International Journal of Communication 19(2025), 3377–3395 1932–8036/20250005

Habits and Motivations of Citizens in Receiving and Disseminating Disinformation on Social Media

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A main problem in the fight against disinformation is the lack of knowledge about the sociodemographic profiles of both recipients and disseminators of false messages circulating on social networks. This research is based on a survey conducted in the Autonomous Region of Madrid (*N* = 840) aimed at revealing the digital habits and behavior of people over the age of 18 regarding disinformation. The cross-referencing of variables reveals a group composed mainly of women, averaging 31 years and ideologically left-leaning, as the main disseminators of news on social media and, simultaneously, the group most exposed to disinformation. At the opposite end of the spectrum, the group averaging 73 years old reports never sharing news on social media and, rarely, if ever, receiving fake news. When respondents did share disinformation, they argued it was because they believed it to be true and trusted the source.

Keywords: information disorders, social networks, digital habits, false messages, ideology

Despite efforts in recent years to combat information disorder, the public domain continues to suffer from massive amounts of misleading content and hoaxes spread through online platforms. This is confirmed by figures released in the biannual report published by the European Commission on September 23, 2023, in the Transparency Centre's Code of Practice on Disinformation (European Commission, 2023).

According to the report, in the first six months of 2023, more than 40 million pieces of content on Facebook and more than 1.1 million on Instagram received a fact-checking label. TikTok reported that "140,635 videos with over 1 billion views were removed from the platform for disinformation policy

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Date submitted: 2024-03-07

violations" (European Commission, 2023, p. 2). Moreover, Microsoft "prevented the creation, or restricted the creation, of more than 6.7 million fake LinkedIn accounts" (European Commission, 2023, p. 2).

The fact that the verifiers tagged more than 40 million pieces of Facebook content in just six months demonstrates the magnitude of the problems society faces regarding the quality of information circulating in the public domain. However, one finding from this same report deserves to be highlighted because of its effective design of an action plan against disinformation; according to the references provided by Meta, 95% of Facebook users decided not to click on content that had received a warning label from the verifiers, and 37% who had intended to share it refrained from doing so after seeing the warning.

If these changes in user behavior are confirmed in successive reports (some signatories to the Code report every six months and others once a year), it can be expected that labeling by verifiers and the commitment by online platforms will help mitigate the spread of misleading information and hoaxes on social media. In any case, understanding the receiver and their behavior remains crucial for designing effective countermeasures against disinformation, as different studies have shown that hoaxes can persist despite fact-checking efforts in certain contexts.

For example, this is evident in the United States, where belief in the hoax about alleged electoral fraud that supposedly brought Joe Biden to the White House has remained largely unchanged. In November 2020, 32% of Americans believed the fraud narrative; three years later, despite extensive fact-checking, the percentage remains nearly the same at 30% (Monmouth University Polling Institute, 2023). It is worth considering whether this persistence of falsehood in people's beliefs occurs in all areas, or whether it is more characteristic of politics, which has proven to be the favorite arena for propagating disinformation.

Partisanship in the Reposting of Fake News

Political leaning is an important variable in the consumption of both information and disinformation. As argued by Wong, Levin, and Solon (2016), in highly polarized contexts, individuals tend to consume content that confirms their own opinions. This confirmation bias (Watson, 1960) leads to the avoidance of opinions contrary to their own (Rochlin, 2017).

In a survey of 150 academic experts on disinformation, Altay, Berriche, Heuer, Farkas, and Rathje (2023) conclude that the most widely accepted explanation for why people believe and share disinformation is partisanship. Specifically, 96% of experts agree that partisanship is one key reason why people share disinformation, and 93% of experts also agree that partisanship is the key to explaining why people believe disinformation.

Group identification, confirmation bias, purposeful reasoning, and lack of trust in institutions received very high levels of agreement (between 73% and 93%). Repeated exposure, a shortage of attention, a deficit of cognitive reflection, and a lack of digital and media literacy also received relatively high levels of agreement (between 54% and 84%). However, less than 50% of the experts agreed that a lack of education and scarce access to reliable news were the reasons why people believed and shared disinformation.

In line with political position and the inclination to believe and share misleading content, Sádaba, Salaverría, and Bringué (2023) conducted an experimental study to analyze the effect of media literacy on the ability of Spaniards over the age of 50 to identify fake news. They aimed to measure the improvement attained by adults in identifying political disinformation, thanks to a digital competence course offered through WhatsApp. The study comprised a total sample of 1,029 individuals, subdivided into a control group (n = 531) and an experimental group (n = 498), from which a qualified experimental subsample (n = 87) was drawn.

The results revealed that the political position of the participants, which ranged from left-wing to right-wing, influenced their ability to detect misinformation. A progressive political stance was associated with higher accuracy in identifying headlines with a right-wing bias but lower accuracy in pinpointing headlines with a left-wing viewpoint. By contrast, a conservative position was associated with higher accuracy in detecting news headlines with a progressive bias but lower accuracy when the headline was conservative. It follows that users are more discerning when the headline reflects a bias contrary to their own and more likely to believe news that confirms their convictions.

Identifying and Reposting Fake News

Therefore, in line with the theory of confirmation bias, the aforementioned studies suggest a tendency to perceive as false any information that offers a negative image of one's own political position, whereas the information that criticizes the opposing political view is seen as true. However, it is not clear whether this perception indicates a greater or lesser tendency to share dubious or misleading content, which is a variable that represents a qualitative leap in the understanding of this phenomenon. The reason for this greater insight is that the problem we need to address is not only about people's beliefs and perceptions of information. It is also about identifying the types of people who are likely to share false content.

In an experimental study conducted with 2,000 participants in 16 countries and 9 languages, Arechar et al. (2023) found a correlation between people's ability to distinguish between true and false headlines and their willingness to share such information on their networks. To carry out the study, the participants were shown 20 headlines about COVID-19 that were half-true and half-false, and they were asked to rate the level of accuracy of the headlines and their likelihood of sharing the content on social media. The researchers observed that the participants were less discerning when sharing than when checking the veracity of the news stories. This suggests that people sometimes share false headlines that they possibly identify as inaccurate.

However, when the purpose of the research was explained to the participants afterward, most said that truthfulness was very or extremely important to them when deciding what to share online, which was inconsistent with their responses in the previous experiment. As such, there is dissonance between the ability to discern truth from falsehood and the tendency to repost false content. These findings also suggest that educational interventions related to media literacy and awareness of the importance of truthfulness can make users more mindful about sharing false information.

Other Factors Involved in Reposting

Without intending to delve into psychology, a discipline that is contributing valuable insights to the study of social communication, we briefly mention some psychological drivers that explain the belief in disinformation and its resistance to correction. Ecker et al. (2022) explain the illusory truth effect, which occurs when people use peripheral cues that reinforce their tendency to believe information, such as familiarity (a sense that a message has been encountered before), processing fluency (encoded and retrieved effortlessly), and cohesion (a signal that the elements of a message have references in memory that are internally consistent) as signals for truth, and the strength of these cues increases with repetition. These factors act as signals of truth that are reinforced by repetition.

Interestingly, repetition works in both directions, increasing the belief in both truth and falsehood. This illusory truth effect can linger for months after the first exposure, regardless of cognitive ability, and despite advice to the contrary from an accurate source or prior knowledge. On social media, the content that captures attention is often shared the most. Likewise, words that are morally or emotionally charged, such as "fight," "greed," "evil," and "punishment," are prioritized in early visual attention and induce more reposting. Anger can also drive the spread of false information. As social media algorithms promote content that is more likely to be shared, psychological tendencies and technological optimization can easily lead to the viral spread of disinformation. "Lazy" or intuitive thinking can also lead people to share content that they might have recognized as false if they had thought more about it.

There is a line of work on algorithmic determination of the characteristics of fake news redistributors, their profiles, their writing styles, or their personality traits. Shu, Wang, and Liu (2018) lay the foundation for automated detection of the personality traits of fake news redistributors and find that older people are more likely to trust fake news and that women are more likely to believe fake news than men. Shrestha and Spezzano (2022) study the correlation between user characteristics and their probability of being fake news redistributors. In this regard, they find that users under 18 and over 40 may be more vulnerable to spreading fake news and that women are more likely to spread it than men. In addition, fake news redistributors tend to express more negative emotions and stress in their tweets, and their political orientation usually aligns with that of the source spreading the fake news. Dourado (2023) analyzes digital accounts that published fake news on social media in Brazil during the 2018 presidential elections, examining the type, relevance, and propensity to robotization of 1,073 users. The study shows that fake news is more widely disseminated through personal profiles than through bots. Similarly, Giachanou, Ghanem, and Rosso (2023) propose ConspiDetector, a model based on a convolutional neural network that combines word embeddings with psycholinguistic features from users' tweets to detect conspiracy spreaders. With this model, they demonstrate that anti-conspiracy spreaders tend to have more followers, friends, and favorites compared with fake news spreaders. The accounts of anti-conspiracy spreaders are created earlier than those of conspiracy spreaders, and the spreaders use more swear words.

Research Questions, Hypotheses, and Objectives

As indicated above, people's ability to discern true from false information has no correlation with an attitude that is more or less cautious when sharing dubious content on social media. Moreover, based on previous research, we find that when it comes to politically related news, confirmation bias creates significant anomalies in recognizing the veracity of information that is contrary to one's ideology.

The findings regarding these audience characteristics lead us to ask the following:

RQ1: Is there any social group or population segment more prone than others to disseminating news of questionable veracity?

H1: People who share the largest amount of news on social networks are also the most likely to share hoaxes, even consciously.

Furthermore, as previous research suggests that partisanship is the most important factor in discerning between true and false information, we ask the following questions:

RQ2: Are the most ideologically polarized social groups also the most likely to share information of dubious truthfulness?

H2: Ideologically polarized individuals tend to share hoaxes whenever they are detrimental to the political view that opposes their own.

This study aims to contribute to the body of knowledge about information disorders that threaten the stability of our liberal democracies, based on the assumption that the various measures aimed at containment, proposed both now and in the future, require deeper knowledge of the person who receives disinformation, specifically concerning his or her critical ability to distinguish hoaxes, as well as the degree of willingness to share them.

This research has allowed us to identify the characteristics of the people most likely to share fallacious content. In other words, it adds another step in the flow of dissemination of fake news, as it introduces the reason why someone would broadcast content presumed false.

Based on this point, the specific objective of this research is to establish a typology of hoax disseminators. The proposal consists of delimiting taxonomic characteristics, which will help the agents involved in the fight against disinformation to make more appropriate decisions. The agents to which we refer are the following: digital platforms, which are responsible for establishing technological mechanisms of containment; institutions with the ability to finance both theoretical and applied research and training programs; digital verifiers who work directly with the messages and their coding; academics who are making progress in analyzing and describing the phenomenon from comprehensive perspectives; and educators, who have the responsibility of teaching citizens how to engage in critical thinking when the latter are forced to coexist with lies.

This study is part of a broader research project on vulnerability and digital culture, which enabled the hiring of the demoscopic consultancy firm *40dB* to design a 75-question survey on digital habits and attitudes toward disinformation. The questions relevant to this article's specific objectives were drawn from that survey.

Methodology

The research sample responded to an online and telephone survey, which the researchers commissioned from the company *40dB*. The sample involved 840 people residing in the Autonomous Region of Madrid, Spain, representing various ages and municipalities. The geographical definition of the sample was because of the specifications of the research project, funded by the Autonomous Region of Madrid, among other institutions. In any case, this geographic limitation does not diminish the results, as the macrodata in Madrid are consistent with those of the rest of Spain (Comunidad de Madrid, 2023). Both the capital city of Madrid and the wider region have consistently received migrant populations from other parts of the country (Instituto Nacional de Estadística [INE], 2022). Since the survey was conducted not only in Madrid city but also in surrounding towns, socioeconomic distribution is guaranteed. In terms of political positions, although right-wing parties received seven percentage points more support in Madrid in 2019, the difference between left- and right-wing support in Spain and Madrid overall is not significant—only two percentage points (Junta Electoral Central, 2019). The only slight divergence between Madrid and the whole of Spain relates to the population pyramid; however, because of the age groups chosen for the study, among those over 65 are not considered relevant (INE, 2024).

Various characteristics of the participants were collected and used as independent variables for the study, as follows:

Table 1. Demographic Characteristics of the Population Surveyed.

Variable	Characteristic	No. (%)
Gender	1-male	408 (48.6)
	2-female	432 (51.4)
Age*	18–24	184 (21.9)
	25–34	118 (14.0)
	35–44	151 (18.0)
	45–54	151 (18.0)
	55–64	93 (11.0)
	>64	143 (17.0)
Education	1-No schooling or unfinished primary education	0 (0.0)
	2-Completed primary school	8 (0.9)
	3-Completed compulsory secondary education	39 (4.6)
	4-Completed 6th form or Intermediate Vocational Training	316 (37.6)
	5-Diploma of higher education or a certificate in engineering	132 (15.7)
	6-Bachelor's or university degree	216 (25.7)
	7-Master's degree	113 (13.5)
	8-PhD	15 (1.8)
	Other-Do not answer (DNA)	1 (0.2)
Population of the town or city	1-<10,000	28 (3.3)
	2-10,000 a 20,000	28 (3.3)
	3-20,001 a 50,000	61 (7.3)
	4-50,001 a 100,000	103 (12.2)
	5-100,001 a 500,000	182 (21.7)
	6->500,001	438 (52.2)
Social class (SC)**	1-A1 (>3,005 €/month—Upper Class)	104 (12.4)
	2-A2 (from 2,452 to 3,005 €/month—Upper class)	218 (25.9)
	3-B (from 2,146 to 2,451 €/month—Upper-middle class)	149 (17.7)
	4-C (from 1,603 to 2,145 €/month—Middle class)	230 (27.4)
	5-D (1,313 to 1,602 €/month—Lower-middle class)	63 (7.5)
	6-E1 (from 745 to 1,312 €/month—Lower class)	67 (8)
	7-E2 (<744 €—Lower class)	9 (1.1)
Political ideology***	0-1-2-Extreme left	117 (13.9)
	3-4-Left	200 (23.8)
	5-Centre	193 (23.0)
	6-7-Right	1.9)
	8-9-10-Extreme Right	(7.3)

*Although age was registered according to the age of each participant, it is presented by age range in Table 1.
**The social class categorization is based on the Estudio General de Medios (EGM) [General Media Studies] (Asociación para la Investigación de Medios de Comunicación [AIMC], 2015).
***The measure of political ideology was derived from respondents' self-placement on a 0–10 scale, where 0 represented the extreme left and 10 represented the extreme right. This method of assessing an

individual's self-perceived political alignment has been standardized since Thurstone's pioneering studies on subjective self-perception. More specifically, its adoption can be traced to Cantril's scale, designed for "the measurement of psychological aspects of social structure" (Díez-Nicolás & Torregrosa-Peris, 1967, p. 79).
Source: Created by the authors.

The entire survey comprised 75 questions, including a section focused on determining the propensity to repost misleading messages and news of dubious accuracy. The questions used for this study, which are considered essential to the research objectives, are as follows:

- Q11: How much credibility do you give to the news you access?
- Q12: How often do you share news on your networks (this includes messaging apps such as WhatsApp, Telegram, etc.)?
- Q13: How often do you receive news that you believe to be false?
- Q17: How do you react when you receive news that you believe to be false?
- Q18: If you have ever shared a news item that you doubted, why did you do so?

Once the data had been displayed numerically, the following analyses were conducted:

- The Pearson correlation, to observe possible statistical relationships between the responses to Q11, Q12, Q13, Q17, and Q18, and the sociodemographic variables.
- Multiple linear regression, starting from the dependent variable in response to Q12, to determine whether this propensity to disseminate messages without contrasting them has a linear fit and could predict the ease of forwarding from the rest of the variables taken as independent.
- Regression tree analysis using machine learning techniques to predict the behavior of a particular variable (Lantz, 2019). Sociodemographic variables were used, considering Q12 as the dependent variable and the others as independent. To achieve this, the Classification and Regression Trees (CART) algorithm (Breiman, Friedman, Olshen, & Stone, 1984) was used through the *Rpart* package in *R*: https://cran.r-project.org/web/packages/rpart/index.html.
- A t-test was conducted using a cluster analysis through the *K-means* algorithm to determine groups. This unsupervised automatic learning algorithm aims to divide a set of data into *K-groups* or clusters, where each datum is grouped with others of similar behavior and/or characteristics. In this way, patterns can be found in unlabeled data sets. The number of *K-groups* to be formed has been established in this study following Dunn's index, which determines the quality of the clustering (Rossbroich, Durieux, & Wilderjans, 2022). Thus, from $k = 2$ to $k = 15$, the number of groups that best represent and divide the data set will be tested. This method aims to determine the groups of people most likely to spread messages on social networks without checking their veracity. Since the variables use different scales, all have been rescaled to a common range of [0, 1]. Missing values (i.e., unanswered items or those the respondent chooses not to answer) are replaced with the median instead. This normalization (Rai, 2019) and assignment to empty items (Aschenbruck, Szepannek, & Wilhelm, 2023; Lantz, 2019) do not significantly alter the final result and improve algorithm performance. Finally, once the clusters are determined, they are rescaled to the scale of each variable for better understanding.
- Clustering the *K-means* into four quartiles or consolidated macro-groups according to quantitative and qualitative criteria related to the behavior of the subjects in terms of the dissemination of news

on social media. Based on the identification of these groups, a cross-checking of the data with the sociodemographic variables was conducted.

- All calculated with *RStudio*. Calculations using machine learning and figures were performed using R software advanced statistics, and the *R* interface called Rattle was used to assist in the calculations (Williams, 2011).

Results

The characteristics of the surveyed sample are as follows: the gender distribution is slightly skewed toward women (408 vs. 432 men); age is evenly distributed; the most common educational level is 6th form, followed by a bachelor's degree; and most respondents belong to the middle or upper class. In terms of political ideology, the majority of respondents say they are in the center. All respondents live in Madrid, Spain. The survey was conducted between February 2, 2022, and March 3, 2022, with a sampling error of ± 2.67% (95.0% confidence).

As explained above, to understand whether there is any relationship between the sociodemographic variables and the answers to questions Q11, Q12, Q13, Q17, and Q18, a Pearson correlation analysis was first conducted. The results show that there is no linear relationship between the variables and the answers. The only slight correlation worth mentioning is an R^2 *value* of 0.402 between Q12 and Q13, so it can be affirmed that no single variable defines the others, and each appears to be linearly independent from the rest.

For a more comprehensive analysis and to determine whether a true dependence exists between the sociodemographic variables and the target question, a linear fit ANOVA was performed. The results of the linear regression are presented in Table 2.

The expression *Pr* (> *Chisq*) refers to the p value associated with the chi-square hypothesis test in a polynomial linear regression analysis. The p value associated with this test is calculated based on the chi-square distribution and provides a measure of how likely it is to obtain the observed data under the null hypothesis that there is no relationship between the variables. Based on this calculation, and with a $p < 0.001$, a significant relationship between sociodemographic variables is observed in three cases: age and the responses to Q13 and Q17. Lowering the confidence interval to 95% ($p > 0.05$), the relationship with the gender variable remains statistically significant. Finally, a $p > 0.1$ is observed in response to Q18. All variables have 5 degrees of freedom (*Df*). Therefore, age and the responses to Q13 and Q17 will mainly determine news dissemination, followed—though to a lesser extent but still significantly—by gender and, to an even lesser degree, by the response to Q18.

Table 2. Linear Regression With the Response to Q12 as a Dependent Variable.

LR	*Chisq* (*R²*)	*Df*	*Pr* (> *Chisq*)	Coding
Gender	13.106	5	0.02241	*
Age	33.121	5	0.0000036	***
Inhabitants	1.629	5	0.89770	
Education	5.624	5	0.34455	
Social class	3.677	5	0.59675	
Q11	5.879	5	0.31815	
Q13	102.596	5	<2.2*10-16	***
Q17	21.491	5	0.00065	***
Q18	9.571	5	0.08835	
Political ideology	3.759	5	0.58463	

Coding symbols: *** = 0., ** = 0.001, * = 0.05, . = 0.1, ' ' = 1. Source: Created by the authors.

The presence of variables that are statistically significant can also be determined by applying the classification decision tree algorithm (CART) shown in Figure 1. Here, we can see how the different answers to Q12 are considered based on the variables of age, Q11, Q13, Q17, and Q18.

In this way, the tree already provides an initial conclusion about who spreads information on a daily basis: people who trust their sources and do not question them (Q18) and people who repost what they receive, even if they believe it to be false. This group represents just 1% of the total survey sample, yet they are individuals who repost messages every day without contrasting them. They are aware that they often receive fake news (*p*13 < 3) but show no concern for the consequences.

If we look at those who spread messages every week (Value 2), we see that these are people under 50 years old (19% of the total), yet they do not trust or give much credibility to the news they receive. By contrast, those who say they never receive fake news (*p*13 = 5) are those who say they never spread news on social media (15% of the sample).

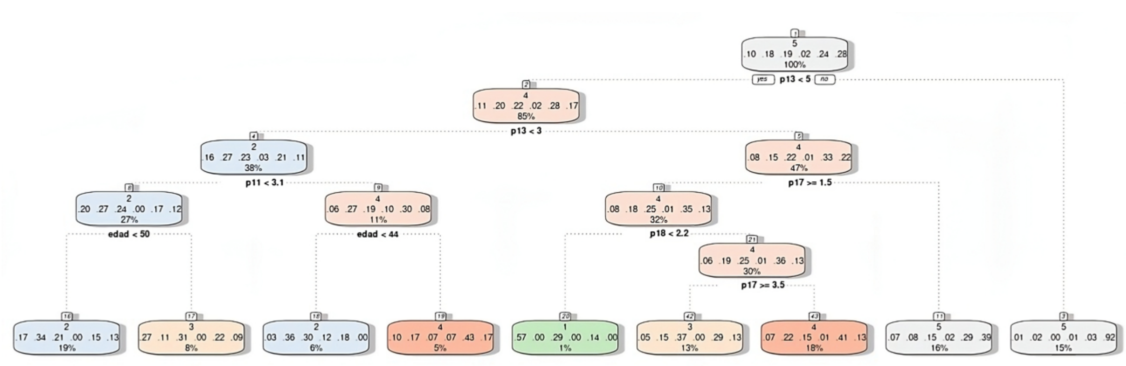

Figure 1. Regression tree regarding the dependent variable Q12. Source: Created by the authors.

It can be seen that both the polynomial linear regression and the tree-based ranking algorithm determine the importance of the same variables, with only one personal variable, age, appearing as a determinant.

On the other hand, there is a lack of concern among those who say they receive fake news and yet share it without verification. This is mainly the case for respondents who trust the source and believe the message to be true.

To determine the existence of groups or profiles of people according to their behavior, a machine learning study was carried out using a k-means algorithm to analyze these relationships in greater depth and to determine the groups most likely to disseminate these messages.

To obtain the number of clusters (K), Dunn's index was used, which evaluates grouping quality, with its highest value indicating the greatest separation and compactness between each cluster. Values from $K = 2$ to $K = 15$ were tested, with Dunn's value reaching its maximum value (0.167) at $K = 11$. Therefore, 11 clusters were established (see Table 3).

Table 3. Cluster Grouping by Applying the K-means With K = 11.

Quartile		Q12	Gender	Age	Inhabitants	Education	Social class	Q11	Q13	Q17	Q18	Political ideology	Cluster size
Q1	1	2.83	1.46	24.77	5.17	5.52	2.42	3.08	2.56	2.71	2.42	4.88	8.16%
Q1	2	3.02	1.57	32.24	5.52	5.74	2.93	3.08	2.55	2.70	2.40	3.26	7.14%
Q1	3	3.10	1.69	37.94	5.08	5.02	3.27	3.23	2.75	2.67	2.39	5.90	8.84%
Q2	4	3.18	1.47	49.20	4.92	5.32	3.16	3.20	2.65	2.22	2.38	4.84	12.76%
Q2	5	3.18	1.36	55.66	4.59	5.11	3.16	3.34	3.02	2.68	2.40	5.41	7.48%
Q2	6	3.19	1.42	20.41	4.91	4.21	3.95	3.03	2.57	2.58	2.36	5.53	13.78%
Q3	7	3.38	1.53	43.47	5.15	5.42	2.90	3.24	2.71	2.68	2.34	4.88	12.24%
Q3	8	3.41	1.56	63.53	4.96	4.87	3.40	3.02	2.83	2.11	2.44	4.76	10.03%
Q4	9	4.26	1.44	72.50	5.07	5.11	3.22	3.03	3.79	2.47	2.39	5.56	5.78%
Q4	10	4.44	1.41	79.12	5.07	5.11	3.22	3.13	4.24	2.83	2.54	5.12	2.89%
Q4	11	4.67	1.66	67.97	5.07	5.11	3.22	3.16	4.53	2.32	2.37	5.47	10.88%

Source: Created by the authors.

After establishing the 11 *K-means* groups determined according to the sociodemographic variables and considering the behavior of the subjects with regard to the dissemination of news (Q12), a quantitative-qualitative study of each group was carried out. The aim was to discover the characteristics of the people who share the most news on social media, their perception of the amount of fake news they receive, and how they behave with regard to the latter.

For clarity, the 11 groups were ranked from lowest to highest according to the response to Question 12: "How often do you share news on your social media sites?" There were five possible levels of response: (1 = Every day, 2 = Every week, 3 = Sometimes during the month, 4 = Sporadically, 5 = Never). Thus, by analyzing the column named Q12 in Table 3, we observe that values closer to 1 represent people who share the most news on social media, while values closer to 5 represent those who never share news on their sites.

To establish meaningful profiles, we divided the groups into quartiles and gave them adjectival names to distinguish them (see Table 4).

Table 4. Description of the Quartile Groups.

Category	Quartile	Average level of dissemination	Sociodemographic features
Proactive	Q1	2.98	This group is mainly composed of women with an average age of 31 years, residing in cities with more than 100,000 inhabitants, with a Diploma of Higher Education or a Diploma in Technical Engineering, from the upper class or upper-middle class.
Moderate	Q2	3.183	This is a group in which there are more men than women, with an average age of 41 years, residing in cities of 50,000 to 100,000 inhabitants, with Advanced Vocational Training or a Diploma of Higher Education, from the upper-middle class.
Sporadic	Q3	3.39	These are mainly women, with an average age of 53 years, residing in cities with more than 100,000 inhabitants, with Advanced Vocational Training or a Diploma of Higher Education, from the upper class or upper-middle class.
Inactive	Q4	4.45	This group is divided equally between men and women, with an average age of 73 years, residing in cities with 100,000 inhabitants, with a Diploma of Higher Education or a Diploma in Technical Engineering, and from the upper-middle class.

Source: Created by the authors.

The first notable finding is a perfect correlation between the level of news dissemination and age. Consequently, the people who disseminate the most—proactive users—are the youngest in the survey (average age 31), followed by moderate transmitters (41 years), sporadic users (53 years), and inactive users (73 years), who never or seldomly share news on their social media sites.

The rest of the sociodemographic variables do not show significant differences for the surveyed population as a whole, although there are fluctuations among individuals regarding the responses to Q11, Q13, Q17, and Q18, as we discuss below.

Q11 (How much credibility do you give to the news you access?) shows that the entire sample gives "sufficient" credibility, with women aged 41 (Quartile 2) ranking the highest at 3.34 of 5.

Q13 (How often do you receive news that you believe to be false?) is directly related to the objectives of this research. The respondents could choose among the following: 1 = Every day, 2 = Every week, 3 = Sometimes during the month, 4 = Sporadically, and 5 = Never.

According to this scale, the closer the indicator is to 1, the more fake news these people receive, or at least the more aware they are of receiving it.

The two most striking results are found in Quartile 4 (average age 73), whose response is higher than 4; that is, they never receive fake news. On the other hand, in Quartile 1 (average age 31), we found values below 3, which indicates they receive fake news every week. Among Quartiles 2 and 3, we found a disparity in the range between 2 and 3, indicating that they receive fake news every week or sometimes during the month.

For Q17 (How do you react when you receive news that you believe to be false?), there were four possible answers: 1 = I do nothing (neither verify nor share it); 2 = I share it, even if I believe it to be false; 3 = I try to check its authenticity to see if it is true; and 4 = I check its veracity and warn others if it is false. This question aimed to understand how respondents behave when faced with news that they believe to be false, thereby establishing a behavioral range that goes from inaction (indifferent attitude toward disinformation) to checking and alerting the community (proactive attitude in fighting disinformation).

All the groups fall between 2 and 3; that is, those who share a news item while doubting its veracity and those who try to determine whether it is authentic. No group is at the extremes, and those closest to 3 were the 73-year-olds.

Regarding Q18 (If you have ever shared a piece of news that you believed was possibly false, why did you do it?), five possible options emerged: 1 = I trusted the person who sent it to me; 2 = I thought it was true; 3 = I agreed with the content; 4 = I was talking badly of a political party opposed to my own; and 5 = I had received it through many channels. This question sought to explore respondents' motivations for sharing news of dubious veracity, including options reflecting common psychological biases.

As with the previous question, all groups fell between options 2 and 3; that is, they shared the news item either because they thought it was true or because they agreed with the content, confirming the presence of confirmation bias. There were no other significant differences between the groups.

Finally, the survey included the variable of political ideology using a scale from 0 to 10, grouped into five levels: 0-1-2 = Extreme Left; 3-4 = Left; 5 = Center; 6-7 = Right; and 8-9-10 = Extreme Right. This variable aimed to obtain data that would eventually be significant when cross-checked with the level of dissemination of fake news and the attitude toward disinformation.

The first observation is that the average of 5.06 places respondents at the political center. Moreover, the distribution between center right and center left appears random and does not correspond with any other sociodemographic variable. The most random values are found between a Quartile 1 segment consisting mainly of 32-year-old women, with a value of 3.26, placing them clearly on the political left, and another Quartile 1 segment composed mostly of 38-year-old women, with a value of 5.90, placing them almost on the right. Notably, both the extreme left and the extreme right come from the youngest age group and from the largest disseminators of news on social media, called the proactive.

Discussion and Conclusions

This research has achieved the overall objective of increasing the body of knowledge related to information disorders, as well as the specific objective of describing some of the characteristics of how and by whom false or untruthful content is shared on social media. This has been possible thanks to the statistical treatment of data using advanced algorithmic techniques, which have allowed us to draw some relevant conclusions.

First, it has been found that the most active people on social media (including messaging apps), who say they repost news every day, are also the ones who claim to receive more fake news. Conversely, those who say they never receive fake news are the same people who say they never spread any news on their social media sites. Furthermore, those who say they read more news are those more likely to spread disinformation.

In terms of age, those who report receiving more fake news are the youngest group (average age 31), while older individuals do not acknowledge receiving fake news in a considerable amount (average age 73).

The first conclusion to be drawn from these data is that young people feel more exposed to fake news than older people, although the research does not reveal why older people report not receiving fake news, whether because of a lack of knowledge, inadequate skills in identifying it, or simply less exposure from spending less time on social networks. In any case, a direct relationship has been found between those who are most active on social media and those who receive the most disinformation, which could explain a certain indifferent attitude toward disinformation, insofar as they are familiar with it and accept it as part of the game.

However, when we analyze the reasons why respondents say they share fake news, all groups fluctuate between two explanations: first, because "I thought it was true," and second, because "I agreed with the content." Although the variations are small, it is noticeable that in group 10 (average age 79), the explanation "I agreed with the content" is stronger. This group—older individuals—reports receiving the least fake news, yet they are among the most likely to it, often because they agree with the content. Strangely, they are also the group most likely to verify the authenticity of dubious messages.

Similarly, the second group that disseminates the most because they agree with the content (Group 8) is the third oldest group (average age 63.53), which tends to do so more often than the previous group (every week). In contrast, young people generally recognize that they spread fake news because they believe it to be true (Groups 6 and 7, with average ages of 20.41 and 43.47, respectively).

These data suggest that most respondents spread fake news because they believe it to be true, although older people, who repost much less than younger people, admit to doing so because it reaffirms their convictions, even though they claim to verify the news most often. From this affirmation, it can be inferred that although older individuals verify information most often, they also repost news that aligns with their beliefs—suggesting they may share fake news consciously. Nevertheless, they do so sporadically and far less frequently than younger people, who disseminate to a greater extent simply because they are naiver.

This finding aligns with the conclusions of Arechar et al. (2023), which established a correlation between individuals' ability to distinguish between true and false news and their willingness to share it. Our research reinforces the notion that a dissonance exists between the perception of truth and the behavior of sharing misleading information, despite the stated importance of veracity.

Another significant finding relates to the reasons that induce people to repost without verifying news that they believe to be dubious. This occurs mainly among respondents who claim to believe that fake news is true because they trust the source and among those who simply believe the message was true. This finding supports the thesis that the identity of the source and the lack of cognitive reflection are two of the most common factors that lead people to believe fake news.

Finally, the data obtained in this research do not allow us to confirm the second hypothesis, which states that the most politically polarized individuals are the largest disseminators of fake news. This has been confirmed by our study because of the fact that the average of the respondents is 5.06, with 0 being extreme left and 10 being extreme right.

This survey does not allow us to identify politically polarized groups. However, it has been shown that the group with the strongest ideological position on the left (3.26 according to the abovementioned scale) coincides with the proactive group, which partly confirms the initial hypothesis.

Our research converges with the thesis presented by Altay et al. (2023), which supports the significance of political ideology as a key factor in the belief and dissemination of misinformation. The experts surveyed by these authors identified political ideology as a central determinant of misinformation-related behavior. This resonates with our conclusion regarding the impact of ideological biases on the consumption and spread of false news.

In summary, the research has allowed us to identify the large disseminators, or the proactive, as a social group comprised mainly of women aged 31, politically positioned on the left and more exposed to disinformation. At the other extreme are the inactive: individuals with an average age of 73, identified politically as being in the center, who claim to never share news on social media and are unaware of being exposed to disinformation.

This study could be broadened in the future by cross-referencing other variables from the general survey with the results obtained in the statistical analysis herein. In this way, it will be possible to deepen our knowledge about both the receivers and disseminators of disinformation on social networks.

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