Media and fake news: An analysis of citizens' attitudes toward misinformation in European countries

Mauro Ferrante, Anna Maria Parroco

1. Introduction

The rapid changes determined by the rise of Internet and by the recent development of social media in everyday life have led to profound consequences on the quantity and quality of information made available and on the mechanisms of their dissemination. Today, information is increasingly shared through decentralized mechanisms in which social media play a role as a distribution channel, thanks to tools and platforms that enable peer-to-peer sharing mechanisms (Baldacci & Pelagalli, 2017). The rapid spread of on-line misinformation is one of the most-discussed issue today and has been identified as one of the top-trends in modern societies by the World Economic Forum (2013). partly because of the link between these processes and political communication. Among the reasons behind the relevance of this phenomenon, in addition to the already mentioned process of decentralization of the information, it is possible to identify also: the loss of control by the media on the dissemination process, now increasingly determined by algorithms that decide what, when and to whom to show in an unpredictable way: the growing power of Internet giants, such as Google, Facebook, and Twitter; to mention but a few, in deciding who to allow to publish news, what news to show, to whom to show it and how to earn from this process. This because among the scope of on-line disinformation, it is possible to identify the intention of generating interaction on social media, to gain profits from advertising or to discredit someone image (Figueira & Oliveira, 2017). It is therefore important to better understand citizens' attitude and trust toward media, and eventually to identify the potential determinants of different attitudes.

Starting from these premises, the present work aims at analysing the attitude of European citizens toward fake news and disinformation. After briefly discussing the growing literature on fake news and disinformation, by virtue of the availability of micro-data from the Flash Eurobarometer survey on "Fake news and disinformation online" (European Commission, 2018), a segmentation of users is proposed according to their attitude towards different types of media. Secondly, clusters are characterized both in terms of socio-demographic characteristics and in relation to users' behaviour and opinions regarding misinformation. In consideration of the social and political relevance of misinformation, potential strategies to face with fake news and online misinformation are discussed.

2. Background

Fake news and misinformation are not new phenomena. However, starting from U.S. Presidential election in November 2016 a rapid increase in the use of the term "fake news" has been observed (Rose, 2020). Also, terms such as "post-fact" and "alternative facts" emerged in new media communications. These terms are referred to deliberate distortion of the news with the aim of having an influence in public opinion and to exasperate the internal divisions in the society (Martens et al., 2018). This determined a rise in preoccupation for fake news and for their capability in generating confusion among the public. When the term fake news is used, the reference is generally to deliberate fraudulent media products. It is indeed a more severe judgement compared to "biased news". Also, fake news is something different from on-line satire. However, except for striking situations, in many cases it is not easy to identify the border between satire and discredit

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intention. Allcott and Gentzkow (2017) define fake news as "news articles that are intentionally and verifiably false and could mislead readers" (Allcott and Gentzkow, 2017, p. 213) with facts entirely false. Dentith (2016) points out that fake news is an "allegation that some story is misleading – it contains significant omissions – or even false – it is a lie – designed to deceive its intended audience" (Dentith, 2016, p. 66), with facts that may be entirely false, contain partial truths, or omissions that would undermine the real fact. Fake news and misinformation have attracted the interest of researchers and institutions in identifying the mechanisms of dissemination of fake news and, eventually, potential strategies for their identification (Shao, 2018). The use of social media to get information has even more amplified the fake news issue: the news, due to its bounce rate, is likely to be contaminated, that is to undergo considerable changes until it becomes itself a fake news. It is undisputed that nowadays mainstream media have been progressively displaced by social media as a source of information. Consequently, individuals must be able to select reliable or unreliable information.

Some studies focused on the principal factors causing fake news and they found that both micro and contextual variables act (Kim & Kim, 2020). People's attitudes and citizens perception towards fake news have been recently investigated by several authors (Reuter et al., 2019; Borges-Tiago et al., 2020; Quan-Haase et al., 2018; Dinev et al., 2009; Fletcher et al., 2018). They agree that age, education, tech-profile, and cultural and ideological differences among users are relevant variables in shaping the attitudes towards fake news and disinformation. Reuter et al. (2018), referring to a survey conducted in Germany, find that people who are younger or more educated show more ability to identify fake news, and liberal or left-wing persons are more critical; Borges-Tiago et al. (2020) show that citizens attitude towards fake news is different among European countries and report that younger and tech savvy users recognize fake news most likely than others. Ouan-Haase et al. (2018), highlight the importance of information literacy characteristics and information technology skills and Dinev et al. (2009) focus on cultural dimension. Finally, Fletcher et al. (2018), in presenting the results on Italian and French attitude towards fake news, stress the relevance of policy makers, private and public companies in acting to regulate information sources. Nonetheless, few studies have assessed whether populations can be segmented according to their attitude toward media. The present work aims at filling this gap and to assess whether these segments exhibit specific characteristics, both in terms of socio-demographic profile and according to media use.

3. Data and Methods

This study uses micro-data from the European Commission Flash Eurobarometer 464 on "fake news and disinformation online" (European Commission, 2018). The survey carried out in 28 Member States in 2018 on a sample of about 26 thousand respondents interviewed via telephone, aims at exploring EU citizens awareness and attitude toward fake news and disinformation online. Detailed information on the survey, as well as the questionnaire and micro-data are made available by the European Commission through the official portal for European data: https://data.europa.eu.

With the aim of identifying the main determinants of consumer attitudes towards misinformation and fake news, in a first step clusters users have been identified in relation to their attitude toward media, for the six different media types considered (i.e. Printed newspapers and news magazines; Online newspapers and news magazines; Online social networks and messaging apps; Television; Radio; Video hosting websites and podcasts). Secondly, the degree of association of socio-demographic characteristics and of media usage with the proposed cluster is explored in order to characterize different profiles of users across European countries.

In consideration of the categorical nature of data concerning the level of trust in media *k*-mode clustering (Huang, 1997) has been implemented. According to this approach, let $A_1, A_2, ..., A_6$ the set of attributes, describing the categorical space Ω , representing the users' opinion on the different media types considered, where the domain DOM(A_j) of each categorical attribute A_j is given by the three answers' categories, namely: *trust, don't trust, don't use that media type.* A categorical object $X \in \Omega$ is represented by the set of attribute-value pair for each of the set of attributes considered,

and it can be represented as a vector $[x_1, x_2, ..., x_6]$. Let $X = \{X_1, X_2, ..., X_n\}$ be the set of *n* categorical objects observed in the *n* sample units. We write $X_i = X_z$ if $x_{i,j} = x_{z,j}$, for $1 \le j \le 6$, i.e. if two generic sample units, *i* and *z*, have the same value for any of the 6 considered attributes.

The *k*-mode algorithm is an extension of the *k*-means clustering procedure to categorical variables (Chaturvedi et al., 2001) and it aims to partition the objects into *k* groups such that the distance from objects to the assigned cluster modes is minimized. A mode of X is a vector $Q = [q_1, q_2, ..., q_6]$ that minimises a dissimilarity measure *d*, which is computed by counting the number of mismatches in all variables (simple-matching distance). The *k*-mode algorithm works iteratively by selecting initial *k*-modes of each cluster, allocating each unit to the cluster with the nearest mode according to *d*, then retesting the dissimilarity of units against the current mode and eventually reallocating the units to the cluster with the nearest mode iteratively, until no unit has changed cluster after a full cycle test of the whole dataset (Huang, 1997). In the present work the package *KlaR* implemented in *R* software has been used for the analysis.

Having been identified the clusters which characterise our sample according to their attitude toward different types of media, a regression modeling approach was undertaken to quantify the degree of association of socio-demographic characteristics and of users' behaviour and opinions regarding misinformation with cluster membership. The covariates included in the model were: 1) *Gender, 2) Age, 3) Occupation, 4) Social network use (How often do you use online social networks?), 5) Reading and sharing attitude on social network (Do you read or share things when using social network?) 6) Presence of fake news and misinformation in the media (Do you come across news which misrepresent reality or are even false?) 7) Confidence in the ability to detect fake news (Are you confident that you are able to identify news or information that misrepresent reality or is even false?) 8) Perception on the danger of misinformation and fake news (Is the existence of news or information that misrepresent reality a problem in your country or for democracy in general?). By considering the categorical nature of the response variable, a multinomial logistic regression model was implemented.*

4. Results

The dataset under analysis is constituted by 26,576 respondents residing in one of the EU28 countries. As also reported by the EU Commission, at an aggregate level, most respondents tend to trust news and information they receive through radio (70%), television (66%) and printed media (63%). However, less than half (47%) trust online newspapers and magazines, and lower proportions trust video hosting websites and podcasts (27%) and online social networks and messaging apps (26%). Also, these results are consistent across all the Member States (European Commission, 2018). Before implementing the clustering algorithm, those cases containing missing data for at least one of the covariates examined for the analyses were removed. This reduced the dataset to 22,384 cases. Then, to implement *k*-mode algorithm, according to the elbow method, a number of clusters equal to 5 was fixed. Modes of each item corresponding to the attitude for the different types of media considered are reported in table 1.

The results of the *k*-mode clustering procedure highlight different segments of users according to their attitude toward different type of media. Those here called *Impatients* are constituted by users which tend to trust on online social network, radio, and television, whereas they tend to do not trust on printed or online newspapers or magazines. On the contrary, it is possible to define as *Traditionalists* those who trust mainly on traditional sources of information, such as printed or online newspapers and radio. Also, they tend not to trust on social network, television, and they do not use video-hosting websites or podcasts. A particular group of users constitute those who can be defined *Sceptics*, which tend not to trust to any type of media. A fourth group are here named as the *News buff*. They trust on media coming from printed or online newspapers, radio, and television. They are very similar to the *Traditionalists*, except for a trust on television compared to *Traditionalists* who do not. Finally, the last group can be labelled as *Credulous*. They believe in almost any type of media; the only exception being represented by video hosting websites which

generally are not used by this type of users.

Cluster ID	Printed newspapers and news magazines	Online newspapers and news magazines	Online social networks and messaging apps	Television	Radio	Video hosting websites and podcasts
Impatients (n = 3024)	Don't trust	Don't trust	Trust	Trust	Trust	Don't trust
Traditionalists $(n = 3401)$	Trust	Trust	Don't trust	Don't trust	Trust	Don't know
Sceptics (<i>n</i> = 3594)	Don't trust	Don't trust	Don't trust	Don't trust	Don't trust	Don't trust
News buff (<i>n</i> = 6428)	Trust	Trust	Don't trust	Trust	Trust	Don't trust
Credulous (<i>n</i> = 5937)	Trust	Trust	Trust	Trust	Trust	Don't know

Table 1. Cluster modes according to the attitude toward different types of media.

Table 2 summarizes beta-coefficients, odds ratios (OR) and related p-values of the multinomial logistic regression model. From an analysis of the results in Table 2, all the considered factors appear significant, although differences emerge in their effects in relation to the various clusters considered. Conditionally to the other variables, and considering the cluster of *Traditionalists* as baseline. *Gender* is significantly associated to the cluster of *Sceptics*, with a risk of being "Male" of about 1.30 higher compared to the baseline, whereas being "Female" is associated with the cluster of *Credulous* (OR=1.11). In terms of Age, being of an age comprised between "25 and 39 years old" and "older than 55 years old", decreases the 'risk' of belonging to the Impatients, compared to the other categories. Also being older than 55 years old decreases the risk of belonging to the News buff, which tend to be younger compared to the Traditionalists. Different occupation profiles characterize the various clusters. Being "manual worker" or "not worker" increases the 'risk' of belonging to the Impatients (OR=1.46 and 1.23, respectively); similarly, "not workers" are more likely to belong to the *Sceptics* (OR=1.23), compared to the other occupation categories. Whereas being "self employed" is negatively associated with the cluster of *Credulous* (OR=0.75). Regarding social network use, frequent users are associated with the Credulous and News buff clusters, whereas being a non-frequent user is associated with the Sceptics. A more active behaviour in terms of *reading or sharing things on social media* characterizes the *Impatients*, the *Sceptics* and the News buff, compared to Traditionalists. On the other hand, Credulous tend not to read or share things on social media, thus indicating a more passive behaviour. Sceptics, as expected, tend to come across news which they think misrepresent reality or are even false. The other clusters perceive less this risk, compared to the Traditionalists. Nonetheless, the Sceptics are less confident on their capability in identifying fake news; the same holds for the Impatients, whereas News buff and *Credulous* are more confident from this perspective. Finally, a perception of fake news and disinformation as a problem in the country or for democracy in general characterizes mainly the *News buff.* On the contrary, those who do not perceive this problem are more likely to belong to the Credulous.

In summary, the analysis of the segmentation results reported in Table 1, jointly with the results of the logistic regression, suggest that *Impatients* and *Credulous* seems to be those at more risk for fake news and misinformation on-line. Also, they do not perceive misinformation as a problem for democracy in general. In the case of the *Impatients* an active behaviour in terms of on-line sharing emerged, thus potentially determining an active role in the spreading of on-line misinformation, also in consideration that both groups are constituted by regular social network users.

Cluster	Variable	Categories	ß	p-value	$Exp(\beta)$
	Gender (Male = Ref.)	Female	0.000	0.997	1.000
		25 - 39	-0.280	0.022	0.756
	Age $(15-24 = \text{Ref})$	40 - 54	-0.204	0.082	0.815
		>=55	-0.304	0.006	0.738
		Self-employed	-0.028	0.754	0.973
	$O_{counstion}$ (Employees = Ref.)	Manual workers	0.376	0.000	1.456
	Occupation (Employees – Ref.)	Not working	0.370	0.000	1.731
Impatients		Almost averyday	0.208	0.002	1.231
	Social network use (several time a month or less= Ref.)	Annost everyday	0.044	0.380	1.043
	$\mathbf{D} = \mathbf{d} = \mathbf{n} \cdot \mathbf{d} = \mathbf{n} \cdot \mathbf{d} \cdot \mathbf{d} \cdot \mathbf{d} = \mathbf{D} \cdot \mathbf{f}$	At least once a week	-0.020	0.789	0.974
	Read, of shale of social network ($NO - Rel.$)	I es	0.210	0.003	1.241
	News misrepresent reality? (No = Ref.)	Yes	-0.152	0.031	0.859
	Able to identify news that misrepresent reality (No=Ker.)	Yes	-0.204	0.000	0.816
	Misinformation is a problem for democracy? (No=Ref.) Yes			0.551	0.942
	Intercept			0.283	
	Gender (Male = Ref.)	Female	-0.266	0.000	0.767
		25 - 39	-0.010	0.932	0.990
Sceptics	Age $(15-24 = \text{Ref.})$	40 - 54	0.010	0.930	1.010
		>=55	-0.202	0.065	0.817
		Self-employed	0.221	0.006	1.248
	Occupation (Employees = Ref.)	Manual workers	0.129	0.222	1.138
		Not working	0.210	0.001	1.234
	Service a start of the service of th	Almost everyday	-0.142	0.062	0.868
	Social network use (several time a month or less= Ref.)	At least once a week	-0.219	0.020	0.803
	Read, or share on social network ($No = Ref.$)	Yes	0.280	0.000	1.323
	News misrepresent reality? (No = Ref.)	Yes	0.449	0.000	1.568
	Able to identify news that misrepresent reality (No=Ref.)	Yes	-0.266	0.000	0.766
	Misinformation is a problem for democracy? (No=Ref.)	Yes	-0.105	0.281	0.901
	Intercept	105	-0.042	0.799	0.701
	Gender (Male = Ref.)	Female	-0.068	0.122	0.935
		25 - 39	-0.216	0.039	0.806
	A = (15 - 24) = R = f	40 - 54	-0.173	0.037	0.841
	Age (15-24 - Kel.)		0.300	0.000	0.677
		Solf amployed	-0.370	0.000	0.792
	$O_{\text{connection}}$ (Employees = P_{conf})	Manual workers	-0.245	0.001	0.783
	Occupation (Employees – Ref.)	Natural workers	-0.100	0.077	0.047
News buff		Not working	-0.312	0.000	0.732
	Social network use (several time a month or less= Ref.)	Almost everyday	0.236	0.001	1.266
		At least once a week	0.159	0.057	1.172
	Read, or share on social network (No = Ref.)	Yes	0.271	0.000	1.311
	News misrepresent reality? (No = Ref.)	Yes	-0.254	0.000	0.775
	Able to identify news that misrepresent reality (No=Ref.) Yes		0.103	0.037	1.108
	Misinformation is a problem for democracy? (No=Ref.) Yes			0.955	1.005
	Intercept			0.000	
	Gender (Male = Ref.)	Female	0.104	0.020	1.109
		25 - 39	-0.041	0.719	0.960
	Age (15-24= Ref.)	40 - 54	0.090	0.409	1.094
		>=55	0.156	0.128	1.169
		Self-employed	-0.291	0.000	0.748
	Occupation (Employees = $Ref.$)	Manual workers	0.052	0.588	1.054
Credulous		Not working	0.022	0.707	1.022
	~	Almost everyday	0.306	0.000	1.358
	Social network use (several time a month or less= Ref.)	At least once a week	-0.192	0.029	0.825
	Read or share on social network ($N_0 = Ref$) Ves		-0 141	0.025	0.868
	News misrepresent reality? $(N_0 - P_0 f)$	Vec	-0.772	0.055	0.000
	Able to identify nows that misropresent reality $(N_2 - R_2f)$	Vac	-0.772	0.000	1 225
	Able to identify news that mislepresent reality ($NO=KeI$.) Miginformation is a problem for domestraty? ($Nc=D=f$.)	1 CS	0.201	0.000	0.707
	Intercont Yes			0.008	0./9/
	Intercept	0.987	0.000		

Table 2. Multinomial regression coefficients, odds ratios $(Exp(\beta))$, and p-values. The baseline is the cluster of "Traditionalists" for the response variable.

5. Conclusion

The results of the present work show different attitudes of European citizens towards the media, and this is related not only to socio-demographic characteristics, but also to their behavior and

opinions regarding misinformation. In considering the relevance of misinformation and fake news in contemporary times, it is important to identify potential strategies for tackling misinformation. Indeed, the role of countering misinformation is the responsibility of a variety of actors. Policymakers could promote a climate of calm discussion around decision that have to be made. The media could make greater efforts to promote unbiased reporting and ensure high standards of quality. It is incumbent on public institutions to provide support and monitoring misinformation, just as social media should pay more attention to the content disseminated through their platforms, playing a role that increasingly resembles that of a publisher. But a key role is represented by education and training, to act on the side of the final recipients of information and make the effects of misinformation less dangerous.

Reflecting on the limitations of this study and future research, it was not possible to include other potentially relevant information, such as the ones regarding tech-profile and cultural background of users since no information are provided from the Eurobarometer survey. It is likely that these aspects markedly affect users' attitude toward media. Finally, the proposed clusters have not been validated in other contexts, a deeper analysis through other data sources and in relation to different geographical areas is required to investigate the validity of the proposed users' segments.

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