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Involvement as a Polarizing Factor?—A Comprehensive Multi-Method Analysis across Representative Datasets

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ABSTRACT

Complex system models of attitudes, such as the Hierarchical Ising Opinion Model (HIOM), suggest that a person's involvement in an attitude object could be linked to attitude extremity and polarization. Despite its potential to integrate various theories of attitude change and despite the implications it could hold for attitude research, this assumption has not yet been studied systematically. We investigate the role of involvement in five large-scale, representative surveys on general political orientation and attitudes towards the EU and COVID-19 vaccines, conducted in 79 different countries over the last 8 years. We propose criteria to classify the degree of ideological divergence and introduce a modality detection measure suited for ordinal data and large sample sizes. We find that involvement is linked to attitude extremity and that predictions of HIOM are validated in a topic-specific dataset on COVID-19 vaccines. Results on political orientation and general attitudes towards the EU show either no effect of involvement or patterns that contradict HIOM's predictions. We discuss implications for the measurement of involvement, complex system models of attitudes and polarization research.

1 | Introduction

Democratic societies rely on fair party competition, their citizens' ability to make informed decisions and the willingness of people holding opposing attitudes to find democratic consensus. Polarization poses a threat to those processes by making individuals less informed and overconfident in their decision-making and opinion formation (Druckman, Peterson, and Slothuus 2013) and by causing a reluctance of opposing camps to negotiate and compromise (McCoy, Rahman, and Somer 2018; McCright, Xiao, and Dunlap 2014; Vegetti 2019).

Research in social psychology can contribute to our understanding of polarization by studying *within-person* dynamics of such processes of attitude change and radicalization. Prominent phenomena which have been identified in this field include resistance to persuasion in individuals who hold extreme attitudes (*persuasion paradox*; Ahluwalia 2000; Eagly and Chaiken 1993; Haugtvedt and Petty 1992; Petty and Cacioppo 1986) and the phenomenon that the mere thought of an attitude object increases attitude extremity towards it (*mere thought effect*; Tesser 1978).

On a *between-person* level, polarization can be conceptualized as *ideological divergence*, the extent to which attitude distributions in a population diverge into opposing camps (Lelkes 2016). Ideological divergence is considered a sub-part of a cluster of different constructs forming polarization, including *affective polarization* (hostility towards people holding differing beliefs) and *partisan polarization* (reluctance of politicians to vote for and agree with policies from other parties; Lelkes 2016). Ideological divergence is the focus of scholarly discussions, theories and models across research disciplines. In political science, there is an ongoing debate of whether societies have in fact diverged ideologically (see Abramowitz and Saunders 2005, 2008; Fiorina and Abrams 2008; Fiorina, Abrams, and Pope 2008; Lelkes 2016). In sociology and sociophysics, a variety of computational models have emerged which aim to identify basic mechanisms that explain why and under which circumstances people diverge in their attitudes when interacting with each other (for an overview, see Bramson et al. 2016; Van der Maas 2024).

To advance our understanding of empirical phenomena of attitude extremity and polarization, it is important to establish a formalized theoretical framework which (A) integrates and explains within-person phenomena of attitudes established in social psychology and (B) explains how these within-person dynamics relate to the divergence of attitude distributions on a population level. Complex system models of attitudes (Dalege et al. 2016, 2018; Latané and Nowak 1994; Van der Maas, Dalege, and Waldorp 2020) provide such a framework. They conceptualize attitudes as complex systems and point at the role of a person's involvement to integrate intra- and inter-personal levels of polarization. Compared to verbal theories often used in social psychology, complex system models of attitudes are formal models which can be used to derive specific hypotheses (see Borsboom et al. 2021; Smaldino, Calanchini, and Pickett 2015). Using five large-scale, representative surveys of involvement, we investigate the validity of complex system models by testing their predictions on the role of involvement in attitude extremity.

1.1 | Complex System Models of Attitudes

1.1.1 | Within-Person Dynamics of Attitudes—The Causal Attitude Network Model

The Causal Attitude Network Model (CAN; Dalege et al. 2016) conceptualizes a person's attitude as an Ising network of interconnected attitude elements (see Figure 1). These attitude elements denote beliefs, feelings and behaviours regarding the attitude object.[1] Each attitude element can be in one of two states: in favour of (state 1) or contra the attitude object (state 1). The overall attitude of a person corresponds to the sum of all positive versus negative attitude elements. Attitude networks in which all attitude elements are aligned and consistently favour (or disfavour) the attitude object (i.e., are exclusively positive or negative; see Figure 1B) will form a strongly positive (or negative) attitude. In contrast, inconsistent networks, in which some elements are in favour and some against the attitude object, will sum up to a less extreme attitude (see Figure 1A). The degree of alignment of attitude elements in the CAN model thus determines attitude extremity.

The states of individual attitude elements are assumed to be influenced by other nodes in the network as well as by external influences, such as the common opinion in one's social network or a government campaign (Dalege et al. 2016; see arrow in Figure 1). Peoples' attitude networks can differ in their susceptibility to those influences, with highly connected elements being more resistant than less connected ones (Dalege et al. 2016, 2019). The alignment of attitude elements is thus affecting attitude strength and stability.

The CAN model allows us to model under which circumstances such alignment occurs. Technically, the CAN model is an Ising model, a mathematical model originally developed for magnetism. The dynamics of the Ising model are well known and understood. Translating the model's elements to interpretable psychological constructs allows for thorough understanding of within-person attitude dynamics and of the mechanisms linking attitude alignment to extremity. In the Ising model, the consistency of the elements is determined by the temperature of the magnet (Finnemann et al. 2021).[2] Dalege et al. (2018) suggest that in the context of attitude networks, this variable corresponds to the level of attention that a person pays towards the attitude object: the more an individual attends to an attitude object, the more consistently the attitude elements behave. This assumption is in line with well-established theories such as cognitive dissonance theory (Festinger 1957), assuming that inconsistencies between attitude elements are perceived as more aversive when a person pays attention to it. This attention-driven aversiveness thereby makes individuals more prone to align their attitude elements, consequently becoming more extreme and stable in their opinions (Dalege et al. 2018).

When hypothesizing which construct affects attitude extremity and stability in the CAN model, a person's involvement in the attitude object might be more suitable than attention. Involvement and attention mainly differ in their timescales: although attention can change within seconds, involvement refers to the long-term engagement with an attitude object over the course of several days, weeks or months (Van der Maas 2024). Following this logic, involvement could be conceptualized as the average attention over longer time periods (i.e., sustained attention), operating on a more-long term time scale which is required to describe attitude change.

Similar constructs from other scholarly disciplines include *cognitive* manifestations of involvement (e.g., thinking about the attitude object, contemplating pros and cons, gathering information; Dalege et al. 2018; Van der Maas, Dalege, and Waldorp 2020), *affective* manifestations (i.e., perceiving an attitude object as important, being emotionally aroused by it and caring about it; Sobkowicz 2012; Latané and Nowak 1994; Dalege et al. 2018) and *behavioural* manifestations (e.g., joining protests, boycotts and activism; Dennison 2019). Drawing from the political science literature, these could be measured at a topic-specific level (such as issue salience; Dennison 2019; Moniz and Wlezien 2020) and on a general level (such as political involvement, Kruikemeier et al. 2014). Based on the potential manifestations of involvement and on similar constructs in other research disciplines, in this paper we focus both on cognitive, behavioural and emotional manifestations of a person's engagement with a specific attitude object, as well as general involvement in politics.

Such manifestations of involvement have been linked to attitude alignment and extremity across research disciplines: Extremity of opinion was shown to significantly correlate with the attitude object's perceived salience (Weaver 1991) and its subjective

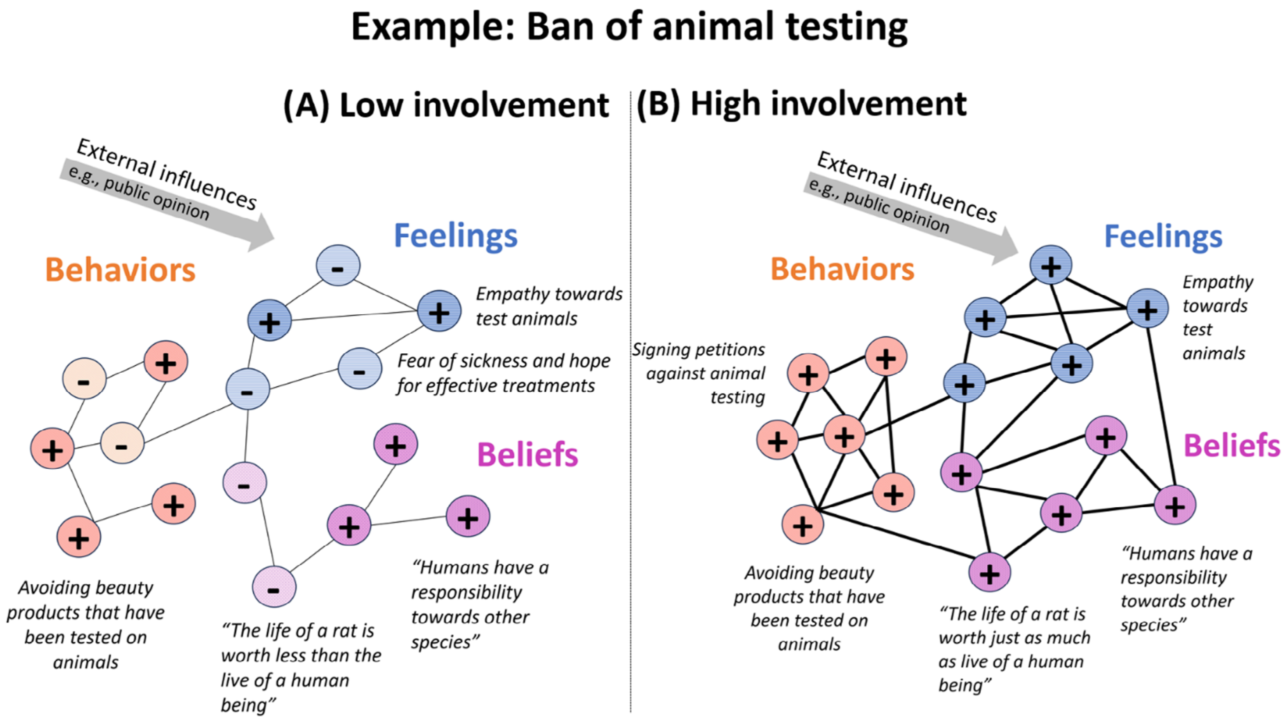

FIGURE 1 | Exemplary attitude networks at high and low involvement. Nodes represent attitude elements, and lines show their correlations across individuals (edges). At high levels of involvement (B), attitude elements are more consistent in their states, more connected to each other and less susceptible to external influence than at low levels of involvement (A). Overall attitude, i.e., the sum of all nodes, is more extreme at high involvement (B) than at low involvement (A).

importance (Latané and Nowak 1994). People are more consistent in their attitudes toward issues that are important to them (Moniz and Wlezien 2020), and ideological divisions were found to be most pronounced among people who are highly interested and informed (Abramowitz and Saunders 2008; Dimock et al. 2014). Although these empirical findings show a clear relationship between involvement and attitude extremity, they did not result in a comprehensive theory describing the mechanisms of how the concepts are linked. Complex system models, such as the CAN model, do provide such a formal theoretical framework and make clear predictions on the complex interplay of involvement and attitude extremity.

1.2 | Connecting Within- and Between-Person Dynamics: The Hierarchical Ising Opinion Model

A complex system model which integrates the within-person dynamics of the CAN model with population-level mechanisms is the Hierarchical Ising Opinion Model (HIOM; Van der Maas, Dalege, and Waldorp 2020). Through mean field approximation, the within-person dynamics of the CAN model are summarized to describe a person's attitude as a non-linear model, the Cusp catastrophe (Latané and Nowak 1994; Sobkowicz 2012; Van der Maas, Dalege, and Waldorp 2020; see Figure 2A). This model describes which states a behavioural variable (here, the person's attitude) can take on depending on a normal axis (α; information about the attitude object) and a splitting axis (β; the person's involvement in the attitude object). Take, for example, the demand to ban animal testing, which people can either support (having positive values of attitude y) or oppose (negative values of y). A person who is not very involved in the attitude object can be found at the back of the Cusp (yellow point in Figure 2A) and has a neutral attitude towards banning animal testing ($y = 0$). In contrast, a person who is highly involved in the attitude object would be found at the front of the Cusp (red point in Figure 2A). At such high levels of involvement there are only two stable states of extreme attitude (here, fully in favour or fully against a ban), whereas a central, neutral attitude no longer exists (see also Figure 2B). Involvement is thus a splitting axis of attitudes since high levels of involvement make people diverge into two opposing camps. On a population level, attitude distributions at high involvement would hence be bimodal, showing strong ideological divergence (see Figure 2C). Furthermore, the highly involved person's attitude (red point) is robust to changes in information: If the red point were to move along the information axis (α; Figure 2A), the height of the plane of the Cusp catastrophe (i.e., the predicted attitude y) would hardly change for a wide range of information values. This characteristic of the Cusp is termed *hysteresis*.

HIOM holds great potential for attitude research. First, it integrates the CAN and the Cusp model into an agent-based model which is informed by research in sociology and formal modelling of opinion spread. It thereby combines psychological models of within-person dynamics with models of between-person interactions from sociology and sociophysics. Second, it can model ideological polarization on the population level which emerges from involvement-related attitude radicalization within individuals: The strong intra-individual alignment of attitude elements at high involvement corresponds to the front of the Cusp where inter-individual attitude distributions show

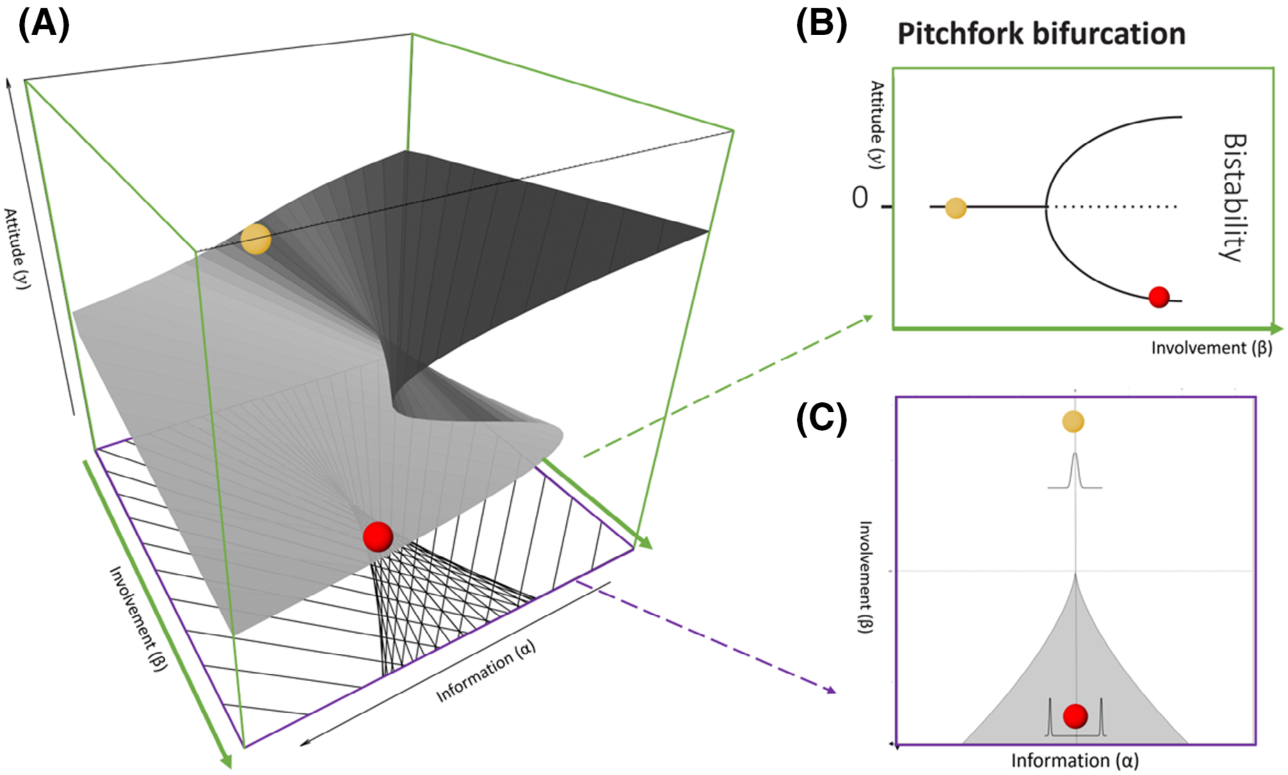

FIGURE 2 | Cusp catastrophe model. (A) Surface of the Cusp catastrophe model with attitude (y) as the behavioural variable (vertical axis), information as the normal variable (α) and involvement as the splitting axis (β). Note that the information variable is not relevant in the context of this study. The splitting axis (β, involvement) determines the extent of bistability of attitudes. (B) Pitchfork bifurcation shows stable states of attitudes for different levels of involvement (one stable state of moderate attitude for low involvement and two opposing states of extreme attitude for high involvement). (C) Bifurcation set; bird perspective of the Cusp. The grey area depicts the bifurcation set, cases where neutral attitudes are unstable and only extreme attitudes exist. In this area, attitude distributions are bimodal, whereas they are unimodal at the back of the Cusp. Note that the yellow point would correspond to the attitude network depicted in Figure 1A and the red point to the one shown in Figure 1B.

ideological divergence. For research in political science and sociology, this incorporation of involvement could imply that ideological polarization might be found especially in samples that are strongly involved in an attitude object, such as social media samples. Third, the within-person dynamics in HIOM (i.e., the integration of the CAN and the Cusp model) can explain established phenomena of attitude radicalization. The mere thought effect, where just thinking about an attitude object increases attitude extremity, could be explained through the assumptions of the CAN model. By being promoted to think about an attitude object, people direct their attention to it. This increase in attention and involvement would in turn increase the alignment of attitude elements in the attitude network, thereby increasing attitude extremity (Dalege et al. 2018). In the Cusp, this increase of attention corresponds to moving to the front of the Cusp where neutral attitudes cannot exist. HIOM furthermore predicts that attitudes of highly involved participants are more resistant to counter-attitudinal information (Van der Maas, Dalege, and Waldorp 2020). In the Cusp model, this can be explained through hysteresis at the front of the Cusp. HIOM can therefore explain the persuasion paradox through increased levels of involvement.

First empirical evidence for complex system models of attitudes shows that involvement predicts the connectivity of attitude networks, which in turn predicts attitude extremity (Dalege et al. 2019). Previous studies have further found self-reported intensity of feeling towards a topic to serve as the splitting axis of attitudes in a sample of US soldiers (Latané and Nowak 1994; Van der Maas, Kolstein, and Van Der Pligt 2003). Although these findings provide preliminary evidence, the role of involvement as a splitting axis has not yet been studied systematically. Given the lack of systematic investigations of this matter, we analyse the relationship between involvement and ideological polarization using five large-scale, representative datasets collected in 79 different countries and covering various attitude objects to investigate whether involvement serves as a splitting axis of attitudes, as predicted by the HIOM.

2 | Methods

2.1 | Samples and Datasets

We investigated the role of involvement in ideological polarization in five large-scale datasets (Table 1): the Politics and Values Questionnaire of the LISS Panel Core Study (Centerdata 2021), the 2020 pre-election survey of the American National Election Studies (ANES 2020), a combined data collection of the European Value Study and the World Value Survey from 2017 to 2020 (EVS/WVS 2021), a six-wave longitudinal survey on attitudes towards COVID-19 vaccinations (Chambon et al. 2022) and the

TABLE 1 | Summary of datasets and measured constructs.

Dataset	Sample (*N*)	Data collection	Measured constructs (number of items)
LISS panel	Dutch (5625)	December 2021–March 2022	Political orientation (1) Involvement (3): interest in politics and in the news; news consumption
ANES	US (8280)	2020 (pre-election)	Political orientation (1) Involvement (2): attention paid to politics and to political campaigns
EVS/WVS	European (59,438); non-European (153,716)	2017	Political orientation (1) Involvement (4): interest in politics; political participation
Eurobarometer	EU (16,502)	February 2022–March 2022	Image of European Union (1) Involvement (1): engagement in discussions about the EU
COVID-19 survey	Dutch (1505)	December 2020–March 2021 (six waves)	Attitude towards COVID-19 vaccines (7) Involvement (1): self-perceived knowledge of vaccines

Note: ANES is the American National Election Studies and EVS/WVS abbreviates the combined data collection of the European Value Study and World Value Survey. Political orientation was measured on a scale from politically left (either 0 or 1) to politically right (10). Involvement in the COVID-19 survey was measured as self-perceived knowledge of COVID-19 vaccines.

Eurobarometer (European Commission 2022). We specifically chose these datasets to cover multiple attitude objects and include participants from various western and non-western countries (see details in Supporting Information A).

Involvement measures were derived from complex system models (Dalege et al. 2016, 2018; Latané and Nowak 1994; Van der Maas, Dalege, and Waldorp 2020) and from related concepts from other scholarly disciplines (namely *issue importance* and *political involvement* in political science and *attitude importance* in social psychology). For a summary of our literature review on related constructs, see Supporting Information B. Based on complex system models, we selected any item in our chosen surveys which measured a person's engagement with the attitude object without allowing for any conclusions about the direction of their attitude (i.e., orthogonal to attitude position). In line with related constructs, our chosen items cover a variety of cognitive and behavioural factors, including interest in politics, attention paid to political topics, whether users follow the news and talk about the attitude objects and self-perceived knowledge of the subject (see Table A1–A5 for all included items and their scales). Our involvement measures include *topic-specific measures* of attitude and involvement as well as *general measures* that form a composite of several issues, including general image of the EU and political orientation. Although topic-specific measures are in line with complex system models of attitudes, general measures are widely used in large-scale surveys and commonly investigated in polarization research (see Lelkes 2016; Fiorina, Abrams, and Pope 2008). Results will be reported separately for general and topic-specific attitudes. Note that although the Eurobarometer measures attitudes towards the EU it can be perceived as a measure of general attitude since the overall image of the EU combines various economic, social, environmental and cultural attitude evaluations. In cases where multiple items were chosen per dataset, we first validate their structure through confirmatory factor analyses and then summarize them as their mean score. See Supporting Information C for all assumed factor structures and fit measures.

2.2 | Measures of Ideological Polarization

2.2.1 | Cut-Off Classification Criteria for Ideological Polarization

The present paper focuses on ideological polarization as a state of strong divergence in attitudes, characterized by the existence of extreme opinions and the absence of a moderate middle category (Fiorina and Abrams 2008). However, there is no standard way to measure ideological divergence and to distinguish polarized from non-polarized cases. Since ideological divergence is associated with the reluctance of people with opposing views to communicate and find consensus (McCoy, Rahman, and Somer 2018; McCright, Xiao, and Dunlap 2014; Vegetti 2019), we classify an attitude distribution as polarized when it is multimodal. Multimodality and bimodality are common measures of polarization in the literature (Jost, Baldassarri, and Druckman 2022; DiMaggio, Evans, and Bryson 1996) as they indicate the existence of subgroups within a sample that diverge in their attitudes. In line with Fiorina and Abrams (2008), we furthermore distinguish weak from strong polarization by investigating whether a considerate proportion of respondents hold a moderate attitude which could serve as common ground for groups with opposing positions: if there is a mode in the middle category in a multimodal distribution, we classify it as weakly polarized, otherwise as strongly polarized (see Figure 3). Our classification thereby suggests clear cut-offs to distinguish between different levels of polarization which are grounded in theory and in common conceptualizations of ideological divergence.

2.2.2 | Modality Detection for Ordinal Scales and Large Sample Sizes

Several methods have been proposed to estimate a distribution's modality based on kernel density estimation (e.g., Silverman 1981), excess mass quantification (e.g., Hartigan and Hartigan 1985) and finite mixture modelling (see Frühwirth-Schnatter

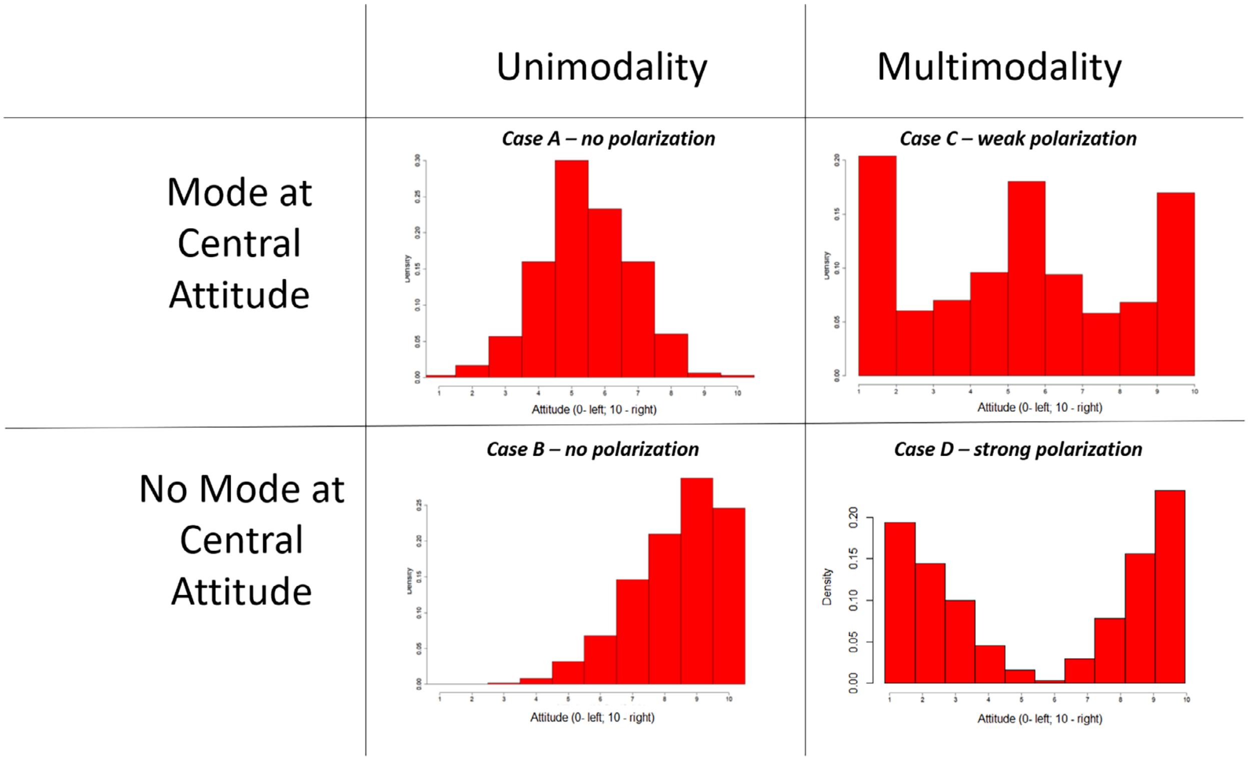

FIGURE 3 | Polarization classification criteria based on number and location of modes. Case B is not polarized but could be classified as a certain degree of extremity and Case C is classified as weak polarization since a middle ground still exists despite high prevalence of extreme attitudes.

2006). However, these methods were developed specifically for continuous data, while the studied attitude surveys rely on ordinal scales. Other methods are often descriptive and therefore volatile to fluctuations (such as the distance from unimodality measure [DFU]; Pavlopoulos and Likas 2023) or cannot discriminate skewed unimodal distributions from multimodality or bimodality from trimodality (such as the Bimodality Coefficent; SAS Institute Inc. 1990; see Downey and Huffman 2001).

To fill this gap, we add the density-based multimodality method introduced by Haslbeck, Ryan, and Dablander (2023), which has been proposed for ordinal data but is still prone to overfit large sample sizes. Our adjusted noise-augmented method (ANAM) incrementally adds Gaussian noise to the data until the categorical distribution is smoothed out. It then estimates the density of the noise-augmented data and counts the number of local maxima of the estimated density function to arrive at the estimated number of modes. In a simulation study, we tested the suitability and accuracy of various modality detection methods for ordinal data and sample sizes and found that our method yields the highest accuracy among the non-descriptive methods (see Appendix B). We therefore apply the ANAM method in the present study and make it available to other researchers at https://github.com/mfhstdt/ANAM.

2.2.3 | Measures of Spread and Dispersion

In addition to applying our classification criteria, we additionally compute measures of spread and dispersion (as proposed by Bramson et al. 2016; Fiorina and Abrams 2008; Van der Maas, Kolstein, and Van Der Pligt 2003) to see whether these increase with involvement. The standard deviation (SD) quantifies the spread of attitudes in a sample and is large in polarized samples due to the high prevalence of extreme attitudes. However, large SDs alone simply imply a large variety of attitudes but not necessarily polarization. Therefore, we additionally quantify the degree of dispersion and how attitudes are centred on the neutral attitude. This is measured as the median of all respondents' absolute deviations from the scale midpoint (Fischer and Frey 2023). In a strongly polarized sample where subgroups diverge into opposing camps, this value will be high. Lastly, in line with the idea of a lack of a central attitude as common ground for consensus in polarized societies (following Esteban and Ray 2012; Fiorina and Abrams 2008), we look at the percentage of respondents who chose the middle category. In strongly polarized samples, this value will be low. For a scale with an uneven number of categories (e.g., 0–10) we define one middle category (here, 5), whereas for an even number of categories (e.g., 1–10) the central category consists of two values (here, 5 and 6).

2.3 | Comparing Ideological Divergence Between Involvement Groups

Complex system models do not assume a unidirectional linear effect of involvement on attitude extremity but rather a dynamic, reciprocal interplay between these constructs (Van der Maas 2024). Exploring the causal direction of the link between involvement and attitude is thus not the focus of this paper. Instead, we test predictions of complex system models in cross-sectional analyses, investigate whether any temporal link between involvement and attitude extremity can be observed in longitudinal data and fit survey data to a Cusp catastrophe.

2.3.1 | Cross-Sectional Group Comparisons

We compare highly involved respondents to those with low involvement by splitting the samples into subgroups according to their involvement scores. Subgroups are either composed of response categories or—in case involvement was calculated as a mean score of several items—of involvement quartiles. For each involvement group, we classify the degree of ideological divergence according to our criteria and compare measures of spread and dispersion. The significance of differences in SDs is assessed using Levene's test, whereas median absolute deviations from the midpoint and percentages of respondents choosing the middle category are compared descriptively.

2.3.2 | Longitudinal Analysis

We investigate how changes in involvement relate to the intra-individual process of polarization over time by fitting a within-person fixed-effects panel data regression model to the six measurement waves of the COVID-19 vaccination study.[3] In this model, attitude extremity (deviation of a person's attitude from the midpoint of the scale) at time t is regressed on their involvement score at time t. The model analyses the variation within each individual, essentially comparing each participant to themselves over time. By doing so, it controls for all time-invariant characteristics of individuals, whether measured or not. This aspect eliminates the bias in the estimated effects of involvement that could be caused by omitted variables which do not change over time (such as genetic factors, baseline personality traits, etc.). Only participants who took part in all six measurements are included ($N = 744$). Analyses are conducted in R using the package plm (Croissant and Millo 2008).

2.3.3 | Fitting Data to a Cusp Catastrophe

Lastly, we fit all datasets, except for the Eurobarometer, to a Cusp catastrophe in which attitude is the behavioural variable and the splitting axis is predicted by involvement. The normal axis (information) is held constant since we cannot infer which information respondents based their attitudes on. The Eurobarometer was excluded from this analysis since its involvement item consisted of only three response categories and thereby lacked variance. Formulas of the fitted models can be found in Supporting Information D. All analyses are conducted using the Cusp package in R (Grasman, Maas, and Wagenmakers 2009). We assess the significance of involvement for the splitting axis of the Cusp and account for multiple testing using the Bonferroni correction (resulting in a significance level of $\alpha = 0.01$). Statistical significance would imply that attitudes in the population become increasingly spread out when involvement increases. We furthermore compare the fit of the Cusp models to a linear regression in which extremity of attitude (absolute deviation from the midpoint of the scale) is regressed on involvement. Model fits are compared using the Bayesian Information Criterion (BIC). A better model fit of the Cusp catastrophe compared to a linear model would suggest that a non-linear relationship between involvement and attitude is a better description of the data than a linear relationship.

Based on assumptions of complex system models of attitudes, we furthermore add the following criteria for involvement to be classified as a splitting axis of attitudes:

1. Attitudes among people reporting the lowest level of involvement are unimodally distributed and no modes exist at extreme attitudes.
2. Attitudes among people reporting the highest level of involvement are bimodally distributed and no mode exists at the moderate middle category.
3. A person's involvement is assumed to be independent from the value of their attitude. We therefore expect no significant difference in mean attitudes between involvement levels in an ANOVA ($\alpha = 0.01$ after the Bonferroni correction).

2.4 | Robustness Analysis and Transparency

For each dataset, any participant with missing data on at least one of our selected variables is excluded from analyses (25.6% of respondents from the LISS panel, 12.45% from ANES, 28.46% from EVS/WVS, 1.2% from the Eurobarometer and no respondents from the COVID-19 survey). To test the robustness of our results we report how strongly our results and conclusions change when using different item combinations (see Supporting Information E). All studies, measures, manipulations and data exclusions are reported in this study and in the Supporting Information. Code to replicate our analyses can be found at https://github.com/mfhstdt/involvement_polarization.

3 | Results

3.1 | Results on Comparing Ideological Divergence Between Involvement Groups

3.1.1 | General Political Involvement and Orientation

The distribution of general political involvement in the LISS panel and the Eurobarometer remain unimodal across all levels of general involvement in politics. Yet, in both cases, the SDs are significantly larger and the percentage of moderate attitudes is lower among highly involved people. Thus, although the distributions are flatter at high involvement levels, no polarization can be observed at any stage of involvement for neither the LISS panel nor the Eurobarometer (see Figure 4). See Supporting Information F for exact measures of spread and dispersion for each dataset and each involvement level.

In the EVS/WVS dataset, attitude distributions of respondents in involvement quartiles 1–3 are weakly polarized. Distributions in these groups show modes at the central attitude as well as the extreme left and right ends of the political spectrum. The attitude distribution in the highest involvement quartile is classified as unimodal by the ANAM method (see Figure 5). However, measures of spread and dispersion indicate that ideological polarization is strongest in the highest involvement quartile: the percentage of people choosing the middle category is smallest (47.4% in the lowest vs. 31.9% in the highest involvement

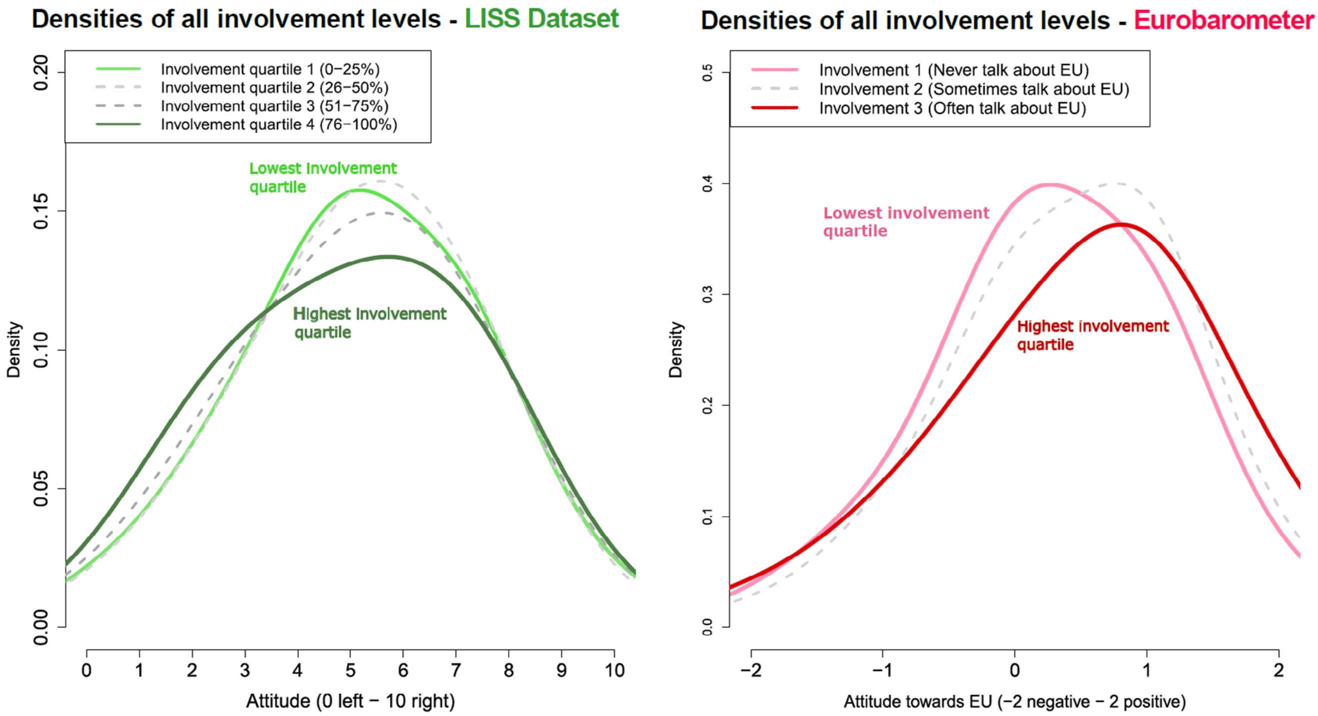

FIGURE 4 | Density estimates for each involvement quartile for the LISS panel and the Eurobarometer. All distributions were unimodal, showing no polarization.

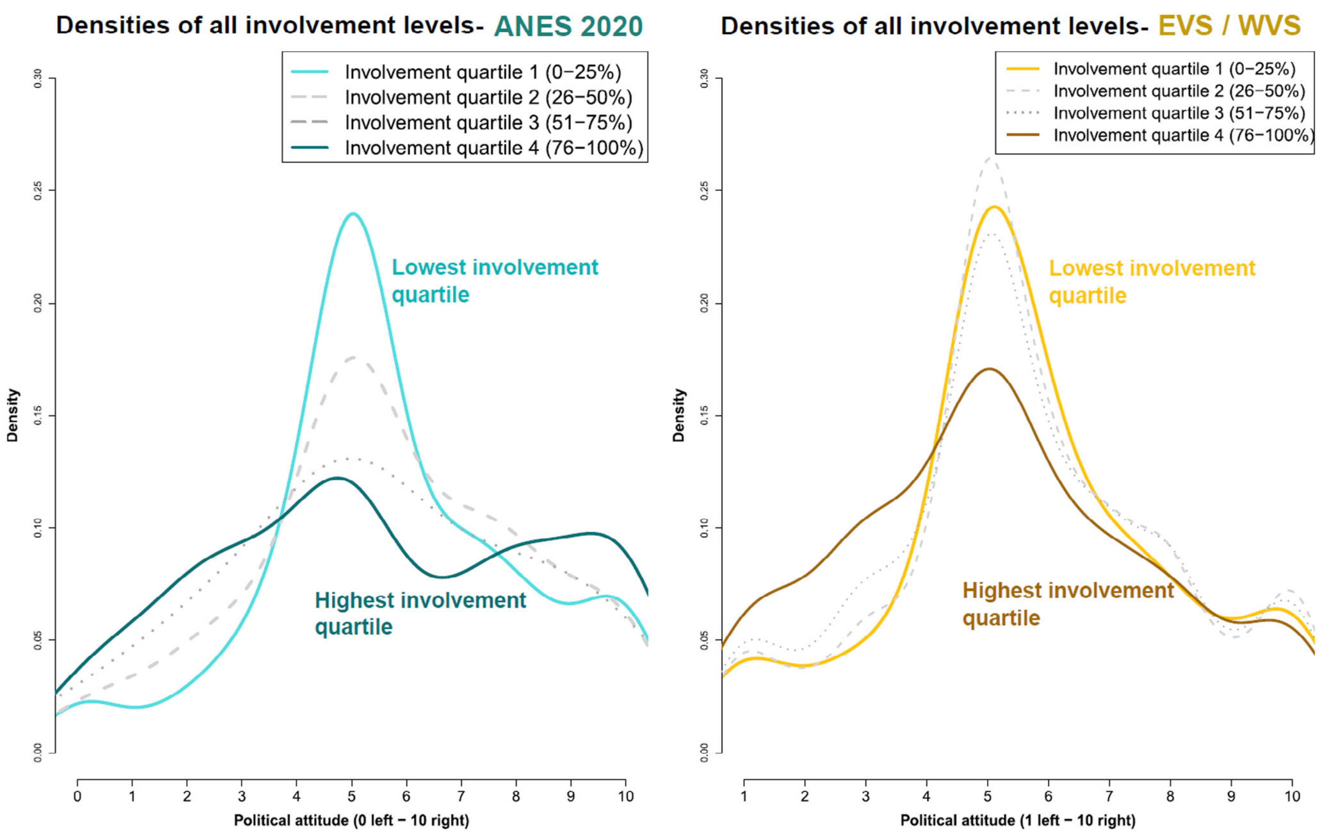

FIGURE 5 | Density estimates for each involvement quartile for the ANES and the EVS/WVS dataset. In both datasets, modes were detected at extreme attitudes in the lowest involvement quartile.

quartile) and the proportion of extreme attitudes (i.e., fully left- or right-wing) is largest (16.9% in the highest vs. 15.2% in the lowest quartile) among the most involved respondents. Additionally, the SD of attitudes is significantly larger in the highest involvement quartile than in the lowest ($F(1, 53872) = 420.73$, $p < 0.001$). Across involvement quartiles, the median absolute deviation from the scale midpoint stays constant (Mdn = 2.22). Although we would classify the EVS/WVS dataset as a case where polarization exists among the least and moderately involved individuals based on our decision criteria, it must be noted that measures of spread and dispersion do not support this conclusion.

In the ANES dataset, the distribution of political ideology among the 25% most involved respondents is bimodal, with two modes appearing at a centralist attitude and a far-right attitude (see Figure 5). All involvement measures indicate the highest level of polarization among the most involved individuals: SDs are largest for the highest involvement quartile ($F = 92.06$, $p < 0.001$), as is the median absolute deviation from the mean (4.45 in the highest vs. 1.48 in the lowest quartile). The percentage of respondents choosing the middle category is smallest for highly involved individuals (36.4% in the lowest vs. 16.7% in the highest quartile). However, density estimates in the lowest involvement quartile were also weakly polarized, with modes detected at the extreme left- and right-wing positions.

3.1.2 | Topic-Specific Involvement and Attitude

Our datasets included a topic-specific survey on involvement in and attitudes towards COVID-19 vaccines. In this dataset, we find strong levels of polarization among highly involved respondents. For all six time points, attitude distributions at the highest two involvement levels are bimodal, whereas attitudes at the lowest involvement levels are unimodal (see Figure 6). At high involvement, neutral attitudes are extremely rare and even non-existent for measurement points T1 and T4. SDs and the median absolute deviation from a neutral position are both largest at the highest involvement level for all six time points, whereas the percentage of respondents reporting a neutral position towards COVID-19 vaccines is the lowest at those levels.

3.2 | Longitudinal Results on Involvement and the Dynamics of Polarization Over Time

The slope of involvement in the within-person fixed-effects panel data regression model is significantly larger than zero ($\beta_1 = 0.06$, $p < 0.001$, see Table 2). This indicates that a person's increase in involvement over time is significantly associated with increases in attitude extremity.

TABLE 2 | Estimates of within-person fixed-effects panel data regression model for COVID-19 dataset.

	Estimate	*p*-value
Involvement	0.06	< 0.001
R^2	0.016	< 0.001

3.3 | Results on Fitting Attitude Data to the Cusp Catastrophe

3.3.1 | General Political Involvement and Orientation

All datasets on general political orientation fit the Cusp catastrophe better than a linear regression of attitude extremity on involvement (see Supporting Information G), indicating that a non-linear relationship between involvement and polarization is a more suitable description than a linear relationship. Involvement significantly loads on the splitting axis of the Cusp model for three out of four datasets (except the LISS panel), showing that variances in attitudes increase with increasing involvement. However, attitude distributions among the most involved respondents of the Eurobarometer, the LISS panel and the EVS/WVS survey were not bimodal and showed modes at centralist attitudes, which contradicts HIOM's predictions. Additionally, the appearance of modes at extreme political orientations amongst the least involved respondents in the ANES and EVS/WVS datasets (see Figure 5) are not in line with predictions of HIOM. These results are also reflected in the bifurcation set plots of the Cusp predictions. After fitting the Cusp model, we would expect predictions for highly involved individuals to appear in the bifurcation set—where opinions diverge in two opposing camps. This is however only true for the ANES dataset (Figure 7), whereas the predictions for the remaining datasets remained at the back of the Cusp where no divergence takes place (see Supporting Information G). This lack of predictions in the bifurcation set reflects the lack of bimodality at high involvement.

3.3.2 | Topic-Specific Involvement and Attitude

A Cusp model of attitudes towards COVID-19 vaccines fits the dataset better than a linear regression, and involvement loaded significantly on the splitting axis of the Cusp ($\beta_1 = 0.56$, $p < 0.001$). Cusp predictions appeared in the bifurcation set, the area where two stable attitudes coexist and the population is polarized (see Figure 7). These findings are reflected in the unimodal distribution of attitudes at low involvement levels and the bimodal distribution of strong ideological polarization at high levels of involvement in all measurement waves of the COVID-19 survey.

3.3.3 | Dependence of Involvement and Attitudes

As the splitting axis (involvement) of a Cusp catastrophe is assumed to be orthogonal to the behavioural axis (attitude), we test whether attitude is independent from involvement levels. There is no significant main effect of involvement on mean attitudes in the LISS panel ($F(3, 41) = 2.51$, $p = 0.057$) and in the ANES dataset ($F(3, 54) = 2.41$, $p = 0.065$). However, mean attitude differs between involvement groups in the combined EVS/WVS dataset ($F(3, 9876) = 590.7$, $p < 0.001$): people in higher involvement quartiles report more politically left attitudes. All six COVID-19 measurement waves also show a significant main effect of involvement level on mean attitude ($p < 0.001$ for all waves): higher levels of involvement are associated with being

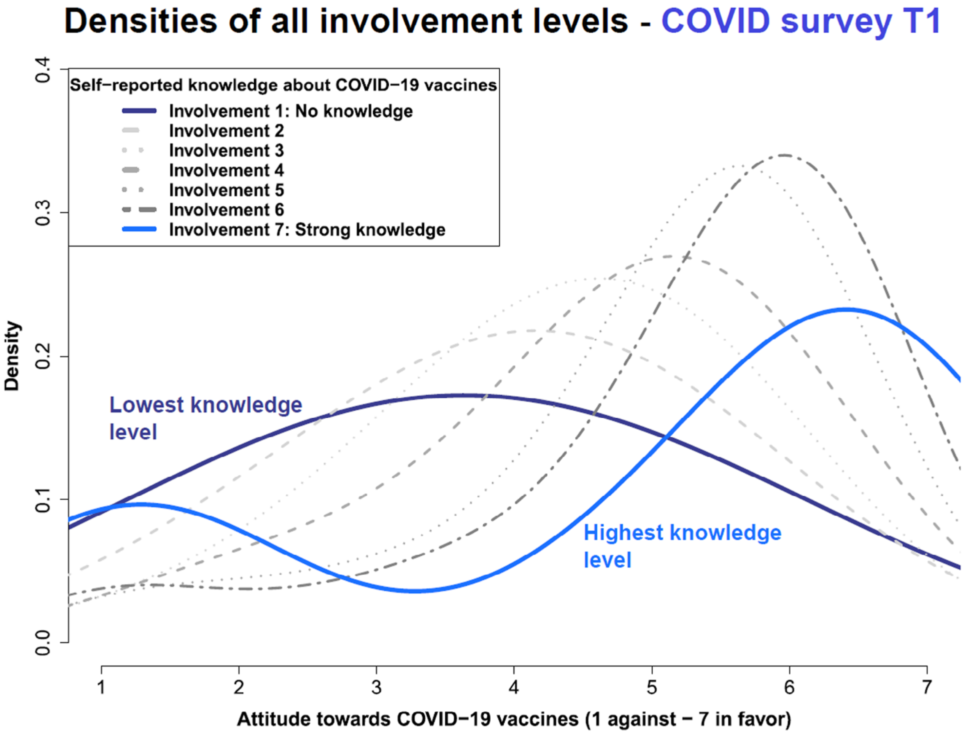

FIGURE 6 | Density estimates for each involvement response category for the COVID-19 dataset. Exemplary illustration of Time Point 1. Distributions for involvement levels 1–5 are unimodal, whereas distributions in involvement levels 6 and 7 are bimodal with a mode on both sides of the attitude scale, thereby being strongly polarized. Involvement is measured using the seven-point scale item 'I know much about COVID-19 vaccines' (1: totally disagree to 7: totally agree).

in favour of COVID-19 vaccinations. Likewise, main attitudes towards the EU reported in the Eurobarometer differ significantly between involvement groups ($F(2, 139) = 91.2$, $p < 0.001$) with more involved respondents on average having a more positive image of the EU than people with low involvement in EU politics.

3.4 | Results on Alternative Involvement Items in the COVID-19 Vaccination Survey

Based on our literature review, two additional items in the COVID-19 dataset qualified as involvement measures, namely 'I

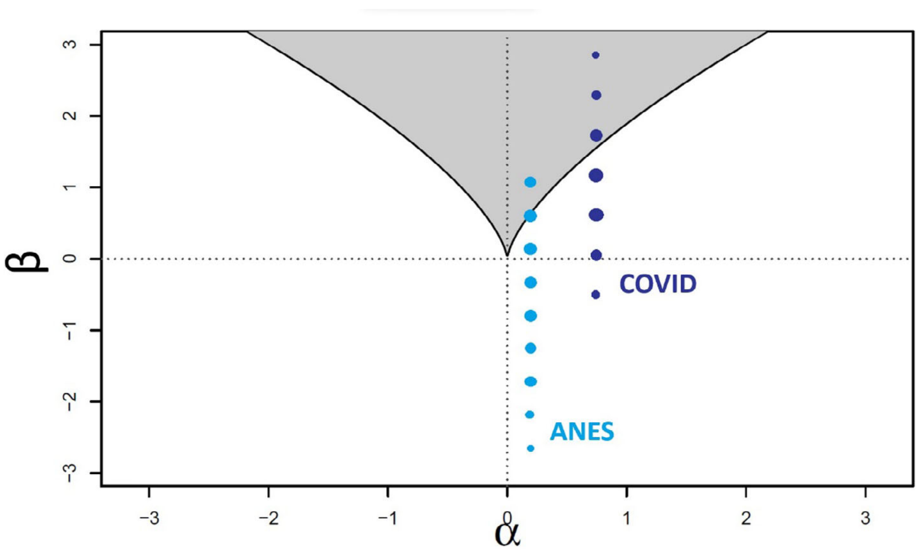

FIGURE 7 | Predictions of attitude values in the Cusp model for the ANES (light blue) and COVID-19 (dark blue) datasets. For both cases, predictions at high levels of involvement (high β) appear in the bifurcation set (highlighted in grey). The bifurcation set corresponds to the front of the Cusp in Figure 2A, where no neutral position exists. This is especially the case for the COVID-19 dataset, whereas only a few predictions of ANES land in the bifurcation set. These findings reflect that attitude distributions in both datasets are bimodal among the most involved respondents.

TABLE 3 | Overview of results per dataset and comparison to predictions of HIOM.

	LISS	ANES	EVS/WVS	Euro	COVID-19	HIOM
Multimodality at high inv	X	✓	X	X	✓	✓
Multimodality at low inv	X	✓	✓	X	X	**X**
SD highest at high inv	✓	✓	✓	✓	✓	✓
% mid. lowest at high inv	✓	✓	✓	✓	✓	✓
Mdn highest for high inv	X	✓	X	X	✓	✓
Mode at mid. for high inv	✓	✓	✓	✓	X	**X**
Mean difference in attitudes	X	X	✓	✓	✓	**X**

Note: The 'HIOM' column denotes theoretical predictions of HIOM and of complex system models of attitudes. 'inv' stands for involvement and '% mid.' stans for the percentage of respondents choosing the middle category. 'Mdn' abbreviates the median absolute deviation from the midpoint and 'mid.' stands for midpoint. The last row codes whether mean attitudes significantly differed between involvement groups/quartiles.

think COVID-19 vaccines are an important topic' and 'I follow the news on COVID-19 vaccines' (both on a scale of 1—totally disagree to 7—totally agree). The majority of participants who reported to totally disagree with these statements also indicated to strongly oppose COVID-19 vaccinations. Conversely, those perceiving the topic as important and those who follow the news on COVID-19 vaccines indicated to be highly in favour of them (see Supporting Information H for plots). These patterns indicate that these two involvement measures are confounded with attitude measures and were therefore excluded from our main analyses. Potential explanations and implications are addressed in the discussion.

3.5 | Summary of Results

In all five datasets, SDs of attitudes were the largest, and the percentage of respondents choosing the middle category was the lowest among the most involved respondents. Findings on general attitudes and involvement were not in line with our expectations: although no divergence in attitudes could be detected in any involvement group in the LISS panel and Eurobarometer, weak polarization appeared among the least involved respondents in the EVS/WVS and the ANES datasets. In turn, topic-specific attitudes towards COVID-19 are in line with complex system models of attitudes. The most involved respondents were strongly polarized, whereas attitude distributions among the least involved were unimodal. Intra-individual increases in involvement in the topic of COVID-19 over time were linked to increases in attitude extremity. Involvement furthermore significantly loaded on the splitting axis of the Cusp, and predictions clearly appeared in the bifurcation set. Yet, various patterns emerge across all datasets which contradict the assumption of complex system models of attitudes of involvement being a splitting axis of attitudes. See Table 3 for an overview of all results.

4 | Discussion

The present study analysed the role of involvement in ideological divergence in five large-scale, representative surveys on general political orientation and attitudes towards the EU and COVID-19 vaccines, conducted in 79 different countries over the past 8 years. Our findings give insights into the role involvement appears to play in polarization and to what extent predictions of the HIOM hold true in real-world empirical data.

4.1 | Methodological Contribution to the Measurement of Ideological Polarization

We propose criteria to classify ordinal attitude distributions into not polarized, weakly polarized and strongly polarized cases based on modality estimation and detecting whether a mode exists at a moderate attitude. These classification criteria are grounded in the established definitions of ideological divergence (Jost, Baldassarri, and Druckman 2022; Lelkes 2016) and derived from research on its consequences for democracies (McCoy, Rahman, and Somer 2018; McCright, Xiao, and Dunlap 2014; Vegetti 2019). However, measuring ideological divergence in large-scale survey data is challenging. Here, we show in a simulation study that commonly used modality detection methods—such as Silverman's method (Silverman 1981) or the Bimodality Coefficient (SAS Institute Inc. 1990)—are not suited for ordinal distributions when sample sizes are large, such as in large representative attitude surveys (see Appendix B for results). We overcome this limitation by developing a noise-augmented density-based modality detection method (ANAM) and show that it yields accurate modality estimates under these conditions. The method is made openly available as R code on github at https://github.com/mfhstdt/ANAM.

4.2 | The Role of Involvement in Ideological Polarization

Based on complex system models of attitudes (Dalege et al. 2016; Latané and Nowak 1994; Van der Maas, Dalege, and Waldorp 2020), we expected polarization to show among respondents who are highly involved in an attitude object or politics in general. Across all five datasets, we consistently find that opinions are more spread out and that moderate attitudes are less common among highly involved individuals than at low involvement.

Results for the dataset on attitudes towards COVID-19 vaccinations are in line with predictions of complex system models of attitudes. This was both found in inter-individual cross-sectional analysis (finding strong polarization at high involvement and no polarization at low involvement) and in intra-individual longitudinal analysis (showing that increases in involvement over time are significantly associated with attitudes becoming more extreme). Findings when fitting the COVID-19 dataset to a Cusp catastrophe reflect these results, indicating that attitudes diverge into two opposing camps at high involvement levels.

In contrast, we could not establish this pattern in datasets on general political orientation (the LISS panel, ANES and EVS/WVS) and on general attitudes towards the EU (Eurobarometer). Two datasets, namely the LISS panel and the Eurobarometer, were non-polarized across involvement levels. In all four datasets a mode was detected at a moderate attitude among the most involved respondents. In turn, attitude distributions at low involvement showed modes at extreme left and right ends of the attitude scales in the ANES and the EVS/WVS datasets. Although all datasets fit the Cusp catastrophe better than a linear model, Cusp predictions either only marginally appeared in the bifurcation set or not at all. While general attitudes in all surveys are thus more spread out when involvement is high, they either show no bimodality at high involvement or also multimodality at low involvement. For these datasets, involvement cannot be assumed to be a splitting axis of attitudes. Results thus differ between general and topic-specific attitudes, with results being in line with the prediction of complex system models of attitudes for the topic-specific dataset on COVID-19 vaccines but not for general attitudes. The set-up of this study only allows for speculations about potential reasons for this difference in results. These will be discussed below.

Furthermore, we found the direction of attitudes (not merely attitude extremity) to be dependent on involvement in three out of five datasets: respondents at the highest level of involvement are significantly more oriented towards the political left, have a more positive image of the European Union and hold a more favourable attitude towards COVID-19 vaccines. These findings contradict HIOM which assumes attitude and involvement to be independent, meaning that knowing that a person is highly involved in an attitude object should not tell us anything about the direction of their attitude.

4.3 | Potential Explanations for the Dependency of Attitudes and Involvement

The significant effect of involvement on attitude direction found in the Eurobarometer, the COVID-19 and the EVS/WVS surveys could be caused by several factors. First, high involvement could in fact be more common in politically left than right circles. However, political engagement was found to be equally frequent on both sides of the political spectrum in a US sample (Dimock et al. 2014). Second, all surveys included in this study assessed attitude and involvement on response scales, meaning that general response tendencies (such as a tendency to choose low values) could cause a correlation between these two measures. Lastly, this dependency could emerge due to confounded measurements of involvement caused by the phrasing of items. Results from the COVID-19 vaccines survey suggest that specific phrasings of involvement questions might lead a subset of highly involved participants to score low if those items involuntarily measure attitude. For instance, when being asked 'do you think COVID-19 vaccines are an important topic' and 'do you follow the news on COVID-19 vaccines', the majority of respondents who indicated 'totally disagree' (i.e., low perceived importance and news interest) also reported to strongly oppose COVID-19 vaccines. On first sight, holding an extreme opinion about a topic which one does not find important might seem contradictory. However, a person who did not believe vaccines to be a solution to the pandemic might have been likely to indicate that they did not perceive the topic and the debate as relevant—despite feeling highly involved and being highly attentive in the topic itself. Individuals who are deeply involved in an attitude object may therefore still score low on involvement measures if those measures are worded in a particular manner.

This could particularly be the case when involvement items measure anti-establishment sentiments and political scepticism. For instance, highly engaged Republicans in the US have been shown to be more sceptic towards mainstream news media, whereas Democrats tend to be more supportive (Dimock et al. 2014), meaning that liberal participants might score higher on involvement items about news consumption. This could explain why higher involvement is on average associated with more liberal, pro-EU and pro-vaccine attitudes in our study.

4.4 | Potential Explanations for Divergent Results Between General and Topic-Specific Attitudes

We find a difference in results between the datasets measuring general attitudes and the dataset measuring topic-specific attitudes towards COVID-19 vaccines. Although the differences in findings between the datasets could be caused by differences in general versus topic-specific involvement, the results could also be driven by differences between surveys, such as cultural background of participants and time of measurement. Yet, there are some hypothetical explanations why the role of involvement could differ between general and topic-specific attitudes.

A pattern shared by all datasets on general attitudes but not by the COVID-19 dataset is the presence of modes at the midpoints of attitude scales at high levels of involvement. Methodologically, this could be related to these attitude measures being a composite of evaluations of various attitude objects (such as economic, social and environmental issues). Averaging over several bimodal distributions which are not highly correlated can result in a normal distribution. The composite nature of the general attitude and involvement questions might thus mask potential patterns of polarization. This might also apply to the measurement of general attitude towards the EU in the Eurobarometer, since this question likely combines multiple dimensions, such as economic, social, agricultural or immigration policies. Additionally, people might truly identify as moderates overall while still holding extreme attitudes towards single-attitude objects. For instance, our results from the LISS panel show that 31% of voters of the Dutch populist right-wing Party for Freedom (PVV) report to identify as centralists (choosing value 4, 5 or 6 on a scale from 0 to 10), although the PVV is well known for its radical stances on certain issues such as immigration (Harteveld et al. 2022).

A second common pattern found in several datasets on general attitudes but not in the COVID-19 survey is the existence of modes at extreme attitudes when involvement is low. This could potentially stem from the involvement measures of the respective studies. As mentioned above, some of our measures of peoples' involvement in politics and attitude topics might falsely classify certain highly involved individuals as uninvolved. If we were to accidently classify people with extreme attitudes and high involvement as uninvolved, this could explain the existence of modes at extreme attitudes in the lowest involvement quartiles in the ANES and EVS/WVS datasets. In contrast, extreme attitudes were not prevalent in low involvement groups in the COVID-19 dataset where confounded involvement items were clearly identified and removed from analyses.

Lastly, the cause of our divergent results might not lie in the distinction between general and domain-specific measures but instead in the unique characteristics of the COVID-19 pandemic. Measurements of the COVID-19 survey were taken between winter 2020 and summer 2021 in the Netherlands. During this period, the first COVID-19 vaccines were released to the market, and the topic of vaccinations was highly prevalent in the media. This might have contributed to the strong bimodal distribution of attitudes towards COVID-19 among highly involved individuals. Yet, these explanations remain purely speculative.

4.5 | Limitations and Future Directions

There are some limitations to our study concerning the measurement of attitudes and involvement. We outline these limitations and propose directions for future research.

The first limitation concerns our measures of involvement. The potential confounding of involvement by attitude does not let us clearly discriminate between truly uninvolved respondents who hold extreme beliefs and those who are in truth strongly involved but scored low on involvement items due to their phrasing. Responses to involvement items asking for interest in news and behavioural engagement could furthermore be influenced by social desirability. Less confounded involvement items should aim at measuring how deeply a person cares about an attitude object, focusing on the affective dimension of involvement. To prevent confounding measurements of personal importance with a person's attitude, we suggest that the phrasing of items should stress the affective dimension of involvement and make sure that both sides of the attitude spectrum are mentioned (e.g., 'I feel strongly about whether COVID-19 vaccines are safe or not').

Second, three of our chosen datasets measure attitude as general political orientation. As outlined above, these constructs are a composite of various attitude objects, thereby potentially masking topic-specific polarization and failing to capture extreme attitudes. Since complex system models of attitudes (like HIOM) model unidimensional attitudes towards a specific topic, future studies should focus on topic-specific measures of attitudes. Although many topic-specific attitude questions exist in established large-scale surveys, topic-specific measures of involvement are rare. The development of these topic-specific involvement measures can be promising for future research.

Third, the interpretation of the middle category is ambiguous. As pointed out by Downey and Huffman (2001), central modes are prevalent in Likert scale data and could be attributed to true neutral attitudes as well as to indifference or uncertainty. The reluctancy to choose extreme response options can vary based on item characteristics (Nadler et al. 2015) but could also reflect trait-like response styles which are stable over time (Weijters, Geuens, and Schillewaert 2010; Wetzel, Carstensen, and Böhnke 2013) and which can be measured (see Cronbach 1946; Zhang and Wang 2020). A more advanced model which can account for this person- and item-specific reticence and reluctance to report extreme positions is the Blume–Capel model of attitudes (Van der Maas 2024, Chapter 6). Measuring response styles and controlling for them could be especially fruitful for investigations of whether highly involved people can hold neutral attitudes.

Lastly, future research should consider what a person's involvement in an attitude object includes conceptually. According to complex system models of attitudes, attention towards (Dalege et al. 2016, 2018; Van der Maas, Dalege, and Waldorp 2020) or long-term involvement in (Van der Maas 2024) an attitude object causes people to reduce inconsistencies in their thoughts, beliefs and behaviours regarding a certain topic. This in turn makes their attitude more extreme. Based on similar constructs in other research disciplines, we chose survey items which measure cognitive, behavioural and emotional manifestations of a person's engagement with an attitude object. Yet, research into complex system models of attitude lacks a clear theoretical framework about the construct's structure and definition. Further investigations into this could contribute to our understanding of what affects attitude extremity and stability.

5 | Conclusion

In the present paper, we proposed theoretically informed classification criteria for different levels of ideological polarization and combined them with established measures of spread and dispersion. For their practical applications to ordinal response scales and large sample sizes, we introduced a modality detection method and made it openly available on Github at https://github.com/mfhstdt/ANAM. Applying these methods, we found that involvement is linked to attitude extremity and ideological polarization cross-sectionally and across time for the *topic-specific* case of attitudes towards COVID-19 vaccines. These findings are generally in line with HIOM's predictions and fit a Cusp catastrophe model. For *political orientation* and *general attitudes towards the European Union*, we either found no link between involvement and ideological polarization or patterns which contradict HIOM's assumptions. As the existence of extreme attitudes among less involved respondents and the dependency between involvement and attitude direction could be an artefact of our involvement measures, future research should investigate whether these patterns still emerge when using less ideologically confounded involvement measures. Our results furthermore show that central attitudes even exist when looking at the most involved respondents, thereby contradicting assumptions of current complex system models of attitudes. These findings call for measurement and controlling of response styles, as well as potential extensions of complex system models of attitudes, such as the Blume–Capel model (Van der Maas 2024).

Ethics Statement

Given the secondary analyses of openly available datasets, no ethics approval was required for this manuscript.

Consent

All datasets were collected in anonymized format with the participants' informed consent. Where applicable, we got permission to download and analyse the datasets.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

All code required to replicate our analyses, including datasets can be found in the following repository: https://github.com/mfhstdt/involvement_polarization. R code for our proposed density estimation method can be found at https://github.com/mfhstdt/ANAM.

Endnotes

[1] Note that in the present manuscript, the term attitude object is used to describe any object of subjective evaluation, ranging from specific issues to general approaches towards politics.

[2] In the Ising model, the degree of alignment of nodes (i.e., network elements) depends on the connectivity between those nodes and an external field. The impact of this external field and other connected nodes, and thereby the consistency of attitude elements, are determined by the temperature of the magnet (for an introduction, see Finnemann et al. 2021). At an extremely high temperature, nodes flip randomly, independent of the network and external magnetic field. At moderate temperature, the external field has a large influence on nodes, whereas at low temperature, nodes are strongly resistant to external influences. In the CAN model, attention conceptualizes *inverse* temperature, meaning that attitude networks at high attention are more resistant to change than at low attention.

[3] The remaining longitudinal attitude surveys in our study were not suited for these analyses as they either did not assess the same individuals across measurement waves or since the lags between measurements were likely too long to capture complex short-term interactions between involvement and attitude, as assumed by complex system models.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Appendix A

Overview of All Datasets and Items Included in Our Analyses

TABLE A1 | Items from the LISS Panel included in our study.

Construct	Item	Scale
Political attitude	In politics, a distinction is often made between 'the left' and 'the right'. Where would you place yourself on the scale below, where 0 means left and 10 means right?	0–10
Cognitive involvement	Are you very interested in the news, fairly interested or not interested?	1–3
	Are you very interested in political topics, fairly interested or not interested?	1–3
	Do you not follow the news or hardly follow the news?	'Yes'–'no/hardly'

Note: 'Do you follow the news item' is a recoded version of the original item in the LISS Panel.

TABLE A2 | Items from the American National Election Studies included in our study.

Construct	Item	Scale
Political attitude	Where would you place on this scale (0: politically left; 10: politically right)?	0–10
Cognitive involvement	How often do you pay attention to what's going on in government and politics?	1–4
	Some people don't pay much attention to political campaigns. How about you? Would you say that you have been (very much interested, somewhat interested or not much interested) in the political campaigns so far this year?	1–3

TABLE A3 | Items from the EVS/WVS survey included in our study.

Construct	Item	Scale
Political attitude	In political matters, people talk of 'the left' and 'the right'. How would you place your views on this scale, generally speaking? (1: left; 10: right)	1–10
Cognitive involvement	How interested would you say you are in politics?	1–4
Behavioural involvement	Have you, might you or would you never… join a boycott?	1–3
	sign a petition?	1–3
	attend lawful demonstrations?	1–3

TABLE A4 | Items from the Eurobarometer survey included in our study.

Construct	Item	Scale
Image of European Union	In general, do you have a positive, rather positive, neutral, rather negative or negative image of the EU?	−2 to +2
Behavioural involvement	When you are around friends or family would you say that you often, sometimes or never discuss European politics?	1–3

TABLE A5 | Items from the survey on attitudes towards COVID-19 vaccines included in our study.

Construct	Item	Scale
Attitude towards COVID-19 vaccines (mean score)	I am hopeful about COVID-19 vaccines.	1 (totally disagree) to 7 (totally agree)
	I have a good feeling about COVID-19 vaccines.	
	People who do not want to get vaccinated against COVID-19 make me angry.	
	COVID-19 vaccines protect well against COVID-19.	
	To stop the pandemic, it is important that most people get vaccinated against COVID-19.	
	COVID-19 vaccines are safe for one's health. The side effects of COVID-19 vaccines have been sufficiently studied.	
	People without a COVID-19 vaccination should no longer be allowed everywhere.	
	I encourage people to get vaccinated against COVID-19.	
	I avoid people who do not get vaccinated against COVID-19.	
	By getting vaccinated against COVID-19, I am protecting others from COVID-19.	
Involvement in the topic of COVID-19 vaccines	I know much about COVID-19 vaccines.	1 (totally disagree) to 7 (totally agree)

Appendix B

Simulation to Assess the Accuracy of Modality Detection Methods for Categorical Data With Large *N*

Below we report the simulation study conducted to assess which modality detection method is suited for ordinal data with large sample sizes.

Description of Modality Detection Methods Included in the Simulation

Silverman's Mode Detection Method

This method uses kernel density estimation to estimate the probability density function (PDF) of the underlying distribution of a variable and then counts the numbers of local maxima of this PDF (Silverman 1981). When estimating the PDF, a factor which determines its smoothness is the bandwidth h. The smoother the PDF, the less local maxima it has. Silverman's method leverages this attribute of kernel density estimation: for a specific number of modes k, it detects the critical bandwidth h_{crit} for which the PDF has at most k maxima. Decreasing h_{crit} would lead to a number of modes which are higher than k. To assess the significance of h_{crit}, Silverman's method applies smooth bootstrapping in which noise is added to the resampled observations in each iteration. For the noise-augmented data, the PDF is estimated using the respective h_{crit}, and the number of modes for this PDF is counted. The p-value of h_{crit} is the proportion of iterations in which h_{crit} leads to less than k modes. If this proportion is high (i.e., the p-value is not significant), then h_{crit} is assumed to lead to a robust estimation of the underlying density distribution. Consequently, its number of local maxima is assumed to be a robust estimation of the number of modes in the data.

Bimodality Coefficient

The Bimodality Coefficient (*BC*; SAS Institute Inc. 1990) yields a value between 0 and 1, with a value of 0.555 corresponding to a uniform distribution. Distributions with values above this threshold are classified as bimodal, whereas values below 0.555 indicate unimodality. The *BC* is computed as follows:

$$BC = \frac{{m_3}^2 + 1}{m_4 + \frac{2(n-1)^2}{(n-2)(n-3)}} \tag{1}$$

where ${m_3}^2$ is the skewness (third moment) and m_4 is the excess kurtosis (fourth moment) of the distribution. Thus, *BC* values will be high when the distribution is skewed, excess kurtosis is low and the sample size is large. Consequently, *BC* measures can exceed the threshold of 0.555 even in cases where distributions are unimodal (see Figure B1).

Hartigan's DIP Statistic

Hartigan's DIP statistic (Hartigan and Hartigan 1985) estimates the cumulative density function (CDF) of the observed data and computes its maximum difference from the CDF of a uniform distribution. Although the CDF of a uniform distribution function is linear, the CDF of a bimodal distribution changes from concave to convex in the interval between the two modes. In this interval, the CDF of a bimodal distribution will thus differ strongly from the CDF of a uniform distribution. Through bootstrapping, the method then assesses whether this difference (the DIP) is significant. If so, the distribution is classified as multimodal.

Distance From Unimodality

The distance from unimodality measure (DFU; Pavlopoulos and Likas 2023) also quantifies to what extent a distribution differs from a unimodal one but was specifically designed for ordinal opinion data. It identifies the highest peak in the data and checks whether categories to the right and the left of the peak get sequentially less frequent when moving away from the peak (as it would be the case for unimodal distributions). If the frequencies do not decrease but increase when moving along the scale away from the mode, this increase is noted, and the DFU is defined as the maximum positive increase. Thus, for unimodal distributions, the DFU will be zero, whereas positive values imply multimodality.

Density-Based Mode Detection

Haslbeck, Ryan, and Dablander (2023) propose a density-based modality detection method adjusted to ordinal data in which Gaussian noise is added to the data to smooth out the distribution. The authors choose the standard deviation of the Gaussian noise based on the range of the data by applying a formula specifically developed for a 100-point scale:

$$\sigma = (0.035 + Q) \times 100 \tag{2}$$

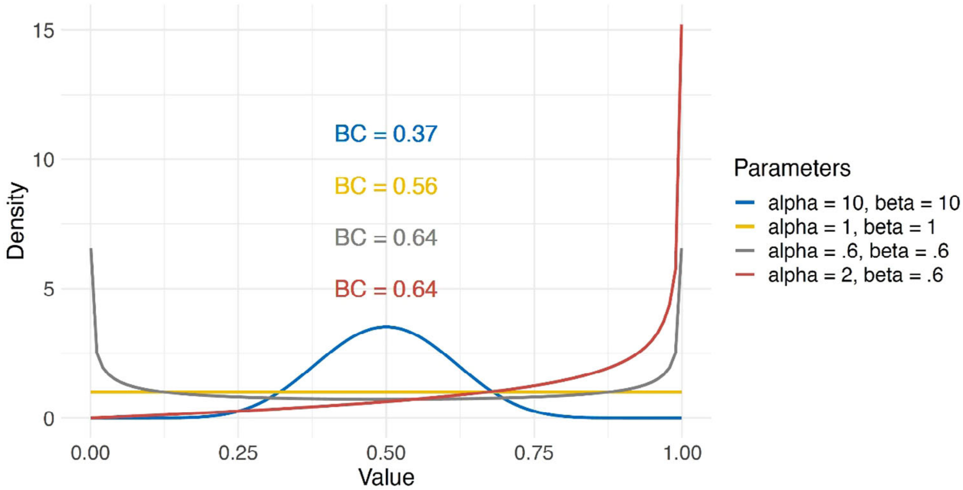

FIGURE B1 | Bimodality coefficients for different distributions, simulated based on four different beta distributions. The unimodal skewed distribution (red line: suggesting extremism) yields the same *BC* as a truly bimodal distribution (grey line: showing strong polarization). The *BC* can thus not distinguish extremism from polarization. Figure taken from Fischer and Frey (2023, 4).

where Q is the proportion of observations with the value of the most frequent category. Then the density of the noise-augmented data is estimated with a Gaussian kernel as proposed by Sheather and Jones (1991) and by scaling the bandwidth by a factor of 2. The number of modes is counted as the number of roots of the density function's derivative. To enhance the method's robustness, this procedure is repeated several times to obtain the most frequently detected mode.

Density-Based Mode Detection With Adjusted Noise

We modify the density-based detection method of Haslbeck, Ryan, and Dablander (2023) in order to make the method more robust to the large sample sizes. For this purpose, we propose a more adaptive rule to determine the level of noise added to the data. We start with a low noise level ($\sigma = 0.01$) and incrementally increase the noise until it has effectively smoothed out the ordinal nature of the response scale. To determine whether this is the case, we create a histogram of the noise-augmented data and for each bar regress its frequency on the distance of this bar from its closest integer (implying a response category):

$$y = \beta_0 + \beta_1 \cdot x_1 + \varepsilon \tag{3}$$

where y is the frequency of a bar in the histogram of the noise-augmented data and x_1 is the absolute difference between the bar's midpoint and the bar's midpoint rounded to the nearest integer. As long as the p-value of the slope is below 0.10, we assume that there is still a detectable effect of the response categories (meaning that a lot of observations can be found in these categories and not in between). We increase the noise by 0.10 until this is no longer the case. This method is applied to each dataset 100 times and the most frequent number of modes is taken as the final modality estimate.

Description of the Simulation Procedure

Each method was applied to various categorical distributions of different sample sizes, modality and skewness. We generated three types of unimodal distributions (Gaussian, truncated Gaussian left-skewed and truncated Gaussian right-skewed), three types of bimodal distributions (mixture of two Gaussians with large overlap, mixture of two Gaussians with small overlap and mixture of two truncated Gaussians with small overlap), three types of trimodal distributions (mixture of three Gaussians with large overlap, mixture of three Gaussians with small overlap and mixture of three truncated Gaussians with small overlap), as well as a uniform distribution. Each distribution was categorized into categories from 1 to 10 and was simulated for $N = 300$, $N = 500$, $N = 20{,}000$ and $N = 30{,}000$ (see Figures B2–B4). We specifically chose these sample sizes since they correspond to the sizes of the various involvement quartiles and groups in our study. All analyses were conducted in R, using the silvermantest package for Silverman's test (Preußner 2019), the mousetrap package for the Bimodality Coefficient (Wulff et al. 2023) and the diptest package for Hartigan's DIP (Maechler 2024). To enhance the robustness of results, both the density-based modality detection method proposed by Haslbeck, Ryan, and Dablander (2023) and our adjusted version were repeated 100 times for each dataset and the most frequent number of modes was taken as the final estimate.

TABLE B1 | Accuracy of different methods in discriminating unimodal distribution from multimodal distribution.

Method	Accuracy
Silverman	0.763
BC	0.684
DIP	0.632
DFU	**0.947**
Haslbeck, Ryan, and Dablander (2023)	0.757
Our adjusted noise method	**0.816**

Simulation Results

Silverman's method and the detection method proposed by Haslbeck and colleagues (2023) overestimated the number of modes when N was large. Silverman's method detected the correct number of modes in 31.6% and Haslbeck and colleagues' method in 39.5% of all cases. In contrast, our method using adjusted noise levels correctly detected the number of modes for 78.9% of the distributions. Our method failed only for multimodal distributions with large overlap (Figure B3, Panel A). With regard to discriminating unimodality from multimodality, the distance from unimodality measure (DFU) and our adjusted version of the density-based modality detection method achieved the highest accuracy (see Table B1). The DFU failed only for the uniform distributions, classifying them as multimodal. This illustrates the weakness of the DFU measure: as soon as there are small fluctuations in the data, a small increase in frequencies when moving away from the mode will cause the DFU to classify a distribution as multimodal. Without an application of a bootstrapping procedure, it is therefore less robust than our method. We thus decided to apply the latter to our analyses.

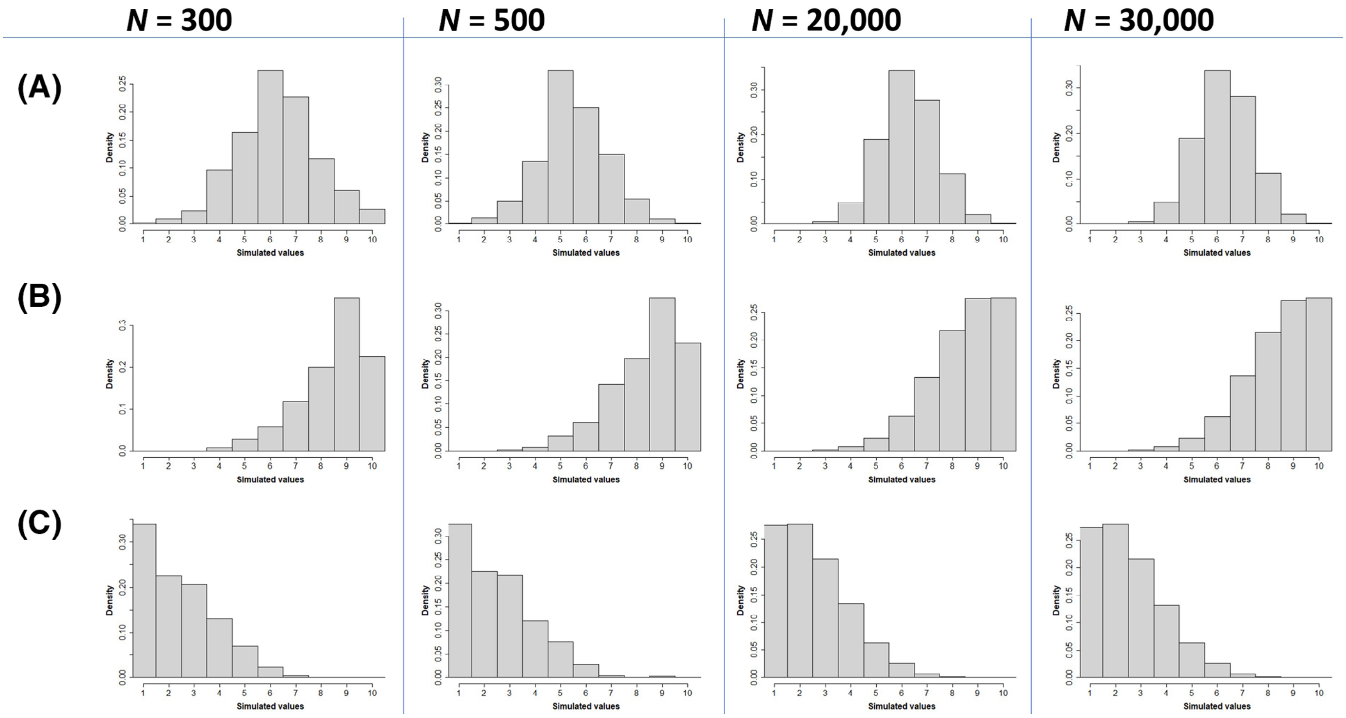

FIGURE B2 | Simulated unimodal distributions: Gaussian (A) and truncated Gaussian distributions (B and C) for different samples sizes (*N*).

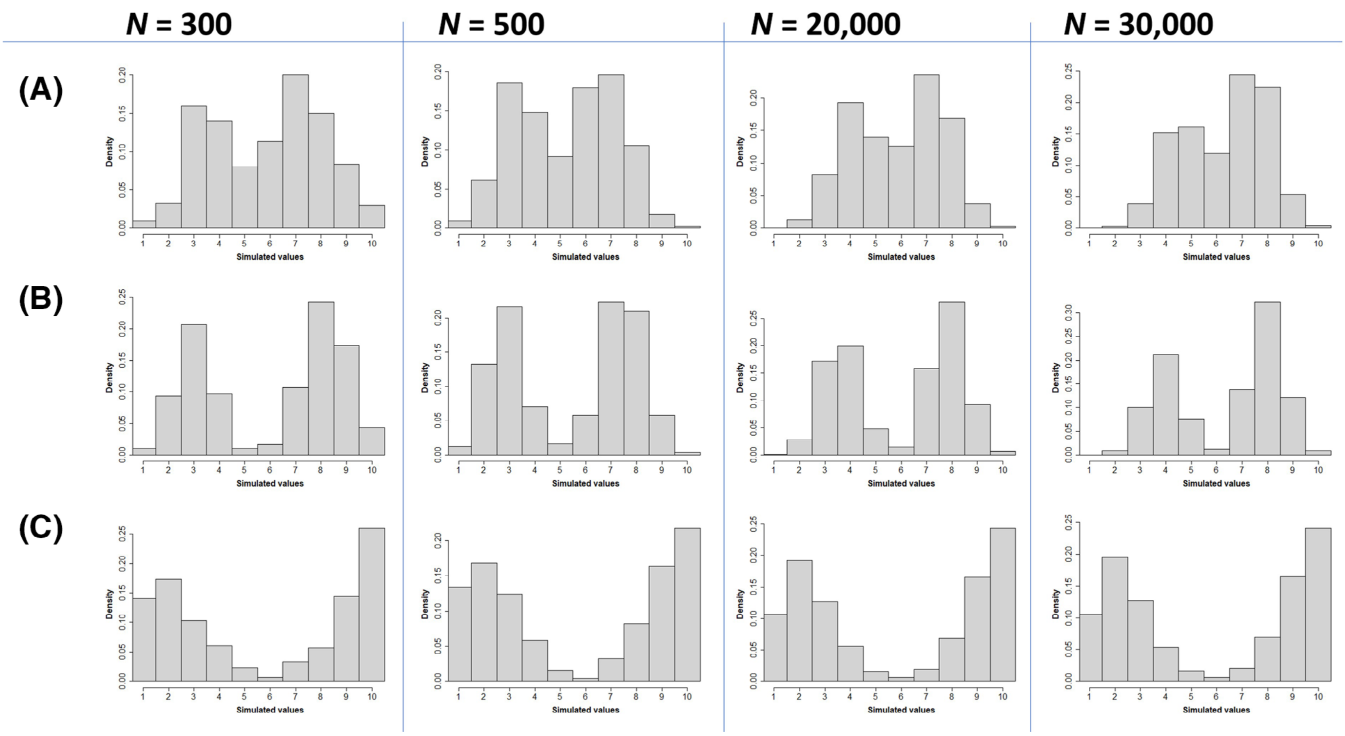

FIGURE B3 | Simulated bimodal distributions.

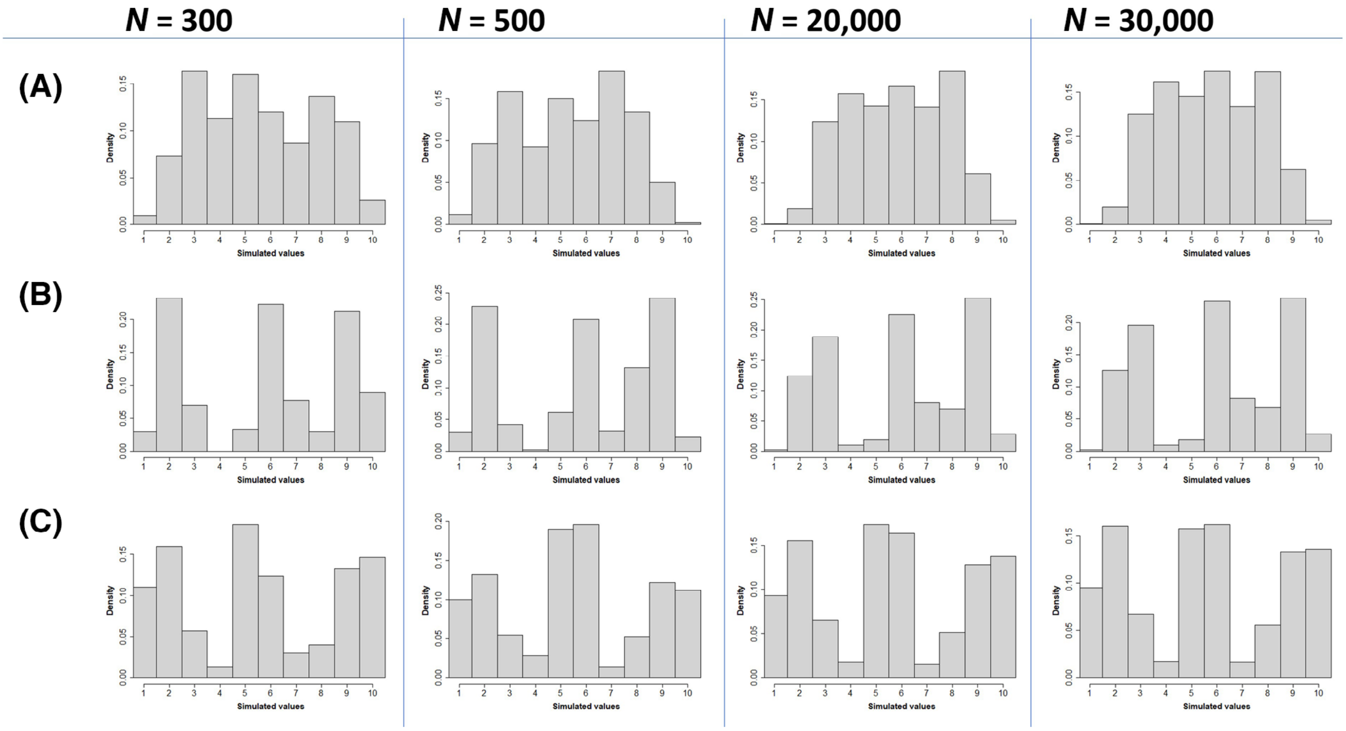

FIGURE B4 | Simulated trimodal distributions.