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Attitude networks as intergroup realities: Using network-modelling to research attitude-identity relationships in polarized political contexts

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Abstract

We apply a newly developed attitude network-modelling technique (Response-Item Network, or ResIN) to study attitude–identity relationships in the context of hot–button issues that polarize the current US-American electorate. The properties of the network–method allow us to simultaneously depict differences in the structural organization of attitudes between groups and to explore the relevance of organized attitude–systems for group identity management. Individuals based on a sample of US-American crowd workers ($N = 396$) and the representative 2020 ANES data set ($N = 8280$), we model an attitude network with two conflictive partisan belief-systems. In the first step, we demonstrate that the structural properties of the attitude-network provide substantial information about latent partisan identities, thereby revealing which attitudes 'belong' to specific groups. In a second step, we evaluate the potential of attitudes to communicate identity-relevant information. Results from a vignette study suggest that people rely on their mental representations of attitude-identity links to structure and evaluate their social environment. By highlighting functional interdependences between (macro level) attitude structures and identity management, the presented findings help advancing the understanding of attitude-identity dynamics and socio-political cleavages.

INTRODUCTION

challenges, however, boundaries between different scientific disciplines are blurring. The presented research aims to support this process and suggests a methodological approach that permits scholars to connect intraindividual representations of group membership with macro-level attitude-structures. We develop this research on two premises: the first premise states that coordinated attitude-structures, as exposed by network-modelling, can reveal and inform latent social identities hence making network-modelling a fruitful approach to study intergroup phenomena of interdisciplinary interest such as polarization. Two interdisciplinary research traditions lie at the core of this reasoning: A *relational* understanding of attitudes in which the meaning of one attitude is at least partially defined by its relation to other attitudes – an approach that has been advanced by sociologists interested in cultural schemas (Boutyline & Soter, 2021; DiMaggio, 1997; Goldberg, 2011) – and a social psychological understanding of attitudes as a substrate for shared selfhood (Bliuc et al., 2007; McGarty et al., 2009). To validate this premise, we model an attitude network of competing belief-systems based on a set of hot-button issues that polarize the current US-American electorate. The underlying computational process is inductively data driven which allows us to obtain a realistic image of the structural organization of the selected attitude set at the time of data collection across a sample. We spatially locate each individual participant in the network to connect the obtained macro level network properties with mechanisms relevant for group identity management. We demonstrate that participants' network position correlates strongly and significantly with self-reported levels of (a) partisan identification and (b) group-bias. Based on these findings, we conclude that the extracted attitude space can be understood as a snapshot of a social reality in which social identities are actively constructed and enacted.

A second premise deriving from this first set of findings is that because individuals hold internal representations of attitude-identity relationships, *expressed* attitudes should convey identity-relevant information about the person that holds them. Hogg and Smith (2007, p. 1) illustrate this aspect when describing attitudes as “windows on identity”. Quayle (2020) carries this point further by claiming that attitudes only become socially meaningful once they are expressed (using an analogy of a card game in which a card that is held on the hand only becomes meaningful when played). Simply put, here we claim that by knowing a person's opinion on certain issues, one should often be able to make a pretty good guess about that same persons' identity. With data from a vignette experiment, we demonstrate that learning a single attitude (e.g., one's standpoint towards abortion rights) allows people to estimate an interlocutor's partisan identity with striking accuracy. Additionally, we show that people not only use attitudes to categorize others as ingroup and outgroup members, but also to evaluate a person more or less favourably. Together, these two premises hold that attitudes are both the material

The presented findings are theoretically and practically meaningful. On a theoretical level, the results corroborate the idea that multiple attitudes are organized and represented in the form of socially meaningful belief-systems that can be depicted as networks. These belief-systems recursively and dynamically interact with symbolic representations of group identity (and are themselves a form of symbolic identity). These mutual dependencies should make attitudes socially functional as they allow people to exchange information about group identities and use this information for social judgement (Quayle, 2020). On a practical level, the results stress the importance of attitudes for interpersonal communication. While expressing and observing attitudes can help people to navigate and structure their social environment, these "advantages" are not without costs. Particularly in highly structured (i.e., polarized) opinion contexts, expressing an attitude that "trespasses" an outgroup belief-system may quickly lead to false categorization and misjudgement which may increases contextual pressures for individuals to "choose sides" and act in congruence with normative standards of the ingroup (Ton et al., 2023).

Attitude-identity relationships as bipartite networks

The concept of belief-systems as a constrained set of functionally related attitudes that informs and can be informed by (political) identities is not new (Converse, 2006). However, with increasing computational power, the possibilities for researchers to quantify these complex relationships have expanded as well. Computational network modelling provides researchers with methodological opportunities to reveal and study the structural organization of political belief-systems, for instance by documenting changes in belief-systems structures across societies (Boutyline & Vaisey, 2017; DellaPosta et al., 2015) or by studying functional dependencies between attitudes within a belief-system (Brandt & Sleegers, 2021). The present research adds to this growing literature branch and considers attitude networks from an intergroup angle. Drawing on the social identity approach (Reicher et al., 2010; Turner & Oakes, 1986), we conceptualize attitude networks as the overlaying reflection of an interactively and dynamically constructed intergroup reality that provides a specific set of affordances and demands to organize intergroup relations.

We follow the idea that attitudes, and the people who are holding them, can be depicted as a bipartite network (Quayle, 2020). In such a bipartite network, attitudes are related if they are jointly held by different people, hence forming a symbolic layer of *socially meaningful belief-systems*. People are connected if they are holding similar attitudes in common, thereby forming a layer of *interconnected agents*. A simple example of a bipartite network structure would be the following: in the current US-political landscape two socially plausible sets of opinions are (1)

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people are holding the two attitudes in either of the described ways. Now let us consider three individuals of which two are holding either one of the outlined attitudes combinations while a third person supports gun control *and* abortion regulation. In a bipartite network, the two individuals with the opposed attitude-sets would be unconnected with each other as they do not hold any attitude in common (they would be, however, fully connected if they would agree on both issues). On the other hand, the third individual who is holding an “implausible” set of opinions would be connected to each of the two former individuals via one attitude, respectively. In such a model, the social dynamics between those different individuals (e.g., categorizations, evaluations, influences) are a direct consequence of the attitudes that unite and divide them.

Applying this mind game to socio-political reality highlights its relevance for intergroup phenomena. Political scientists interested in the topic of partisan polarization suggested that the number of people who are holding cross-cutting attitudes is declining with the result that Democrats and Republicans are embracing increasingly exclusive and, hence, conflictive socio–political narratives (Abramowitz & Saunders, 2008; DellaPosta et al., 2015). Following the proposed social identity perspective on attitude-identity relationships, one can state that the normative understanding of partisan-based group membership is becoming increasingly interwoven with a specific set of issue positions that the members of each partisan group are expected to hold. In such highly structured attitude–identity systems, attitudes should serve as functional social markers that allow individuals to determine whether someone belongs to an ingroup or to an outgroup.

Attitudes as informative and functional social identity elements

Attitudes allow individuals to communicate aspects of who they are and to make inferences about the identity of others (Hogg & Smith, 2007; Lüders et al., 2022). Recent research by Dias and Lelkes (2021) offers empirical support for these ideas by showing that attitudes inform social judgements in an experimental research setting. Dias and Lelkes sought to disentangle effects of partisanship and issue disagreement on affective polarization and exposed participants to a series of vignettes, each transmitting manipulated information about a bogus persona that participants had to evaluate on a feeling-thermometer. The findings suggested that participants' judged others, not primarily based on the extent of actual political disagreement, but rather on a person's partisanship that was signalled by specific policy standpoints. In other words, participants seemed to use attitudes to make inferences about a person's group membership and judged them accordingly. Data reported by O'Reilly et al. (2022) suggests that attitudes do not only signal well-consolidated social identities (like political partisanship), but also provide a substrate for newly emerging social identities. Data significantly higher level of reported social identification between participants who agreed with each other as compared to participants who disagreed or who were grouped based on arbitrary criteria.

Advancing the understanding of attitude-identity relationships

The present research connects individual-level representations of attitude-identity links with macro-level attitude-structures (i.e., depicted as network), hence bridging two typically disconnected layers of analyses. Modelling attitude-structures as networks allows us to explore inter-attitude links through inductive computation, meaning that no “top-down” assumptions about the structural and distributional properties of attitudes are required. This approach provides us with more flexibility as compared to “standard” models that require psychometrically validated attitude-scales or experimental stimulus control to predict variation in an outcome of interest. Conversely, here we propose that group identities and some of their relevant mechanisms can be predicted from network characteristics. Specifically, we expect that the more structured or *polarized* an attitude network is, the more it should convey distinguishable (and potentially competing) group identities. The proposed links between attitudes and identities should hold direct implications for micro-level processes as we expect people to rely on their knowledge about attitude-identity links when they evaluate their social environment.

ResIN: a network-based approach to explore attitude-identity relationships

The Response-Item Network (ResIN, Carpentras et al., 2021) has been developed as a modelling technique for complex attitude systems. Like other belief network analyses, ResIN builds up a correlation network based on responses to a defined set of attitude items. However, it incorporates elements of Item-Response Theory which significantly enhances its flexibility. Specifically, ResIN treats each item-response as a single nominal variable (i.e., chosen vs. not chosen), hence breaking up the items' ordinal structure, which is then re-built under consideration of the full network. For instance, a survey that includes 10 Items, each answered on a 5-point scale, would result in a network of 50 interrelated nodes. These nodes would be organized based on correlations between item-responses (not based on correlations between single items as in conventional belief network analysis, e.g., Boutyline & Vaisey, 2017), thereby locating associated item-responses in relative spatial proximity. ResIN therefore allows the depiction of multiple belief-systems within a single network without supposing an underlying symmetry. These belief-systems may each comprise extreme, moderate, and central attitude responses from the underlying items, which provides researchers with a deeper understanding

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periphery, or outside of a specific belief-system. To this aim, ResIN adds a spatial variable (reflected as an X-axis ranging from −1 to +1) that assigns a numeric value to each participant that indicates each participants specific position in the network. This final step is critical for the present research aims, as the obtained network-position score can be used as a predictor variable.

PRESENT RESEARCH

The present manuscript uses ResIN (Carpentras et al., 2022) to explore attitude-identity relationships in the context of the US-American electorate. In the first step, we model an attitude network based on participants' responses to a set of economical and socio-cultural issues. Since our primary aim is to demonstrate functional relationships between attitude structures and group identity mechanisms, we preselected issues known to reflect polarization of the current US-American electorate (Dinkelberget, O'Sullivan, al., 2021; Malka et al., 2014). Because of the polarizing nature of the selected issues, the corresponding attitude network should contain two distinguishable partisan belief-systems. Our first hypotheses correspond to the idea that attitudes are organized in form of socially meaningful belief-systems that provide both a substrate and a reflection of group identity. To evaluate this claim, we calculate a network-position score for each participant that we then use to predict symbolic and affective partisan identity elements. We pre-registered the following two formal hypotheses:

H1. The position of a participant within the obtained attitude network correlates significantly with self-reported partisan identification (i.e., as Democrat or Republican).

H2. The position of a participant within the obtained attitude network correlates significantly with self-reported group-bias (i.e., a relative preference for the ingroup over an outgroup).

To enhance the robustness of our findings, we repeat this analysis with representative data from the 2020 American National Election Survey (ANES). For our second set of hypotheses, we follow a quasi-experimental design to test the expected functionality of attitudes for social judgements. Specifically, we test whether attitudes can inform social categorization and affective evaluation processes. To this aim, we pre-registered the following two hypotheses:

H3. The extent to which participants categorize someone as an ingroup or outgroup member based on an observed attitude will be informed by that same attitude's network position.

H4. The relative distance between a participant's position in the network and the position of an observed attitude will significantly correlate with participants' affective evaluation of another person that is holding an observed attitude.

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Ethics statement

The presented research received ethical approval from the ethical advisory board of the University of Limerick, Ireland.

Participants

We recruited a sample of $N = 402$ paid participants through the crowd working platform Prolific Academic. The sample size was determined by the available funds. Participants were eligible if they were (a) at least 18 years old, (b) US residents, (c) native English speakers, (d) in support of US Democrats, Republicans, or Independents, and (e) received at least 98% approval from previous surveys. We excluded six participants who did not pass an attention check at the beginning of the survey, leading to an effective sample size of $N = 396$. The gender distribution was 50.5% males, 48.7% females, and 0.8% non-binary persons. Most participants were White Americans (83.6%), followed by African Americans (7.8%), leaving 8.6% to other ethnicities. The mean age was 34 years ($SD = 11.7$; Range = 18–81). On a categorical scale, 58.1% self-identified as Democrats, 28% as Independents, and 13.9% as Republicans. Since the network analysis is trying to capture a sociometric property of society, we re-weighted each group using recommended weights (Gallup, 2021).[1]

Material

Participants were invited to take part in an online survey with a mean completion time of 8 min and 20 s. After providing informed consent, participants responded to a set of items that assessed political viewpoints and indicated their partisan identification.

Political attitudes

A set of eight political attitude items (Supporting information A.1 in Appendix S1) covered hot-button topics such as abortion, immigration, gun control, and gay marriage. Each item followed a 5-point scale format ranging from strong disagreement to strong agreement. All items were (re)coded so that disagreement referred to liberal positions and agreement to conservative positions (e.g., “abortion should be illegal;” “The federal government should make it more difficult to buy a gun” [reversed]).

Partisan identification

on a 7-point scale with 1 indicating maximum disagreement and 7 indicating maximum agreement.

Group-bias

We asked participants to rate their feelings towards Democrats, Republicans, and Independents on a 100-point scale ranging from 1 = *cold/unfavourable* to 100 = *warm/favourable*. We calculated affective group-bias as relative group scores by subtracting Republican from Democrat evaluations (Druckman & Levendusky, 2019).

Vignette study

The second part of the survey followed a quasi-experimental protocol. We introduced this section to our participants with a short description of the upcoming task: "On each of the following pages you will see a person expressing a view on one of the political issues we asked you about earlier. Based on what you know about them, you will be asked to guess their political orientation and say how you feel about them."

We randomly presented each participant eight attitude vignettes from a pool of 40. Each vignette expressed one of the five possible response-options for one of the eight political issues (Figure 1). Each vignette was followed by a set of questions that measured social categorization and social evaluation. To measure social categorization, we asked participants to evaluate on three items whether the person represented by the manikin on the vignette was a Democrat, a Republican, or an Independent. Each item followed a 100-point format, ranging from 1 = *definitely not a* [e.g., *Democrat*] to 100 = *definitely a* [e.g., *Democrat*]. A second item assessing affective social evaluation used the feeling thermometer described previously. We calculated relative group scores (i.e., Republican – Democrats) to operationalize social categorization and evaluation. Although we additionally ask participants to provide similar feedback about political Independents, we did not include this information into our analysis since it was not included into our pre-registration protocol.

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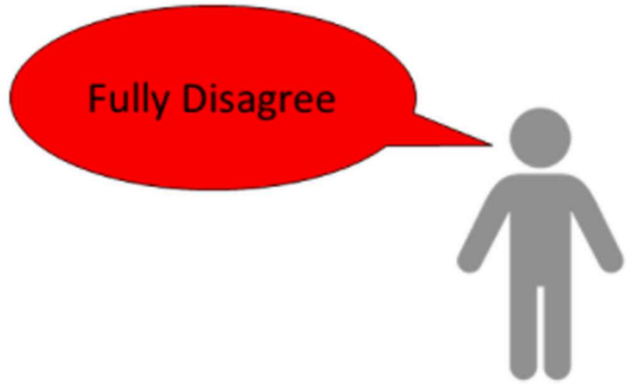

In terms of political orientation, this person is....

definitely not a Democrat | **definitely a Democrat**

0 10 20 30 40 50 60 70 80 90 100

definitely not a Republican | **definitely a Republican**

0 10 20 30 40 50 60 70 80 90 100

FIGURE 1

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Example of stimuli as used in the vignette study.

NETWORK MODELLING

To model the attitude network, we dummy-coded each scale position (i.e., response-option) in the original dataset. This resulted in a new dataset in which each column reflected a different item (e.g., *gun control:strongly agree*) and each row a different participant. This new dataset contained only ones and zeros: one if a participant selected the response-option of a column; and zero if a participant did not select the response-option of a column. Since each of the eight items followed a 5-point format, the resulting dataset comprised 40 columns (8 items × 5 response-options = 40) corresponding to 40 network nodes. To estimate links between two selected attitudes, we calculated phi correlation coefficients (Guilford, 1941) with the following formula:

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The letters *i* and *j* represent two different response options (which correspond to two columns in the dataset and two nodes in the network). The symbol n_{yz} represents the number of rows in which the first column is equal *y*, and the second column is equal *z*. For example, n_{11} is the number of rows in which both columns equal one (i.e., the number of participants who selected both response options). Conversely, n_{00} is the number of rows in which both columns equal zero (i.e., the total number of participants who selected neither of the two response options). When one of the two entries is marked with a dot, such as in $n_{y\bullet}$ a variable may be either one or zero. Therefore, $n_{0\bullet}$ reflects the number of participants who did not select the first response option but may or may not have selected the second response option. Finally, $n_{\bullet 0}$ reflects the number of participants who may or may not have selected the first response option, but not the second. We did not calculate this value for response options that belong to the same item as they would be mutually exclusive (i.e., participants could not mildly and strongly agree with a single item).

To build up the attitude network, we estimated the cartesian position of each attitude position via the *Networkx force-directed positioning algorithm* (Hagberg et al., 2008) in Python. The algorithm treats edges as springs (holding nodes close) whereas the nodes themselves are treated as repelling objects. Attitudes that participants frequently selected together are therefore located in relative proximity in the network whereas attitudes that rarely co-occurred in a single participants' responses are placed further apart.

RESULTS

Figure 2a depicts the extracted attitude network. A visual inspection of the network reveals two attitude clusters. To understand whether partisanship was a latent factor overlaying the two clusters, we generated a heatmap by correlating the selection of each node with participants' self-reported partisan identification.[2] As shown in Figure 2b, the cluster reflecting the Democrat belief-system almost exclusively contained extreme attitudes as indicated by strong disagreement with each of the eight items. Conversely, the cluster reflecting the Republican belief-system contained a wider range of attitude responses ranging from mild disagreement to maximum agreement. Note that these nuances would remain undetected by methods that consider Likert-type items as intervals or use arbitrary cut-offs. Supporting information B in Appendix S1 provides an overview of the specific issue positions that correspond to each cluster.

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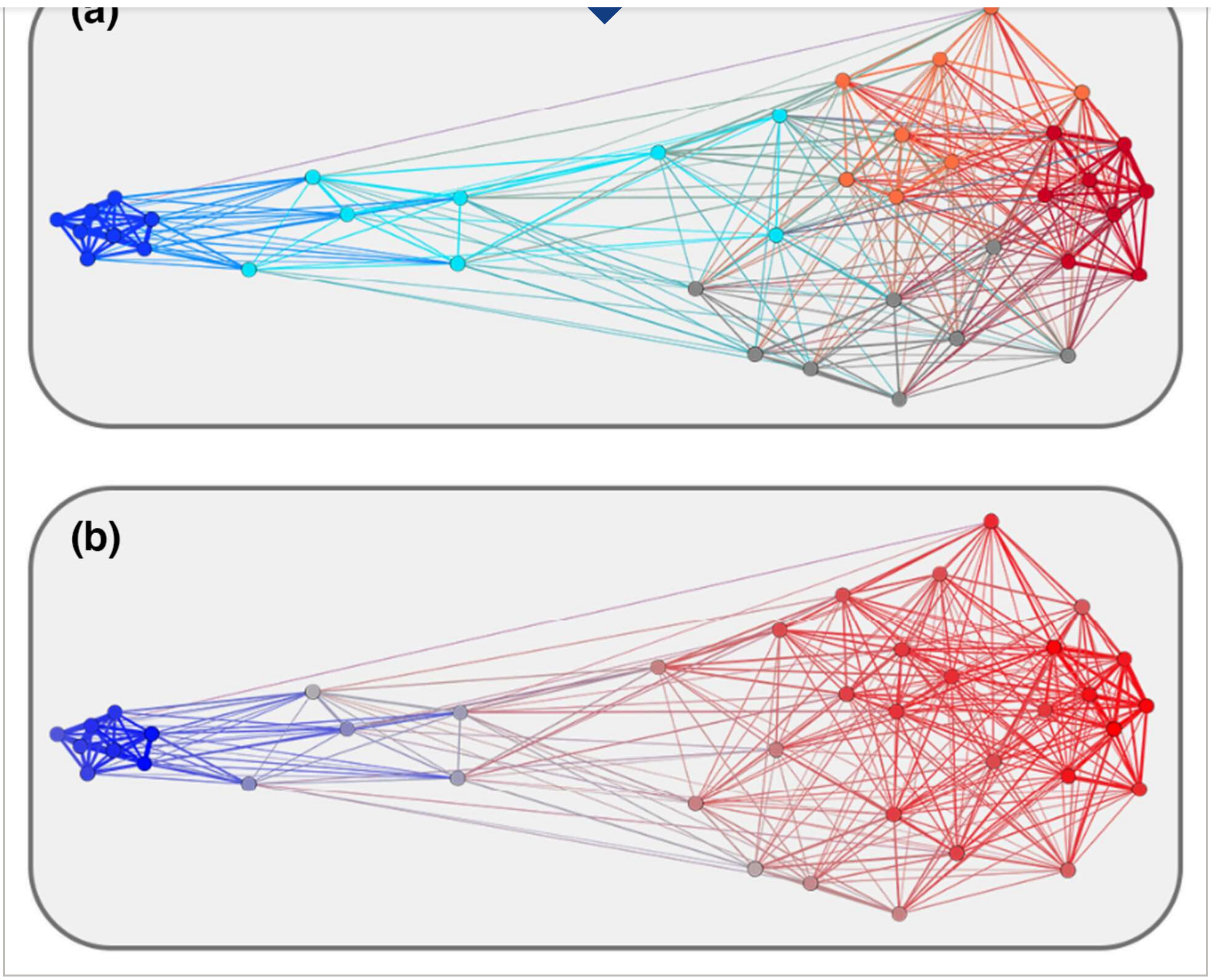

FIGURE 2

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Extracted attitude network. (a) A visual representation of the extracted attitude network revealing a distribution of forty attitudes into two clusters. *Note*: Dark Blue = Strong Disagreement; Pale Blue = Moderate Disagreement; Grey = Neutral; Orange = Moderate Agreement; Red = Strong Agreement. (b) Two attitude clusters depicting latent Democrat (blue) and Republican (red) belief-systems.

Step 2: Confirmatory analysis

To test our first set of hypotheses, we located each participant within the attitude network. To this end, we calculated each participant's network position scores by averaging the location of all nodes corresponding to a participant's responses to the eight political issues. Since the

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participant who strongly disagrees with all eight items, would obtain a strong negative value (close to −1) reflecting a position in the Democrat cluster. Conversely, a participant who strongly agrees with half of the items and is neutral towards the other half, would obtain a positive value (between 0 and 1) and hence be located near to the Republican cluster (Figure 3).

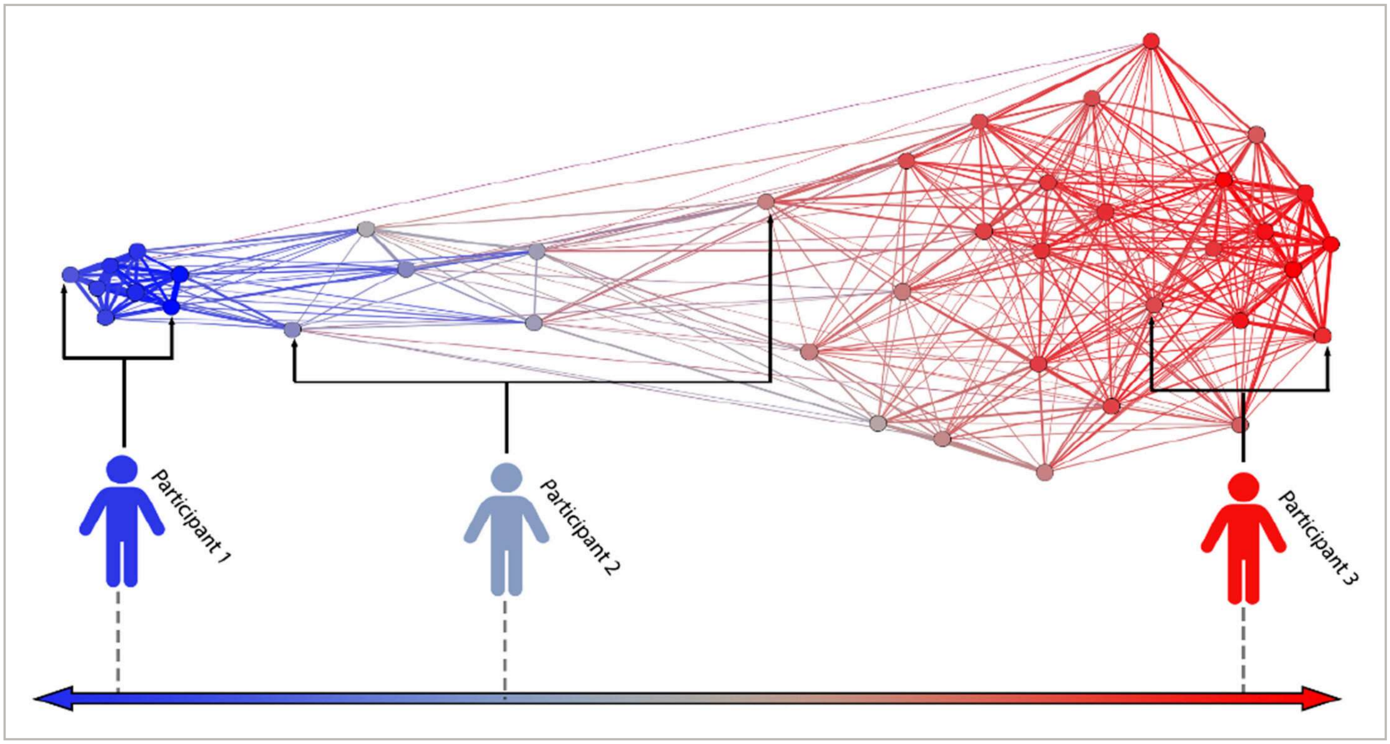

FIGURE 3

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Participants' network position based on averaged item-responses. Simplified illustration with two (out of eight) attitudes per participant. Left: A participant who is holding only Democrat attitudes; Centre: A participant holding one Democrat and one Republican attitude; Right: A participant holding two Republican attitudes.

We tested our first hypothesis by correlating participants' network positions with their relative identification as Democrat or Republican. The results supported our prediction, indicating strong and significant associations between participants' network position and self-reported partisanship, $r = .72$, $p < .001$. The more precisely participants were located within one of the two clusters (see Figure 3 for a visual example), the more they identified as a Democrat or as a Republican. Following the same procedure, we correlated participants' network position with self-reported group-bias to test our second hypothesis. Again, the results revealed strong and significant relationships between the two variables, $r = .73$, $p < .001$. The results therefore

Robustness check

To validate the robustness of the obtained findings, we replicated our analyses based on the 2020 ANES dataset (ANES, 2021). The dataset is particularly well suited for our research aims as it includes items similar or equal to those that we used in our own survey (Supporting information A.2 in Appendix S1). The 2020 ANES dataset includes responses from 8280 participants representing the national adult US-American society. The survey was conducted in two waves (i.e., before and after the 2020 presidential election). For our analysis we used mainly the first wave (two items, however, were only available in the second wave). Replicating the described procedure, we modelled an attitude network based on the correlations that underlie participants´ item responses to eight political issues. The obtained network (Figure 4) was comparable to the one we obtained based on our convenience sample with a tighter Democrat cluster of mainly extreme attitudes and a looser Republican cluster with moderate to extreme viewpoints. We calculated participants' network position and correlated the obtained values with partisan identification (H1) and group-bias (H2). The resulting correlation coefficients mirrored those obtained with our convenience sample with $r = .73$, $p < .001$ for partisan identification and $r = .79$, $p < .001$ for group-bias.

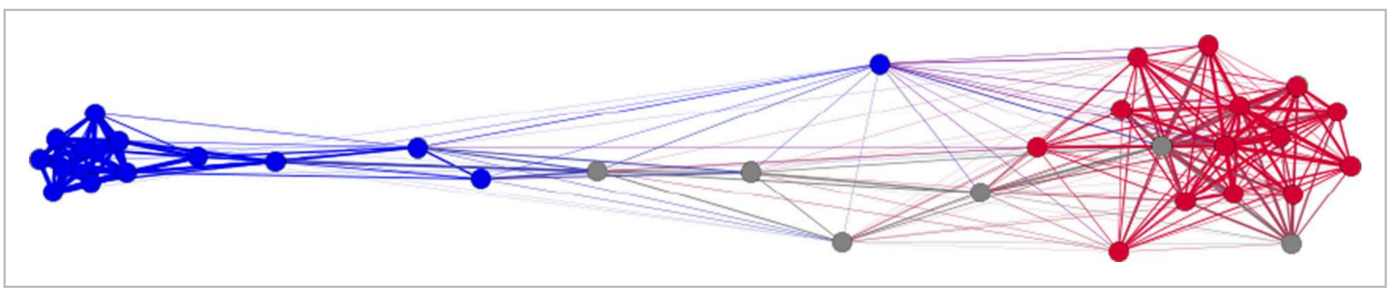

FIGURE 4

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Attitude network from the representative ANES dataset. The midpoint of each scale has been coloured as grey, while all the others have been coloured as either blue (Democrat) or red (Republican). Items with an odd number of levels (such as abortion) have been split only into red and blue as no central level was available.

Vignette study

The previous findings suggest that network characteristics can inform intrapsychological perceptions of group identity, hence supporting a bipartite model in which attitudes are linked if commonly held by people, while people are linked through the attitudes that they share. [3] We mechanisms (H3), we correlated participants' categorization of others as Democrats and Republicans with the position of an observed attitude in the network. The results revealed a strong, positive correlation, $r = .90$, $p < .001$, suggesting that the obtained attitude network overlapped largely with participants' social representation of whether a specific attitude "belongs" to a Democrat or Republican belief-set. Finally, we tested the prediction that observed attitude differences can likewise inform affective judgements, hypothesizing that larger attitude divergence should lead to more negative social evaluations (H4). We correlated participants' own network position with their submitted evaluation scores (Figure 5). The results suggested a moderate significant correlation, $r = .49$, $p < .001$, thus corroborating our fourth and last hypothesis.

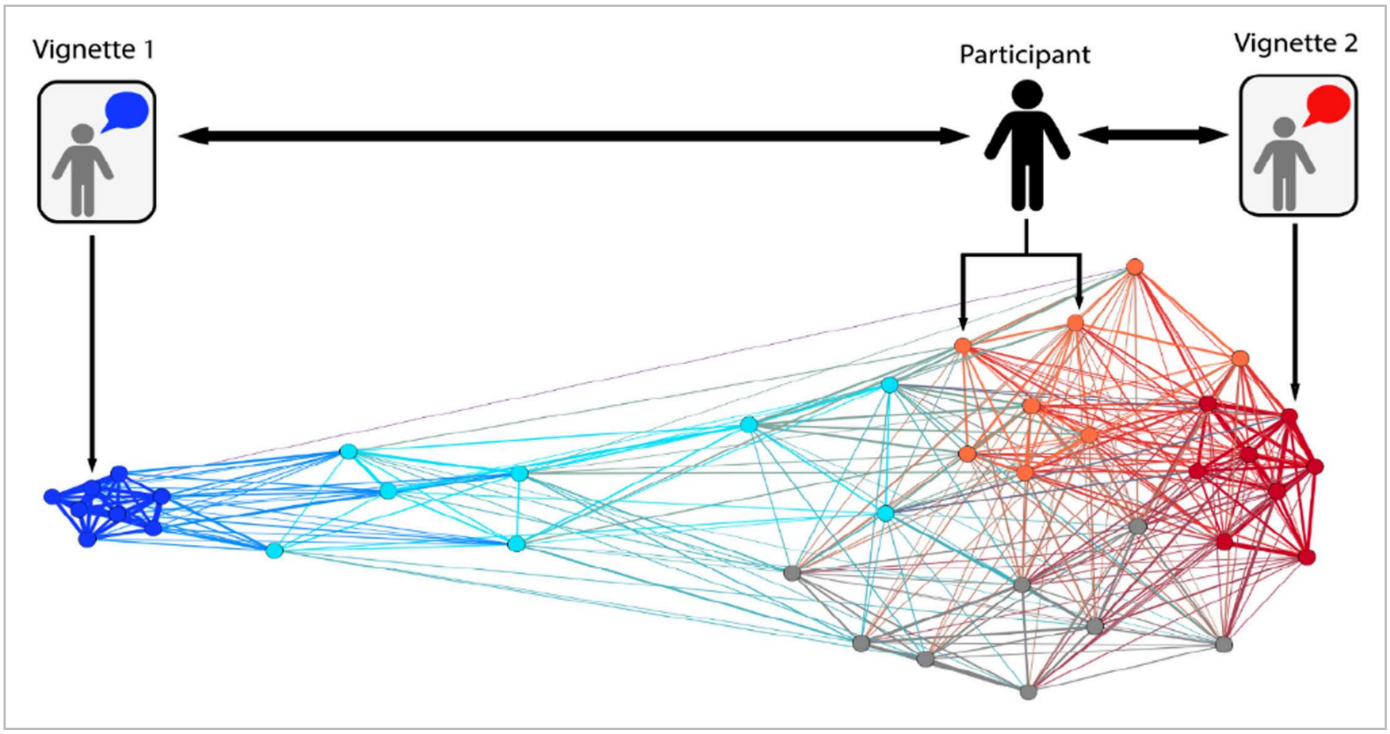

FIGURE 5

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Social evaluation based on relative attitude divergence. Graphical illustration of Hypothesis 4: Attitude divergence depending on participants' network position and the position of an observed attitude. In this example, Vignette 2 (expressing a Republican attitude) would be closer to a fictive participant than Vignette 1 (expressing a Democrat attitude) because of that same participant's network position (here simplified defined as resulting from two Republican attitudes).

DISCUSSION

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Republicans. Going beyond existing belief network methods (Boutyline & Vaisey, 2017; Brandt & Sleegers, 2021), this approach enabled us to observe partisan belief-systems without assuming an underlying symmetry. Furthermore, unlike methods such as hierarchical clustering (Murtagh & Contreras, 2012), ResIN does not make binary classifications of participants into one group or the other. Instead, people can hold attitudes of different groups and be located on the periphery of one, or in-between different belief-systems. In that same way, ResIN also differs from other network approaches that studied attitude-identity links on the intergroup level by clustering survey respondents into like-minded "communities" (therefore treating nodes as people and edges as connections between two people) (Dinkelberg, O'Reilly, et al., 2021; Maher et al., 2020). In Supporting information E: Appendix S1, we also compare our findings with results obtained from a more conventional procedure that relies on composite mean scores from participants' survey responses rather than on network-position scores. Whereas both approaches produced similar results for H1–H3, ResIN outperformed the conventional approach for H4 in which participants evaluated others based on an observed attitude. The proximity of the results from the two approaches, however, should not conceal the fact that the two attitude clusters that corresponded to competing partisan belief-sets were completely inductively obtained. This is a very different approach to the common practice of averaging items into scales, which not only permitted us to include items without having strong a priori assumptions about their interrelatedness, but, as we will outline in the further discussion, also avoids abandoning a lot of useful information about an items' ordinal structure and its nuanced meaning for particular identities.

Capitalizing on the described methodological advantages, we demonstrated the potential of ResIN to advance the understanding of attitude-identity relationships on the intergroup level. Our theorizing was informed by the social identity approach (Reicher et al., 2010) which proposes intragroup synchronization and outgroup contrasting as important identity mechanisms, and, more specifically, by a bipartite network model of attitude-identity relationships (Quayle, 2020) in which socially shared attitude combinations form socially meaningful belief-systems that differentiate people into groups based on attitude (dis)agreement. In the first step, we correlated participants' network position with self-reported levels of partisan identification and group-bias to demonstrate a functional dependency between macro-level attitude structures and intrapsychological self-regulation. The obtained results indicated strong and significant relationships of $r > .70$ in a convenience as well as in a representative sample, thus corroborating our first hypotheses. The closer participants were located to one of the two belief-systems, the more they identified as partisan members and the more biased was their emotional representation in favour of their ingroup.

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based group identity. Such a holistic view on partisanship challenges interpretations of polarization as a largely emotional phenomenon (c.f., Iyengar et al., 2012). The results also show that the embedding of attitude positions into partisan identities is highly asymmetrical and thus more complex than bivariate polarization models would predict. Not only does the presented data suggest that Democrats embrace more extreme viewpoints on the selected issues compared with Republicans, but also that the Republican cluster includes some surprising issue positions that (under interval assumptions) might be assumed to fall into the Democrat cluster (c.f., Figure 2a). These differences may hold important practical implications. Starting with an optimistic interpretation, group cleavages might be easier to overcome based on issues in which identities are not tied to a specific position. For instance, the present data suggests that normatively acceptable viewpoints for Republicans on gay marriage, abortion rights, and environmental protection through business regulation range from mild agreement to extreme disagreement, hence, providing a potential space for political negotiation (c.f., Supporting Information B in Appendix S1). A pessimistic interpretation, however, would be that because neutral issue positions are largely embedded into the Republican belief-system (rather than being equally distributed between Republicans and Democrats), they may get "pulled over" to the Republican extreme. A similar dynamic has been suggested by previous research on vaccine hesitancy where the isolation of pro-vaccine attitudes (i.e., reflected by long edges between pro-vaccination and neutral attitudes and short edges between neutral and anti-vaccination attitudes) were associated with lower vaccination coverage in the following year (Carpentras et al., 2022). Returning to the present context, such dynamics would increase bipartisan polarization due to a gradually disappearing centre.

The vignette study in the second part of our research tested another claim of the bipartite model, namely that attitudes (due to their alignment with identities, as demonstrated in H1 and H2) carry identity-relevant information hence making them functional tools for social judgement. The results showed that participants were able to categorize a person as Democrat or Republican based on a single attitude with remarkable accuracy (reflected by a correlation index of $r = .90$). In other words, participants were seemingly well aware of the organization of Democrat and Republican belief-sets. Participants also showed noticeable differences in their evaluation of others depending on the relative distance between their own position and the position of the other's attitude in the network ($r = .49$). Findings by Dias and Lelkes (2021) suggest that attitudes signal partisan identities and therefore drive social judgements. We perfectly agree with this conclusion. One aspect that is important to emphasize, however, is that the present approach did not force us to define a priori which attitude would correspond to which group. The advantage of this gain in flexibility is that we can explore the degree of "tolerance" for different attitude positions in different groups. According to the present

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these positions are likely to be considered as outgroup members (extremity should thereby be understood as a function of both, the formulation of the item and the response). It is possible that holding extreme (and thus unnegotiable) attitudes on important social-political issues has become increasingly identity defining for Democrats, not least in response to Donald Trump's controversial presidency. The pattern does not imply that Republicans are more tolerant than Democrats, nor that Republicans could deal better with attitudinal uncertainty. It does imply, however, that –at this particular moment in time– Democrats and Republicans are constructing and managing their partisan identities differently in relation to the topics reflected in these questionnaire items. Research suggests that social category membership (e.g., being White, Christian) is more important for the construction of Republican identity than it is for Democrat identity (Mason & Wronski, 2018). Fulfilling such normative criteria may hence qualify someone as a valid group member even if that same person may hold somewhat liberal views on, for example, gay marriage.

Ultimately, the association between identity and its material (e.g., attitudes; clothing; manners; language; food preferences; morality etc.) are dynamically and actively constructed through the activities and attributes of group members and group leaders. The aim of this manuscript was to introduce ResIN as a network-modelling approach that may help research to further explore the dynamic interplay between attitudes and identities and their functional expressions in intergroup contexts. Here, we have focused on well-established political partisan identities and on a set of attitudes strongly embedded into these identities to provide a comprehensible overview of the suggested approach. An obvious future step will be to extend the method to visualize intersecting identities. For example, Republican women may be more ambivalent about abortion than Republican men; perhaps along with highly religious Democrats. Additionally, future research applying the method may exploit its potential in contexts of newly emerging ideological narratives and group identities that feed on them. We believe that the insights obtained from such efforts would have important implications for a range of pressing social phenomena, including, among others, the politicization of lifestyle behaviour, the formation of social movements, and polarization in light of current and future challenges.

AUTHOR CONTRIBUTIONS

Adrian Lüders: Conceptualization; data curation; investigation; methodology; project administration; writing – original draft. **Dino Carpentras:** Conceptualization; formal analysis; methodology; visualization; writing – review and editing. **Michael Quayle:** Conceptualization; funding acquisition; supervision; writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

None to declare.

OPEN RESEARCH BADGES

This article has earned Open Data, Open Materials and Preregistered Research Design badges. Data, materials and the preregistered design and analysis plan are available at https://osf.io/345yv/?view_only=895cf9b8f854420393235cdf7b1d8e8a.

DATA AVAILABILITY STATEMENT

Supplementary and research documentation material can be retrieved from: https://osf.io/345yv/.

Supporting Information

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