From Virality to Veracity: Examining False Information on Telegram vs. Twitter

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Abstract

The COVID-19 pandemic gave rise to various false information including that Ivermectin is effective against COVID-19 disease, which spread on social media. Because Telegram's structure poses a high risk for radicalization, it is imperative to understand the underlying spreading processes. Therefore, we gathered a network of German-speaking channels that spread false information about Ivermectin to analyze the network structure and the spread of false information. By comparing results from Telegram to Twitter network, important insights are gained for research and practice. Results revealed that opinion leaders play a significant role in the spreading process of false information. This is evident because false information on Telegram can reach more users and requires fewer distributors compared to Twitter. The study outlines avenues for future research regarding false information on Telegram.

Keywords: False information, information diffusion, Telegram, Twitter, Social Media Analytics

1. Introduction

The rise of social media platforms has ushered in an unprecedented era of connectivity, enabling individuals to effortlessly share ideas, opinions, and news on unprecedented scale. With millions of users sharing and disseminating content in real time, social media has changed the landscape of information sharing and the role of trust in information, given individuals a new way to contribute to, challenge, and shape the narratives that permeate our society (Jung et al., 2022; Stieglitz, Mirbabaie, & Potthoff, 2018). In addition, the COVID-19 pandemic impacted individuals, society, and organizations (Chen et al., 2020; Sudo, 2022; Tramontano et al., 2021). Besides the health and social restrictions, there have also been side effects that had a huge impact on society (e.g., lacking trust in the healthcare industry and politics) (Sudo, 2022). Especially, between 2020 and 2021, the COVID-19 pandemic emerged as a dominant social problem since trust in politics continued to erode (Unzicker, 2022). One negative outcome was the rapid spread of and belief in false information and conspiracy narratives that have circulated through various social media (Bunker et al., 2017; Unzicker, 2022). Particularly during the COVID-19 crisis, social media platforms such as Instagram, Twitter, and Telegram have emerged as major venues for individuals to seek and exchange information regarding politics and healthcare (Li et al., 2022; Meyer et al., 2022; Stieglitz, Hofeditz, et al., 2022). Thereby, the underlying problem is that the spread of false information was able to have a significant impact on individuals' stances by forming groups and sharing false opinions and views, especially on social media (Brachten et al., 2018; Bui & Lam, 2022; Vosoughi et al., 2018). As a result, it became apparent that the study of false information related to the COVID-19 pandemic was of great interest among researchers in the field of IS research (Li et al., 2022; Zheng et al., 2022). Even the World Health Organization (WHO) warned of an "infodemic" – an overabundance of information that makes it difficult for people to identify trustworthy sources regarding the COVID-19 pandemic (WHO, 2020).

A common example of the impact and spread of false information and conspiracy theories is the "Querdenker" movement in Germany during the COVID-19 outbreak (Zehring & Domahidi, 2023). A large number of people in Germany joined this movement because of the restrictions on public life and the discussions about compulsory vaccination (Zehring & Domahidi, 2023). A related issue that kept appearing on social media platforms was the idea that the antiparasitic drug "ivermectin" could prevent the SARS-CoV-2 virus from replicating (Schraer & Goodman, 2021; Shaw et al., 2022). However, research already revealed that this assumption can be classified as false since there is no scientific evidence that ivermectin can

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is a legit and effective cure against the COVID-19 virus (Popp et al., 2022). This demonstrates that topics going viral on social media (online world) can have a major impact on reality (offline world) (Koohikamali & Gerhart, 2022; Popp et al., 2022). Besides social media platforms like Twitter and Instagram, Telegram is one platform that had significant growth in Germany during the COVID-19 pandemic (Urman & Katz, 2022a; Vergani et al., 2022). Telegram is a messenger service that runs on all major operating systems[1]. The service is popular since it provides an open API and allows users to access the source code publicly[2]. A unique characteristic of Telegram as a messenger is the fact that, in addition to texting, it also integrates other features that are similar to other social networks. This is especially evident in Telegram's channel feature, which makes it a kind of hybrid between messenger and social networks (Dargahi Nobari et al., 2021): Besides group chats, Telegram offers the possibility to create channels to share content like on a social network feed[1]. A common approach to disseminating messages on Telegram is to forward messages from other users or channels, like the retweet feature on Twitter (Dargahi Nobari et al., 2021). The closed structure of the platform (e.g., closed (private) chats and encrypted chats[1]) and the low level of moderation and censorship ensures that false information and conspiracy narratives spread more easily, and debunking is made more difficult, which can lead to an increasing radicalization on the platform (Urman & Katz, 2022a).

One major risk of false information is, that it diffuses faster and further than truthful information on social media (Vosoughi et al., 2018). Vosoughi et al. (2018) found that false information is more novel and is more emotionally charged than true information, and it therefore spreads faster because people are more likely to disseminate novel and emotional information. In addition, the retweeting mechanism in particular plays a crucial role in the spread of false information, as it allows tweets to spread virally without verification of the content (D. Wang & Qian, 2021). While previous research already suggested that echo chambers were identified on Twitter, where users share COVID-19-related false information (Villa et al., 2021), opinion leaders play an important role in spreading false information on Telegram (Peter et al., 2022). Since previous research already focused on the spread of false information on Twitter, this paper seeks to get an understanding of the impact Telegram has on spreading false information within social media. This is particularly important as Telegram is more widely used than Twitter in Germany and played a vital role during the COVID-19 pandemic (Urman & Katz, 2022a; Vergani et al., 2022). Furthermore, since Telegram poses a high risk of user radicalization due to its network structure, it should be analyzed how COVID-19-related false information spreads within this social media platform (Dargahi Nobari et al., 2021). Especially due to its closed structure and low content moderation, Telegram provides an environment that creates a lower inhibition threshold for sharing false information, making it easy for members to post false information unfiltered[1]. Therefore, the network structure of the platform should be analyzed, since it is a critical factor in the spreading process of false information and the success of debunking (Jung et al., 2020). Due to these factors, it is crucial to expand research on the spread of false information on Telegram, to gain insights that can be applied to reduce radicalization and harm from medical false information. This leads to the following research question (RQ):

RQ1: *How does COVID-19-related false information spread within the network of channels on Telegram?*

Due to Telegrams particular characteristics, it is crucial to situate the findings of the first research questions within the current state of research on the spread of false information in social media (Dargahi Nobari et al., 2021). Therefore, we chose the comparison of two social media platforms to investigate how false information spread in different social networks and to gain further insights on how to combat false information in times of crisis. Previous research already identified the increasing use of Twitter in crisis communication and therefore focused on investigating false information on this social media platform (e.g., Mourad et al., 2020; Wei et al., 2022). Additionally, Twitter is a platform, that is considered highly political (Villa et al., 2021) and is known for political communication, as demonstrated by the increased use of Twitter by politicians (Mourad et al., 2020). The comparison between Twitter and Telegram was chosen because Telegram has gained a lot of relevance in recent years and thus acts as a comparable social media platform on the German market. In 2021, Telegram was only able to gain a percentage share of 10.2% of the active use of the population (Kemp, 2021), while Twitter reached a percentage share of 22.1%. In 2022, Telegram showed a share of 20.3% (Kemp, 2022), while Twitter remained at 22.8%. Given similar sizes regarding the audiences and that both platforms offer a feature that allows users to share content easily it is reasonable to compare those platforms. We therefore derived the following second research question:

[1] https://telegram.org/ (2022, December 4)

[2] https://core.telegram.org/ (2022, December 4)

RQ2: *How does the spread of COVID-19-related false information on Telegram differ from Twitter?*

We address these questions by examining how false information spread within the network of channels on Telegram and compare these findings with an additional social media platform Twitter. To this end, we adhere to the social media analytics framework (Stieglitz et al., 2014; Stieglitz, Mirbabaie, Ross, et al., 2018). In the first step, we gathered a dataset of German-speaking Telegram channels in which false information about Ivermectin is forwarded, which leads to a forwarding network in which the channels represent the nodes, and the forwarded Telegram messages represent the edges. To identify relevant nodes, we employed the PageRank algorithm (Peter et al., 2022). Secondly, we applied the same analysis to the Twitter dataset, which also consists of German false information tweets about Ivermectin. By comparing the spreading process on both platforms, we gain insights into the role Telegram has in the dissemination of false information.

With this research, we contribute to Information Systems (IS) research by extending our understanding of the role of Telegram's network structure in spreading false information within crisis to drive further research in this field. Our findings inform the understanding of network structures' impact on information diffusion within social media platforms. Practical implications for prevention and debunking strategies can also be derived.

2. Related work

2.1. False information on social media

Especially due to the increasing impact social media has on people's daily life and the behavior of its users, posting false information on social platforms can be devastating (Li et al., 2022). False information "refers to the phenomenon of false or harmful information created" (p. 3) and diffused by users on social media (Eccles et al., 2023). The hazard in the dissemination of false information arises primarily from the fact that information is distributed in huge flows so that it can reach a vast amount of people at the same time and that any kind of information can be spread (Ceron et al., 2021). This highlights the fact that the information provided on social media is not filtered to detect false information (Ceron et al., 2021; Kocur et al., 2023). The resulting effects can be fundamental for individuals but also for society, especially in times of crisis like the COVID-19 pandemic (Li et al., 2022). The fact that false information poses a serious threat to society is particularly evident since it may harm the economy, create emotional distress, and decrease trust (Tran et al., 2019). Hence, false information can mislead society (Meel & Vishwakarma, 2020) and endanger society's health (Naeem et al., 2021). During the COVID-19 pandemic, the role of social media for sharing and seeking information became apparent, since people used those kinds of platforms to create an understanding of the current health and political situation (Kocur et al., 2023). Especially Telegram is a quickly growing platform that has received a huge amount of hype since its structure is ideal for sharing and spreading information without any censorship or content moderation from third parties (Herasimenka et al., 2023; Urman & Katz, 2022a; Vergani et al., 2022). Hence, Telegram was often used to spread false information on health topics, current politics, and conspiracy theories during the COVID-19 pandemic (Curley et al., 2022; Vergani et al., 2022). In fact, false information spread virally on Telegram despite the absence of algorithmic content promotion (Herasimenka et al., 2023).

While Telegram is a messaging application, it provides features similar to micro-blogging platforms (i.e., channels) (Dargahi Nobari et al., 2021). Previous research already addressed the impact and diffusion of false information on social media platforms like Telegram or Twitter, to identify effective strategies to debunk false information in the long term (Featherstone & Zhang, 2020; Tully et al., 2020). However, debunking and fact-checking efforts are often "too little, too late" (Weiss, 2017, p. 427). Thus, we want to take a step back and examine exactly (1) how false information spread on the understudied platform Telegram and (2) how the spreading is different to the dominantly studied platform Twitter.

2.2. Opinion leaders

The rapid spread of false information on social media increasingly relates to certain individuals with a wide audience, which are viewed as authoritative sources of information (Y. Zhang & Hara, 2020). Previous research in this field often refers to the role of opinion leaders, who can exert sharp influence on their followers (e.g., Iyengar et al., 2011; Ruiz et al., 2021). Therefore, opinion leaders can be defined as "people who influence the opinions, attitudes, beliefs, motivations, and behaviors of others" (Valente & Pumpuang, 2007, p. 881) Thus, they have a greater ability to influence and shape others' opinions and beliefs about certain topics (Liu et al., 2020). Opinion leaders, according to Lazarsfeld et al. (1948), were reliable information providers who were politically interested, informed, and trusted sources within their social network. According to the two-step-flow model of communication (Katz & Lazarsfeld, 2017), information is largely disseminated to the general public by opinion leaders rather than directly by traditional media sources. Examining the mechanisms underlying the influence of opinion leaders and their interactions with information sources is therefore critical to understanding the dynamics of information dissemination and the potential for the spread of false information. On the one hand, opinion leaders can be valuable by recommending products to their followers or providing personal insights on specific topics that positively influence others (Guo et al., 2019). On the other hand, opinion leaders can also negatively influence their followers' social behavior by spreading untruths and exploiting their power for wrong purposes (e.g., spreading false information) (Mirbabaie et al., 2020). Using this influence, opinion leaders have a significant impact on the spread of false information on social media platforms like Telegram (Leask et al., 2014; Ruiz et al., 2021; D. Zhang et al., 2021). To combat this, Mirbabaie et al. (2020) suggested that "it becomes imperative to amplify the spreadability of response measures through influential individuals". However, in contrast this work tries to investigate whether these opinion leaders are responsible for the spreading of false information on social media. Therefore, we want to identify those opinion leaders to understand how COVID-19-related false information spread on Telegram and in comparison to Twitter.

3. Methodology

Since our research is concerned with social media, we adhere to the social media analytics (SMA) framework by Stieglitz et al. (2014; 2018) to answer our research questions. The framework includes three stages, namely (1) tracking, (2) preparation, and (3) analysis. Therefore, we structure the description of our methodology along these stages.

3.1. Tracking

According to our research questions, we require data from both Telegram and Twitter. Further, to enable fruitful comparison, both datasets should be similar in terms of the timeframe covered and topics discussed. To this end, we select COVID-19-related false information about the alleged cure called ivermectin. It is an antiparasitic agent, which drew attention after the publication of an unreliable (and now withdrawn) preprint claiming high effectiveness against COVID-19 (Lawrence et al., 2021; Reardon, 2021). Ivermectin became an exemplary issue in false information research (Ceron et al., 2021; Charles et al., 2022; Ul Hussna et al., 2021). This temporal and thematic focus provides us with a distinct keyword to search for using Twitter's and Telegram's API (Stieglitz et al., 2014).

Since Telegram's API does not provide a keyword-based search, we followed the snowball sampling strategy, which was already shown to be beneficial in the case of Telegram (Peter et al., 2022). To this end, we started with an initial set of channels known for spreading false information and gradually added channels from which messages were forwarded in already selected channels. We retrieved all Telegram messages from these channels and filtered those messages containing the keyword 'ivermectin'. We found messages covering the period from 2020-04-27 to 2022-11-14. Due to the snowball sampling, the data was retrieved from November 1st to November 4th, 2022. Twitter provides an API that allows a keyword-based search. Thus, we queried data that contains 'ivermectin' and was created between 2020-01-01 and 2022-31-12 using the SMART portal (Stieglitz, Basyurt, et al., 2022). The date of retrieval was March 17th, 2022.

3.2. Preparation

Given the datasets, we created a network for further analysis. In the Twitter network, nodes represent users, while retweets are denoted by the links between the corresponding users. We obtain the Telegram network similarly. However, nodes represent the channels and links are created for each forward of a message.

We observed that Telegram users frequently copy a message and modified it slightly instead of using the forward feature. These modifications primarily include recommendation regarding which channels readers should follow, while the main statement was not changed. Hence, it is reasonable to consider these slightly modified copies of Telegram messages as forwards too. To capture this, we employ the Levenshtein distance (Levenshtein, 1966) to assess the messages' similarity computationally. After several rounds of manual evaluation, we found 25% to be a suitable threshold that allowed us to cover the observed adaptions and maintain a message's main statement. In total, 59.72% forwards happened traditionally, while 40.28% underwent modifications. Subsequently, we sort the posts (henceforth, we use this term to refer to both messages on Telegram and tweets on Twitter) according to their shares (i.e., retweets and forwards respectively). To allow an in-depth analysis, our further analysis considers the top ten false information posts, which we classified manually (similar to Ackland & Gwynn, 2021; Peter et al., 2022). That is, we only considered the ten most shared false information posts and their forwards and retweets on Telegram and Twitter respectively. By limiting our analysis to the most viral posts and their forwards/retweets, we could classify the posts veracity manually according to the current state of research.

Finally, our Telegram dataset comprised 13,029 messages from 9,943 channels. The resulting Twitter dataset contains 26,783 tweets authored by 12,730 users.

3.3. Analyses

To understand how COVID-19-related false information spread, we employ multiple methods known from SMA research. Since RQ1 pertains the Telegram data only, but RQ2 enquires about the platforms' differences, both questions and both datasets require an analysis using the same methods. Hence, we describe the necessary methods only once and report results for both Telegram and Twitter.

First, we assess the nodes' centrality in the network to identify those that are deeply involved in the spread of false information (known as opinion leaders). We employ PageRank (Page et al., 1999) to identify central nodes in a network as suggested by previous research (Lu et al., 2012; Peter et al., 2022). During our analysis we use the centrality to compare the users and channels on Twitter and Telegram respectively. The top 1% channels/authors are determined by sorting them according to their centrality and taking the 1% of the channels/authors with the highest centrality.

Second, to assess the diffusion's speed, we calculate the spreading rate. That is, the empirical probability that a user shares a post (Moreno et al., 2004). Since the diffusion's speed depends on the density of the network, we assess the degree of clustering too (Newman, 2003). To this end, we calculate the clustering coefficient c (Watts & Strogatz, 1998).

Finally, we reconstruct the posts' spreading cascades. Spreading cascades capture the distinct steps and timeframes of sharing posts in a social network (Jung et al., 2020; Vosoughi et al., 2018). We reconstruct the spreading cascades for the top ten posts, which we classified earlier.

4. Results

First, we observed that the distribution of Telegram messages' views is heavily tailed. That is, a message is viewed 9,766.74 views on average, whereas the median is 327. This suggests that there are a few messages that are seen by many users while the majority receives less attention. We made a similar observation regarding the number of forwards: On average, a message is forwarded 229.75 times, but the median is 5 only. The tailed distribution is caused by Telegram messages with a high number of forwards. The top message, for instance, was forwarded 26,120 times.

Second, we found nodes with a substantially higher centrality than the majority in both networks. Regarding Telegram, the top 1% of the channels (i.e., nine channels) constitute 18% of the network's entire PageRank. These channels' average centrality is approximately 19 times as large as the entire channels' average centrality. Similarly, the top 1% of the Twitter network's users (i.e., 119 users) constitute 55% of the network's overall PageRank. Their average centrality is roughly 53 times higher than that of the entire set of users. Table 1 summarizes the PageRank centralities.

Considering the channels from which the ten false information messages on Telegram originate, we found that they have an average centrality that is nine times greater than overall centrality. Moreover, three of these original channels were among the top 1%. On Twitter, on the other hand, all ten false information authors were among the top 1% of the users. The Twitter authors' average centrality is 330 times greater than the overall average. Thus, the authors are among the most central users of the top users on both platforms.

Table 1: Average PageRank centralities

	Telegram	Twitter
Top 1%	0.020205	0.004591
Overall	0.001057	0.000084
False information' original channels/authors	0.009863	0.027767

Regarding the networks' density, our analysis revealed substantial differences between Telegram and Twitter. In fact, the clustering on Telegram is twice as high as it is on Twitter (i.e., $c_{Telegram} = .058$, and $c_{Twitter} = .025$). This densely connected structure is further emphasized by an average path length of 4.2 in the Telegram network. Figure 1 visualizes the networks.

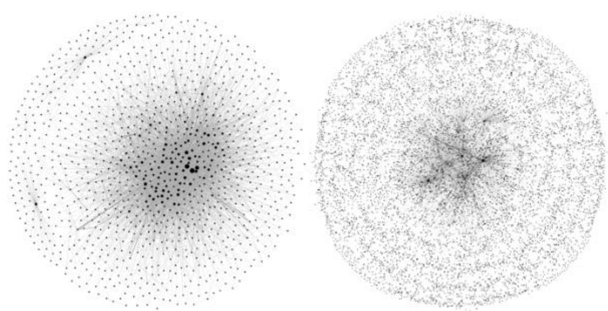

Figure 1. Visualization of the networks on Telegram (left) and Twitter (right).

Finally, we analyzed the false information posts' spreading cascades. Primarily, we observed that tweets spread faster, but Telegram messages reached more users. In more detail, the Telegram false information messages were forwarded by 104 users and viewed by 1,016,563 users in total. The false information tweets were retweeted by 274 users and seen by 328,478.

Hence, this results in spreading rates of 0.01% and 0.08% for Telegram and Twitter, respectively. Figure 2 visualizes the relative reach over time. That is, the percentage of the total audience reached at the respective point in time. We observed that the tweets reach 50% of their final audience within approximately 5 hours, whereas it took roughly 15 hours to reach 50% of the Telegram audience. In line with prior research, we note that the number of users on Telegram is likely to be underestimated because Telegram's API allows only to collect channels from which messages were forwarded, but channels that only consume forwards cannot be discovered (Peter et al., 2022).

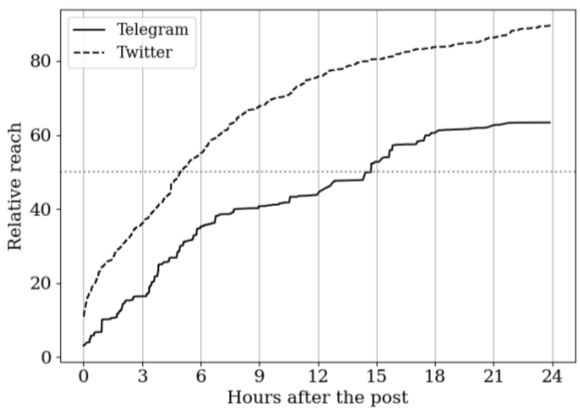

Figure 2. Relative reach (in %) of the final audience in the first 24 hours.

5. Discussion

In the scope of this research, the information diffusion of false information on Telegram has been examined and compared with the popular micro-blogging platform Twitter. The data collected and the diffusion of false information on Telegram have revealed and confirmed that Telegram has indeed gained a significant role in the communication around COVID-19, especially false information. It therefore is in line with previous research (Urman & Katz, 2022b; Vergani et al., 2022) indicating the importance of the role of Telegram which is why research needs to evaluate the role of Telegram in information diffusion around false information due to the platform characteristics (Dargahi Nobari et al., 2021; Herasimenka et al., 2023; Peter et al., 2022).

5.1. False information spread on Telegram

The analysis of the spreading cascades answers RQ1 by showing that the reach and interactions of false information on Telegram increase sharply in the first few hours (~ 35% relative reach after 6 hours vs. 50% relative reach after ~ 15 hours). Thus, false information diffuses fast and receives the most attention at an early stage, which confirms the findings of Vosoughi et al. (2018). A large proportion of the overall network receives Telegram messages from nodes that have been originated from users with a high PageRank centrality (PageRank of 0.02 for the top 1%), which is in alignment with the two-step flow model (Katz et al., 2006; W. Y. Wang & Yang, 2015). This indicates that opinion leaders play a significant role in the information diffusion process on Telegram (Peter et al., 2022; Valente, 2012) which is reflected in the average views of Telegram posts. Especially those users that have been identified as authors of false information in comparison to the average users are attributed a higher centrality (0.009863 vs. 0.001057) thereby contributing to the diffusion process. Due to the high network centrality in the Telegram network, the messages from influential nodes are able to spread in the far and reach a high number of users resulting in higher views and reach.

While echo chambers in the context of disinformation have already been identified on other platforms (Villa et al., 2021), Telegram's network characteristics as well as the results of information diffusion indicate that users on Telegram channels may be at risk of high biased information exposure, which supports previous findings (Willaert et al., 2022).

5.2. Platform comparison

To answer RQ2 the diffusion of false information has been compared indicating that false information spreads even faster on Twitter than on Telegram. However, false information messages on Telegram reach substantially more users compared to Twitter, while needing less spreaders. Even though Twitter has more users who participated actively in the spreading process, and it thus has a larger spreading rate. However, the spreaders on Telegram have a greater impact. The average Telegram user/channel member has a higher ability to influence the network in terms of false information spread than the average Twitter user which is based on the average centrality scores of the channel-to-channel Telegram network as well as the user-to-user Twitter network. The same effect can also be observed for the top influential users, that is, the opinion leaders. This can be explained by the differences in audience size of the channels spreading false information posts on Telegram. Hence, false information spreaders reach more people on Telegram. Furthermore, the denser clustering in the Telegram network can be attributed to platform differences contributing to the diffusion process. Fundamentally, Telegram as it is designed as a messaging app might be more conducive to frequent and continuous interactions amongst users around channels which is reflected by stronger network ties. In addition, the network is smaller which increases the possibility of dense clustering.

However, the cumulative centrality of the top users on Twitter is three times as high compared to the cumulative PageRank of the top channels on Telegram. This indicates that looking at the influence of the opinion leaders, the top Twitter users all together play a more important role in disseminating information in the network than the top Telegram channels all together. However, this finding can be explained by the network size since the top Twitter users result in a higher number of individuals than the top channels on Telegram. It remains that according to the individual average PageRank, a single top channel on Telegram has more influence than a single top user on Twitter. Yet, the role and impact of a low number of very influential nodes in comparison to a high number of relatively influential nodes in the networks needs to be discussed in the context of false information. Recent research has already examined the impact of the degree of influence and popularity (micro- vs. macro-influencer) in marketing (Kay et al., 2020; Sivizaca Conde et al., 2023) but the impact of opinion leaders' degree of influence on public discourse about false information remains unclear.

Another platform difference is that the interactions on Twitter mostly revolve around a specific Tweet in a public sphere which is why the communication might be more occasional and one-way oriented by the means of retweets and likes and which might explain the difference in numbers. Additionally, the authors of the top Telegram messages even have a higher average PageRank than the average of the top users on Twitter. This is mainly because two of the users, each of these contributed three of the ten false information messages alone. These two users had a very large PageRank (7% and 1% respectively of the whole network) further indicating the importance of a small number of individual nodes for the entire network. Messages on Telegram revolve in channels rather than in the public sphere. Other research has shown that on Telegram, radicalization and the proliferation of conspiracy theories have found fertile ground and even increase over time (Schulze et al., 2022). Taking into account the results that information is able to spread faster on the platform and that the network is strongly clustered in comparison to other social media platforms, this poses a risk for democracy and society because not only the spread of false information but also the spread of conspiracy theories and radicalization can be diffused more strongly on the platform. Considering that Telegram has a higher sense of anonymity and weaker regulation and moderation compared to Twitter or other popular social media platforms (Semenzin & Bainotti, 2020) leads to Telegram having a higher potential of spreading harmful information and influencing communication due to the opinion leaders, who were found to have a higher influence on Telegram than on Twitter.

6. Conclusion

6.1. Contributions

This work provides contributions to IS research by offering insights about false information spreading on Telegram and differences to Twitter in this regard. Our findings suggest that false information spreads widely on Telegram and reaches many users. False Telegram messages spread further than on Twitter even though Telegram does not employ algorithmic content promotion. In fact, Telegram's immense spreading capabilities are grounded in a few powerful opinion leaders that exert a strong influence. Compared to tweets, substantially more users see false information messages on Telegram. Thus, the design of countermeasures can consider this difference by tailoring approaches to fewer active spreaders.

Furthermore, our results reveal stronger ties among the network of channels on Telegram than among users on Twitter. This implies a high level of interconnectivity among the channels on Telegram. In contrast, Twitter's users do not form such strong connections even though there are more actively spreading users, which leads to a higher spreading rate, relatively speaking. This emphasizes the potential for polarization on Telegram.

Finally, we observed an oddity in the sharing behavior on Telegram. Besides using the default forward feature that shares a verbatim copy message, users sometimes copy a message manually and apply minor modifications that are relevant to their channel (e.g., suggestions for other channels to follow but no changes regarding the core message). The manual forwarding bypasses the default feature and messages are not marked as forwarded, therefore. Hence, we suggest future research to explore their Telegram dataset to account for such manual forwards to receive a better representation of the network structure. Also, considering these modifications can contribute to methods to identify false information on Telegram by serving as an indicator.

This study contributes to research on false information by shedding light on the dissemination of false information on Telegram and comparing the prevalence and network differences with Twitter. It contributes to the study of false information simulations (with e.g., agent-based modelling) by providing valuable insights into network characteristics and propagation behavior among different platforms. The different impacts of opinion leaders on Telegram and

Twitter also highlight that the role of opinion leaders in false information in terms of the two-step-flow model is highly dependent on the community and network structure of the platform. Moreover, it underscores the importance of considering such network and propagation differences when addressing strategies to counter false information campaigns. In doing so, it adds a more nuanced perspective to the scientific discourse on combating false information.

6.2. Limitations and future research

This study is subject to limitations. First, this study focused on one topic (i.e., ivermectin). This limitation allowed us to collect data from both platforms and to avoid thematic differences simultaneously. Second, the focus on the German language attaches a cultural context to the use of the platforms. Third, similar to other studies that collected Telegram data, this study suffers from the "Unknown Recommendation Problem". This refers to the fact that the snowball-sampling approach only adds channels *from* which messages were forwarded into one of the known channels (Peter et al., 2022). Hence, channels that only receive forwards but do not forward messages to other channels remain undiscoverable.

We suggest future research to address these limitations. Moreover, we emphasize the need to examine why channels attract more members than a user on Twitter has followers. Further, Telegram's unique environment (e.g., no content moderation and no algorithmic content promotion) allows for in-depth content-level analyses to better understand the framing and influence that users on this platform can exert. Closing these knowledge gaps can ultimately support the design of countermeasures.

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