HOW MEDIA DIRECTLY IMPACT SOCIETY: A PSYCHOMETRIC ANALYSIS OF LEADING TWITTER NEWS PROFILES AND THEIR FOLLOWERS IN SERBIA

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Abstract: We conducted a quantitative psychometric analysis on Twitter posts, belonging to 20 leading Serbian media, for a period of three months. We did the same kind of processing for their followers, including more than half a million tweets. The analysis has been done using Twitter API on posts data from 24 October until 30 January of 2019, applying the Serbian LIWC psychometric dictionary, and further statistical processing. We show that the language used by the media differs according to their nature and the contents they produce. At the same time, we found that categories and words related to family, feel, sex, spirituality, negative emotions and work, expressed in the posts, are predictors for the tweets of their followers. This actually means that if media reports consist of these elements, they will reflect the language of their followers. Thus, the impact of media on their audiences is clearly registered in the language of Twitter

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users. Such findings confirm the power of media and indicate how important it is to carefully choose media contents, having in mind various potential hazards, including media addiction. Results align with emotional contagion theory. This research was the first one to indicate that various psychometric categories could spread on social media, beyond solely emotions. This research is limited to the assessment of media impact in one country, namely in Serbia. The study suggests that it is important to focus further research on negative news and how they affect multiple groups of people, and to establish a live Media Negativity Index on a global level.

Keywords: psychometric analysis; Twitter; social media impact; big data; LIWC.

Introduction

Today, social media are one of the most important channels of news sharing and consumption, significantly changing the patterns of traditional public communication (Kalsens & Larsson 2017; Chadwick, 2006; Couldry, 2003; Carey & Adam, 2008; Perse & Lambe, 2016; Curran & Hesmondhalgh, 2019). Despite their growing importance, social media are often blamed "as a hotbed of bad news" (Park, 2015, p. 2). After a decade of joint efforts of social science scholars and data scientists to understand the spreading of emotions and behaviours in the online sphere, it is still not clear to what extent and in what ways social media affect emotional states and behaviour of people (Coviello et al., 2014).

In general, when debating the advent of new media, scholars usually tend to focus on its impact on traditional media (Larsson, 2013; Rogstad 2016; Newman 2009;

Atkinson et al., 2019). Unfortunately, the inverse effects of the mainstream media on these new forms of communication remain fairly under researched. Nevertheless, recently, this topic has gained some interest among media researchers, and the results suggest that traditional mass media might still have substantial power in setting the attention of the whole media sphere. For example, some authors have argued that we need to introduce "news story" approach to track the way information spreads through the media sphere, and that traditional media outlets on Twitter have a "vastly more agenda-setting influence than other actors do" (Harder et al., 2017, p. 275). Another study (Conway-Silva et al., 2017) that analyzed 2016 US elections have found that although Twitter as a platform is quite likely to break from "media gatekeeping" its agenda still remains under the influence of traditional media. In a similar vein, Vargo et al. (2015) have shown that, even though agenda salience on Twitter is more volatile when compared to mass-media (due to its openness to real-time occurring events), the overall agenda was to large degree settled by the mainstream media.

Earlier research has demonstrated that human emotions can spread through different social networks affecting physically distant actors, and this phenomenon is known as the emotional contagion (Hatfield et al., 1994; Pugh, 2001; Hill et al., 2010). Recent studies show that emotions can be transferred in online settings through computer mediated communication (Harris & Paradice 2007; Guillory et al. 2011; Dang–Xuan & Stieglitz, 2012; Kramer et al., 2014). For example, Coviello et al. (2014) found that the negative emotions expressed on Facebook are spread to other users, despite the fact that they do not directly relate to the event that struck the person that expressed negative emotions in the first place. Several other studies (Kramer et al., 2014; Ferrara & Yang, 2015; Tang et al., 2012) found that manipulating posts on news-feeds can impact the emotions of social network users.

Socio-psychological research has shown that negative emotions generally have stronger impact and elicit more intensive responses than positive or neutral stimuli. The potency of negative emotions is recognized within the theory of negativity bias (Rozin & Royzman, 2001; Baumeister et al., 2001; Derks et al., 2008), and it was explored in recent studies on computer mediated communication. These studies show that negative sentiment posting elicits more interaction on social media than those with positive emotions (Stieglitz & Dang-Huan, 2013). They suggest that political posts with more negative emotions are retweeted to a greater extent than those with less negative emotions. Similar results by Kramer (2012) indicate that individuals that express negative emotions on Facebook impact their network of friends to do the same. Additionally, research by Wheaton et al. (2021) showed that consumption of media about COVID-19 predicted unease about the pandemics. Choudhury (2014) found that user's attributes and language of posts were key factors in the diffusion of moods in social media.

The main objective of this research inquiry is to contribute to the existing - although rather limited and ambiguous - knowledge on the effects of social media on emotions and emotional wellbeing of people, by employing an innovative research methodology. The gap in the existing knowledge that we particularly wish to address relates to the understanding how social media content created by powerful mass-media companies (e.g. inter/national TV and radio networks, newspapers and periodicals) and distributed via social networks affects the emotions of their followers.

The objective of this research is to conduct a comparative online research with the aim of testing the hypothesis derived from the theory of emotional contagion (Hatfield et al., 1993) and from the theory of negativity bias (Rozin & Royzman, 2001), stating that negative emotions spread via social media contribute to the rise of negative emotions in a society. More precisely, we aim to explore to what extent and in what ways the Twitter content produced by leading Serbian media influences the emotions of their followers. The main research hypotheses are stated as follows:

- Language used by leading Serbian media differs depending on their nature and contents they produce.
- Emotional contagion hypothesis: Negative emotions expressed in tweets of the media affect the emotional states of their followers, which is manifested in more negative content in their Twitter posts.
- Other psychological and linguistic categories that can be found in the content posted by media profile owners will also be reflected in the posts of their followers.

Methodology

In this research inquiry we draw on theories and findings of previous sociological and socio-psychological studies on the spread of emotions in the online context. We also consider the uneven power structures of social media, and the influence of the powerful media actors (mass-media companies) on computer mediated communication. Our theoretical approaches of emotional contagion and negativity bias are expanded with the sociological approach that considers the uneven distribution of power between mass-media companies present on social networks and ordinary users.

Earlier studies have used controlled experiments to test the influence of social media content on users' emotions (Centola, 2010; Bond, 2012; Kramer et al., 2014). Although they have been able to discern certain causal mechanisms, this methodological approach is not particularly suitable due to the scale limitations, lack of external validity and, above all, ethical concerns. To address this, current research is designed to explore the relationship between the emotional content of the Twitter messages of the mass media companies, and the emotional content of the subsequent posts of their followers. Therefore, this research inquiry relies on nonexperimental methods that respect user privacy and anonymity.

Empirical analysis conducted in this research involved gathering data from Twitter, deploying an appropriate linguistic dictionary to get word count per day and linguistic category, and then conducting statistical analyses to either confirm or reject the hypotheses. What follows is a description of key aspects of the research process.

In this research, data will be acquired from public social media profiles on Twitter, including both the official Twitter accounts of leading media from Serbia, and their followers on that social media account. Twitter is the micro blogging and social networking site launched in 2006. It now represents one of the largest social networking sites. It has about 330 million active data users worldwide. Twitter is a social network mostly used for news acquiring, sharing and discussion (Stieglitz & Dang–Xuan, 2013; Park, 2015), and that is the primary reason why we chose this platform for the research. Another reason why Twitter would be used as the primary source of data for this research is technical, as well as legal in nature. In contrast to Facebook and other social networks, Twitter provides public data and API access for research applications, without major restrictions.

Once data is acquired, the primary analysis tool to be deployed is Linguistic Inquiry Word Count (LIWC). LIWC psychometric dictionaries have been in development since 1992, and tests performed in dozen studies show that LIWC dictionaries may be used to accurately identify emotions in texts (Kahn et al., 2007; Alpers & Pauli, 2006; Tausczik & Pennebaker 2009). Thus far, LIWC dictionaries exist in nine languages (English, French, German, Spanish, Portuguese, Italian, Dutch, Russian and Serbian). Linguistic categories measured by LIWC are divided into standard linguistic dimensions, psychological processes, personal concerns and spoken categories. These categories encompass functions, pronouns, personal pronouns (e.g. we, you, she, he, they) articles, verbs, auxiliary verbs, adverbs, prepositions, negations, quantity-related expressions and numbers. The categories include society issues (e.g. family, friends), affect (positive emotions, negative emotions), cognitive mechanisms (e.g. inhibition, inclusive, exclusive), perception (e.g. seeing, hearing), biological issues (e.g. body, health, sexual functions, ingestion), dynamic categories (motion, space, time), economy topics (work, achievement, leisure, home, money) and religion issues.

As previously noted, the data in this project was gathered through Twitter API. Our research methodology operates on the following principle: every word in the selected corpus of Twitter messages is classified into one of the pre-existing categories, based on the LIWC dictionaries. After going through all the words in the selected corpus of Twitter messages, we counted how many of them fall in a specific LIWC category, during each day.

The procedures for execution of quantitative analysis involved throughout preparation to define both media and their followers. The first step was to decide which

Twitter profiles of the media that would be analyzed. As the intention was to analyze leading media, both news and entertainment related ones, the decision was made to consult a list of mass-media companies on Socialbakers platform (Socialbakers, 2019). Thus, we took the first 20 media outlets from Serbia with active profiles on Twitter, according to the criteria represented by the number of account followers. These media outlets were: Vice, Tracara, Tanjug, Svet, RTS, Prva, Pescanik, Novosti, Noizz, NIN, N1, Kurir, Insajder, Informer, Hello, Danas, Blic, Birn, BBC and B92.

After this, the process started to get data about the followers of all these media, that is, their public profiles, while excluding personal data which allows identification, such as usernames, thus including an anonymization procedure (Zhou et al., 2008). A decision was made to filter followers and retain only the ones who do not follow other media from the Socialbakers list, including media that were ruled out from the analysis in the first step. This means that we completed a list of unique followers for each of the 20 profiles. An additional filter was applied to the number of tweets. That is, we excluded the followers in each of 20 groups that have less than 500 or more than 100.000 tweets in order to get followers that post frequently. The previous two filters were automatic, involving basic coding to conduct defined tasks. An additional third filter was deployed in regards to media followers. Each list was filtered out manually by looking at Twitter profiles and excluding the ones that represented companies and organisations instead of persons, and also maintaining only those profiles contributing in Serbian. The goal was to maintain only those profiles that were used by people to express their emotions and attitudes. After this, a coding script was deployed to get 1000 random followers, per profile.

Further, a code was made to get tweets posted both by both the media profiles owners and the followers of the account, from 24 October until 30 January of 2019, without any retweets. This means only the tweets written by both media profile owners and their followers were taken into account in the analysis that we will present. To get the posts, Twitter API was used. The total number of tweets gathered during that period was 525321. The tweets posted by the media profile owners were in one group, while tweets of their followers were placed in separate groups. Additionally, the number of tweets per day of each group was noted.

A code was designed to count words in all Twitter posts per day that fall into LIWC categories. The Serbian LIWC dictionary was used for that purpose, as this was the language of analysis. This dictionary was developed by Bjekic et al. (2014). Data were further normalized by dividing the number of tweets per day with counts of all categories from the LIWC dictionary, thus getting values between 0 and 1, as in each case the number of tweets per day was higher than the number of measured linguistic categories from the LIWC dictionaries. In terms of data, 20 tables were generated with rows as dates and columns as LIWC categories.

These tables were then imported to SPSS software (Ho, 2013) for statistical analysis. Following statistical operations were performed to check hypotheses: canonical discriminative analysis and fixed effect estimate.

Results

First, canonical discriminative analysis is deployed to learn how linguistic categories are structured in posts of media. One discriminative function was found that fulfilled statistical criteria. Data for this function were Eigen value of 2,389, taking 59,9% of variance, cumulative of 59,2%

and canonical correlation of,843. Linguistic categories that were taken into account by this discriminative function were: affect (,848*), positive emotions (,838*), relativity (,833*), space (,889*), social (,875*), achievement (,806*), negative emotions (,675*), work (,651*), motion (,659*), humans (,638*), see (,609*), senses (,493*), money (,432*), hear (,426*), spirituality (,349*) and friends (,272*). Media are grouped according to this discriminative function, as depicted on Figure I.

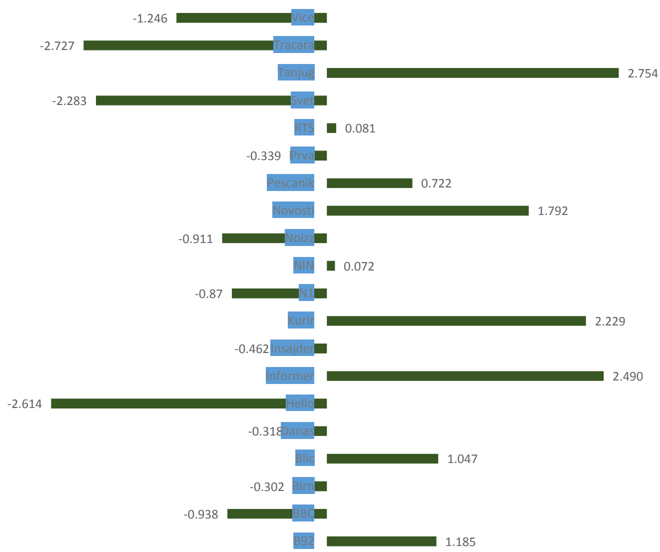

Figure I. Leading mass media in Serbia on Twitter, depicted according to the discriminative function involving 16 linguistic categories.

Further, the tweets of the media profile owners and their followers were analyzed. A fixed effect estimate is done with the predictor being the linguistic categories of media profile owners, while the dependent variables were the linguistic categories of their followers, expressed in their posts. The analysis was put in context of time to see if linguistic categories expressed in media affected tweets of their followers. It was found that tweets of media profile owners were predicting tweets of their followers, in terms of following linguistic categories: family, feel, hear, negative emotions, sex, social, spirituality and work, as represented in Table I.

Table I. Mixed model fixed effect estimate of linguistic categories found in posts of media, as predictor for linguistic categories found in posts of their followers.

LIWC category	***t***	***sig***
Family	1,773591	0,048
Feel	7,700267	0,042
Hear	-5,279311	0,024
Negative emotions	8,459362	0,021
Sex	6,727369	0,039
Social	12,593083	0,003
Spirituality	8,769932	0,0002
Work	8,302284	0,023

Discussion and conclusion

This research tackles the issue of media impact on the public sphere, which continues to fundamentally change the modern mass society. Therefore, in large perspective, the attempt of this research inquiry was to examine and illustrate the complex relation between often conflicting interests of more powerful actors such as journalists, politicians, the business sector and civil society, and "ordinary" users and consumers of new media platforms, whose voice has, at least formally, never been more “heard”.

This process profoundly impacts the way in which media communication is conceptualized today. The idea behind this research was to strengthen capabilities to see through the often unnoticed affective nature of modern media and biases produced through that affectivity leading towards a more democratic and objective media sphere. Knowing that the media impact might be especially important in the times of global pandemics, by bringing constant negative news and fear based reporting. This is why similar research inquiries are of vital interest for societies of today.

Findings presented in the results section confirm both hypotheses. First of all, language used by the media profile owners differs depending on the kind of content they create and publish. As shown in Figure 1, after conducting canonical discriminative analysis, were divided into two groups, one high and other one low in following linguistic categories: affect, positive emotions, relativity, space, social, achievement, negative emotions, work, motion, humans, see, senses, money, hear, spirituality and friends.

The group that was high in those linguistic categories consisted of news media such as: Tanjug, RTS, Pescanik, Novosti, Kurir, Informer, Blic, NIN and B92. All these media report on current news, as their main activity, while other kinds of programs are of secondary importance for them. Most of them (n=7) promote the narratives of the government: Tanjug, RTS, Novosti, Kurir, Informer, Blic and B92. The remaining two media promote an oppositional narrative, i.e. Pesanik and NIN. Some of them rely on sensationalistic reporting, such as Kurir, Informer and Blic.

Another group that was low in noted linguistic categories consisted of mixed media involving: Vice, Svet, Tracara, Prva, Noizz, N1, Insajder, Hello, Danas, Birn, BBC. The group could be further broken into the following sub-groups, one consisting of analytical, documentary based and opposition narrative media, such as Vice, Insajder, BBC, Birn, N1, NIN and Danas; and a second one consisting of entertainment media, such as Svet, Tracara, Noizz and Hello. However, one of media falling into the group low in measured linguistic parameters cannot be characterized as opposition oriented, although it can be said that Prva is analytical and low in sensationalistic reporting.

Based on previously presented results and analysis it could be concluded that news reporting media are high in emotional reporting involving both positive and negative emotions and lots of affect. In terms of words used by these media, many of them involve emotional content (both positive and negative emotions and affect), society (categories such as humans, friends) and economy categories (such as work, money and achievement) and religious issues (spirituality). Additionally, cognitive categories are high in this group, which helped convey messages in a persuasive manner (Roberts et al., 2016). Other linguistic categories that were also registered as part of this function were relativity, space and motion, indicating dynamic contents, typical of news reporting. These findings warn of how potentially impactful news reporting might be, as it contains lots of emotions and affect.

Secondly, our findings show the language used by th followers of the analyzed media on Twitter is impacted by the language expressed by those media profile owners. To be precise, linguistic categories indicating negative emotions (affective processes), social and family (social processes), feel, hear (perceptual processes), sexual (biological processes) all fall into a larger category of psychological processes. Remaining correlated categories, spirituality and work fall into personal concerns, as defined by Kahn et al. (2007). These particular findings mean mass-media are hugely impactful to their followers on Twitter. The result of this research surpasses the issue of negative affect. Mass media contents change the ways social media users express in their posts, but most likely in their daily lives as well. This may just give us a glimpse on how deep may be psychological repercussions of what mass media publish, as they successfully engrave patterns into the language of their audiences.

However, given the fact of such a large importance of emotional contagion theory in terms of society, finding that negative emotions from mass-media are reflected in posts of their followers might indicate how powerful media might be and their importance altogether. We live in an era of media being overwhelmed with negative news reporting, spreading fear without any idea about effects of this kind of content and responsibility of editors, journalists, owners of media and, most importantly, nation states in regulating this field to establish balanced and realistically based reporting.

Other findings indicate again the power of media to impact perceptual processes. This means, if more senses related words are used by the media, this would reflect in the posts of their followers. Knowing the importance of cognitive mechanisms, this result can additionally confirm media reporting quickly affects psychological processes of those that consume them.

However, a group of findings relating to social processes might offer hope if media professionals start to understand their roles, impact and responsibility. According to these findings, if the media promote values such as socializing and family, this would reflect in the posts of their followers. This part may be important because research inquiries connect family and social connections with happiness (Bojic, 2018). Additionally, if the media promote work related topics, which could inspire society members towards business, this might boost the economy, which could be beneficial for society at large. Similar conclusions could be drawn for spirituality. If these kinds of topics are exploited by mass media, this might help individuals understand their personal purposes, which might lead to subjective feelings of wellbeing.

The results presented here capture the scientific proof that mainstream media influence the emotions of society members through their use of social media. These findings could be important for societies to understand the responsibility of realistic reporting and the consequences of negative news. As a result of this and further research inquiries in the same direction, journalists and media may be stimulated to report more realistically. Additionally, if legislators consider the results, this could advance media laws to protect the public from negative news and promote more balanced and realistic reporting. Finally, this and other research inquiries indicate the importance of obligatory media literacy education at all levels.

The results suggest not only the relationship between media and its consumers, but also how emotions are spread online. As we have in mind that technology companies control social media in entirety, thus deciding what citizens will see or consume, the question that arises is if this space of individual expression could be considered as public sphere, as the impact of podcasts and social media profiles will be much be much greater in future than the impact of conventional mass media. This leads to the question whether algorithmic recommendations should be regulated, as they are used to suggest content to billions of people online, instead of having few topics primed for the whole country, as it was in the past with traditional media.

This research is limited to the examination of the media impact in one country, further inquiries should be directed towards analysis in multiple countries. The goal would be confirming findings noted in this inquiry and checking if results would be the same in terms of other societies, especially in terms of media impact and emotional contagion. The findings of this study could be applied to check the impact of other social media platforms, not only the relationship between traditional mass media and their followers on Twitter. Given the fact that online content is consumed in an increasing manner, mass media are getting less important in modern societies. Further research could focus on echo chambers and fake news, as these occurrences could be consequences of recommender systems and artificial intelligence that endanger societies by priming topics (which once was done by mass media only), polarize societies, create hostilities between people, promote populism, conspiracy theories, cause protest and unrest (Ognjenović, 1995).

Furthermore, the outcome of this inquiry could stimulate the international scientific community and wider public to focus on this important topic of representation, media distortion, and negative news. Results of this quantitative analysis open new avenues of research. The clear potential that arises relates to establishing a live online media distortion index monitoring to depict differences between emotions expressed by media and those expressed by their followers, indicating emotional contagion is a major social issue that needs to be tackled.

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