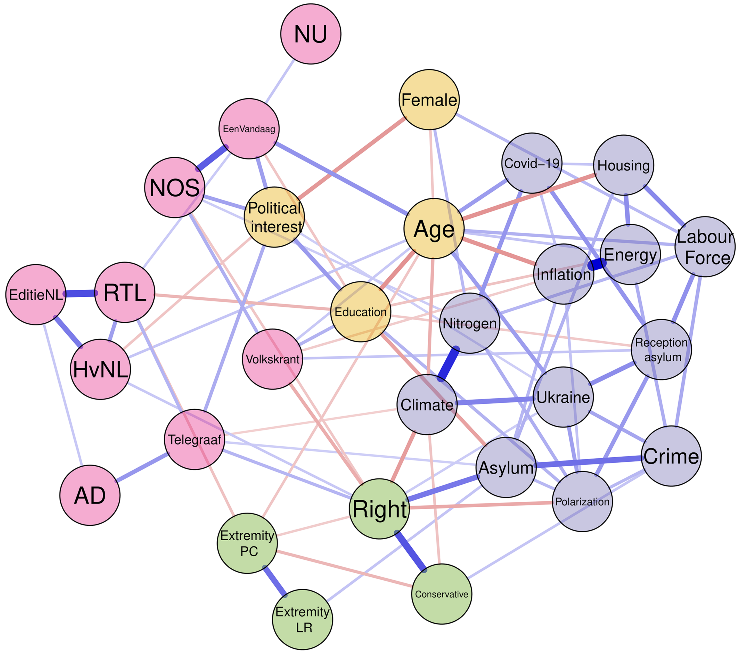
ggmModSelect algorithm first calculates a regularized network model as starting point, in which some small edges are pulled to zero through an optimization technique to aid model sparsity. Then, a stepwise model search algorithm iteratively adds or removes edges from this first model until the Bayesian information criterion metric (BIC), which expresses a balance between low model complexity and high model fit, is lowest, meaning that the model can no longer be improved (Blanken et al., 2022). In sum, the ggmModSelect strategy creates network models by optimizing fit and minimizing complexity at multiple steps of the fitting procedure.

Figure 4 shows the network model estimated on data of participants that completed waves 1-6 (N = 685).[5] Results from a network on Wave 1 data (N = 2215) are in line with the ones we report here, see Appendix E.4. We calculated the centrality indices strength and closeness for the nodes in this network and plot them in Figure 5. Both centrality indices for the network were stable enough to interpret, see the stability assessment of the centrality indices in Appendix E.3.

5) To assess the edge weight accuracy, we conducted a non-parametric bootstrapped accuracy analysis that estimated 95% confidence intervals around the edge weights. This analysis indicates that there is some uncertainty pertaining to the strength of the edges. This uncertainty does not affect the accuracy of the signs of the edges, or their presence in the regularized network (Epskamp et al., 2018). When interpreting the edge weights in the network, we are careful not to overinterpret small differences between edge weights. The edge weights with accuracy confidence intervals can be found in Appendix E.2.

Figure 4

Network Model of Societal Threat Perceptions and Ideological, News Consumption, and Demographic Correlates



Note. Network model of societal threat perceptions (in purple) and ideological (in green), socio-demographic background and political interest (in yellow), and news consumption correlates (in pink). Nodes represent variables. Edges between nodes represent partial correlations and depict their strength (i.e., edge weight). Blue edges indicate positive, red edges indicate negative partial correlations.

Ideology

Right-wing ideology[6] was the most central ideological node in the overall network (strength: 1.7; closeness: 1.42), see Figure 5, and had the highest number of edges to threat perception nodes. Right-wing ideology was positively related to being threatened by the influx of asylum seeker ($w_{Right-Asylum}$ = .29) and the war in Ukraine ($w_{Right-Ukraine}$ = .09), and negatively related to being threatened by climate change ($w_{Right-Climate}$ = -.20) and polarization ($w_{Right-Polarization}$ = .17). Conservatism, the other ideology dimension, was less central (strength: -.65; closeness: .12) and had fewer edges to societal threat perception nodes than right-wing ideology. Conservatism was positively related to being

6) Ideology is commonly measured with two dimensions (e.g., Malka et al., 2019). In our sample, ideology was measured with the variables right-wing ideology and conservatism. The two variables are correlated with each other (bivariate correlation: r = .56), which is consistent with previous findings (e.g., Aspelund et al., 2013). The strength of this correlation does not pose a risk to the network model's robustness (Epskamp & Fried, 2018).

threatened by crime ($w_{Conservatism–Crime}$ = .10), and negatively related to being threatened by climate change ($w_{Conservatism–Climate}$ = -.11). Contrary to the rigidity-of-the-extremes perspective (e.g., Zmigrod et al., 2019), political extremity was (largely) unrelated to societal threat perceptions in the network, with only one edge between extremity on a left-right spectrum and the influx of asylum seekers ($w_{ExtremityRight–Asylum}$ = .11).

The edges between ideology and societal threat perception nodes are thus not fully in line with any of the competing threat-politics expectations. At best, some of the associations in the network provide suggestive evidence for the threat ownership perspective (e.g., Eadeh & Chang, 2020). However, this is limited to climate change, the influx of asylum seekers, and crime, while other threat perceptions—for example, inflation and energy costs—are fully unassociated with ideology.

Socio-Demographic Background and Political Interest. Age was the most central node in the overall network (strength: 2.6; closeness: 2.03) and the node with the most edges to societal threat perceptions. We find that age was positively related to being threatened by Covid-19 ($w_{Age–Covid-19}$ = .20), the war in Ukraine ($w_{Age–Ukraine}$ = .20), the labour shortage ($w_{Age–Labour}$ = .15), and energy costs ($w_{Age–Energy}$ = .11). Age was negatively related to being threatened by the housing shortage ($w_{Age–Housing}$ = -.22), inflation ($w_{Age–Inflation}$ = -.21), and climate change ($w_{Age–Climate}$ = -.15). Education was moderately central in the overall network model (strength: .85; closeness: 1.57). Having a higher level of education was mostly negatively related to being threatened by societal issues: Higher levels of education were negatively related to being threatened by the influx of asylum seekers ($w_{Education–Asylum}$ = -.18), energy costs ($w_{Education–Energy}$ = -.11), and the reception of asylum seekers ($w_{Education–Reception\ Asylum}$ = -.09), and only positively related to being threatened by polarization ($w_{Education–Polarization}$ = .14). Political interest was moderately central in the overall network (strength: .3; closeness: .31), and mostly unrelated to societal threat perceptions, apart from being positively associated with being threatened by the war in Ukraine ($w_{Interest–Ukraine\ Asylum}$ = .08). Finally, identifying as female was relatively low in centrality in the overall network (strength: -1.1; closeness: -.50), and positively related to being threatened by the labour shortage ($w_{Female–Labourer}$ = .13) and the nitrogen problem ($w_{Female–Nitrogen}$ = .13).

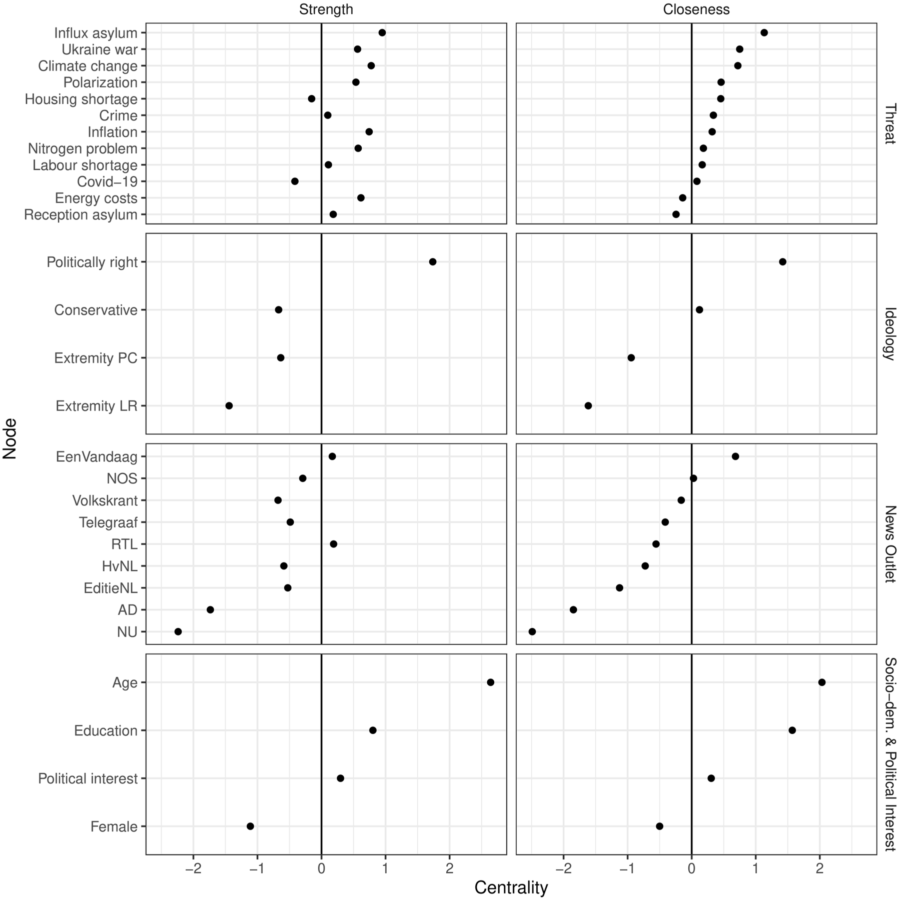
News Consumption

News consumption, across the board, was only weakly related to societal threat perceptions, as can be seen from the relatively low strength of news outlet nodes, see Figure 5, and the few and weak edges between news outlets and societal threat perceptions, see Figure 4. Two news outlets stand out. Consuming news through the Telegraaf—a right-wing tabloid news outlet—while relatively low in centrality (strength: -.5; closeness: -.41), was positively related to being threatened by the influx of asylum seekers ($w_{Telegraaf–Asylum}$ = .08) and negatively related to being threatened by climate change ($w_{Telegraaf–Climate}$ = -.08). Reading the Volkskrant—a progressive broadsheet newspaper—was also relatively low in centrality (strength: -.6; closeness: -.16), and positively related to being threatened by the inhumane reception of asylum seekers as threatening ($w_{Volkskrant–Reception}$ = .1), and negatively related to being threatened by inflation ($w_{\text{Volkskrant–Inflation}}$ = -.08).

To summarize, taking a network approach to the correlates of societal threat perceptions, we find that ideology, age and education are important—based on their associations with societal threat perceptions and their centrality in the overall network—when trying to understand societal threat perceptions.

Figure 5

Centrality Indices of the Network Model of Societal Threats and Their Correlates



Note. Centrality indices strength and closeness (both z-standardized), grouped by node type and ordered by strength.

Replicating Societal Threat Perceptions and Their Associations Over One Year

To investigate the temporal dynamics of individual societal threat perceptions we conducted preregistered equivalence tests and conclude that most societal threat perceptions are stable over the span of one year. The threat perceptions of the war in Ukraine and Covid-19 are the notable exceptions: the level of threat decreases over time. For conciseness, we refer to Appendix F for details on analysis and results.

To replicate the network of societal threat perceptions over time (RQ3b), we performed paired Network Comparison Tests (NCTs) with the NetworkComparisonTest package (van Borkulo et al., 2023). The NCTs indicated no statistically significant differences between the networks in three of the four performed comparisons, apart from one edge between crime and polarization in the comparison of Waves 5 and 6, see Appendix G for detailed results. The preregistered NCTs—with the exception of one node in one comparison—thus indicated that the associations between societal threat perceptions replicate over the span of one year.

Discussion

Our study has three main conclusions. First, our results indicate that societal threat perceptions are structured by interrelations of varying degrees, instead of suggesting that threat perceptions are determined by a general threat sensitivity trait (e.g., Hibbing et al., 2014). Some threats, in particular the security threats crime, the war in Ukraine, and asylum-related threats, are more central to our network model than other threats, such as the housing shortage and Covid-19. Second, we find some, but not very consistent, evidence for a link between ideology and some threats. At the same time, age and education were highlighted as relatively important in relation to our set of societal threats. Third, we find that, within our study, the conclusions we draw hold in replications over one year. This offers a first indication of the stability of threat perceptions and their interrelational structure. In what follows, we discuss the implications of our contributions and outline an agenda for the next generation of theory and research on societal threat perceptions.

Starting with our first research question, our study obtained information about the centrality of a broad set of societal threat perceptions. In our study, threats related to security—such as crime, the war in Ukraine, and asylum-related threats—stand out as the most central threats, while other threats—such as inflation and the housing shortage—are less central. Further theorizing may therefore focus on security threats, as these are the most central in our network models and, as a consequence, should have the strongest effect on citizens' political behavior and political engagement (Dalege et al., 2017). This is consistent with previous theorizing and research that focuses on security threats, rather than economic threats, in explaining political attitudes and behavior (Costello et al., 2023; Mutz, 2018). Moreover, security threats may pose a relevant starting point for tailoring interventions to influence the system of societal threat perceptions, and thus mitigate their consequences (Brandt & Bakker, 2022; Chambon, Dalege, Waldorp et al., 2022). At the same time, we should not disregard threats that are less central as irrelevant altogether: Less central threats like climate change and the housing shortage may still be perceived as highly threatening, but are simply less strongly related to the overall system of societal threat perceptions.

Moving to the interrelations of societal threat perceptions, our study provides important insights into the structure of our set of threat perceptions. If the estimated network model had indicated distinct, stable clusters of societal threat perceptions, this would have suggested that our set of societal threat perceptions is structured by underlying latent dimensions (e.g., Kahn et al., 2022; Onraet et al., 2013). If the model had indicated a single, stable cluster, with strong interrelations of all societal threat perceptions, this would have suggested that societal threat perceptions are mainly determined by individual threat sensitivity (e.g., Hibbing et al., 2014; Jost, 2017). However, our results support neither of these perspectives. Instead, many societal threat perceptions are, to varying degrees, interrelated. We recommend the next generation of research and theorizing on societal threat perceptions to consider the varying degrees of interrelations exhibited among our set of threats, and conceptualize networks of interrelated threats.

Our study brings new evidence to the debate in the threat-politics literature about the extent to which ideology and societal threat perceptions are associated with each other (Brandt & Bakker, 2022): in our sample, we find no support for the ideological asymmetry (Jost, 2017), or the rigidity-of-the-extremes perspectives (Zmigrod et al., 2019). In the best case, the associations of crime right-wing ideology and climate left-wing ideology align with the predictions from the threat-ownership perspective (Eadeh & Chang, 2020; Godefroidt et al., 2019). Yet, the majority of our set of societal threats are not associated with ideology. This highlights the relevance of modeling relations between threat perceptions and ideology in a way that allows different threats to vary in their links to ideology. On a theory level, our study supports recent theorizing that threat and ideology may not be inseparably linked to one another (Brandt & Bakker, 2022).

Accordingly, we suggest that the threat perception literature should move beyond the ideology-threat link: we find that besides political ideology, age and education are also important correlates of societal threat perceptions. Future research may further explore how and why age and education are so central to understanding societal threat perceptions. For instance, the associations between age and societal threat perceptions may be driven by generational differences in the response to different societal threats (e.g., Jennings & Niemi, 1981). At the same time, the associations between education and societal threat perceptions suggest there might be a cleavage between the low and highly educated (e.g., Lucassen & Lubbers, 2012; Stubager, 2013). Our findings indicate that socio-demographic characteristics are important correlates of societal threat perceptions. Ultimately, our results highlight the need for more comprehensive theorizing and research on the correlates and potential predictors and consequences of societal threat perceptions beyond ideology.

Finally, our results replicate over multiple time-points in one year. 2022–2023 was a turbulent year, as it spanned the fall of the Dutch government, an election campaign, and new elections; see Figure 1. The replicability of our findings over a one-year period suggests that once a societal threat has been established and placed in the system of threats, the extent to which it is perceived as threatening and its position within the system of threats may not change much. This is consistent with literature on the stability of political attitudes (e.g., Ansolabehere et al., 2008). Future theorizing on societal threat may therefore look at long-term, structural factors to further understand threat perceptions—for example, ideology, age, and education, which were relevant correlates in our study.

We welcome more research on societal threat perceptions and see multiple suggestions for follow-up research. First, our results are context-specific and our conclusions limited to a single, democratic, Western country (the Netherlands). We note that research on societal threat perceptions often replicates across Western democracies (Brandt & Bakker, 2022; Kesberg et al., 2022). Yet, the nature and extent of the threat–ideology link may depend on a nation's history (e.g., Malka et al., 2014) or other, largely unknown, context characteristics (Brandt et al., 2021). We therefore encourage future work to extend our findings to Western and non-Western contexts. Cross-national studies may assess the replicability of our cross-sectional results, while longitudinal and additional network methodology (e.g., correlational class analysis) may explore individual-level variation of threat perception networks.

Second, our conclusions are limited to the threat perceptions we included in the survey. We believe that our sample of societal threats provides a comprehensive perspective on threat in society, as it includes relevant issues, both politicized and non-politicized, that cover a range of commonly examined threat types (see Methods section). At the same time, we welcome future efforts that employ extended or different sets of societal threat perceptions.

Third, we relied upon single-item measures of threat perception (Allen et al., 2022), but do not think that this limits the validity of our findings: A potential measurement error caused by the use of single items would make it harder to detect replicability over time (Ansolabehere et al., 2008; Brandt, 2020), as a measurement error would make it more likely to find change. Our conclusion that threats replicate over a one-year period is therefore based upon a more conservative test. Fourth, we studied threat perceptions over a one-year period. We welcome future research that replicates societal threat perceptions and their networks over even longer periods of time.

To conclude, our study on the structure, correlates, and temporal replicability of societal threat perceptions deepens and broadens theory and research on societal threat perceptions, and helps us understand how threatening issues are perceived within society. Doing so, we directly inform the literature on societal threat perceptions (e.g., Brandt & Bakker, 2022; Kesberg et al., 2022), the broader threat-politics literature (e.g., Cassario & Brandt, 2024; Godefroidt et al., 2019; Holman et al., 2022), as well as the broader literature on public opinion systems and their dynamics (Boutyline & Vaisey, 2017; Dalege et al., 2017). Ultimately, this paper sets the stage for future work on studying the structure, correlates, and replicability of societal threat perceptions using a network approach.

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Data Availability: All data and analysis code are available on this study's OSF page (see Bomm et al., 2024b).

Supplementary Materials

For this article, the following Supplementary Materials are available:

- Preregistration (see Bomm et al., 2024a)
- Data, analysis code (see Bomm et al., 2024b)

Index of Supplementary Materials

Bomm, L. C., Bakker, B. N., Schumacher, G., & Hopp, F. R. (2024a). *Societal threat perceptions: Stable, structured, politicized* [Preregistration]. OSF Registries. https://doi.org/10.17605/OSF.IO/E8KFB

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Appendices

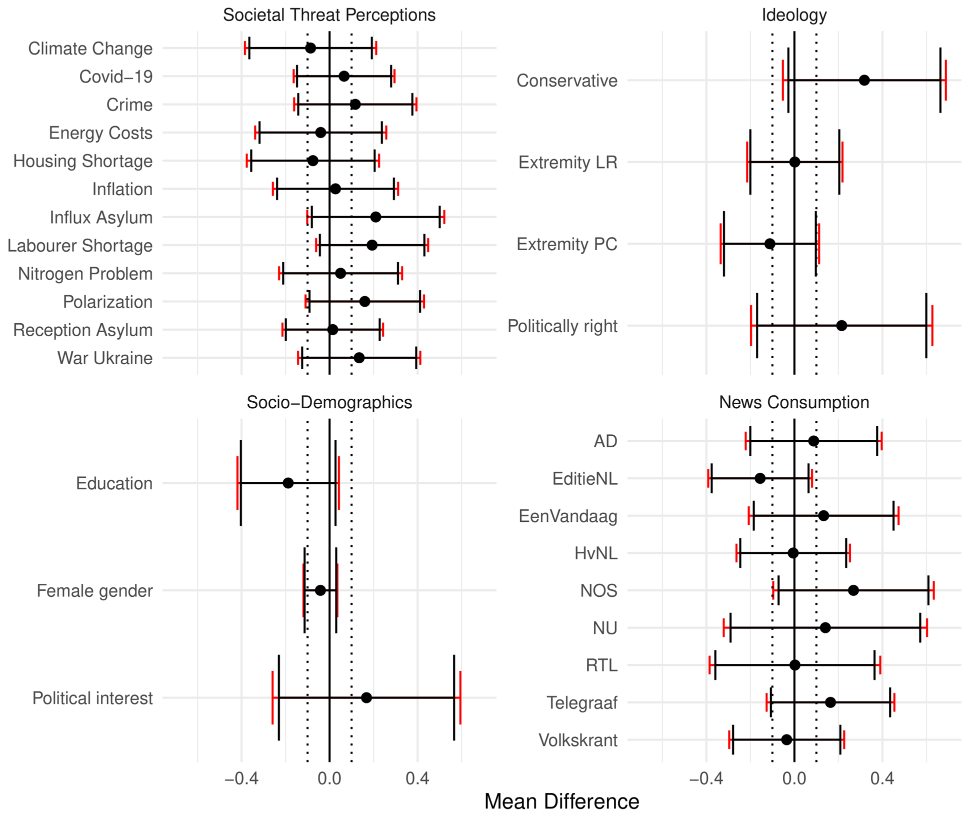
Appendix A: Equivalence Tests Comparing Complete and Incomplete Responses

To assess whether our results may have been confounded by systematic variations between participants who completed all six waves and participants who dropped out during data collection, we performed equivalence tests with the TOSTER package (Lakens et al., 2018), null-hypothesis t-tests with the stats package (R Core Team, 2023), and null-hypothesis Hedge’s g effect size calculations with the effsize package (Torchiano, 2016). We compared our final sample of participants who completed all six data collection waves (N = 685) with those who dropped out of the survey at any point (N = 1040) on their societal threat perceptions, ideology, news consumption measures, and socio-demographics, collected in Wave 1. We chose standardized equivalence bounds, as the analyzed and plotted variables were measured on different scales (Lakens, 2017; Lakens et al., 2018), and Bonferroni-corrected α levels of α = .0017 (.05 / 29 (number of compared variables) = .0017). Figure 6 provides the estimates and confidence intervals for the performed equivalence tests with standardized effect size equivalence bounds of Δ_L = -.2 and Δ_U = .2, confidence intervals for equivalence test effect sizes in black, and confidence intervals for null-hypothesis t-test effect sizes in red.

We conclude statistical equivalence for most societal threat perceptions, some news consumption variables, and extremity on a left-right spectrum, as their effect size CIs fall within the equivalence bounds, see Figure 6. Participants who dropped out of data collection were statistically significantly younger than those who completed all six survey waves ($M_{Completed}$ = 55.2, $M_{Dropout}$ = 50.4, $t(1501) = 6.04$, $p < .001$, g_{Age} = .30). For other variables, the data are inconclusive, as their effect size CIs overlap both with 0 and with the lower or upper equivalence bounds, meaning we can neither conclude statistical difference nor equivalence. However, all effect size estimates except for that of age are small (between $g_{Education}$ = -.13 and $g_{Conservative}$ = .14) (Funder & Ozer, 2019). We thus acknowledge that our final sample was significantly and meaningfully younger than the initial full sample in Wave 1, but include all variables in our subsequent analyses.

Figure 6

Societal Threat Perceptions, Ideology, Socio-Demographics, and News Consumption Comparison Between Dropouts and Complete Responses



Note. Results of equivalence tests comparing societal threat perceptions, ideology, socio-demographics, and news consumption between participants with complete and incomplete data, with standardized equivalence bounds of Δ_L = -.2 and Δ_U = .2, indicated by dotted line. Bonferroni-corrected 95% equivalence effect size CIs are depicted through black lines and error bars. Bonferroni-corrected 95% null-hypothesis significance test effect size CIs are depicted through red lines and error bars.

Appendix B: Descriptive Statistics

We present descriptive statistics of societal threat perceptions across six different waves spanning one year, and ideology, socio-demographics, and news consumption in Wave 1, in Table 2.

Table 2

Descriptive Statistics of Societal Threat Perceptions and Correlates Across Waves 1–6

	Wave 1		Wave 2		Wave 3		Wave 4		Wave 5		Wave 6	
Variable	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Societal Threat Perceptions												
Climate Change	4.02	1.92	4.00	1.84	3.96	1.93	4.14	1.92	3.95	1.91	3.89	1.97
Covid-19	2.45	1.48	2.38	1.40	2.06	1.30	1.96	1.31	2.24	1.39	2.16	1.37
Crime	3.73	1.80	3.76	1.69	3.71	1.68	3.82	1.73	3.82	1.70	3.71	1.79
Energy Costs	4.33	1.95	4.12	1.81	3.92	1.88	3.94	1.86	4.07	1.87	4.03	1.93
Housing Shortage	3.07	1.92	2.97	1.81	2.91	1.83	3.00	1.87	3.06	1.89	3.14	1.90
Inflation	4.28	1.85	4.10	1.74	4.06	1.76	4.08	1.79	4.07	1.77	3.99	1.81
Influx Asylum Seekers	3.39	2.03	3.24	1.89	3.21	1.95	3.38	1.99	3.37	1.95	3.39	2.02
Labour Force Shortage	2.85	1.66	2.78	1.55	2.68	1.56	2.75	1.66	2.83	1.56	2.80	1.61
Nitrogen Problem	3.16	1.82	3.09	1.73	3.29	1.85	3.20	1.78	3.08	1.71	3.06	1.75
Polarization	3.92	1.73	3.79	1.67	3.69	1.69	3.78	1.70	3.74	1.66	3.74	1.71
Reception Asylum Seekers	2.37	1.46	2.34	1.41	2.26	1.47	2.32	1.44	2.26	1.38	2.25	1.41
War in Ukraine	3.84	1.79	3.96	1.77	3.65	1.78	3.64	1.75	3.48	1.74	3.21	1.69
Correlates												
Conservative	5.24	2.32										
Politically right	6.16	2.71										
Extremity left-right	8.37	1.33										
Extremity progressive-conservative	8.03	1.36										
Age	55.16	15.76										
Political interest	6.97	2.75										
Telegraaf	1.93	1.94										
AD	2.07	2.00										
EditieNL	1.52	1.35										
EenVandaag	2.58	2.13										
HvNL	1.67	1.57										
NOS	4.71	2.34										
NU	3.67	2.87										
RTL	2.68	2.39										
Volkskrant	1.72	1.63										

Note. Descriptive statistics of the societal threat perception and continuous correlate variables, based on the final sample of $N = 685$ participants.

Appendix C: Construction of News Consumption Measures

News consumption was measured only in Wave 1, by consumption in days per typical week of various news outlets. To construct indices of news consumption, we first explored the distributions of the news consumption variables and selected those that were the most frequently consumed, leaving out more niche outlets (e.g., “Nederlands Dagblad”, a small newspaper with a Christian signature).

Next, we converged consumption across domains (web, TV, newspaper) for the different news outlets, following the rationale that when measuring news consumption, news media should be converged across domains if their content is similar (de Vreese & Boomgaarden, 2006). In the survey we analyze, participants only provided their consumption of different outlets, grouped by domain (web, TV, newspaper), if they had indicated that they consume news from that domain. In the context of our study, this meant averaging consumption of, e.g., the news outlet Volkskrant across newspaper and website measures only if a participant had provided data on both measures. If data from a participant was only available for either the newspaper Volkskrant or the website Volkskrant, their converged score for consumption of the Volkskrant consisted entirely of the data they had provided. If a participant had not provided data for the Volkskrant on either of the domains, their data on the variable Volkskrant was missing.

Appendix D: RQ1: Method, Wave-by-Wave Analyses, bootEGA, Centrality Stability

D.1 Method

Exploratory Graph Analyses (EGAs) study the network structure and dimensionality of nodes in a network (Golino & Epskamp, 2017). As pre-registered, the Gaussian Graphical network model in the EGA was created with the graphical least absolute shrinkage and selection operator (GLASSO). Following this procedure, the EGA function uses the EBICglasso from the qgraph package, generating 100 graphs that vary in their amount of regularization (i.e., sparseness) (Epskamp et al., 2012), selecting the graph with the smallest Extended Bayesian Information Criterion (EBIC). Following our pre-registration, the EGA then ran a Walktrap algorithm over the created Gaussian Graphical network model to obtain its clustering structure.[7]

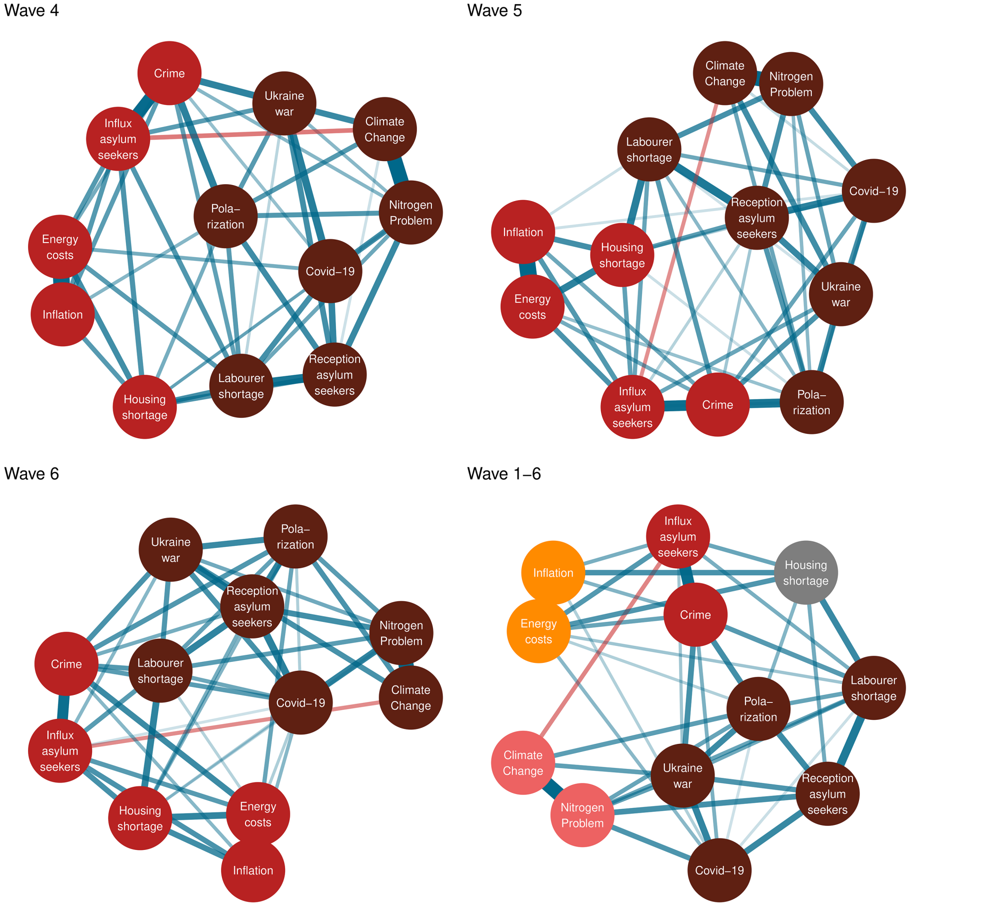
D.2 Wave-by-Wave Analyses

We performed EGAs on the individual Waves 4, 5, and 6 to assess their network structures and clustering solutions. Figure 7 depicts the networks resulting from the EGAs on societal threat perceptions based on the individual Waves 4, 5, and 6. As in the network on the aggregated societal threat perceptions based on person means across Waves 4-6, we found three consistent associations in all three EGAs between pairs of threats.

7) See explanation of the Walktrap algorithm in Christensen and Golino (2021, p. 480): “The Walktrap algorithm estimates the number and content of a network’s communities using “random walks” over the network [...]. These random walks iteratively traverse over neighboring edges, with larger edge weights (i.e., partial correlations) being more probable paths of travel. Each node is repeatedly used as a starting point where steps - a jump from one node over an edge to another - are taken away from that node, forming a community boundary. A node’s community is then determined by its proportion of many densely connected edges to few, sparsely connected edges (commonly optimized by a statistic known as modularity) [...]. The algorithm is deterministic, meaning the number and variable content of the communities are estimated without the researcher’s direction.”

Figure 7

EGAs of Societal Threat Perceptions on Waves 4, 5, 6, and Person-Mean Scores Across Waves 1–6



Note. Preregistered EGAs on the individual Waves 4 (top left), 5 (top right), and 6 (bottom left), and person-mean scores across Waves 1–6. All EGAs were created with the GLASSO modelling strategy and the Walktrap algorithm. The edges between nodes represent partial correlations and depict their strength (i.e., edge weight). The stronger an edge, the thicker and more opaque its depiction. Blue edges indicate positive, red edges indicate negative partial correlations.

D.3 Bootstrapped Exploratory Graph Analysis

Bootstrapped exploratory graph analyses (bootEGAs) formally evaluate the stability of obtained EGA results by comparing them to a sampling distribution of bootstrapped EGA results based on the same data (Christensen & Golino, 2021). We performed an exploratory bootEGA on the person-means from Waves 4–6 to assess the stability of the results we obtained with the preregistered EGA. We find evidence that the clustering solution is not stable: In the aggregated data across

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Waves 4 to 6, the two-cluster solution proposed by the EGA was found 48.6% of the time across 500 bootstrapped samples, while three clusters were found 20% and four clusters 31.4% of the time. Furthermore, the structural consistency estimates (i.e., how often an empirical EGA dimension is exactly replicated across the bootstrap replicates) of both clusters indicate that they are unstable (structural consistency$_{cluster1}$= 0.488; structural consistency$_{cluster2}$= 0.516; see Christensen & Golino, 2021, p. 490, for an interpretation of a structural consistency of .574 as ”very unstable”). To summarize, preregistered and exploratory tests indicate that the twelve investigated societal threat perceptions do not cluster in a stable set of clusters.

D.4 Centrality Stability

We recreated the obtained network model with the same parameters on the same data using the bootnet package (Epskamp et al., 2018) to assess the stability of the centrality estimates. We assessed the centrality stability by calculating correlation stability (CS) coefficients for strength and closeness, which indicate the percentage of cases of the original sample that can be dropped to retain, with 95% certainty, a correlation of at least .7 with the centrality indices of the original network (Epskamp et al., 2018). Both the strength (CS = .75) and the closeness (CS = .71) centrality estimates were stable enough to interpret, as their correlation stability coefficients were above the recommended instability cutoff of CS = .25 (Epskamp et al., 2018).

Appendix E: RQ2: Network Modelling and Accuracy, Network Model on Wave 1, Centrality Stability

E.1 Method

We created the network model to assess RQ2 with the stepwise model search selection technique with the ggmModSelect algorithm from the bootnet package (Epskamp & Fried, 2018) with a tuning parameter of γ = .1 and pairwise deletion for missing values. The ggmModSelect algorithm searches for the network with the optimal balance between specificity and sensitivity by adding and removing edges to optimize the Bayesian Information Criterion (BIC) (Epskamp & Fried, 2018).

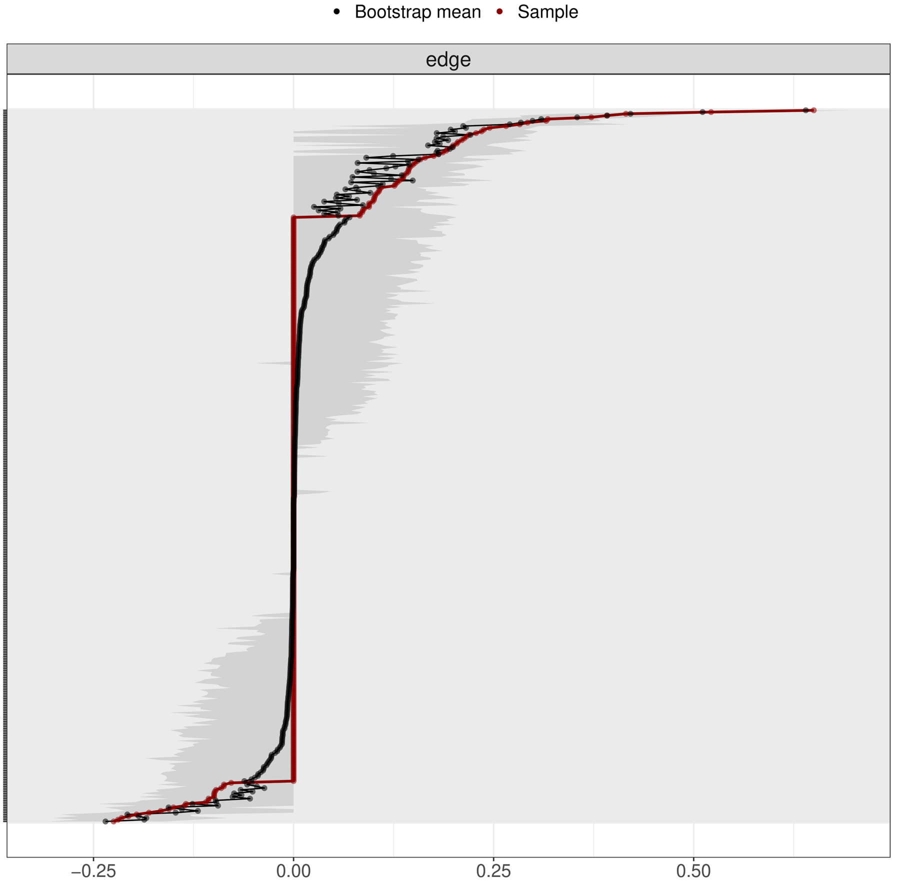
E.2 Accuracy Estimation of Edge Weights

As preregistered, we assessed the accuracy of the obtained edge weight estimates with the bootnet command from the bootnet package (Epskamp et al., 2018). We obtained non-parametric 95% bootstrap samples (i.e., resampling with replacement), as advised for networks estimated with the GLASSO regularization (Epskamp et al., 2018).

Figure 8 shows the distribution of edge weights based on the original sample and the resamples (i.e., bootstrapped samples), and 95% confidence intervals around them. As indicated by the relatively wide confidence intervals (dark grey) around the edge weights, the edge weight estimations in this network are considered relatively low in accuracy. The order of the most edges in the network should thus be interpreted with care (Epskamp et al., 2018).

Figure 8

Accuracy Estimates of the Network Model on Waves 1 to 6



Note. Network accuracy estimates, depicting 95% confidence intervals (dark grey) around edge weight sample values (red) and means of the bootstrapped edge weight values (black).

Table 3 shows 95% confidence intervals of edges between ideology, socio-demographic background, and news consumption variables that indicate which threat perception edges in the network differed statistically significantly from each other.

Table 3

Edge Weights and Confidence Intervals

Threat	Correlate	Sample edge weight	Bootstrap mean edge weight	Bootstrapped CI lower	Bootstrapped CI upper	Percentage edge excluded
Ideology						
Climate	Ideology left-right	-0.20	-0.20	-0.27	-0.12	0.00
Polarization	Ideology left-right	-0.17	-0.11	-0.31	-0.03	0.24
Ukraine	Ideology left-right	0.09	0.03	-0.02	0.19	0.79
Asylum	Ideology left-right	0.29	0.28	0.22	0.36	0.00
Climate	Ideology conservative-progressive	-0.11	-0.06	-0.23	0.02	0.46
Crime	Ideology conservative-progressive	0.10	0.06	-0.03	0.23	0.52
Asylum	Extremity left-right	0.11	0.08	-0.01	0.22	0.28
Socio-demographic Background and Political Interest						
Housing	Age	-0.22	-0.20	-0.30	-0.14	0.00
Inflation	Age	-0.21	-0.19	-0.32	-0.11	0.01
Climate	Age	-0.15	-0.15	-0.22	-0.08	0.00
Energy	Age	0.11	0.07	-0.02	0.24	0.41
Labour	Age	0.15	0.13	0.04	0.25	0.12
Covid-19	Age	0.20	0.17	0.12	0.27	0.01
Ukraine	Age	0.20	0.20	0.13	0.27	0.00
Asylum	Edu	-0.18	-0.15	-0.26	-0.10	0.02
Energy	Edu	-0.11	-0.09	-0.22	0.00	0.24
Reception asylum	Edu	-0.09	-0.04	-0.21	0.03	0.66
Polarization	Edu	0.14	0.08	0.01	0.28	0.40
Labour	Female	0.13	0.12	0.00	0.26	0.19
Nitrogen	Female	0.13	0.11	0.01	0.24	0.17
Ukraine	Political interest	0.08	0.05	-0.03	0.20	0.55
News consumption						
Reception asylum	Volkskrant	0.10	0.06	-0.03	0.23	0.55
Asylum	Telegraaf	0.08	0.04	-0.04	0.2	0.63

Note. Edge weights between societal threat perceptions and correlate nodes (ideology, socio-demographic background, and news consumption), mean bootstrapped edge weight, boots-trapped 95% confidence interval limits, and the percentage of times an edge was excluded from the network model across all network permutations. Non-overlapping CIs indicate that edges differ statistically significantly from each other. Edges with overlapping CIs may still significantly differ (Epskamp et al., 2018).

E.3 Centrality Stability

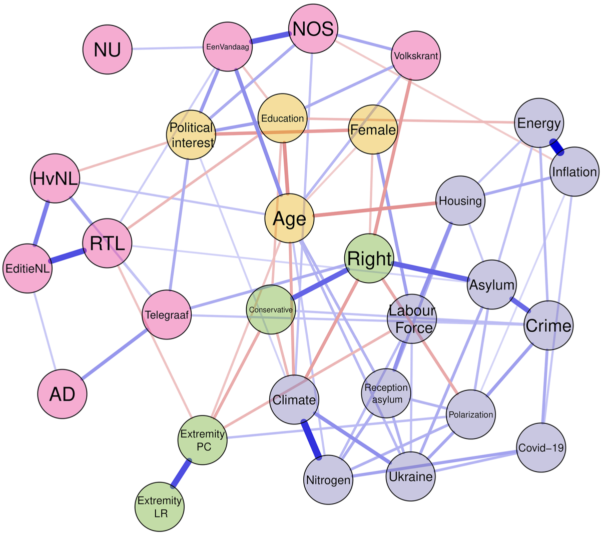
As preregistered, we assessed the stability of the strength and closeness indices of the network model in the results section by calculating correlation stability (CS) coefficients.[8] Both the strength (CS = .60) and the closeness (CS = .64) centrality estimates were stable enough to interpret, as their correlation stability coefficients were above the preregistered instability cutoff of CS = .25.

E.4 Network Model on Wave 1

To supplement the network model in Figure 4, which modelled data from Waves 1 and 6, we present the network modelled only on data from Wave 1 in Figure 9. The conclusions we can draw from this network are in line with the conclusions we draw from the network on data from Waves 1 and 6 in the results section.

Figure 9

Network Model of Societal Threat Perceptions and Ideological, News Consumption, and Demographic Correlates on Wave 1



Note. Gaussian Graphical network model of societal threat perceptions (purple) and ideological (green), socio-demographic (yellow), and news consumption (pink) correlates, created on Wave 1 data. Nodes represent variables. Edges between nodes represent partial correlations and depict their strength (i.e., edge weight) through edge width and opaqueness. Blue edges indicate positive, red edges indicate negative partial correlations. The network was modelled with stepwise model selection with a tuning parameter of gamma = .1.

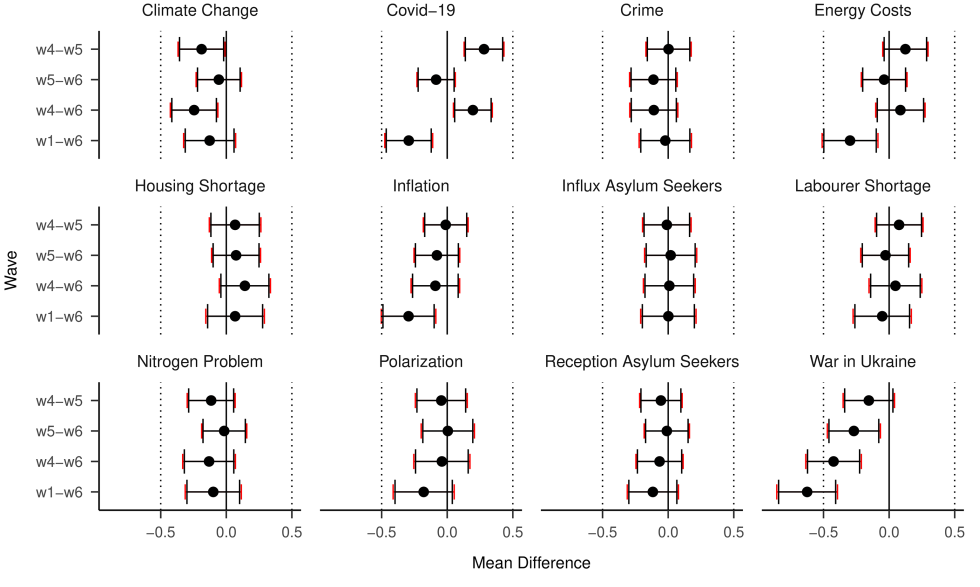
8) Note that we calculated 2000 instead of 1000 bootstrapped centrality estimations, as in some bootstrap subsamples, some nodes were no longer connected to any other nodes, leading to a closeness estimation of 0 for all nodes in the network. We excluded these samples from the stability estimation of the closeness indices, deriving at a final number of 1097 bootstrap samples for the closeness stability estimation, and 2000 bootstrap samples for the strength stability estimation.

Appendix F: RQ3a: Equivalence Tests and Null-Hypothesis Significance Tests

To investigate the stability of societal threat perceptions between Waves 4 and 5, Waves 5 and 6, waves 4 and 6, and Waves 1 and 6, we performed a series of equivalence tests with the TOSTER package (Lakens et al., 2018) and null-hypothesis *t*-tests with the stats package (R Core Team, 2023). We chose raw instead of standardized equivalence bounds, as recommended (Lakens, 2017), and Bonferroni-corrected α levels of α = .001 (4 (number of wave comparisons) * 12 (number of societal threats) = 48 equivalence tests, leading to a Bonferroni-corrected alpha level of .05 / 48 = .00104, which we round to .001). Figure 10 shows mean difference estimates and confidence intervals for equivalence tests in black and confidence intervals for null-hypothesis t-tests in red. We deviate from our preregistered raw equivalence bounds of -.1 and .1, as we believe that this is unreasonably narrow for our 7-point scale. Instead, we present raw bounds of -.5 and .5, see Figure 10 (dotted line). Table 4 provides the detailed equivalence test results (estimate, bounds, CI) for the 48 comparisons of (twelve societal threat perceptions; compared in Wave 4 vs. 5, 5 vs. 6, 4 vs. 6, and 1 vs. 6). As all threat perceptions apart from the threat perceptions of the war in Ukraine were stable over time, we conclude that most societal threat perceptions are stable over time.

Figure 10

Equivalence Test and Null-Hypothesis Significance Test Results Comparing Societal Threat Perceptions Between Waves



Note. Results of twelve equivalence tests with raw mean bounds of Δ_L = -.5 and Δ_U = .5, indicated by dotted line. Mean difference and Bonferroni-corrected 90% equivalence CIs are depicted through black lines and error bars. Bonferroni-corrected 95% null-hypothesis significance test CIs are depicted through red error bars.

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Table 4

Results of Equivalence and Null-Hypothesis Significance Tests

				Equivalence Test				Null-Hypothesis Significance Test			
Threat	Raw mean diff	*t* (TOST Lower)	*p* (TOST Lower)	*t* (TOST Upper)	*p* (TOST Upper)	Lower CI TOST	Upper CI TOST	*t* (NHST)	*p* (NHST)	Lower CI NHST	Upper CI NHST
Wave 4 vs. 5											
Corona	0.28	8.29	0.000	3.93	1.000	0.14	0.42	6.11	0.000	0.13	0.43
Influx asylum seekers	-0.01	1.60	0.055	-1.97	0.025	-0.18	0.16	-0.18	0.855	-0.20	0.17
Reception asylum seekers	-0.06	0.91	0.182	-3.17	0.001	-0.21	0.10	-1.13	0.259	-0.22	0.11
Inflation	-0.01	1.71	0.044	-2.16	0.015	-0.17	0.15	-0.23	0.821	-0.18	0.16
Energy costs	0.12	4.29	0.000	0.46	0.678	-0.04	0.29	2.38	0.018	-0.05	0.30
Ukraine war	-0.15	-0.92	0.822	-4.30	0.000	-0.34	0.03	-2.61	0.009	-0.35	0.04
Nitrogen Problem	-0.12	-0.28	0.609	-3.90	0.000	-0.29	0.06	-2.09	0.037	-0.30	0.07
Climate Change	-0.19	-1.63	0.948	-5.32	0.000	-0.36	-0.02	-3.47	0.001	-0.37	-0.01
Housing shortage	0.07	2.81	0.003	-0.55	0.290	-0.12	0.25	1.13	0.259	-0.13	0.26
Polarization	-0.05	0.91	0.180	-2.43	0.008	-0.23	0.14	-0.76	0.450	-0.24	0.15
Labourer shortage	0.08	3.19	0.001	-0.44	0.331	-0.10	0.25	1.38	0.170	-0.11	0.26
Crime	0.00	1.97	0.024	-1.86	0.032	-0.16	0.16	0.06	0.955	-0.17	0.18
Wave 5 vs. 6											
Corona	-0.08	0.35	0.364	-4.18	0.000	-0.22	0.05	-1.92	0.056	-0.23	0.06
Influx asylum seekers	0.02	1.98	0.024	-1.35	0.089	-0.17	0.21	0.32	0.752	-0.18	0.22
Reception asylum seekers	-0.01	1.72	0.043	-2.11	0.018	-0.17	0.15	-0.20	0.845	-0.18	0.16
Inflation	-0.08	0.40	0.344	-3.39	0.000	-0.24	0.08	-1.49	0.136	-0.25	0.10
Energy costs	-0.04	1.18	0.120	-2.62	0.005	-0.20	0.13	-0.72	0.472	-0.21	0.14
Ukraine war	-0.27	-2.75	0.997	-6.02	0.000	-0.46	-0.08	-4.39	0.000	-0.47	-0.07
Nitrogen Problem	-0.02	1.61	0.053	-2.23	0.013	-0.18	0.15	-0.31	0.758	-0.19	0.16
Climate Change	-0.06	0.82	0.205	-3.00	0.001	-0.22	0.11	-1.09	0.277	-0.23	0.12
Housing shortage	0.07	3.09	0.001	-0.45	0.325	-0.10	0.25	1.32	0.187	-0.11	0.26
Polarization	0.00	1.70	0.045	-1.56	0.060	-0.19	0.19	0.07	0.943	-0.20	0.21
Labourer shortage	-0.03	1.27	0.103	-2.24	0.013	-0.20	0.15	-0.49	0.627	-0.22	0.16
Crime	-0.11	-0.23	0.589	-3.87	0.000	-0.28	0.06	-2.05	0.041	-0.29	0.07
Wave 4 vs. 6											
Corona	0.20	6.60	0.000	2.14	0.983	0.06	0.33	4.37	0.000	0.05	0.34
Influx asylum seekers	0.01	1.82	0.035	-1.53	0.064	-0.18	0.19	0.15	0.884	-0.19	0.21
Reception asylum seekers	-0.07	0.63	0.264	-3.05	0.001	-0.23	0.10	-1.21	0.228	-0.25	0.11

Threat	Raw mean diff	Equivalence Test: *t* (TOST Lower)	*p* (TOST Lower)	*t* (TOST Upper)	*p* (TOST Upper)	Lower CI TOST	Upper CI TOST	Null-Hypothesis Significance Test: *t* (NHST)	*p* (NHST)	Lower CI NHST	Upper CI NHST
Inflation	-0.09	0.17	0.433	-3.40	0.000	-0.26	0.08	-1.62	0.107	-0.28	0.09
Energy costs	0.09	3.27	0.001	-0.24	0.404	-0.09	0.26	1.51	0.131	-0.10	0.27
Ukraine war	-0.42	-5.05	1.000	-8.17	0.000	-0.62	-0.22	-6.61	0.000	-0.63	-0.21
Nitrogen Problem	-0.13	-0.52	0.697	-3.81	0.000	-0.32	0.06	-2.16	0.031	-0.33	0.07
Climate Change	-0.25	-2.65	0.996	-6.30	0.000	-0.42	-0.08	-4.48	0.000	-0.43	-0.06
Housing shortage	0.14	4.10	0.000	0.71	0.760	-0.04	0.32	2.40	0.017	-0.05	0.34
Polarization	-0.04	0.91	0.181	-2.18	0.015	-0.24	0.16	-0.63	0.528	-0.25	0.17
Labourer shortage	0.05	2.43	0.008	-0.85	0.198	-0.14	0.24	0.79	0.429	-0.15	0.25
Crime	-0.11	-0.17	0.568	-3.78	0.000	-0.28	0.06	-1.98	0.049	-0.29	0.07
Wave 1 vs. 6											
Corona	-0.29	-3.50	1.000	-7.12	0.000	-0.46	-0.12	-5.31	0.000	-0.48	-0.11
Influx asylum seekers	0.00	1.59	0.056	-1.54	0.062	-0.20	0.20	0.02	0.982	-0.21	0.21
Reception asylum seekers	-0.12	-0.28	0.612	-3.67	0.000	-0.30	0.07	-1.98	0.048	-0.31	0.08
Inflation	-0.29	-3.10	0.999	-6.28	0.000	-0.49	-0.10	-4.69	0.000	-0.50	-0.09
Energy costs	-0.30	-3.07	0.999	-6.18	0.000	-0.50	-0.10	-4.63	0.000	-0.51	-0.09
Ukraine war	-0.62	-7.49	1.000	-10.35	0.000	-0.84	-0.41	-8.92	0.000	-0.86	-0.39
Nitrogen Problem	-0.10	0.01	0.495	-3.08	0.001	-0.30	0.10	-1.54	0.125	-0.31	0.11
Climate Change	-0.13	-0.45	0.674	-3.79	0.000	-0.31	0.06	-2.12	0.034	-0.33	0.07
Housing shortage	0.07	2.47	0.007	-0.49	0.314	-0.14	0.28	0.99	0.321	-0.16	0.29
Polarization	-0.18	-1.13	0.871	-3.97	0.000	-0.40	0.04	-2.55	0.011	-0.41	0.05
Labourer shortage	-0.05	0.71	0.240	-2.27	0.012	-0.26	0.16	-0.78	0.434	-0.27	0.17
Crime	-0.02	1.29	0.098	-2.02	0.022	-0.21	0.17	-0.36	0.717	-0.22	0.18

Note. Results of the equivalence and null-hypothesis significance tests for the comparisons of Wave 4 vs. 5, Wave 5 vs. 6, Wave 4 vs. 6, and Wave 1 vs. 6. Equivalence tests were two one-sided *t*-tests ('TOST'). Null-hypothesis significance tests were two-sided *t*-tests. Degrees of freedom were $df = 684$ for all reported *t*-tests

Appendix G: Network Comparison Tests (RQ3b)

To investigate the replicability of the network of societal threat perceptions (RQ3b), we performed paired Network Comparison Tests (NCTs) with the NetworkComparisonTest package (van Borkulo et al., 2023). These allow us to compare the edges in the networks of societal threat perceptions estimated for data from Waves 4 and 5, 5 and 6, 4 and 6, and 1 and 6. The NCTs indicated no statistically significant differences between the networks in the compared waves: The p-value of the maximum test statistic M, which indicates the significance of the omnibus network invariance tests in NCTs, was above the pre-registered cutoff of .05 in three of the four performed comparisons ($M_{w4\ vs.\ w5}$ = .10, $p_{w4\ vs.\ w5}$ = .758; $M_{w4\ vs.\ w6}$ = .10, $p_{w4\ vs.\ w6}$ = .718, $M_{w1\ vs.\ w6}$ = .12, $p_{w1\ vs.\ w6}$ = .515). In these cases, no edges differed statistically significantly between the compared networks. However, the network invariance test between wave 5 and wave 6, $M_{w5\ vs.\ w6}$ = .17, $p_{w5\ vs.\ w6}$ < .05, indicated that there was at least one statistically significantly different edge weight between the threat networks of wave 5 and wave 6. Closer inspection showed that the only statistically significantly different edge between the networks of waves 5 and 6 between was the edge between crime and polarization ($E_{w5\ vs.\ w6}$ = 0.17, p < .001). To summarize, the preregistered NCTs—with the exception of one node in one comparison—indicated that the associations between societal threat perceptions replicated over time.

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