Received 15 July 2024, accepted 18 July 2024, date of publication 22 July 2024, date of current version 31 July 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3431999

APPLIED RESEARCH

Methodology for Measuring Individual Affective Polarization Using Sentiment Analysis in Social Networks

RAQUEL MARTÍNEZ-ESPAÑA [1], JULIO FERNÁNDEZ-PEDAUYE [2], JOSÉ GINER-PÉREZ DE LUCÍA [3], JOSE MIGUEL ROJO-MARTÍNEZ [4], KAOUTAR BAKDID-ALBANE [5], AND JUAN JOSÉ GARCÍA-ESCRIBANO [5]

[1]Department of Information and Communications Engineering, Faculty of Computer Science, University of Murcia, 30003 Murcia, Spain
[2]SensingTools Company, 46015 Valencia, Spain
[3]Department of Computer and Systems Informatics, Faculty of Computer Science, Polytechnic University of Valencia, 46022 Valencia, Spain
[4]Department of Political Science, Public Finance and Social Anthropology, Faculty of Law, University of Murcia, 30003 Murcia, Spain
[5]Department of Sociology, Faculty of Economics and Business, University of Murcia, 30003 Murcia, Spain

Corresponding author: Raquel Martínez-España (raquel.m.e@um.es)

This work was supported by the Science and Technology Agency of the Region of Murcia under Grant 21876/PI/2022. The work of Jose Miguel Rojo-Martínez and Kaoutar Bakdid-Albane was supported by the Ministry of Universities of the Spanish Government through the FPU under Grant FPU20/01033 and Grant FPU21/04363. The work of José Giner-Pérez de Lucía was supported in part by the CIN/AEI/10.13039/501100011033 under Grant TED2021-130890B, and in part by the European Union NextGeneration EU/PRTR.

ABSTRACT Affective polarization has important consequences for societies and institutions. At the institutional level, it hinders agreement among political actors, which damages the stability of the system. At the social level, it increases tensions and conflicts between people, damaging coexistence. Until now, affective polarization has been studied essentially through surveys, which are generally very costly if large and representative samples are to be obtained and in which the answers of the interviewees may not be totally sincere. Through this article, we apply sentiment analysis techniques to measure affective polarization without resorting to surveys, simply by monitoring the non-self-reported behavior of individuals in social networks. To do that, a novel methodology and a new indicator of affective polarization has been proposed using data from social networks. The proposed methodology and new indicator have been applied to the real case study of the regional elections in Spain, specifically to the autonomous Region of Murcia. The application of the methodology has been satisfactory, as well as that of the new indicator of affective polarization, providing a cost-effective way of calculating polarization. The results show that all political groups are polarized to a greater or lesser extent. Furthermore, the results conclude that the winning ideology in the elections, i.e., the right, was the one whose supporters behaved differently from the supporters of other ideologies.

INDEX TERMS Affective polarization, lexicon-based techniques, natural language processing, sentiment analysis, social networks.

I. INTRODUCTION

Affective polarization has become one of the most relevant phenomena for contemporary social sciences. Between 2021 and 2023, the Web of Science search engine (all databases) recognizes 382 papers that include the concept "affective polarization". The great academic interest it has aroused is due to the important consequences on social life produced by this growing hostility on a personal level for political reasons [1]. Partisanship as a strong group identity generates a tendency to segregation and distancing among those who support different political options, which makes coexistence difficult and turns politics into a factor of interpersonal discrimination based on prejudicial cognitive biases [2]. Increased intolerance toward the outgroup caused by affective polarization impacts not only personal relationships, but also democratic systems by undermining the recognition of legitimacy of adversaries [3] or even

The associate editor coordinating the review of this manuscript and approving it for publication was Barbara Guidi.

hindering the functioning of governments [4]. Ideological disagreement ceases to be the center of the political conflict and feelings of aversion and the moralization of debates increase, turning politics into an emotional and identitarian field full of sectarian attitudes [5]. This could even lead to episodes of radicalization and political violence preceded by the dehumanization of the opponent [6].

After defining affective polarization as a manifestation of growing hostility between partisan groups that also leads to interpersonal distrust [7], [8], we proceed to present the three main approaches that have been put forward to explain its origins or drivers. We will call the first approach "the effects of social identity" (a), the second "the effects of ideological or moral disagreement" (b) and the third– which is the focus of our attention– "the effects of communication strategies, forms and environments" (c). They are not mutually exclusive explanations, but complementary, and the difference between them lies only in the determination of which is the main atom or the most powerful cause that later originates a multicausal feedback loop.

The explanatory approach based on the theories of social psychology assumes that people do not have pronounced ideological differences, but partisan identity has been consolidated as a form of social identity and this causes a tendency to tribal behavior: favoring the ingroup and, above all, rejecting the outgroup [9]. The distance between partisan groups, far from having a rational basis linked to policy preferences, is explained by the growing social segregation that has generated a consistent alignment of certain non-political identities within partisan lines [10]. Party voters share less and less, they are isolated from each other, and this increases the sense of rivalry and remoteness. Among ordinary people there is a widespread sense of false polarization based on misperceptions about what others think, cognitive biases that generate stereotypes and lead us to think of our rivals more negatively than they really are [11].

Faced with the idea that we are separated by our group identity more than by our ideas –a sociological rather than political perspective–, other authors understand that, although affective polarization is characterized by emotional distancing, its origins are ideological [12]. Affective rejection is a response to a growing level of ideological disagreement among political elites, which in some cases is linked to highly sensitive moral issues [13]. As the parties' positions on different issues have shifted away from each other, citizens have begun to perceive the outgroup ideas as actually threatening to their ways of life. This is especially evident when discussions focus on cultural issues [14].

These two approaches address attitudes rooted in the individual such as feelings of belonging, values or political preferences. The role of ideology, personal interests, social cleavages or identity has already been discussed by some of the great theories of political science in the 20th century. However, the beginning of the 21st century has generated three processes that force us to look beyond the structural or attitudinal dimension: the weakening of the links with the parties, which makes political behavior sensitive to less predictable matters and increases the personalization of politics [15], the loss of importance of social position and cleavage voting [16] and the emergence of digital communication, something that has changed the ways of accessing and relating to political information and the nature of the public sphere [17].

Several authors argue that the new forms of online communication, especially since the expansion of social networks, have intensified political segregation by forming echo chambers that reinforce the biases and opinions of individuals and isolating them from other viewpoints [18], [19]. In fact, echo chambers would be another form of selective exposure as was already happening in traditional media [20], but in a more intense and continuous way. The echo chamber effect would be reinforced through the filter bubble of search algorithms, which would show us personalized content that matches our preferences, generating cognitive gaps in our own knowledge of reality [21].

In summary, early hypotheses about the contribution of social networks to polarization noted a bias of algorithms towards the creation of distant tribes that continuously received identity-reinforcing content. Social networks polarize us because they increase our contact with the ingroups and with evidence favorable to their position, i.e., they promote homophily [22]. Nowadays, this theory is strongly contested [23]. There is significant evidence that social networks favor exposure to content that does not coincide with the political position of the users [24]. Contrary to expectations, what social networks promote is not isolation, but interaction outside the local bubble which tempers partisan classification, generating an adverse emotional reaction that reinforces our identity [25]. According to an experiment carried out in the United States, individuals became more polarized when they came into contact with outgroup content [26]. This leads us to think that the fundamental causal mechanism of the polarization generated by the networks is not the attitudinal reinforcement by isolation, but rather the adverse emotional reaction to the conflictive interaction.

In any case, the line of research based on the influence of the new forms of communication has a bearing on how social networks platforms such as Facebook o X (former Twitter) has changed the way in which we come into contact with political information, while at the same time promoting a more exacerbated and negative tone in the political debate that could increase the perception of polarization [27]. The increased perceived polarization may be related to higher actual levels of polarization, as in a kind of self-fulfilling prophecy [28]. Although many authors believe that social networks increase affective polarization, there is not much data measuring the phenomenon in the specific environment of social networks. This makes it necessary to conduct experiments or surveys, but not much is known about the actual behavior of voters on these platforms. Therefore, it is also not possible to explain the origin of the emotional reactions triggered by social networks.

Knowing this previous context, the objective pursued in this manuscript is to innovate and search for a new way of calculating a person's level of affective polarization. Thus, we propose a general methodology to calculate polarization, not only in politics but in any issue. This methodology aims to obtain information that can be combined to create a new indicator that provides information on polarization at user level. To the best of our knowledge, social networks and social network analysis has been used to identify and analyze a large number of issues, but it has not been used to create a methodology and a polarization indicator. Sentiment analysis and machine learning algorithms have been the tools used to create the novel methodology and the polarization indicator. Although the proposed methodology is general, in this manuscript we have carried out a real case study, using the autonomic elections of May 2023 in Spain, specifically we have analyzed the case of the Region of Murcia.

The innovation and originality of this proposal is doubly justified. On the one hand, until now the calculation of political polarization has always been based on surveys. The disadvantage of surveys is the need for funding and a structure that can be biased, both in terms of questions and individuals. However, with the proposed methodology, individuals are not biased in their opinions, because users give their opinions without being under any scrutiny or control. With this methodology, the indicator obtained is based on spontaneous and real behavior (not in an artificial context such as a survey). Although initially it could be seen as a limitation of the methodology the type of users that operate in social networks, as it depends on a certain digital training, this limitation is reduced as the number of users in social networks is varied and is grouped according to preferences and interests [29].

On the other hand, the originality and innovation are justified by the use of sentiment analysis and the use of machine learning techniques that allow users to be tagged in order to subsequently analyze their interactions. The use of sentiment analysis and its multiple contributions will be studied in the related work in depth. Machine learning techniques allow us to group and classify individuals based on their interactions. Text and sentiment analysis are used to identify whether the interaction is positive or negative. These categorizations of interactions will allow us to create the new polarization indicator. Thus, all in all, the major contributions of this paper are:

- Develop a new methodology to measure affective polarization by using advanced sentiment analysis techniques from social networks, reducing the cost and bias of measuring this phenomenon through surveys and enabling real-time monitoring.
- Propose robust mechanisms for the political classification of users based on their activity in social networks.
- Desing a new indicator to determine a person's level of affective polarization.
- Understand intergroup emotional relations in social networks and the political dynamics of a given context. This contribution is particularly interesting for the field of social psychology, sociology, and political science.

This paper is organized as follows. Section II discusses existing advances in sentiment analysis techniques applied to the study of social networks. Section III presents the methodology used to create an indicator of affective polarization. This methodology is based on the concept of "Social Sensing", an approach that incorporates computational techniques for the investigation of social phenomena. Section IV explains the case to which this methodology was applied, the decisions taken to classify users as members of political groups, and the emotional valence (positive/negative) of the interactions with the content created by different political groups. Also, we present the outcome of the affective polarization indicator and discuss some of the observed results. The conclusion and the suggestion of the main challenges for future work are presented in Section V.

II. RELATED WORK

In today's world, social networks have become increasingly important for a greater number of people. According to the *Global Social Media Statistics Report,* in October 2023 there were 4.95 billion people using social networks, equivalent to 61.4% of the world's population. The number of social network users has increased by around 200 million new users in the last year. The average time a person spends on social networks is 2 hours and 26 minutes a day, which represents approximately 15% of waking life. This large presence of social networks in our lives has generated a growing interest in the study of how communication between people takes place in them and how feelings and emotions intervene in that communication.

Although people do not always have the same points of view, the need to communicate is indispensable [30]. However, the communication process takes place in multiple ways: orally, textually, visually or through facial expressions. The great capacity for connectivity provided by social networks has made it possible to generate a large amount of collective information. Social networks have revolutionized the way in which people communicate, becoming a new source of expression and information. The specific logics of social network activity have created a digital space in which spatial, ethnic or class boundaries become invisible. This has influenced the analysis, explanation, observation and discussion of political activities within the public sphere. Also, the growing importance of social networks as platforms for the consumption of political information has raised concerns about how this situation could increase political polarization [31], [32].

The emergence of Web 2.0, as well as the growing use of microblogging social networks, such as Twitter, produces a new form of online communication through messages in their various forms (written, video, images), with an enormous number of opinions available online. Social networks have become a powerful space for the exchange of opinions and information on a wide range of issues that could present pathological dynamics that increase affective polarization [33]. The content produced in the interaction of individuals through social networks has thus become an invaluable source of information that, after carrying out a user classification [29], can be examined and analyzed through the application of sentiment classification or labeling techniques, in order to find patterns or trends in people's behavior.

Sentiment analysis has crystallized as an active research area with an increasing number of published articles [34]. From 2008 to 2022 the number of articles including the concept "sentiment analysis in social networks" has grown at a geometric rate of 34% year-on-year [35]. Until 2020, publications have focused on two main issues: 1) the techniques used, i.e., machine learning or lexicon-based methods and 2) the specific application domains (health, business intelligence, marketing, election results prediction…) [35].

Given the large amount of information generated through the use of social networks, it has been necessary to develop systems for searching, retrieving, classifying and automatically presenting the different perspectives of opinions. Thus, the so-called "Opinion Mining" (OM), also known as "Sentiment Analysis" (SA), has emerged [36]. Sentiment analysis is an area or specialization of "Natural Language Processing" (NLP), which has made remarkable progress since its emergence in the late 1990s, due to both rapid advances in deep learning techniques and the abundance of shared digital data [37]. However, recent research reveals a notable absence of interdisciplinary efforts (from sociology, economics, political science) to try to understand the social dimensions of sentiment analysis [34].

The concept of "Opinion Mining" appears early in an article by Dave, Lawrence and Pennock, published in 2003, to refer to the ideal tool for opinion extraction, which allows processing a set of search results for a given item, "generating a list of product attributes (quality, features) and aggregating opinions about each of them (poor, mixed, good)" [38]. Much of the research that self-identifies as OM conducted subsequently fits this description. But recently, the concept has been interpreted more broadly to include different types of evaluative text analysis [39].

The word "sentiment", referring to the automatic analysis of texts and the monitoring of the predictive judgments contained in them, appears in Das and Chen [40] and Tong [41] in relation to market analysis. Subsequently, Turney [42], Pang et al. [43] and Nasukawa and Yi [44] were among the first authors to use "Sentiment Analysis" and "Natural Language Processing" methods. Since that time, quite a few articles applying "Sentiment Analysis" have focused on knowing, through texts, the polarity of the attitude (positive/favorable or negative/unfavorable) of a person towards another person, group, product or event, something that has led different authors to indicate that the concept alludes specifically to this operation. Notwithstanding, today many interpret the term in a broader way, having as its main objective the computational treatment of opinion, sentiment and subjectivity of the text [45], assessing opinions and classifying them as positive or negative with the aim of understanding the sentiment behind the unstructured information [37].

Being a very broad topic, a more exhaustive review of the different approaches to "opinion mining" or "sentiment analysis" is not possible in these pages, as it is not their purpose, but a review of the classical and modern approaches in this respect, as well as the different techniques employed in each of the subareas, can be found in Messaoudi et al. [46]. Also, Li [47] systematizes the current state of sentiment analysis and its potential impact on different fields of analysis, covering a wide range of topics, including advances in NLP techniques, challenges of SA in social networks, ethical considerations, and future directions of different approaches.

In relation to political analysis, there have been many investigations that have used SA. Without being exhaustive, we could highlight some research, such as that of Tumasjan et al. [48], in which, through the analysis of more than 100. 000 Twitter messages, they study the degree to which these validly reflect the political sentiments of the population as a whole in Federal Germany, concluding that the number of messages mentioning a political party reflects the electoral result and becomes a valid indicator of the political sentiment of the citizenry. In turn, O'Connor et al. [49] investigated the extent to which public opinion polls correlated with political sentiment expressed in Twitter messages posted in 2008 and 2009. Indian authors such as Ansari et al. [50] analyze Twitter messages related to the 2019 Indian General Elections and conduct the study of sentiments among Twitter users towards the major national political parties participating in the electoral process.

Later on, the sentiment-based classification model predicts the inclination of tweets to infer the election outcome. Ringsquandl and Petkovic [51] developed their research by using sentiment analysis on the campaign issues of U.S. Republican Party presidential candidates. Caetano et al. [52] implemented their political sentiment analysis to identify political user classes and homophily during the 2016 U.S. presidential election. They collected data from 4.9 million tweets from 18,450 users from August to November 2016. The authors specified six types of user classes representing their sentiment words toward Hillary Clinton and Donald Trump. For their part, Bor et al. [53] applied SA to Twitter data and developed quantitative analyses for six political groupings defined based on voting records. They explored the levels of polarization generated by some issues in relation to politics and, of the political issues analyzed, gun control was the most politically polarizing, with significant polarization results for all groups. In second place, immigration and border control, fossil fuels and the Ukraine-Russia war appear as the most polarizing issues and, interestingly, the least polarizing political issues are Taiwan, LGBTQ rights and the Chinese Communist Party. Finally, Del Valle and

De la Fuente [54] have conducted a systematic review of the progress made in sentiment analysis methods for politics and hate speech contents in Spanish language.

To sum up, SA is a technique increasingly used to monitor changes in public opinion and the way in which certain trends are propagated [55]. In an increasingly polarized world, this technique can also be useful for detecting sources of conflict between groups. For this reason, it seems pertinent to integrate the political science literature on affective polarization with advances in the field of computer science. The approach presented below is completely original because, until now, no sentiment analysis techniques have been applied to the creation of individual metric indicators of intergroup affective polarization. The formulation of these indicators will enable statistical analyses that provide robust explanations of the behavior of large samples of users, which will increase our knowledge of human behavior. Similarly, as the polarization approach is based on the determination of the ingroup and the outgroup, the measurement of the phenomenon requires the classification of users, determining their membership. This has been one of the great challenges of scientific research in social networks and we present evidence on strategies that allow us to respond to it and some limitations.

III. PROPOSED METHODOLOGY FOR CALCULATING AFFECTIVE POLARIZATION

Social networks have been a tool for the dissemination of information allowing anyone to share information about themselves, their environment or issues without limit, allowing for an unprecedented scale of information [56]. In previous studies, polarization has always been measured through survey fieldwork and from a more manual and biased point of view. Thus, in this study we intend to propose an open methodology without making a prior selection of the study sample. This can be carried out thanks to social networks, which provide us with a large amount of information. When analyzed and filtered, it provides us with useful knowledge and information. To the best of our knowledge, there is currently no methodology provides a quantitative index for measuring affective polarization in these environments. Although, initially, the proposed methodology was focused on the calculation of affective polarization, it has finally become a generic methodology that can be applied to more fields and areas.

The proposed methodology is based on the concept of ''Social Sensing''. Social Sensing is a technique that takes advantage of the interconnected nature and the immense amount of data available in social networks to detect and analyze patterns and trends in human behavior in social networks.

In the proposed methodology, we use Twitter as a social network and as our primary source of data as it is the platform most closely linked to political affairs. However, this methodology could be used with any other social network that provides minimum metadata. Twitter is a real-time platform that allows users to post ''tweets'' or short messages that can be viewed and shared by other users. In addition to tweets, there are also interactions such as retweets (sharing another user's tweet), likes and replies. These user actions generate a rich matrix of data that can be analyzed to better understand social dynamics.

A Twitter account also comes with several metadata that are relevant to our study. This includes, among others, the number of profiles that a particular user is followed, the number of tweets they have posted, the number of likes they have received and given or the replies generated. This metadata can help us enhance our comprehension of the influence of platform users and how their actions can contribute to affective polarization.

The methodology has adopted an agnostic approach to data collection, with the aim of maintaining objectivity in the analysis. However, this approach may also lead to a greater amount of noise in the data, as it will include tweets that are not relevant to the study topic. Despite this challenge, we believe that the inclusion of this data is essential to get a complete picture of the dynamics on Twitter.

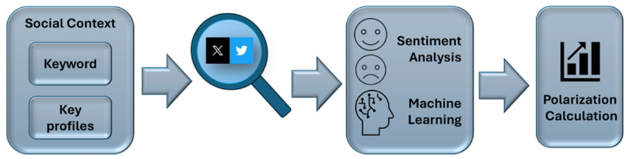


FIGURE 1. Outline of the proposed methodology.

Figure 1 shows the process of the proposed methodology for calculating affective polarization using social networks. This figure depicts two key approaches to social context determination. Context setting is a fundamental part of the methodology. The context will be center on the theme or problem to be addressed. In order to establish the count, two approaches are necessary. A first approach is based on keyword selection and the second approach is based on key profiles. These two approaches will allow us to create a dataset, from which we can obtain information or create the desired polarization indicator.

The keyword-based approach involves monitoring the opinions of Twitter users related to the issue to be addressed. For each keyword, included in the dictionary, we asked Twitter for the tweets that contained this word. While this broad approach brings with it the challenge of filtering out ''noise'' or irrelevant tweets, it maintains objectivity by not limiting the opinions collected to a specific group of users. This approach, in addition to providing tweets, also identifies the individuals who are giving their opinion on the topic in question. Therefore, this approach will provide us with unclassified raw users, who are interested in the problem.

The second approach, based on profiles, consists of carrying out an in-depth study of individuals, entities and/or companies that are on social networks and that are directly linked to the problem. Among these individuals/companies/entities we can highlight, for example, newspaper reporters or public figures who are influential in the problem to be addressed. Here it is also important to determine and agree on who these profiles will be, since these profiles will be decisive in subsequently being able to classify users. Thus, the key-profiles approach focused on tracking the conversations of key entities or individuals in the issue at hand. Although this approach is more targeted and therefore collects less "noise" compared to the keyword-based approach, it is also theoretically more limited in scope as it focuses on a specific set of users.

These two approaches are deterministic to obtain the context for selecting the sample of Tweets. Taken together, these two approaches give us a complete picture of the problem at hand during the period under study. They allow us to understand not only what was being discussed, but also who was leading the discussion and how these conversations were disseminated on the platform.

Once the context has been shaped, the methodology proposes to extract the tweets based on this context in order to subsequently pre-process them and obtain all the information and connections needed from them.

With all the information collected, the tweets are first classified using sentiment analysis techniques, noting the user who made the tweet or who liked the tweet or who retweeted the message. Afterwards, a classification of the users is carried out based on the classification of the problem to be treated. The objective is to use the information from the profiles that you follow or interact with. After assigning this category, each of their interactions (like, tweets, retweets) is recalculated and assigned to said user and classified into positive and negative ones. Once all the information and all the categories have been catalogued, a polarization index can be created and analyzed.

As a limitation of this methodology, it is possible that in the classification of users, there are users that cannot be classified, because they are cataloged in several categories. This limitation can be converted into an extension of future work, studying a new way of classifying users or trying to introduce exogenous information for the classification. Another approach could be to use fuzzy classification.

IV. STUDY CASE: REGIONAL ELECTIONS IN MURCIA

Once the proposed methodology for calculating affective polarization using social networks has been presented, it is applied to a real case study. Specifically, this methodology is applied to the calculation of affective polarization in the Region of Murcia (Spain) in the regional elections that took place at the end of May 2023.

Thus, in order to apply the methodology, we first have to define the context. For this, we use the keyword-based approach and the key profiles-based approach. In the keyword-based approach, a number of specific keywords were selected that were considered relevant to the political and social climate in the Region of Murcia. These keywords included, among others, the names of the political parties, the names of the main candidates, the most debated political issues and the significant events that took place during the study period. Some of the most relevant words included were: "Vox", "PP", "PSOE", "Podemos", "Ciudadanos", "votar", "inseguridad", "campo", "huerta", "Confederación Hidrográfica del Segura", "sequía", "Mar Menor", "peces muertos". Through this approach, we collected over 29,000 tweets (50,000 including tweets in conversation threads) from 1 January 2023 to the election day (28 May 2023). For each tweet, we recorded the identity of the Twitter user, the text of the tweet and associated metadata, including the number of likes, quotes and replies each tweet received.

The key profiles approach focused on tracking the conversations of key entities or individuals in the Region of Murcia. We selected a set of users who were considered influential or representative in the political discourse of the region. These users include politicians, journalists, academics, activists and opinion leaders whose views can have a significant impact on affective polarization. This approach allowed for the collection of more than 21,000 tweets (1,000,000 including tweets on threads), which demonstrates the richness and density of the political discussion among these users. Each tweet collected under this approach includes information about the user, the text of the tweet and additional metadata, such as the number of likes, quotes, replies and retweets. This data allows us to analyze both the content of conversations and their reach and impact on the Twitter social network. Some of the most relevant entities included were "Fernando López Miras", "Abascal", "Pedro Sánchez", "Feijóo", "José Ángel Antelo", "José Vélez" and "María Marín". A total of 78 different entities including organizations and political leaders, media and relevant users in the Region of Murcia have been considered. It should be noted that these entities have been manually labelled with an "ideology" according to their political affiliation.

After the collection of information, we move on to the stage of calculating the affective polarization using all the information collected. Thus, calculating affective polarization from Twitter data mining requires an original methodical approach that considers several elements. Following the formulas applied for the survey questions, the calculation of affective polarization is based on distinguishing emotions expressed towards the ingroup (the group with which an individual identifies) and those expressed towards the outgroup (groups with which the individual does not identify). A greater demonstration of ingroup favoritism– expressed as positive emotions towards one's own group and negative emotions towards others– indicates a greater degree of identification, discrimination and hostility [9].

Therefore, the key element in this process is the calculation of differences in affective expressions. For this purpose, two fundamental tasks have been carried out. First, it is necessary to classify individuals into groups and calculate the differences between the numerical indicators in the interactions with the different groups. In order to calculate the differences between the numerical indicators, we previously have to calculate the positive and negative interactions according to the groups.

A. THE PRE-PROCESSING AND PROCESSING OF DATA

In the realm of social networks analytics, the effective analysis of user interactions is contingent upon the meticulous preprocessing of voluminous and diverse data streams. The algorithm presented herein is dedicated to unraveling the intricacies of user behaviour on Twitter, with a particular emphasis on user classification and affective polarization. At the core of this algorithm lies a robust preprocessing phase, which serves as the indispensable foundation for subsequent analytical endeavours.

The preprocessing pipeline comprises a series of systematic steps aimed at refining raw data into a format conducive to nuanced analysis. These preparatory measures are instrumental in distilling meaningful insights from the wealth of information embedded in users' tweets and interactions. The algorithm addresses this preprocessing challenge through a multi-faceted approach, encompassing data extraction and information refinement.

Algorithm 1 shows the structure and functions of the models proposed. This algorithm consists of three main functions, each serving a distinct purpose in preparing and analysing user data. This algorithm plays a pivotal role in understanding and categorizing user behaviour on Twitter. By extracting and processing various interaction metrics, including likes, retweets, replies, mentions, and entities, it provides a comprehensive overview of user engagement. This information is essential for user classification, enabling the identification of distinct political groups and facilitating the assessment of affective polarization. The algorithm's systematic approach ensures that relevant data is processed efficiently, laying the foundation for in-depth analyses and insights into online user dynamics.

The purpose of obtaining the sentiment expressed in relation to the political debate is twofold: to identify the group membership of the individual and to estimate their differential levels of affection. It is therefore a matter of not classifying anyone only according to inconclusive manifestations (followers, following), but of making decisions based on the behaviour demonstrated.

Each tweet is processed using RoBERTuito to obtain its sentiment, an Artificial Intelligence (AI) model developed by Pérez et al. [57]. RoBERTuito, a RoBERTa-based model, served as the base architecture for sentiment analysis in this task. The model underwent pre-training on the TASS 2020 corpus, consisting of approximately 5,000 tweets in various Spanish dialects. The pre-training phase involved 500 million tweets, following RoBERTa guidelines and specifically targeting user-generated content in Spanish. This rigorous training ensures RoBERTuito's ability to generalize across diverse linguistic contexts within the Spanish language. The parameters used were the default ones indicated by the authors.

Algorithm 1 Triple-Function Algorithm for Classifying and Measuring User Interactions

```
   // Define Function to Process User Data for Metrics
Function ProcessUser(user_data)
   Initialize structures: followers, following, likes, retweets, replies,
mentions, hashtags, entities, sentiment
   For each social interaction in user_data
      social interactions: likes, retweets, replies, mentions
      content features: hashtags, entities, sentiment
      social connections: followers, following
   EndFor
   Return extracted_data
EndFunction
// Define Function to Process Interaction Metrics
Function ProcessUserInteractions(user_data, interaction_data)
   Initialize users_interactions_matrix
   For each user pair:
      Initialize counters: likes = 0, retweets = 0, replies = 0,
replies_{SENTIMENT} = 0, mentions_{SENTIMENT} = 0,
entities_{SENTIMENT} = 0
   For each interaction in interaction_data
      Increment counters based on interaction type and content
features
   EndFor
   Return users_interactions_matrix
EndFunction
      // Define Function to Process User Metrics
      Function ProcessUserMetrics(users_matrix)
   Initialize metrics_structure: interactions = 0, positive_interactions
= 0,
negative_interactions = 0, positive_interactions_{IDEOLOGY} =
0,
negative_{IDEOLOGY} = 0
   For each user_data in users_data
      Count interactions: likes, retweets, replies, mentions
      Extract ideology of each user
      For each interaction in user_data
         If interaction's user ideology is known
            Update metrics_structure with interaction's ideology
         EndIf
      EndFor
   EndFor
   Return metrics_structure
EndFunction
// Main Execution Logic
Function Main()
   user_data = LoadUserData()
   interaction_data = LoadInteractionData()
   Initialize user_metrics = []
   For each user in user_data
      extracted_data = ProcessUser(user)
      users_interactions_matrix = ProcessUserInteractions(user,
extracted_data)
      user_metrics_entry =
ProcessUserMetrics(users_interactions_matrix)
      user_metrics.append(user_metrics_entry)
   EndFor
   Output user_metrics for storage
EndFunction
```

Note: {SENTIMENT} and {IDEOLOGY} are placeholders used to handle multiple tags. Positive, negative, neutral for SENTIMENT. Radical Left, Left, Right and radical Right for IDEOLOGY.

The task of processing and calculating all the interactions within the social network Twitter involves examining various components, including sentiment analysis, previous manual classification of key-users, and the assignment of political tags. The result is a set of carefully calculated parameters, each serving as key metrics to extract insights into the dynamics of user interactions on the Twitter platform.

These parameters act as metrics, capturing facets of engagement and sentiment and reflecting the complexity of interactions within the Twitter ecosystem. Through a computational process, the following parameters have been derived for every user, with distinct values calculated for both their global impact and their association with specific political groups:

a) Likes count: the total count of likes received by a user, indicating positive engagement.
b) Retweets count: the overall number of times a user's content has been shared, measuring the amplification of their messages.
c) Positive texts count: the count of positive texts written, representing constructive engagement and support.
d) Negative texts count: the count of negative texts written, highlighting instances of disagreement or criticism.
e) Neutral texts count: the count of neutral texts written.

Additionally, these parameters are computed separately for each political group to provide insights into user interactions within specific affiliations. This concludes in the calculation of:

- Positive interactions: The total count of positive interactions within a political group. Consisting of likes, retweets and positive texts.
- Negative interactions: The total count of negative interactions within a political group. Consisting of negative texts.
- Neutral interactions: The total count of neutral interactions within a political group.

By considering these parameters at both the global and political group levels, the analysis becomes more granular, enabling a comprehensive examination of the diverse interactions that shape the Twitter landscape. One aspect to note is that while the pseudocode is abstracted from implementation details, the process has been partially optimised with parallel processing due to some computationally intensive segments.

Once all the information has been collected and after the qualification of users explained in the following section, a database is obtained that contains for each user: the total number of interactions, retweets, likes and both positive and negative interactions. Neutral interactions are counted in the total number of interactions. In addition, after these interactions after the classification of the user, the positive and negative interactions are obtained according to the classification of the user towards the rest of the political groups. A total of eight characteristics are obtained, which are the positive and negative interactions towards their political group and towards the opposing groups. With this information, the proposed indicator is calculated, as explained below. The dataset is built dynamically, including information as it is analysed. It is a tabular dataset, where the analysed values of the tweets are collected numerically.

B. THE CLASSIFICATION OF INDIVIDUALS INTO GROUPS

To classify individuals, we have opted for a categorization of individuals on the basis of their identification or affinity with the political parties that predominate in the current regional political landscape in Spain. These political parties have been classified into four main groups:

i. Right: this group includes users who identify or show affinity with the Partido Popular (PP). Those users who express support for political leaders or institutions related or akin to the PP are classified within this right-wing group.
ii. Left: this group consists of users who support or identify with the *Partido Socialista Obrero Español*(PSOE). Support for or affiliation with the PSOE is interpreted as an indication of alignment with left-wing ideologies.
iii. Radical Right: this group incorporates users who have shown affinity with the political party Vox. In our analysis, we have considered the majority following of political leaders or institutions closely related to Vox as an indication of alignment with the radical right.
iv. Radical Left: this group refers to users who express support for or identify with the political party PODEMOS. We consider support for PODEMOS to be indicative of an alignment with the far left.

In addition, we have included an additional category, ''Undetermined'', for those users for whom there is insufficient evidence to classify them in any of the above groups. This could be because they do not express a clear political affiliation in their tweets or because they don't show affinity with mainstream political parties. It is convenient to be strict when classifying an individual as a member of a political group, only assigning those whose manifested behaviour makes clear a political tendency. This is a demanding criterion, but it guarantees the quality of the results. This classification scheme allows us a deeper and more detailed analysis of the affective polarization between the followers of the different political parties in the Region of Murcia on Twitter. It allows us to compare the emotions expressed towards the different parties and to calculate the affective polarization based on these differences.

For the classification of the Twitter users collected in the database according to their political identity, we adopted a two-step approach. The first step consists of a study of the Twitter user according to his or her followers, using the set of entities of organizations and political leaders previously classified manually. This is the least conclusive and rigorous step. This enables us to know the user by their own choices when receiving tweets from different users. However, it could be the case (not very usual) of a user who follows different political leaders or parties to know what they say, without supporting them. The second step focuses on positive interactions, defined as any action that reflects support or affinity for a group or representative group member. These actions include likes or retweets of posts of a specific group, as well as responses with associated positive sentiments. For this purpose, we started to apply sentiment analysis techniques. The manifestation of positive feelings towards a group is more decisive than being part of a community of followers.

For each user i, we calculated the total number of positive interactions they had with each group j. The group with the highest number of positive interactions was selected as the user's political group (ingroup):

$$Ingroup(i) = argmax_j(Pos_{i,j})$$

For instance, if a user had 10 positive interactions with posts related to VOX, and only 5 with PP, 2 with PSOE and none with PODEMOS, that user would be classified as radical right. In situations where there are no positive interactions with any party, or in case of a tie between more than two parties in terms of positive interactions, we assign the user to the category 'Undetermined'.

Figure 2 shows a visual representation of how users are distributed among the different ideological groups. Surprisingly, a total of 147,534 users, or 55% of the total sample, could not be classified into any of the ideological categories and were labelled as 'Undetermined'. This result is interesting because it demonstrates the main limitation to the study of intergroup relations in social networks (how we classify individuals into groups). It also informs us that most Twitter users do not have a very close relationship with partisan content or are not overtly outspoken on political issues. They are passive recipients of content without interacting with it.

It is also interesting to note that there is a uniform decrease in the number of users as they move towards more right-wing ideologies, which could suggest a trend in the activity of Twitter users in the Region of Murcia. This does not mean that in this social network there are fewer users close to right-wing parties, but at least they are more difficult to detect because they interact less with political content or participate less in the discussion of political issues. In other words, they are apparently less mobilized or more affected by a social desirability bias that causes them not to show their political preferences. Applying the proposed classification methodology, there is the possibility for other researchers to demonstrate whether this trend also occurs in broader contexts outside Spain.

C. POSITIVE AND NEGATIVE INTERACTIONS ACCORDING TO GROUP IDENTITY

By classifying users into political groups based on their activity on Twitter, we are able to further examine the trends of both positive and negative interactions between these groups. Tables 1 and 2 provide data of users' average positive and negative interactions with different political parties based on their ideology. Table 1 shows a clear ingroup favoritism behavior, the tendency to show more positive feelings towards those who share our identity or ideas. As expected, we observed that users have a higher number of positive interactions with those who belong to their

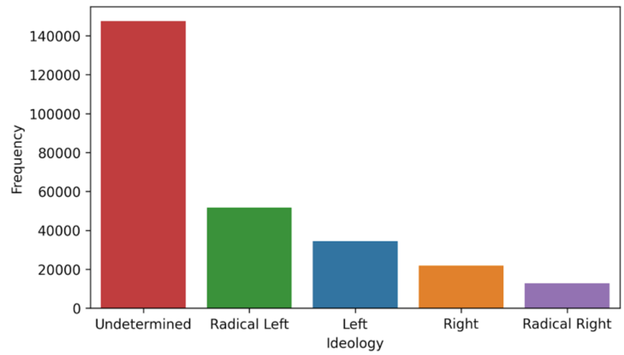


FIGURE 2. Frequency of political groups according to user classification.

own political group. However, a high standard deviation is observed for positive interactions with the ingroup. Within the same group, there can be very engaged hooligans and users who are not very likely to show their support.

TABLE 1. Positive interactions on average towards groups according to own group.

Group	Positive Interactions Radical Right	Positive Interactions Right	Positive Interactions Left	Positive Interactions Radical Left
	Mean (std)	Mean (std)	Mean (std)	Mean (std)
Radical Right	6.421734 (25.71584)	0.124087 (1.022214)	0.039896 (0.335338)	0.044216 (0.337250)
Right	0.053705 (0.790311)	9.725389 (50.952722)	0.069854 (0.573135)	0.039250 (0.477612)
Left	0.007338 (0.625955)	0.077641 (1.211508)	7.818759 (35.942417)	0.170596 (1.956711)
Radical Left	0.00559 (0.097915)	0.030481 (0.277084)	0.148787 (1.173609)	6.410791 (22.309015)

The differences in positive interactions with the ingroup and with the rest of the groups are high, even with those parties that are close to each other within ideological blocs (radical right with right, radical left with left). Beyond this evidence, it is surprising that users from the most extreme groups are not the ones who describe a more intense positive attachment to their ingroup. On the contrary, users on the right (identified with the PP, the party that won the elections) had the most positive interactions with their ingroup. Levels of positive sentiment with the ingroup can anticipate certain electoral trends demonstrating the extent to which the members of a group have a strong attachment to it. Another notable finding is that right users have on average more positive interactions with the left than with the radical right, group with which they are currently governing in coalition. This result may reflect other dynamics, such as a greater degree of moderation among right-wing users, or possibly the existence of topics or issues on which the traditional right and the traditional left can find common ground.

As for negative interactions, the patterns observed are somewhat different. Except for the radical right, users tend to have the highest numbers of negative interactions with members of their own group. Although it may seem counterintuitive, this result is explained by the greater propensity of the ingroup in general to come into contact with its own content. According to these findings, members of political groups may also be using social networks to express their disagreements with their own parties, waging internal battles. This would show a more critical and less tribal user profile than expected. Notwithstanding, the level of negative interactions with the ingroup is much lower than the level of positive interactions with the ingroup in all the cases analysed (ingroup favouritism prevails).

It is possible that some users have higher levels of negative interaction with their groups because, in turn, the levels of contact with them are higher. As total interaction increases, the likelihood that some of that interaction will be negative increases. Besides, users may pay more attention to their own group's content and analyse it more and, at the same time, they may care more about expressing their opinion in these cases (including disagreements), trying to assert their position among their co-supporters.

In this regard, a relatively high number of negative interactions towards members of their own group are observed for the radical left. This could suggest certain divisions or differences of opinion inside this group, or perhaps a higher level of internal confrontation. The radical left got fewer votes in the 2023 regional elections than in the 2019 elections and was the party with parliamentary representation least voted. Again, the SA of interactions in social networks can anticipate the direction of electoral behaviour. This should always be qualified by remembering that not everyone is on social networks. Nevertheless, it is possible to think that social networks reproduce a political climate that is generalized in the offline sphere.

In the case of the radical right, the pattern is different. These users stand out for having a high number of negative interactions towards members of other parties, especially the radical left. This finding suggests a marked propensity towards confrontation and criticism of opposing parties among radical right users and an inclination towards protecting their own group by showing less critical positions towards it. It also informs us how the radical right maintains a sharp antagonism with the other side of the spectrum.

This analysis provides a deeper insight into the dynamics of positive and negative interactions on Twitter in the context of politics in the Region of Murcia, providing a better understanding of users' attitudes and behaviours according to their political preferences. On the one hand, we found that positive feelings with the ingroup are the most recurrent interaction. This would challenge the widespread view that political debate in networks is dominated by negativity. On the other hand, we showed that the radical right has a behaviour more favourable to the preservation of the ingroup and that the radical left was deeply divided. Lastly, given that the highest level of negative interactions occurs with the ingroup in three of the four cases, we question the implications of the echo chamber theory. It is true that when we relate to our group, positive feelings prevail, but this does not imply that disagreements cannot appear and even that it is more common for these disagreements to appear with our ingroup, with whom we interact more frequently. Interaction is a basic element of friction.

TABLE 2. Negative interactions on average towards groups according to own group.

Group	Negative Interactions Radical Right	Negative Interactions Right	Negative Interactions Left	Negative Interactions Radical Left
	Mean (std)	Mean (std)	Mean (std)	Mean (std)
Radical Right	0.270321 (2.846441)	0.517160 (2.876687)	0.715699 (5.485299)	0.892563 (4.119456)
Right	0.046386 (0.735006)	1.063403 (6.042926)	0.632204 (5.270638)	0.706770 (3.896779)
Left	0.039241 (1.302631)	0.749674 (7.032823)	1.006236 (23.247219)	0.626294 (10.22645)
Radical Left	0.040932 (0.507891)	0.405179 (3.107335)	0.433183 (2.633070)	2.186623 (8.604381)

D. CALCULATION OF AFFECTIVE POLARIZATION

An essential part of this study is the formulation of two key indicators that allow us to measure affective polarization (AP) based on Twitter interactions: ingroup AP (IngroupAP) and outgroup AP (OutgroupAP). These indicators are based on the difference between the positive and negative interactions a user has with their own group (ingroup) and with other groups (outgroup). We define the most affectively polarized users as those who, comparing interactions with their ingroup and outgroups, have higher levels of ingroup *vs*. outgroup positive sentiment and higher levels of outgroup *vs*. ingroup negativity.

The $\mathrm{AP}(i)_{\mathrm{In}}$ for a user i classified in a political group j is defined as the subtraction between the total number of positive and negative interactions i has with j. More formally:

$$AP(i)_{In} = Pos_{i,j} - Neg_{i,j}$$

Similarly, the affective polarization of the outgroup ($\mathrm{AP}_{\mathrm{Out}}$) is the subtraction between the total positive and negative interactions that user i has for all parties j' (where $j' \neq j$), such that:

$$AP(i)_{Out} = \Sigma_j (Pos_{i,j} - Neg_{i,j})$$

A higher $\mathrm{AP}(i)_{\mathrm{In}}$ value indicates more support and loyalty towards Twitter users labeled in the same political group, so we would expect this value to be positive and far from 0. Conversely, a lower $\mathrm{AP}(i)_{\mathrm{In}}$ means more rejection towards people with other political identities, usually being negative.

Joining the above, the affective polarization of user i is calculated as the difference between the affective polarization of the ingroup and outgroup. The higher the level of ingroup favoritism and negativity towards opponents, the higher the level of AP:

$$\mathrm{AP}(i) = AP(i)_{In} - AP(i)_{Out}$$

The affective polarization values of the $AP(i)_{In}$ are illustrated in Figure 3 grouped by each political space. The right wing has more users who are very loyal and attached to their group as they have a high number of positive interactions with entities and contents of the same group. It can also be seen that, in all groups, there are some users with a negative score, meaning that they have more negative interactions than positive ones with their own group. The lowest scores are found on the radical left, indicating that there is more tension among its supporters, although there are also many tensions present on the left and the right. The same is not true of the radical right, which does not seem to have as much internal tension as the other ideologies. This leads us to conclude that this group seems to be more homogeneous and have a more biased behaviour.

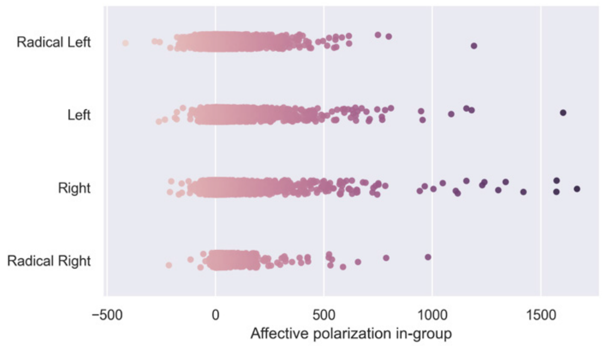


FIGURE 3. Individual AP scores towards the ingroup according to political groups.

Figure 4 shows the $AP(i)_{Out}$ scores. As expected, these scores are mostly negative. Relations with outgroups are dominated by expressions of hostility and rejection, as is foreseeable according to the Social Identity Theory [58]. However, there are cases in which users have a positive perception towards other parties than their own. In all groups there are some users who attack copartisans more.

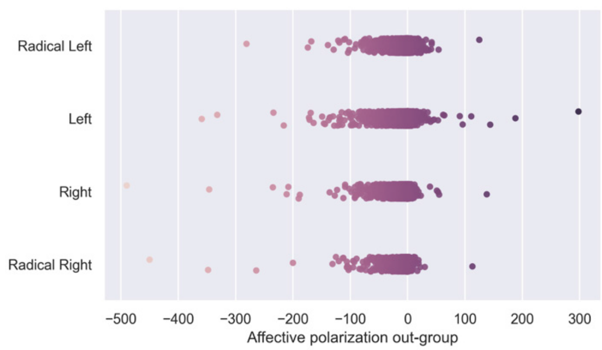


FIGURE 4. Individual AP scores towards the outgroup according to political groups.

The final AP values are shown in Figure 5. Higher values occur more frequently on the right and on the radical right, but the differences between groups are not very noticeable. It is worth noting the number of users on the radical left that have more often a polarization score below 0, a fact that could be due, although it would require an in-depth analysis, to the internal tension between its members. These results are unexpected because, until now, survey analysis has repeatedly shown that members of the most extreme groups are the most polarized [59]. Of course, in our case, we did not analyze all the people from a party, but only those who actively participate in social networks. In any case, the fact that the ideological bloc with a slightly higher level of affective polarization is that of the right may reflect the political situation in Spain at that time, which was characterized by a strong rejection of the left-wing national government on the part of the right. At the same time, it shows a high degree of mobilization of this bloc, which finally won most seats in parliament.

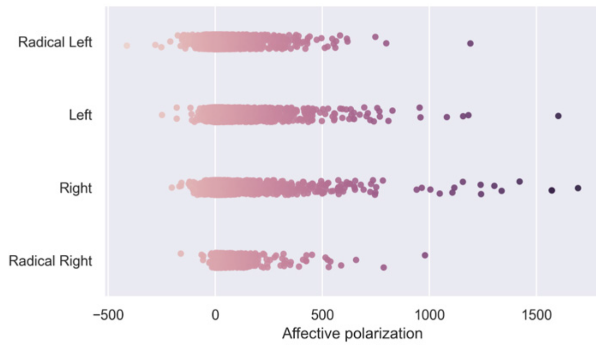


FIGURE 5. Individual AP scores according to political group.

The ideological hypothesis of affective polarization based on spatial theories (the position of a group in the spectrum predicts polarization, the farther from the center the more polarized) would be questioned –at least for the social network users in our case study–. As long as the radical left is not more polarized than the left and the radical right and right have similar levels of polarization, the spatial-ideological hypothesis seems does not seem to work in this case. This also invites us to think that the profile of the social network user does not necessarily coincide with the average profile of the partisan of each group. Social networks are only a small part of reality.

To refine our analysis, the levels of AP shown for each group will be analyzed in the form of a ranking. In this case, we will consider the mean value of the AP and its standard deviation, which are 3.16 and 23.75 respectively. These values will be the reference point for calculating the polarization ranking. Thus, we will consider a low AP when the value is -26, a medium value when the AP value is between -26 and 26. Finally, it will be a high value when the value is higher than 26. The decision to take the statistical values of mean and standard deviation for the ranking is due to the large dispersion we found in the data and the possibility of including the outliers within the range.

Table 3 shows the percentage of users found at each of the proposed ranking levels. It can be observed that all users of all political parties are polarized, which is the initial and proven hypothesis. With the proposed AP calculation, this hypothesis holds and furthermore, there are no major differences between the parties. Therefore, what is relevant may not be the type of party you belong to, but the fact of strongly feeling part of a political group.

TABLE 3. **Individual ap percentage for each political group (3 levels of polarization).**

	Low	Medium	High
Radical right	0.04%	93.61%	6.35%
Right	0.54%	92.92%	6.55%
Left	0.22%	94.14%	5.64%
Radical left	1.07%	94.09%	4.84%

Table 4 contains the matrix with the aggregated APs by group. Each cell contains the average affective polarization value of the ranking in the political group (row) for the parties in the columns. The diagonals are the APs of the ingroup, and they are all positive as expected, with Podemos being the lowest of the four (the group with the least enthusiastic members). With respect to the outgroup APs, those of Vox and PP have a more negative perception (−0.84 and −0.66 respectively) than those of Podemos and PSOE (−0.67 and −0.37 respectively).

TABLE 4. **AP scores for each political group.**

Group	PA VOX	PA PP	PA PSOE	PA PODEMOS
	Mean (std)	**Mean (std)**	**Mean (std)**	**Mean (std)**
Radical Right	6.151412 (25.647974)	-0.393071 (2.923730)	-0.675803 (5.440866)	-0.848347 (4.016227)
Right	0.007319 (1.060735)	8.661985 (51.150471)	-0.562351 (5.215297)	-0.667520 (3.839818)
Left	-0.031903 (1.419014)	-0.672032 (6.815339)	6.812523 (42.372333)	-0.455698 (10.365161)
Radical Left	-0.035339 (0.494198)	-0.374700 (3.014090)	-0.284395 (2.823516)	4.224168 (23.527974)

The calculation of AP from the formula used so far proposes a final value determined by the actual number of positive or negative interactions of the user towards the different parties, without somehow normalizing the number of positive or negative interactions with respect to the total number of interactions. It could be argued that the higher level of interaction is demonstrative of a higher level of group commitment and polarization. However, we show an alternative calculation that avoids bias due to the amount of interaction (online hyperactivity).

The values are then normalized by the total number of interactions (n_i) of user i, adapting the formula proposed by Wagner [60]. In this formula, pos_{ip} and neg_{ip} are the number of positive and negative interactions of i towards the political group p, respectively. We call this indicator "spread":

$$spread = \sqrt{\frac{\sum_{i=1}^{n} (\mathrm{pos_{ip}} - neg_{\mathrm{ip}})^2}{\mathrm{n_i}}}$$

The scatter plot in Figure 6 contains the scores recalculated with the above formula for the users, which are classified into their political groups. Consequently, there are no longer negative values, and the ranges of values are narrower than in Figure 5. It can be seen that there are polarized users in all ideologies, and one left-wing user has an excessively high score.

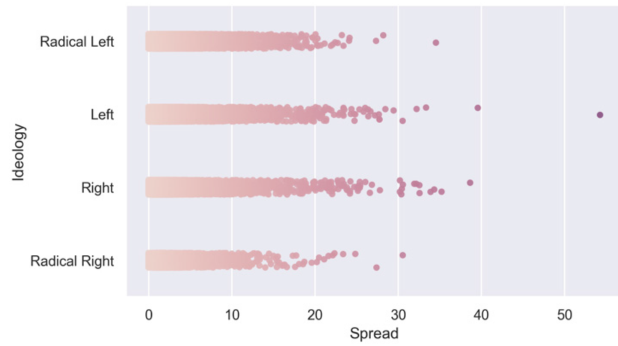


FIGURE 6. **Individual AP scores according to political group.**

As with the AP calculation, we now proceed to establish a ranking of the users for the "Spread" calculation. In this case the mean value is 1.16 and the standard deviation is 1.52. Thus, the ranking thresholds classify users with a 0 spread as a low threshold, users with values greater than 0 and less than 2.68 as a medium threshold, and users with values greater than 2.68 as a high threshold. Table 5 displays the percentages of this classification. The results are similar to those presented in Table 4, but when normalized by the number of interactions, the right stands out as the group with the highest percentage of highly polarized individuals. The coincidence between the group that won the elections, and the most highly polarized group is a significant finding for studies on political behavior. The predisposition to ingroup favoritism and rejection of opponents may be a condition that informs a party's capacity for electoral mobilization. During the entire pre-campaign the PP (the right wing) was perceived as the clear winner of the race. This may have provoked in their followers a greater propensity to reinforce the ingroup and reject the outgroup. The feeling of being ahead may have led to affective polarization. The cost in terms of social status of showing favor to the ingroup is low because it is known that the ingroup will be the winner.

In turn, the reduction in the differences in the levels of polarization among the rest of the groups again supports the idea that what is important is not the type of party in which the partisans belong, but their own partisan status. Finally, I would support the idea that affective polarization in social networks is symmetrical. This assumes that all groups have

TABLE 5. Individual ap percentage (wagner´s formula) for each political group (3 levels of polarization).

	Low	Medium	High
Radical right	1.33%	85.62%	13.05%
Right	2.69%	81.43%	15.89%
Left	1.95%	84.70%	13.35%
Radical left	3.62%	80.82%	15.57%

within them people with high predispositions to behave like hooligans, favoring their tribe and attacking the rest.

TABLE 6. AP scores for each political group.

Group	Spread Mean (std)
Radical Right	1.7320255 (1.670497)
Right	1.874452 (2.299107)
Left	1.748230 (1.997068)
Radical Left	1.763020 (1.728984)

Lastly, in the Table 6 the average AP values is exposed according to the adaptation of the Wagner formula, where the right is more polarized than the rest of the groups. Overall, the data do not indicate excessively high average levels of affective polarization. This could be due to the fact that the methodology has been applied to a regional election. Regional elections are second-order elections, i.e., people pay less attention to them and participate less in them. Perhaps that is why the PA levels are not too high. Given that the mean values are so similar, we performed a statistical test to see if there are significant differences between the polarization of the 4 political groups. An ANOVA test was applied, with a Bonferroni post-hoc test [61]. The ANOVA test indicates that there are significant differences at a 95% confidence level. Analyzing the results with the Bonferroni test, we obtain that the right-wing ideology has significant differences with respect to the rest of the ideologies. While the other three ideologies have no differences in polarization among themselves. This result leads to a secondary conclusion that the right-wing ideology was the winner of the regional elections. This fact and the statistical test indicate that the behavior of the users sympathetic to the winning ideology was different from that of the other ideologies, and therefore, this event should be studied in more detail for other elections. This result allows us to provide another utility of our study, which is that the affective attitudes of a group in the pre-electoral period can anticipate the results of the elections.

V. CONCLUSION AND FUTURE WORK

Affective polarization has important implications for society and institutions. It is important to detect it early in order to avoid escalating tensions and conflicts among individuals, impairing coexistence and damaging the stability of the system. Thus far, affective polarization has primarily been examined through surveys, which can often be costly when aiming for large and representative samples, and where respondents' answers may not always be entirely truthful. Thus, throughout this study we have presented an innovative methodology that integrates results from sentiment analysis to create a new individual indicator of affective polarization. The methodology created and the indicator designed are generic and can be applied to any aspect or problem of polarization. This proposal is a relevant contribution for the study of this phenomenon, as it will allow us to monitor the levels of intergroup hostility in social networks and try to explain them at user level. Among the main findings we can highlight the controversy over the results using surveys that the radical parties are the most polarized, in this case and regarding the radical right, this is not the case. This may be due to a differential attitudinal profile between the social network user and the general population responding to the surveys.

Overall, the data do not indicate excessively high average levels of affective polarization and show a polarization of symmetrical morphology between groups. But it is relevant that the group that won the election is the most polarized, indicating a greater tendency among its supporters to reinforce the ingroup and reject the outgroup. This difference in polarization has been statistically validated. The feeling of being ahead may have provoked a greater level of affective polarization through positive reinforcement mechanisms of ingroup membership. Also, we have already been able to demonstrate that individuals tend to ingroup favoritism and to reject those who do not think like them (also in social networks). And we have also been able to observe how the description of the interaction dynamics of a group can give an account of its levels of cohesion and thus anticipate certain electoral tendencies. Anyway, it is also important to highlight the limitations of the work, which, despite having a larger number of users and information available, is limited to users who use social networks and takes place in a specific context (a regional election). In addition, there is the added difficulty of classifying users.

In future work, researchers should explain this indicator data through multivariate analysis models to predict polarization levels as a function of different variables such as the intensity of the interaction with the ingroup and with the outgroup or the depth of the echo chamber of each user. New research will also have to improve the system for classifying users according to their group affinities to avoid the high percentage of "undetermined" users, which can bias the results of some groups. This being the starting requirement to later analyze their group relationships (in/out). Another future research is to look for behavioral patterns in the data extracted from the study, with the aim of obtaining a predictive model of polarization based on a selection of features.

REFERENCES

[1] D. Baldassarri and S. E. Page, "The emergence and perils of polarization," *Proc. Nat. Acad. Sci. USA*, vol. 118, no. 50, Dec. 2021, Art. no. e2116863118, doi: 10.1073/pnas.2116863118.

[2] M. D. Luttig, "The 'prejudiced personality' and the origins of partisan strength, affective polarization, and partisan sorting," *Political Psychol.*, vol. 39, no. S1, pp. 239–256, Feb. 2018, doi: 10.1111/pops.12484.

[3] S. Iyengar, Y. Lelkes, M. Levendusky, N. Malhotra, and S. J. Westwood, "The origins and consequences of affective polarization in the United States," *Annu. Rev. Political Sci.*, vol. 22, no. 1, pp. 129–146, May 2019, doi: 10.1146/annurev-polisci-051117-073034.

[4] M. J. Hetherington and T. J. Rudolph, *Why Washington Won't Work: Polarization, Political Trust, Governing Crisis*. Chicago, IL, USA: Univ. Chicago Press, 2015.

[5] E. J. Finkel, C. A. Bail, M. Cikara, P. H. Ditto, S. Iyengar, S. Klar, L. Mason, M. C. McGrath, B. Nyhan, D. G. Rand, L. J. Skitka, J. A. Tucker, J. J. Van Bavel, C. S. Wang, and J. N. Druckman, "Political sectarianism in America," *Science*, vol. 370, no. 6516, pp. 533–536, Oct. 2020, doi: 10.1126/science.abe1715.

[6] J. A. Piazza, "Political polarization and political violence," *Secur. Stud.*, vol. 32, no. 3, pp. 476–504, May 2023, doi: 10.1080/09636412.2023.2225780.

[7] L. Huddy and O. Yair, "Reducing affective polarization: Warm group relations or policy compromise?" *Political Psychol.*, vol. 42, no. 2, pp. 291–309, Apr. 2021, doi: 10.1111/pops.12699.

[8] A. H.-Y. Lee, "Social trust in polarized times: How perceptions of political polarization affect Americans' trust in each other," *Political Behav.*, vol. 44, no. 3, pp. 1533–1554, Sep. 2022, doi: 10.1007/s11109-022-09787-1.

[9] S. Iyengar, G. Sood, and Y. Lelkes, "Affect, not ideology," *Public Opinion Quart.*, vol. 76, no. 3, pp. 405–431, Sep. 2012, doi: 10.1093/poq/nfs038.

[10] L. Mason, *Uncivil Agreement: How Politics Became Our Identity*. Chicago, IL, USA: Univ. Chicago Press, 2018.

[11] J. N. Druckman, S. SKlar, Y. Krupnikov, M. Levendusky, and J. B. Ryan, "(MIS) estimating affective polarization," *J. Politics*, vol. 84, no. 2, pp. 1106–1117, 2022, doi: 10.1086/715603.

[12] J. C. Rogowski and J. L. Sutherland, "How ideology fuels affective polarization," *Political Behav.*, vol. 38, no. 2, pp. 485–508, Jun. 2016, doi: 10.1007/s11109-015-9323-7.

[13] A. M. Enders and R. N. Lupton, "Value extremity contributes to affective polarization in the U.S.," *Political Sci. Res. Methods*, vol. 9, no. 4, pp. 857–866, Oct. 2021, doi: 10.1017/psrm.2020.27.

[14] N. Gidron, J. Adams, and W. Horne, "Who dislikes whom? Affective polarization between pairs of parties in western democracies," *Brit. J. Political Sci.*, vol. 53, no. 3, pp. 997–1015, Jul. 2023, doi: 10.1017/s0007123422000394.

[15] D. Garzia and F. F. da Silva, "Negative personalization and voting behavior in 14 parliamentary democracies, 1961–2018," *Electoral Stud.*, vol. 71, Jun. 2021, Art. no. 102300, doi: 10.1016/j.electstud.2021.102300.

[16] A. C. Goldberg, "The evolution of cleavage voting in four western countries: Structural, behavioural or political dealignment?" *Eur. J. Political Res.*, vol. 59, no. 1, pp. 68–90, Feb. 2020, doi: 10.1111/1475-6765.12336.

[17] P. Staab and T. Thiel, "Social media and the digital structural transformation of the public sphere," *Theory, Culture Soc.*, vol. 39, no. 4, pp. 129–143, Jul. 2022, doi: 10.1177/02632764221103527.

[18] C. R. Sunstein, *Going to Extremes: How Like Minds Unite and Divide*. Oxford, U.K.: Oxford Univ. Press, 2009.

[19] M. Del Vicario, G. Vivaldo, A. Bessi, F. Zollo, A. Scala, G. Caldarelli, and W. Quattrociocchi, "Echo chambers: Emotional contagion and group polarization on Facebook," *Sci. Rep.*, vol. 6, no. 1, p. 37825, 2016, doi: 10.1038/srep37825.

[20] S. Iyengar and K. S. Hahn, "Red media, blue media: Evidence of ideological selectivity in media use," *J. Commun.*, vol. 59, no. 1, pp. 19–39, Mar. 2009, doi: 10.1111/j.1460-2466.2008.01402.x.

[21] E. Pariser, *The Filter Bubble: How the New Personalized Web is Changing What We Read and How We Think*. New York, NY, USA: Penguin, 2011.

[22] Y. Halberstam and B. Knight, "Homophily, group size, and the diffusion of political information in social networks: Evidence from Twitter," *J. Public Econ.*, vol. 143, pp. 73–88, Nov. 2016, doi: 10.1016/j.jpubeco.2016.08.011.

[23] A. Guess, B. Nyhan, B. Lyons, and J. Reifler, "Avoiding the echo chamber about echo chambers," *Knight Found.*, vol. 2, no. 1, pp. 1–25, 2018.

[24] S. Flaxman, S. Goel, and J. M. Rao, "Filter bubbles, echo chambers, and online news consumption," *Public Opinion Quart.*, vol. 80, no. S1, pp. 298–320, 2016, doi: 10.1093/poq/nfw006.

[25] P. Törnberg, "How digital media drive affective polarization through partisan sorting," *Proc. Nat. Acad. Sci. USA*, vol. 119, no. 42, Oct. 2022, Art. no. e2207159119, doi: 10.1073/pnas.2207159119.

[26] C. A. Bail, L. P. Argyle, T. W. Brown, J. P. Bumpus, H. Chen, M. B. F. Hunzaker, J. Lee, M. Mann, F. Merhout, and A. Volfovsky, "Exposure to opposing views on social media can increase political polarization," *Proc. Nat. Acad. Sci. USA*, vol. 115, no. 37, pp. 9216–9221, Sep. 2018, doi: 10.1073/pnas.1804840115.

[27] J. Buder, L. Rabl, M. Feiks, M. Badermann, and G. Zurstiege, "Does negatively toned language use on social media lead to attitude polarization?" *Comput. Hum. Behav.*, vol. 116, Mar. 2021, Art. no. 106663, doi: 10.1016/j.chb.2020.106663.

[28] A. M. Enders and M. T. Armaly, "The differential effects of actual and perceived polarization," *Political Behav.*, vol. 41, no. 3, pp. 815–839, Sep. 2019, doi: 10.1007/s11109-018-9476-2.

[29] A. P. Logan, P. M. LaCasse, and B. J. Lunday, "Social network analysis of Twitter interactions: A directed multilayer network approach," *Social Netw. Anal. Mining*, vol. 13, 2023, Art. no. 65, doi: 10.1007/s13278-023-01063-2.

[30] J. Ruesch, "Pragmatics of human communication: A study of interactional patterns, pathologies, and paradoxes," *Arch. Gen. Psychiatry*, vol. 17, no. 4, p. 506, Oct. 1967.

[31] M. Azzimonti and M. Fernandes, "Social media networks, fake news, and polarization," *Eur. J. Political Economy*, vol. 76, Jan. 2023, Art. no. 102256, doi: 10.1016/j.ejpoleco.2022.102256.

[32] M. Yang, X. Wen, Y.-R. Lin, and L. Deng, "Quantifying content polarization on Twitter," in *Proc. IEEE 3rd Int. Conf. Collaboration Internet Comput. (CIC)*, Oct. 2017, pp. 299–308, doi: 10.1109/CIC.2017.00047.

[33] A. Tyagi, J. Uyheng, and K. M. Carley, "Affective polarization in online climate change discourse on Twitter," in *Proc. IEEE/ACM Int. Conf. Adv. Social Netw. Anal. Mining (ASONAM)*, Hague, The, Netherlands, Dec. 2020, pp. 443–447, doi: 10.1109/ASONAM49781.2020.9381419.

[34] P. Venkit, M. Srinath, S. Gautam, S. Venkatraman, V. Gupta, R. Passonneau, and S. Wilson, "The sentiment problem: A critical survey towards deconstructing sentiment analysis," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, 2023, pp. 13743–13763, doi: 10.18653/v1/2023.emnlp-main.848.

[35] M. Rodríguez-Ibánez, A. Casánez-Ventura, F. Castejón-Mateos, and P.-M. Cuenca-Jiménez, "A review on sentiment analysis from social media platforms," *Expert Syst. Appl.*, vol. 223, Aug. 2023, Art. no. 119862, doi: 10.1016/j.eswa.2023.119862.

[36] E. Martínez-Cámara, Sentiment analysis in Twitter," *Natural Lang. Eng.*, vol. 20, no. 1, pp. 1–28, 2012, doi: 10.1017/S1351324912000332.

[37] N. Raghunathan and K. Saravanakumar, "Challenges and issues in sentiment analysis: A comprehensive survey," *IEEE Access*, vol. 11, pp. 69626–69642, 2023, doi: 10.1109/ACCESS.2023.3293041.

[38] K. Dave, S. Lawrence, and D. M. Pennock, "Mining the peanut gallery: Opinion extraction and semantic classification of product reviews," in *Proc. WWW 12th Int. Conf. World Wide Web*, 2003, pp. 519–528, doi: 10.1145/775152.775226

[39] B. Liu, "Opinion mining and sentiment analysis," in *Bing Liu, Web data mining; Exploring hyperlinks, Contents, and Usage Data*, 2nd ed., London, U.K.: Springer, 2011, pp. 459–526.

[40] S. Das and M. Chen, "Yahoo! for Amazon: Extracting market sentiment from stock message boards," in *Proc. Asia Pacific Finance Association Annual Conf. (APFA)*, 2001, p. 43.

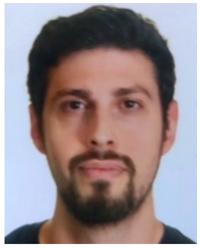
[41] R. M. Tong, "An operational system for detecting and tracking opinions in on-line discussion," in *Proc. Work. Notes ACM SIGIR Workshop Oper. Text Classification*, vol. 1, no. 6, Sep. 2001.

[42] P. D. Turney, "Thumbs up or thumbs down: Semantic orientation applied to unsupervised classification of reviews," in *Proc. 40th Annu. Meeting Assoc. Comput. Linguistics (ACL)*, 2001, pp. 417–424.

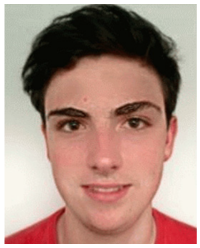
[43] B. Pang, L. Lee, and S. Vaithyanathan, "Thumbs up: Sentiment classification using machine learning techniques," in *Proc. ACL Conf. Empirical Methods Natural Lang. Process. (EMNLP)*, 2002, pp. 79–86.

[44] T. Nasukawa and J. Yi, "Sentiment analysis: Capturing favorability using natural language processing," in *Proc. 2nd Int. Conf. Knowl. Capture*, Oct. 2003, pp. 70–77, doi: 10.1145/945645.945658.
[45] B. Pang and L. Lee, "Opinion mining and sentiment analysis," *Found. Trends Inf. Retr.*, vol. 2, nos. 1–2, pp. 1–135, 2008, doi: 10.1561/1500000011.
[46] C. Messaoudi, Z. Guessoum, and L. B. Romdhane, "Opinion mining in online social media: A survey," *Social Netw. Anal. Mining*, vol. 12, no. 1, pp. 313–340, Dec. 2022, doi: 10.1007/s13278-021-00855-8.
[47] J. Li, Ed., *Advances in Sentiment Analysis—Techniques, Applications, and Challenges*. London, U.K.: IntechOpen, 2024, doi: 10.5772/intechopen.111293.
[48] A. Tumasjan, T. O. Sprenger, P. G. Sandner, and I. M. Welpe, "Predicting elections with Twitter: What 140 characters reveal about political sentiment," in *Proc. 4th Int. Conf. Weblogs Social Media (ICWSM)*. Washington, DC, USA: AAAI Press, 2010, pp. 178–185.
[49] B. O'Connor, R. Balasubramanyan, B. Routledge, and N. Smith, "From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series," in *Proc. 4th Int. AAAI Conf. Weblogs Social Media*, vol. 4, no. 1, 2010, pp. 122–129, doi: 10.1609/icwsm.v4i1.14031.
[50] M. Z. Ansari, M. B. Aziz, M. O. Siddiqui, H. Mehra, and K. P. Singh, "Analysis of political sentiment orientations on Twitter," *Proc. Comput. Sci.*, vol. 167, pp. 1821–1828, Jan. 2020.
[51] M. Ringsquandl and D. Petković, "Analyzing political sentiment on Twitter," in *Proc. Analyzing Microtext Papers From AAAI Spring Symp.*, 2013, pp. 40–47.
[52] J. A. Caetano, H. S. Lima, M. F. Santos, and H. T. Marques-Neto, "Using sentiment analysis to define Twitter political users' classes and their homophily during the 2016 American presidential election," *J. Internet Services Appl.*, vol. 9, no. 1, pp. 1–15, Dec. 2018, doi: 10.1186/s13174-018-0089-0.
[53] D. Bor, B. S. Lee, and E. J. Oughton, "Quantifying polarization across political groups on key policy issues using sentiment analysis," 2023, *arXiv:2302.07775*.
[54] E. del Valle and L. de la Fuente, "Sentiment analysis methods for politics and hate speech contents in Spanish language: A systematic review," *IEEE Latin Amer. Trans.*, vol. 21, no. 3, pp. 408–418, Mar. 2023.
[55] L. Lin, J. Li, R. Zhang, W. Yu, and C. Sun, "Opinion mining and sentiment analysis in social networks: A retweeting structure-aware approach," in *Proc. IEEE/ACM 7th Int. Conf. Utility Cloud Comput.*, Dec. 2014, pp. 890–895, doi: 10.1109/UCC.2014.145.
[56] D. Wang, B. K. Szymanski, T. Abdelzaher, H. Ji, and L. Kaplan, "The age of social sensing," *Computer*, vol. 52, no. 1, pp. 36–45, Jan. 2019.
[57] J. M. Pérez, D. A. Furman, L. A. Alemany, and F. Luque, "RoBERTuito: A pre-trained language model for social media text in Spanish," 2021, *arXiv:2111.09453*.
[58] H. Tajfel, "Experiments in intergroup discrimination," *Sci. Amer.*, vol. 223, no. 5, pp. 96–103, 1970.
[59] E. Harteveld, P. Mendoza, and M. Rooduijn, "Affective polarization and the populist radical right: Creating the hating?" *Government Opposition*, vol. 57, no. 4, pp. 703–727, Oct. 2022, doi: 10.1017/gov.2021.31.
[60] M. Wagner, "Affective polarization in multiparty systems," *Electoral Stud.*, vol. 69, Feb. 2021, Art. no. 102199, doi: 10.1016/j.electstud.2020.102199.
[61] W. R. Rice, "Analyzing tables of statistical tests," *Evolution*, vol. 43, no. 1, p. 223, Jan. 1989.

RAQUEL MARTÍNEZ-ESPAÑA received the Technical Engineer degree in computer systems, in 2007, the M.S. degree in computer science, in 2009, and the Ph.D. degree (cum laude) in computer science from the University of Murcia, in 2014. She is currently a Lecturer with the Department of Information and Communications Engineering, University of Murcia. She has published more than 30 research articles in international journals, as well as more than 50 publications including book chapters and proceedings of conferences. She is also the co-author of two intellectual property patents. Her research interests include machine learning, data preprocessing, data mining, soft computing and deep learning.



JULIO FERNÁNDEZ-PEDAUYE received the B.Sc. degree in computer science from the Catholic University of Murcia, in 2020. He is currently a Computer Scientist with the Department of Computer Engineering, Universitat Politècnica de València, Spain, and SensingTools Company. His research interests include natural language processing and social computing.



JOSÉ GINER-PÉREZ DE LUCÍA received the B.Sc. degree in data science and the M.Sc. degree in artificial intelligence from UPV, in 2022 and 2023, respectively. He is currently a NLP Researcher with Universitat Politécnica de València, Spain. He is working in several social sensing related projects.

JOSE MIGUEL ROJO-MARTÍNEZ received the degree (Hons.) in political science and the degree in sociology, in 2019 and 2023, respectively. He holds the title of Expert in Advanced Statistics from the National University of Distance Education (UNED), Madrid, Spain. He is currently a Research Fellow (FPU) with the Political Communication Laboratory (LABCOM), University of Murcia. He has been a Visiting Researcher (VSR) with Stanford University, since 2023. His research interests include affective polarization, social identities, political psychology, emotions in electoral campaigns, political communication, and electoral behavior.

KAOUTAR BAKDID-ALBANE received the degree in social work, in 2021, and the master's degree in community social work, social service management and evaluation, in 2022. She is currently a Research Fellow (FPU) with the Department of Sociology, University of Murcia. Her research interests include hate speeches, racism, polarization, and public opinion analysis.

JUAN JOSÉ GARCÍA-ESCRIBANO received the degree in political science and sociology from the Complutense University of Madrid, in 1979, and the Ph.D. degree in sociology from the University of Murcia, in 1997. Currently, he is a Professor of sociology with the University of Murcia, and a Principal Investigator (PI) of the Murcian Center for the Study of Public Opinion (CEMOP). He is the Coordinator of the Doctoral Program "Society, Development and Labor Relations." His research interests include public opinion, political sociology, and electoral behavior.