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RESEARCH ARTICLE

Crisis, country, and party lines: politicians' misinformation behavior and public engagement

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Abstract

Politicians with large media visibility and social media audiences have a significant influence on public discourse. Consequently, their dissemination of misinformation can have profound implications for society. This study investigated the misinformation-sharing behavior of 3277 politicians and associated public engagement by using data from X (formerly Twitter) during 2020–2021. The analysis was grounded in a novel and comprehensive dataset including over 400,000 tweets covering multiple levels of governance, including national executive, national legislative, and regional executive, in Germany, Italy, the UK, and the USA, representing distinct clusters of misinformation resilience. Striking cross-country differences in misinformation-sharing behavior and public engagement were observed. Politicians from countries with a high level of political polarization and populist communication (i.e., Italy and the USA) exhibited the highest rates of misinformation sharing, primarily among far-right and conservative legislators. Public engagement with misinformation also varied significantly. In the USA, misinformation attracted over 2.5 times the engagement of reliable information. In Italy, although misinformation and reliable information received similar levels of engagement, crisis-related misinformation, particularly regarding COVID-19, surpassed general misinformation in both prevalence and audience engagement. These insights underscore the critical roles of political affiliation, governance level, and crisis contexts in shaping the dynamics of misinformation. The study expands the literature by providing a cross-national, multi-level perspective, shedding light on how political actors influence the proliferation of misinformation during crisis.

Keywords Political communication · Misinformation · Social media · Crisis · Comparative research

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1 Introduction

Social media platforms are a primary source of news and information [1]. Through either active searches or unintentional exposure, news shared by political actors, such as prominent politicians and government agencies, has become an important part of citizens' media intake [2]. In this hybrid media system, traditional (e.g., newspapers) and digital media (e.g., social media) coexist and interact, while the boundaries between the two types of media are increasingly blurred [3]. The role of professional journalists as primary newsmakers has been challenged by the emergence of social media [3], which enabled politicians and others to join the news-making ecosystem as new actors [4].

Among the types of information shared by politicians, misinformation, broadly defined as any information that is misleading, unreliable, and/or turns out to be false [5], has received considerable attention [5, 6]. Although misinformation represents only a small fraction of the messages shared by politicians [6, 7], its societal impact remains substantial, as it may contribute to the spread of science denial [8] or the promotion of extreme political ideologies [9].

Due to variations in political structures, media traditions, and economic development in different regions and countries, the hybrid media system has distinct cross-territorial characteristics [10, 11]. These distinctions have informed theorization of three clusters of countries, each exhibiting varying levels of resilience to misinformation [11]. The media-supportive cluster includes Western European democracies (e.g., Germany and the United Kingdom [UK]) with low levels of polarization and populist communication along with high levels of trust in established news media. This cluster is the most resilient to online misinformation [11]. The polarized cluster, consisting of Southern European countries such as Italy, is characterized by relatively high levels of political polarization, prevalent populist communication, and low trust in established news media. These factors make it more susceptible to online misinformation [11]. The United States of America (USA) represents a distinct cluster, marked by a politicized and fragmented media environment with similarly low trust in traditional media. This cluster is considered the most vulnerable to online misinformation due to high levels of polarized and populist communication and diminishing trust in established news sources. The size of the U.S. media market al.so incentivizes the production and dissemination of attention-triggering content [11].

Although countries exhibit varying levels of resilience to misinformation, the spreading of online misinformation is widely acknowledged as a global issue [12–17] and poses significant threats during crises. Even countries with high levels of misinformation resilience can be vulnerable to its influence [18]. Tackling misinformation at the global level [13] requires comparative research to assess its impact and to develop effective mitigation strategies [19].

Empirical evidence on the spread of misinformation by politicians and its consequences remains inconclusive [4, 20], and research beyond the United States is notably limited [19]. Our study therefore examined the misinformation-sharing behavior of politicians in Germany, Italy, the UK, and the USA. These countries were selected to represent distinct clusters of misinformation resilience [11] and diverse geopolitical contexts, including both EU member states (Germany, Italy) and non-EU coun-

tries (UK, USA). EU member states have comparatively stricter regulations on online misinformation [21].

Political authority is multi-layered in most countries, with decision-making power distributed across executive and legislative branches at national and regional levels. This highlights another critical research gap, as existing studies have tended to focus on national legislative politicians [7, 20], often overlooking the roles of executive and regional politicians. Nonetheless, these groups can play a substantial role in the spread of misinformation, with potentially far-reaching consequences. For instance, executive politicians typically have greater media visibility and a larger social media audience than legislative politicians [22], which may amplify the reach of misinformation they share. Similarly, regional politicians' communication on social media can strongly shape public opinion on local issues [23] and make misinformation they share particularly impactful in their areas.

To address these overlooked dimensions, we analyzed and compared the misinformation-sharing behavior of national executive (NE), national legislative (NL), and regional executive (RE) politicians in the selected countries. The goal was to provide a more comprehensive understanding of how misinformation proliferates across different political roles and levels of governance. We selected X (formerly Twitter) for the research due to its extensive use by politicians in the selected countries [1]. Our study focused on the years 2020 and 2021 for two main reasons. First, this period was marked by significant political and societal events, including elections, government transitions, and the COVID-19 pandemic, which raised concerns about misinformation and the so-called 'infodemic' [24, 25]. Second, data availability constraints influenced our choice. X was acquired by Elon Musk in 2022, after which the Academic API was discontinued, making further data collection no longer possible. Building on the two identified research gaps, our study addressed the following research question:

– **RQ1**: *How much (mis)information was shared by the politicians (a) across the four selected countries and (b) at the three levels of political hierarchy?*

Politicians may prioritize advancing their agendas over ensuring factual accuracy, potentially using misinformation as a strategic tool to achieve political goals [4, 26, 27]. Due to their high visibility, misinformation shared by politicians might attract substantial public engagement [28], which can in turn increase the perceived credibility of the content [29, 30]. This dissemination could be driven more by the authority associated with politicians than by the factual accuracy of the information [28, 31]. However, it remains unclear whether misinformation shared by politicians consistently outperforms reliable information in engagement.

– **RQ2**: *To what extent did the shared (mis)information attract public engagement in the countries?*

Existing research suggests that misinformation dynamics are context-dependent [18], often shaped by major political and crisis events such as elections or natural disasters [32]. Unlike political events, which tend to have predictable patterns (e.g., elections) or antecedents (e.g., Brexit), crises typically occur abruptly, creating an

information vacuum. During such times, heightened emotions and unmet informational needs can create fertile ground for misinformation to thrive [33]. This was particularly evident during the COVID-19 pandemic, where the overabundance of information, including misinformation, was described as an infodemic [24, 34]. However, it remains uncertain to what extent crises amplify the dissemination of misinformation by politicians and whether misinformation elicits greater public engagement compared to other types of content.

– **RQ3**: *To what extent was crisis-related misinformation (a) shared and (b) engaged with, compared to other types of misinformation, in the four countries?*

Studies have indicated that conservative [20] and far-right politicians [7] are the most frequent sources of misinformation, especially during periods of heightened political or societal tensions [18, 35]. The societal and political turbulence of 2020–2021 likely shaped how politicians from different parties communicated with the public [36], and the extent to which they engaged in sharing misinformation [7, 36]. This context underscores the need to reexamine previous research findings and evaluate how these dynamics impacted public engagement during this period.

– **RQ4**: *To what extent did different political parties share misinformation on X during 2020 and 2021, and how much public engagement did this misinformation attract?*

Addressing these four questions will provide insights into the overall landscape of the misinformation-sharing behavior of politicians in various countries and political hierarchies over two years of severe crises. By analyzing public engagement, we have identified interaction patterns that contribute to the dynamics of misinformation dissemination. Our study thus offers comparative insights into how misinformation propagates in diverse contexts and thus enhances understanding of the roles of political hierarchy and national context in the sharing of misinformation and its impact on public discourse.

2 Data collection and processing

We systematically sampled NE, NL, and RE politicians from the four countries according to official websites and then identified their respective usernames on X [37]. Our research data were subsequently retrieved using Twitter Academic API [38]. We included information about politicians who were newly elected or discontinued from their positions during 2020 and 2021 to build our list. Data that exceed this time range of position were excluded. In addition, accounts that had not posted in 2020 or 2021 were excluded.

For crisis-related posts, we focused on the COVID-19 pandemic. We classified posts as either COVID-related (i.e., crisis-related) or non-COVID-related (i.e., general). To implement this binary classification, we first created manually labeled ground truth datasets (i.e., training sets) for each country. We then assessed the accu-

racy of COVID-19 annotation provided by the Twitter Academic API [39]. According to the results, we identified false-positive posts, i.e., posts that were COVID-related in ground truth but not annotated by X, and subsequently, extracted the most frequent[1] uni-, bi- and trigrams. After a qualitative evaluation, we compiled a list of supplementary keywords, all related to COVID-19, and applied this list alongside the official annotations to improve classification. We validated our results through manually coded test sets for each country, achieving F1 scores between 0.83 and 0.92 in the four countries (further details for the classification are available in SI).

2.1 Misinformation classification

We used both original tweets and retweets. We extracted domains from the attached URLs, decoding and expanding shortened URLs (e.g., bit.ly). Social media links (e.g., twitter.com, facebook.com) were removed. The processed domain lists were then matched against the NewsGuard rating database [40], a third-party independent resource for news domain credibility. According to NewsGuard, news media are evaluated based on nine key criteria related to credibility and transparency [40]. These criteria form the foundation for the rating system, which assigns a total score of 100. Domains with a score below 60 are considered misinformation.

We collected and processed a total of 1,771,518 URLs, of which 411,347 matched with the NewsGuard database as containing a link to an external news domain. These matched URLs served as the final data for our analyses. It is important to note that while NewsGuard provides a consistent method for assessing domain-level credibility [41], its ratings apply to entire websites rather than to individual news items. As a result, a tweet linking to a low-rated domain is not inherently misleading or false, for instance, it may reference misinformation for the purpose of critique or debunking. Conversely, tweets containing misinformation but lacking URLs are not captured by this approach. Despite these limitations, given the large-scale data and comparative nature of our study, NewsGuard provided a pragmatic and reliable solution for assessing the credibility of news-related content on social media [7, 41].

As a result, Table 1 reports the number of politician accounts and the number of (mis)information tweets in the four countries, with percentages in parentheses indicating each country's contribution to the total.

3 Results

To investigate politicians' misinformation-sharing behavior across the four selected countries and the three theorized clusters of misinformation resilience, we start by calculating the proportion of misinformation shared by politicians (Fig. 1, top panel). To distinguish between misinformation and reliable information, we used NewsGuard's trust scores. A source is classified as misinformation if its trust score is below 60 and as reliable if the score is 60 or higher. Each politician's tweet was categorized

[1] We selected unigrams with a frequency of at least 5, and bigrams and trigrams with a frequency of at least 2.

Table 1 Number of politician accounts and (mis)information tweets by country

	National executive politicians	National legislative politicians	Regional executive politicians	Total politicians	Number of tweets	Reliable information tweets	Misinformation tweets
DE	21	652	92	765	68,871 (16.74%)	67,844 (16.95%)	1027 (9.28%)
IT	28	567	97	692	62,212 (15.12%)	56,324 (14.07%)	5888 (53.23%)
UK	38	815	50	903	116,354 (28.29%)	115,974 (28.97%)	380 (3.44%)
US	56	583	278	917	163,910 (39.85%)	160,143 (40.01%)	3,767 (34.05%)
Total	143	2617	517	3277	411,347	400,285	11,062

Politicians who had an inactive X account, i.e., haven't posted anything during 2020 and 2021, were excluded from our analysis

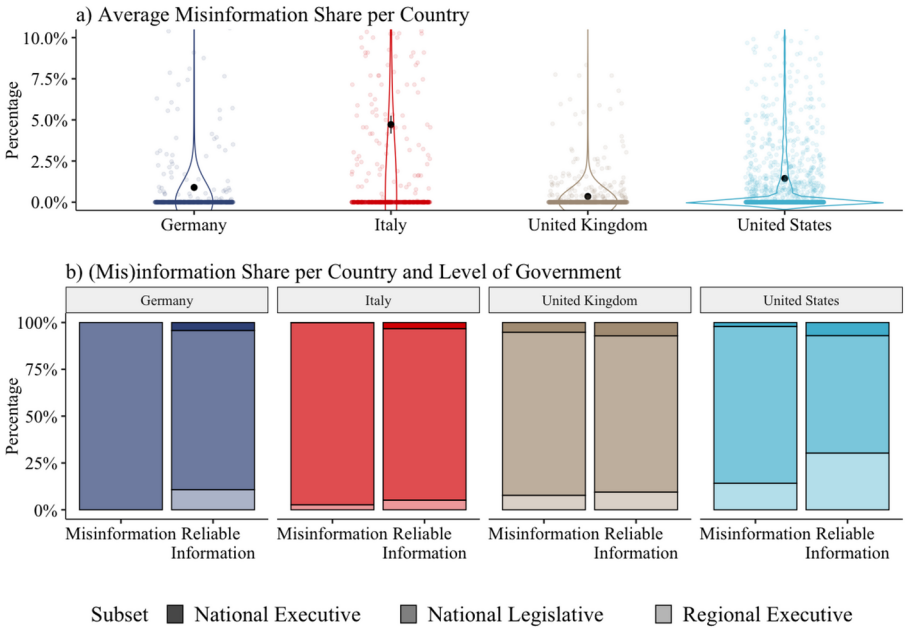

Fig. 1 Misinformation-sharing behavior by country and levels of political hierarchy. **a** Proportion of misinformation shared by politicians in the four countries. The calculation of misinformation sharing ratio was based on individual level. And the violins visualize the distribution of the misinformation sharing ratio per politician and per country. **b** Distribution of shared (mis)information among national executive (high opacity), national legislative (medium opacity), and regional executive (low opacity) politicians in the four countries. In the stacked bar plots, the segments are consistently ordered from top to bottom as national executive, national legislative, and regional executive levels. In the case of Germany, the misinformation bar represents only the national legislative level, as neither national executive nor regional executive politicians shared any misinformation during 2020 and 2021

based on the trust score of the source it referenced (see Methods for details). Among the countries analyzed, Italy exhibited the highest average share of misinformation (M = 0.049, SD = 0.147), approximately 2.2 times higher than the USA (M = 0.022, SD = 0.056), 4.5 times higher than Germany (M = 0.011, SD = 0.055), and 12.3 times higher than the UK (M = 0.004, SD = 0.036). An ANOVA test revealed a significant main effect of country on misinformation-sharing behavior ($F(3, 3116) = 42.65$, $p < .001$). Post hoc comparisons using the Tukey HSD test indicated that Italy exhibited a significantly higher proportion of misinformation compared to the other countries (detailed results can be found in the supplementary information [SI]: Table S1). Further analysis on the three levels of political hierarchy (Fig. 1, bottom panel) revealed that NL politicians shared the most misinformation. Among RE politicians, the highest proportion of misinformation was observed in the USA (11.1%), followed by the UK (6.8%), with notably lower levels in Germany and Italy. Pairwise comparisons using Tukey HSD tests indicated no statistically significant differences in misinformation-sharing behavior across the three levels of political hierarchy within Italy, the UK, or the USA. Germany was not considered in this analysis, as no misinformation was shared by either NE or RE politicians during the study period (further details are available in SI: Tables S2–S3).

The measure of public engagement used in our analysis is the sum of retweets and likes for each tweet. Retweets are generally interpreted as endorsements [42], while likes indicate general user interest [43]. Figure 2 compares user engagement with reliable information versus misinformation over time, offering insights into patterns and variations across countries. Figure 2a illustrates the cumulative sum of engagement of the two types of information over time, along with a linear trend. The slope of the trend line, represented by the beta coefficient, reflects the ratio of engagement between reliable information and misinformation, with a steeper slope indicating higher engagement with misinformation. Deviations from the trend line highlight tweets that went viral with spikes in public engagement.

For the four countries, the beta coefficient consistently falls below 1, indicating that reliable information attracted higher engagement than misinformation overall. However, statistically significant cross-country variations existed, as confirmed by pairwise z-tests across beta values (all significant at the 1% level). The smallest difference was observed between Italy and the USA (z-statistic = 55.230; detailed results are provided in the SI: Table S4). Both countries exhibited high engagement with misinformation: The USA shows a beta of 4.3%, while Italy registers a considerably higher beta of 9.6%, representing a 2.2-, 12-, and 48-fold increase over the US, German, and UK figures, respectively.

In contrast, the results for the UK and Germany, with beta values of 0.2% and 0.8%, respectively, indicate that misinformation received only a fraction of the engagement that reliable information did. Since these comparisons summarize both the volume of tweets and the average engagement per tweet, we investigated the latter aspect (Fig. 2b) by comparing the cumulative average engagement over time. In Fig. 2b, beta coefficients are notably higher than in Fig. 2a. Statistically significant differences between countries persisted (1% level), with the closest comparison again between Germany and the UK (z-statistic = 62.695). The UK and Germany remained ranked similarly, with misinformation receiving 20.3% and 38.4% of the average

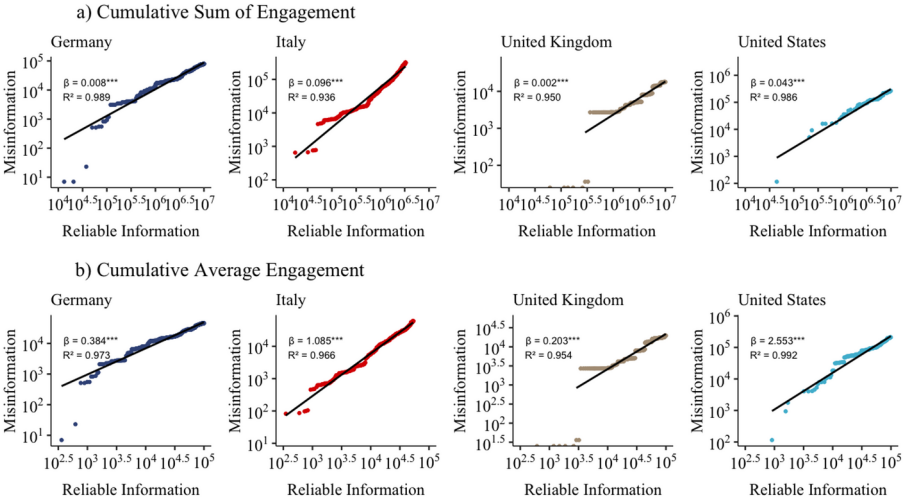

Fig. 2 Public engagement with (mis)information per country. **a** Cumulative sum of engagement with reliable information (x-axis) versus misinformation (y-axis). Daily engagement counts were first aggregated by tweet posting date, then ordered chronologically, and finally cumulatively summed over the course of 2020 and 2021. A linear regression model was fitted to the x- and y-axis values. The slope, indicated by the beta coefficient, reflects the ratio of engagement volumes between reliable information and misinformation. A beta value below 1 suggests higher engagement with reliable information, while a value above 1 suggests higher engagement with misinformation. All linear fits were statistically significant, with significance levels and adjusted R^2 values reported alongside the corresponding beta coefficients. Statistically significant differences were observed across the studied countries. Italy had the highest and the UK the lowest sum of misinformation engagement. **b** Cumulative average engagement with reliable information (x-axis) versus misinformation (y-axis). Here, average daily engagement was calculated instead of daily sums prior to chronological ordering and cumulative summation. The interpretation of the beta coefficient remains the same as in panel (**a**). All the linear fits were statistically significant. Differences are significant across the studied countries. The USA had the highest and the UK the lowest average misinformation engagement

cumulative engagement compared to reliable information. Italy and the USA, however, switched their positions: In Italy, misinformation posts received 1.09 times the average engagement of reliable information, while in the USA, misinformation drew 2.55 times the average engagement. These findings highlight significant cross-country variability in user engagement with (mis)information and align with the patterns suggested by the three clusters identified in the literature [11].

We next distinguished between crisis-related and general tweets shared by politicians during 2020 and 2021. The classification of the two categories was based on the official annotation from X and enhanced by a set of manually validated keyword lists consisting of relevant uni-, bi-, and trigrams (see Methods for details). Figure 3a) compares the share of crisis-related and general misinformation across the four countries over two years. For each politician, we calculated the share of misinformation separately within their crisis-related and general tweets, capturing the relative frequency of misinformation in each context. A two-way ANOVA revealed significant effects for both country ($F(3, 1217)=115.47$, $p<.001$) and misinformation type ($F(1, 1217)=21.83$, $p<.001$). The interaction between country and misinformation type is also statistically significant ($F(3, 1217)=5.46$, $p<.001$). Post hoc analysis

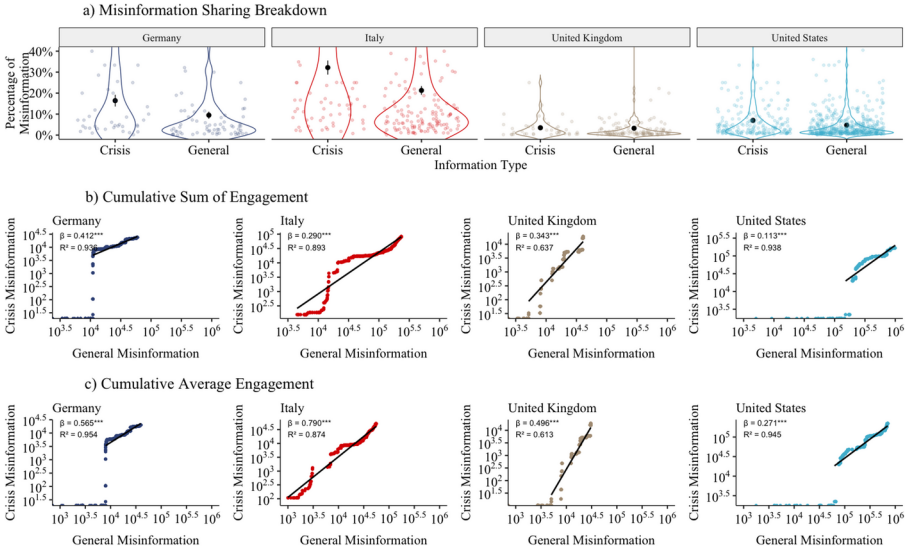

Fig. 3 Comparison of crisis-related and general misinformation by country. **a** Proportions of crisis-related versus general misinformation shared by politicians in four countries. For each politician, the proportion of misinformation was calculated separately for crisis-related and general tweets. In each country, the two violins visualize the distribution of crisis-related misinformation (left) and general misinformation (right) ratio per politician. Statistical analyses reveal significant cross-country variations, with Italian politicians sharing significantly more crisis-related misinformation than general misinformation. **b** Cumulative sum of engagement with general (x-axis) versus crisis-related (y-axis) misinformation over time. Daily engagement counts for general and crisis-related misinformation were aggregated by posting date, chronically ordered and cumulatively summed over the two-year period. The beta coefficient of the linear model indicates the engagement ratio with general and crisis-related misinformation. A beta value below 1 suggests higher engagement with general misinformation; a beta value above 1 suggests higher engagement with crisis-related misinformation. All linear fits were statistically significant; significance levels and adjusted R^2 values are reported alongside the beta coefficients. Significant differences in engagement were observed, with Germany showing the highest and the USA the lowest engagement with crisis-related misinformation. **c** Cumulative average engagement with general (x-axis) versus crisis-related (y-axis) misinformation over time. For each type of misinformation, average daily engagement was calculated, chronologically ordered and cumulatively summed over the two years. All linear fits were statistically significant; the interpretation of the beta coefficient remains the same as in panel (**b**). Significant differences in engagement were observed, with Italy showing the highest and the USA the lowest engagement with crisis-related misinformation

using the Tukey HSD test indicated that Italian politicians shared significantly more crisis-related misinformation compared to general misinformation ($p < .001$). However, no significant differences between misinformation types were observed in the other three countries (further details are provided in the SI: Table S5).

Figure 3b and c compare the cumulative sum and cumulative average engagement with crisis-related and general misinformation over time. This comparison solely focuses on misinformation, reliable information is not included. The y-axis represents the cumulative engagement for crisis-related misinformation, while the x-axis represents general misinformation. In the four countries, the beta coefficient consistently falls below 1 in both panels, indicating that from both perspectives, crisis-related misinformation attracted less engagement than general misinformation.

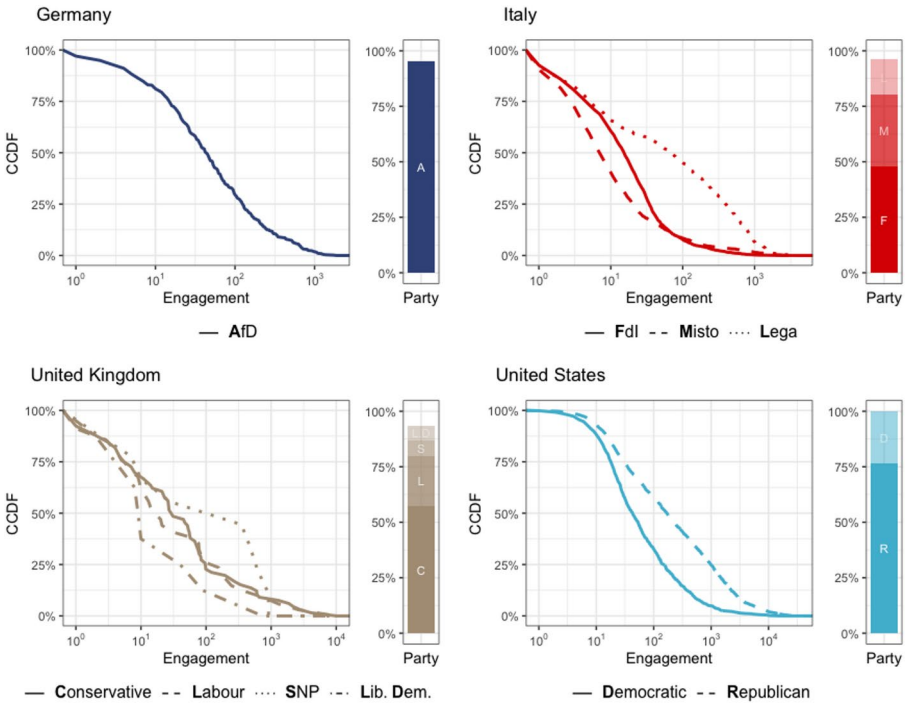

Fig. 4 Misinformation share and engagement distribution by political party. Left plot: Complementary cumulative distribution function of misinformation engagement per political party in each country. Each line type represents a major misinformation-sharing party in its respective country. Right plot: Stacked bar plot showing the proportion of misinformation share per political party in each country. The label on the bar represents the initial of the respective party.

However, variations among the countries existed. From the cumulative sum perspective (Fig. 3b), Germany had the highest engagement with crisis-related misinformation, with a beta coefficient of 41.2%, which is 3.6 times more than that of the USA—the country with the lowest cumulative sum engagement. Regarding cumulative averages, Italy had the highest average engagement with crisis-related misinformation, with a beta coefficient of 79%, which is 2.9 times more than that of the USA, which is still lowest among the countries. Statistical analyses of cross-country variations showed that in both aspects, all the pairs exhibit significant differences (for more details, refer to SI: Table S6).

We then compared the misinformation sharing of political parties. Figure 4 presents the share of misinformation attributed to political parties in the countries, along with the distribution of public engagement for each party. We performed this analysis on NL politicians, focusing on the parties responsible for more than 90% of misinformation tweets within each country. Independent politicians and politicians who did not clearly belong to any party (e.g., Fraktionslos politicians in Germany) were excluded; detailed numbers are provided in the SI: Table S7. The stacked bar plots illustrate the overall share of misinformation for these dominant parties in each country. Notably, far-right (Alternative für Deutschland [AfD, Germany], Fratelli d'Italia

[FdI, Italy]) and conservative (Republican [USA], Conservative [UK]) parties were responsible for the largest shares of misinformation. AfD accounted for 95.5% of misinformation shared in Germany, FdI for 70.7% in Italy, the Conservative Party for 57.3% in the UK, and the Republican Party for 76.4% in the USA.

To compare parties within each country and account for differences in tweet volume, we calculated the proportion of misinformation shared by each party (a breakdown table for misinformation count is available in the SI: Table S8). Specifically, AfD stood out in Germany, where 8.2% ($n = 951$) of the links shared by AfD politicians were misinformation—41 times higher than the second-largest misinformation-sharing group, Die Linke ($n = 23$, 0.2%) and 82 times higher than the third-largest group, CDU/CSU ($n = 7$, 0.1%). In Italy, FdI led with 41.7% ($n = 2{,}747$) of its shared links being misinformation, 4.3 times higher than the second-largest Misto parliamentarian group[2] ($n = 1{,}846$, 9.7%), and 4.5 times higher than the third-largest group, Lega ($n = 927$, 9.2%). In the UK, the Conservative Party ($n = 149$, 0.5%) shared five times more misinformation than the Labour Party ($n = 59$, 0.1%). In the USA, Republicans ($n = 2{,}501$, 4.6%) shared 4.6 times more misinformation than Democrats ($n = 774$, 1.0%). Consistent with previous research [7], these results show that (far-)right parties were significant contributors to misinformation across all the selected countries. However, a notable contrast emerged when comparing Italy to the other countries, nearly 42% of FdI's content consisted of misinformation, a stark difference compared to the far-right parties in other countries whose posts barely reached the 10% mark.

In terms of public engagement, Fig. 4 shows the complementary cumulative distribution functions (CCDFs) of the engagement received by misinformation posts for each party and country. Most of these parties fit a heavy-tailed log-normal distribution (for details see SI: Table S9) indicating that while most misinformation posts received low or moderate engagement, a small portion of them went viral. As mentioned, far-right and conservative parties dominated misinformation sharing. However, notable differences between political parties emerged, particularly in Italy and the USA. For Italy, Lega exhibited a slower decline in its CCDF compared to FdI, indicating that a larger proportion of Lega's misinformation posts garnered higher engagement. This contrasts with FdI, where there was a disconnect between the volume of misinformation shared and the relatively low engagement it generated. The mixed parliamentary group, on the other hand, despite their moderate level of misinformation share, received the least engagement. In the USA, Republicans also experienced higher engagement with their misinformation compared to Democrats, with a larger proportion of Republican misinformation posts receiving significant attention.

4 Discussion

Our findings show a differentiated picture of the role of politicians as sources of misinformation in four countries. To answer RQ1, politicians from countries with a high level of polarization and populist communication (i.e., Italy and the USA

[2] Gruppo Misto, the mixed parliamentary group in Italy, composed of representatives from minority parties.

[11]) shared the most misinformation among the countries, with legislative politicians being the main forces of misinformation sharing. Executive politicians at both national and regional levels shared only a limited amount of misinformation, particularly in Germany and Italy. Addressing RQ2, in media supportive countries (i.e., Germany and the UK), misinformation generally received less engagement compared to reliable information, amounting to two-fifths and one-fifth of the engagement levels in Germany and the UK, respectively. In a polarized system country (i.e., Italy), engagement levels were similar for both types of information. In the USA, where polarization and a large media market coexist, engagement with misinformation was more than 2.5 times higher than with reliable information. However, due to the relatively low volume of misinformation, the cumulative engagement with misinformation remained lower than that of reliable information, peaking at 12% in Italy, a modest 3% in the USA, and being negligible in both media supportive countries. These findings contradict previous evidence that the USA was a unique country where politicians shared much more misinformation than in other countries [7]. Instead, the findings align with research concluding that both Italy and the USA have low levels of trust in established news media, coupled with high levels of polarization and populist communication [11], which contribute to increase misinformation sharing and engagement.

These findings have important implication for existing literature. Commonalities between the media systems in Italy and the USA highlight key factors driving high levels of online misinformation sharing and engagement. However, as the two countries fall into different misinformation resilience clusters, notable difference remain, particularly in media market size [11]. Larger markets are more prone to attention-triggering content and misinformation production [11, 44], yet this does not appear to significantly influence misinformation engagement on X. Despite a smaller media market, Italy exhibited higher levels of misinformation sharing and engagement than the USA. This raises important questions about the actual role of media market size in the spread of online misinformation. While our current study does not directly address this issue, we encourage future research to explore it through more comprehensive analysis.

Regarding RQ3, crisis-related misinformation and general misinformation were shared to a similar extent in most of the countries. The polarized system country (i.e., Italy) was an exception, with significantly higher sharing of crisis-related misinformation than the sharing of general misinformation. Even though crisis-related misinformation tended to receive less public engagement than general misinformation in all the countries, there were cross-country differences. The polarized system country again had the highest public engagement in crisis-related misinformation among the countries. The elevated engagement with crisis-related content may reflect public concern or heightened sensitivity during the COVID-19 crisis [45], as Italy was one of the first European countries to be largely impacted by the pandemic [46]. In all countries studied, approximately half of the misinformation shared was related to crises, supporting the argument that misinformation sharing is largely event-driven [18]. However, our results suggest a need for a more nuanced understanding of the 'infodemic' narrative during COVID-19 [24, 34]. While reliable information dominated social media communication by politicians, a significant portion of misinfor-

mation was unrelated to crises. Furthermore, crisis-related misinformation attracted less engagement compared to general misinformation, which challenges some prevailing assumptions about its impact [24, 47].

While certain countries may be more susceptible to misinformation due to specific media and political characteristics [11], there is no consistent cross-national pattern in the spread of crisis-related misinformation. Even in polarized contexts with strong populist communication, such as Italy and the USA, levels of engagement vary significantly, with Italy showing the highest and the USA showing the lowest engagement among the four countries. Existing frameworks for misinformation resilience often treat misinformation as a uniform phenomenon, limiting their effectiveness in context-specific analyses. A more nuanced, context-sensitive approach is needed, as drivers of misinformation can vary across domains. For example, susceptibility to health misinformation may stem from low trust in science [48, 49], a factor less relevant to political misinformation during elections [5]. Topic-specific variables should therefore be considered to capture dynamics that overarching frameworks may overlook.

Regarding RQ4, at the party level, consistent with previous research [7], our results show politicians from far-right, conservative, and populist parties shared the most misinformation. Moreover, the heavy-tailed log-normal distribution of public engagement in most parties means that only a small amount of misinformation reached a large audience. This disproportionality suggests that those countering misinformation should prioritize addressing highly engaged and deep-impact posts rather than attempt to detect all instances of misinformation. Given the rapid rise of extremism in Europe and the USA, for which misinformation is considered a key driving factor [50], effective and appropriate online content moderation strategies are needed to protect democratic values.

This study has some limitations that also suggest avenues for future research. First, we adopted a source-based approach to classify misinformation by evaluating the reliability of its source (i.e., news domains). This evaluation was carried out by an independent organization using consistent criteria for the analyzed countries, which made it particularly suitable for large-scale cross-country comparisons [7, 18, 51]. However, this approach does not account for misinformation embedded in politician's own original content. In this regard, our source-based method has certain constraints, it may overlook specific instances of misinformation within the text itself, and may fail to capture nuances in political discourse. For example, it cannot detect whether and how a shared source is criticized or framed by politicians.

Despite these shortcomings, the source-based approach remains a reliable method for large-scale comparative research, as it has been repeatedly validated in prior studies [41, 52], and it's grounded in shared evaluation standards [40]. Given the complex and context-dependent nature of misinformation [18], maintaining a consistent and equitable baseline for misinformation detection across diverse cultural, societal, and political environments is challenging. To date, content-based approaches to detecting misinformation in large datasets are unfeasible and often unreliable, particularly in comparative studies. Future research could benefit from a greater focus on reliably classifying the content of posts, potentially by using large language models [53–55]. These tools offer the opportunity to examine the misinformation generated by politi-

cians, its prevalence in different countries and events, and its relative prevalence on social media compared to other sources.

Second, our study was focused on a single platform due to the prominence of X in shaping political discourse during the analyzed period [56]. However, this focus may limit understanding of the broader landscape of online political communication [57]. Given the differences in platform affordances [58] and user demographics [59], patterns of misinformation sharing and public engagement are likely to vary across platforms. Future comparative studies should incorporate additional social media platforms to expand the scope of our findings.

Third, we adopted a broad conceptualization of public engagement, interpreting retweets as endorsement and likes as general interest. However, these metrics may not always reflect support or agreement, as motivation behind online engagements can be heterogenous [60], including negative reactions such as antagonism or irony [61]. and may also result from algorithmic amplification [6]. While such alternative interpretations may be valid in specific contexts, treating likes and retweets as general indicators of support remains consistent with the prevailing consensus in the literature [42, 43], particularly when analyzing large-scale datasets [18, 24, 62], where the nuanced intentions behind individual engagement behaviors are difficult to capture. On X, other forms of engagements, such as replying or quoting, are more commonly associated with negative reactions [63]. Accordingly, aggregating of likes and retweets provides a pragmatic and empirically grounded approach to capturing engagement that is more likely to reflect positive orientation, thereby serving as a proxy for assessing overall support for (mis)information. Nevertheless, a more nuanced conceptualization and measurement of public engagement is warranted for future research.

Finally, this research was limited to high-income countries, which hinders the generalizability of its results on a global scale [13, 19, 64]. The proliferation of politician misinformation is not limited to Western Europe and the USA. In certain cases [12, 14–17], the challenge of misinformation is even more pronounced. Therefore, scaling up the research scope by including low- and middle-income countries is essential [64].

5 Conclusion

Based on an extensive dataset that accounts for a diverse range of countries with different political and media environments, as well as a comprehensive list of politicians at different levels of political hierarchies, this study systematically examined politicians' misinformation-sharing behavior and the corresponding public engagement during 2020 and 2021. Our findings provide a nuanced perspective on how factors such as political affiliation, governance level, and crisis context shape misinformation dynamics in various domains. Despite its limitations, our study provides a cross-national, multi-level analysis of misinformation dissemination and engagement patterns and sheds light on the role of political actors in shaping misinformation dissemination during crises.

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Declarations

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