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ORIGINAL ARTICLE

How COVID-19 affects user interaction with online streaming service providers on twitter

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Abstract
The worldwide diffusion of COVID-19, declared pandemic in March 2020, has led to significant changes in people's lifestyles and behavior, especially when it comes to the consumption of media and entertainment. Indeed, during this period, online streaming platforms have become the preferred providers of recreational content, whereas Online Social Networks proved to be the favorite place to find social connections while adhering to distancing measures. In the meantime, from the online Streaming Service Providers' point of view, Online Social Networks have gained more and more importance both as valuable data sources for business intelligence and as connected and co-viewing platforms. This study starts from these considerations to explore the impact of COVID-19 on user interaction with Streaming Service Providers in Online Social Networks. In particular, our investigation focuses on the Twitter platform; by comparing several large datasets referring to different periods (i.e., before, during, and after COVID-19 emergence), we investigate interesting patterns and dynamics leveraging both Natural Language Processing and sentiment analysis techniques. Our data science campaign, and the main findings derived, adopts a peculiar perspective focusing on the different categories of users and Streaming Service Providers. The main objective of the analysis is to uncover the dynamics underlying the evolution of the interaction between people and businesses during the COVID-19 outbreak.

Keywords Social network analysis · Sentiment analysis · Natural language processing · Streaming service providers · COVID-19 · Twitter

1 Introduction

On January 7, 2020, researchers isolated a novel coronavirus referred as SARS-CoV-2 (or 2019-nCoV) (Ciotti et al. 2020). From that moment on, the everyday life of people around the world has changed rapidly for fear of contagion, but also because self-quarantine has been one of the major ways to stop this pandemic from spreading. As individuals worldwide faced lockdowns, social distancing measures, and limited entertainment options, streaming platforms like Netflix or Prime Video emerged as a crucial source of comfort, news, and connectivity. Indeed, both the customer base of these businesses and the total amount of hours of service usage per client have grown exponentially in the last period (Parnami and Jain 2021). Indeed, there has been an 18% increase in television consumption in the USA during the week at the end of March, especially among teenagers who could no longer go to school, and a 38% growth in TV consumption over the pre-COVID-19 period in India. Moreover, popular Over-The-Top (OTT, hereafter) service providers such as YouTube, Netflix, and Spotify recorded a 140% rise in video streaming apps in Australia, India, Indonesia, South Korea, and Thailand (Gupta and Singharia 2021; Nielsen 2020).

The profound impact of COVID-19 on society has also caused consequences in the disruption of traditional ways

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of communicating and interacting. Indeed, during the pandemic period, Online Social Networks (OSNs, hereafter) have played a pivotal role by facilitating information sharing, maintaining social connections, and fostering community support. This trend is demonstrated also by the fact that in 2019 about 2.95 billion people used social media worldwide, whereas this number is estimated to rise to 4.41 billion in 2024 (Ahmet and Suliman 2021). Moreover, governments and major Centers for Disease Control, including the World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDC), have been exploiting OSN platforms to regularly disseminate updates and provide emergency responses. Due to the concise nature of the format of its posts and the openness and availability of its data, Twitter has become, among the other OSNs, one of the preferred platforms for information sharing and self-documentation (Liu et al. 2010). Indeed, even in the past people have been communicating, expressing, and disseminating information through Twitter about the most variegate natural disasters and public health emergencies, e.g., cyclones (Soriano et al. 2016), Ebola (Kim et al. 2016) or terrorist attacks (Oh et al. 2011). The recent lockdowns related to COVID-19 have not been an exception; indeed, the importance of this micro-blogging site has increased more than ever confirming Twitter as one of the most preferred mediums for information spread during pandemics (Dubey 2020; Kaila and Prasad 2020).

On the other hand, organizations and businesses also continually adapt their Twitter usage to align with their overall marketing and communication strategies, leveraging the platform's features to engage and connect with their audience effectively, but also to promote brand identity and make informed business predictions (Culnan et al. 2010).

Among the others, TV broadcasting companies have experienced a huge impact by this platform. As a matter of fact, the more Twitter grows and becomes pervasive in everyday life, and the more Streaming Service Providers (SSPs, hereafter) evolve as well, reshaping both the strategy adopted to provide their services and the way they connect and communicate with customers (Hennig-Thurau et al. 2010). Moreover, SSPs often make use of social networking websites and apps to engage users and encourage them to develop a user community where they can discuss the content with each other (Gupta and Singharia 2021). As a consequence, the importance of the accounts of SSPs on OSNs has increased in recent years as a means for them to communicate directly with their audience. These companies utilize such a communication channel to address concerns, provide updates on new releases, engage in promotional activities, and showcase commitment to user satisfaction and well-being, especially during the pandemic. Moreover, it allows for the distribution of content through a sort of interactive and socially empowered second screen realizing new forms of customer engagement, namely connected viewing (augmenting television consumption with a second screen) and co-viewing (virtually watching television content together with friends and family while sharing comments on OSNs) (Pittman and Tefertiller 2015). Twitter accounts of these businesses can also be used as a means to control and fight COVID-19 *infodemic*, that is the outbreak of misinformation about the pandemic, both promoting information monitoring (known as *infoveillance*) and spreading legitimate news (Eysenbach 2020).

Of course, since leading global SSPs consistently leverage social media to augment the experience of their customers with their services, they developed different ways to successfully and continuously engage their clients. Recent studies (Arazzi et al. 2023; Sharma et al. 2023) try to shed light on the most successful strategies adopted by SSPs on Twitter to support their activities. In particular, our work starts from the research results described in Arazzi et al. (2023), where the authors compare several aspects of the Twitter accounts of different categories of SSPs by analyzing (i) the adopted posting strategies, (ii) the discussed topics and (iii) the type of engaged users. As done in Arazzi et al. (2023), in our work, we also leverage the Technology Adoption Life Cycle theory (Weinberg 2004), for which businesses can be divided into categories according to the stages of the evolution of their service. For our analysis, we focus on the two most distant categories, namely Emerging SSPs and Pioneers. SSP accounts have been grouped on the basis of their popularity level and the diffusion of the offered service according to (i) the elapsed time since the service was first created and (ii) the dimension of the overall community of users interested in the service (i.e., the total number of Twitter followers).

Starting from these premises, we focus on two interesting aspects with the aim of understanding how they evolved during the COVID-19 pandemic:

- First, we analyze the resilience of the online customer base. In particular, we focus on the user activity level in relation to popularity (i.e., the number of followers). Indeed, previous studies demonstrate that the most active users of younger SSPs have low popularity levels. On the other hand, popular users tend to interact more with Pioneer SSPs. Can this finding be confirmed also during the pandemic spread?
- Then, we analyze the sentiment in the posts published by users about SSPs and the users' reactions to the posts of the different SSPs. Recent findings showed that there is no significant variation in expressed sentiment with respect to the stage of the business in the Technology Adoption Life Cycle. Does this trend vary during the COVID-19 outbreak? Is there any change in users' reactions toward SSP-generated content?

The first analysis is crucial to understand whether the outbreak of a pandemic can influence the most active Twitter users of an SSP category. As a matter of fact, they can act as influencers or hidden influencers; therefore, their identification is important since not only marketers but also public health organizations have been increasingly turning to them as promoters for campaign dissemination (Kostygina et al. 2020). Our analysis can help organizations and businesses in the online streaming services context understand if the popularity distribution of their most active followers remains unchanged after a crisis event, such as the diffusion of COVID-19. The second analysis instead aims at understanding which category of SSP audience is more resilient to a crisis, in terms of the expressed sentiment about the followed SSPs on Twitter.

Observe that the two aspects we aim to analyze have a key role in the characterization of a loyal customer base. During a period of crisis building and retaining the customer base is a crucial issue, especially for small businesses (Fleming 2021). The main actions a company can perform are: (i) building strong communication through various means, including email distributions and social media while providing customer service and responsiveness; (ii) finding appropriate ways to reinvent the business maintaining the ability to engage customers and also exceed their expectations. To do so, deep knowledge coming from studies about Online Social Network users can be useful to the foresight and plan how to behave before and during crisis situations and prepare companies to be resilient to the incredible challenges of future pandemics. For these reasons, we chose to analyze the above-mentioned aspects that can help build a complete characterization of customers interested in the businesses of SSPs (Poecze et al. 2018). Indeed the analyzed features are the most relevant ones that researchers typically focus on when studying communities in Online Social Networks (i.e., user popularity and user sentiment) (Utz et al. 2012; Stieglitz and Dang-Xuan 2013; Wang et al. 2013).

To the best of our knowledge, this contribution offers a fresh perspective and can enhance the research on the impact of COVID-19 on the considered business sector.

Moreover, even if COVID-19 shows peculiar aspects due to the way society reacted to the pandemic, recent studies argue that this crisis resembles, in microcosm and over the short term, the dynamics of global, long-term interrelated sustainability crises (e.g., biodiversity loss, food crisis, and climate change) and hence the findings on this phenomenon can be used to understand how to face future pandemic threats (Engler et al. 2021; Khanna et al. 2020; Coccia 2021). This assures that the conclusions of this paper can have a larger impact and are not limited only to the present pandemic.

The outline of this paper is as follows. In Sect. 2, we present the related literature. In Sect. 3, we describe the dataset used, whereas in Sect. 4 we illustrate our experimental campaign altogether with our main findings. Finally, in Sect. 5, we conclude the paper outlining possible future research efforts related to this current work.

2 Related works

Understanding the impact of COVID-19 on social media platforms has currently garnered significant attention in both academia and industry. Indeed, from the very beginning of the pandemic, researchers have investigated how users behave online to find possible changes in the way they interact among themselves and with the accounts they follow. Amidst the different OSNs, Twitter has always been one of the favorite platforms both for classical social analysis studies (Quattrone et al. 2018; Liakos et al. 2017; Buccafurri et al. 2014) and for carrying out investigations about the trends in user interests during crises or particular events, such as disease outbreaks (Culotta 2010; Kim et al. 2016), earthquakes (Sakaki et al. 2010), cyclones (Soriano et al. 2016) and political elections (Tumasjan et al. 2010). This preference is due to a number of factors, namely (i) the short format of its posts (i.e., tweets), (ii) the openness and availability of its data that can be crawled via the REST API developed by Twitter itself (iii), the ease of categorizing information about specific topics or themes through hashtags and (iv) the rapidity of the dissemination of information.

These features make Twitter a valuable tool to empower businesses and marketers (Culnan et al. 2010; Zhang et al. 2011; Robson and Banerjee 2022; Nocera and Ursino 2012; Arazzi et al. 2023). For instance, the paper presented in Robson and Banerjee (2022) explores the relationship between the characteristics of posts related to a particular brand of a number of start-ups on Facebook, Twitter, Instagram, and LinkedIn. The work proposed in Zou et al. (2015), instead, carries out an empirical investigation on the success of social media used by a number of American libraries with the aim of finding the best practices for libraries to effectively engage their users on Twitter. Although the above papers exploit OSNs to study real companies and brands our paper's aim is quite different from theirs; indeed we focus on a particular type of businesses (i.e., SSP) during the COVID-19 pandemic. Also, SSPs like Netflix, Disney+, and Amazon Prime have started to exploit Twitter consistently in the last decades. Related literature presents a number of studies on Twitter strategies employed by one of the most popular SSPs, namely Netflix, to engage people (Gómez and Quevedo 2018; Pittman and Tefertiller 2015; Lee et al. 2022). In particular, the authors of Gómez and Quevedo (2018) compare the Twitter strategy employed by Netflix in Spain and those pursued by traditional television. Netflix extensively uses original messages and social media conventions such as hashtags, emoticons, and gifs. Moreover, this study demonstrates that brand followers in Spain are more likely to prefer retweets and actions on Twitter than post replies. The authors of Lee et al. (2022) analyze the structure of the networks of the three brands Netflix, Disney+, and OCN to outline the differences between them and explain the interactions between users posting tweets. Since tweets also contain feedback for companies about their services, (Motoyama et al. 2010) developed a system that uses them to detect outages in several Web services, such as Gmail, Amazon, Google, PayPal, Netflix, YouTube, Facebook, and Wikipedia. Also in this context, the framework presented in Cushing (2012); Augustine et al. (2012), called SPOONS (Swift Perceptions Of Online Negative Situations), uses Twitter posts to determine when Netflix users are reporting a problem with any of the Netflix services.

Another well-known use of Twitter is the extraction of user sentiment from users' comments (Desai and Mehta 2016; Tzacheva et al. 2020). Much of the data encoded in tweets contains polar sentiment, and the average sentiment of tweets can be analyzed and proven useful for a variety of application scenarios. In Desai and Mehta (2016), a survey on the techniques for the sentiment analysis of Twitter data is presented. Specifically, the paper illustrates all the classical steps for the extraction of sentiment from a short text. Firstly, during the data cleaning phase, the data gathered from Twitter are preprocessed. Secondly, the most important features are extracted and the training set is prepared (i.e., a portion of the data is manually labeled as positive or negative sentiment tweets). Finally, the extracted features and the labeled training set are provided as input to a classifier to categorize the remaining data and build the test set.

A number of studies started from these techniques to investigate the expressed sentiment of users on tweets during the COVID-19 pandemic. For instance, in Manguri et al. (2020) the authors perform sentiment analysis on tweets containing the hashtags "COVID-19" and "coronavirus" referring to 7 days from April 9, 2020, to April 15, 2020. They analyze both polarity and subjectivity reporting a neutral toll regarding the sentiment expressed and the tendency to be objective rather than subjective in the tweets. These scarce results may be due to the exiguous period of analysis. Similar results are also presented in Raheja and Asthana (2021). The work proposed in Dubey (2020) takes into account the tweets from 12 countries gathered from March 11, 2020, to March 31, 2020. The main result of this study is that while the majority of the people in countries like Belgium, India, and Australia are taking a positive and hopeful approach to the disease in the first period of the outbreak, there are instances of fear, sadness, and disgust exhibited worldwide, especially in France, Switzerland, Netherland, and the USA. The authors of Khan et al. (2020) focus on the Indian subcontinent analyzing three months of data, and finding that the proportions among positive, negative, and neutral sentiments remained constant. The work described in Valle-Cruz et al. (2022) focuses on the relationship between sentiments generated on Twitter and the stock market, demonstrating that Twitter accounts exhibit reactions to financial market behavior within a period of 0 to 11 days during the H1N1 pandemic and 0 to 6 days during the COVID-19 pandemic. The authors of Arpaci et al. (2020) present an evolutionary clustering analysis on Twitter during COVID-19 and identify the tweet patterns in three-level n-grams, frequent occurrences of single words (e.g., COVID), bigrams and trigrams (combinations of two or three words).

A number of researches (Kaila and Prasad 2020; Mourad et al. 2020; Xue et al. 2020; Albahli et al. 2021) focuses on the recent multidisciplinary field of *infodemiology* that studies the rapid spread of news, rumors, misinformation, and conspiracy theories particularly through digital platforms and social media with the aim of mitigating public health problems resulting from an *infodemic*. In particular, the authors of Kaila and Prasad (2020) focus on the COVID-19 information flow on Twitter defining it as quite accurate and reliable; moreover, they also take the sentiment of tweets into account stating that negative sentiment dominated the tweets related to COVID-19. The paper presented in Mourad et al. (2020) deals with the phenomenon of *infodemic* parallel to COVID-19 and consisting in the spreading of panic and confusion through misleading information on OSNs. Fake news can range from selling unreliable cures for the virus to using social media as a platform to launch cyberattacks on critical information systems. The authors of Xue et al. (2020) use sentiment analysis and topic modeling to prove that real-time monitoring and assessment of Twitter discussions and concerns could provide useful data for public health emergency responses.

Table 1 summarizes the main differences between the above-cited studies related to sentiment analysis on Twitter about COVID-19 and our work. Our paper differs in a number of aspects and presents a novel and intriguing perspective. Firstly, we study the characteristics of the Twitter accounts of a number of SSPs, which represent very relevant actors due to their role as entertainers for users, especially during lockdown periods. As a matter of fact, such businesses have undergone a major transformation during the pandemic (Havard 2021). Instead, the above-mentioned papers are not specifically focused on the dynamics underlying the communities built around specific business accounts, but they study the general variation of people's sentiments based on standard posts. Moreover, we leverage both Social Network Analysis (SNA, hereafter) metrics and sentiment analysis techniques to provide interesting insights about how the online customer base of SSPs, at different stages of the technology adoption lifecycle (namely Emerging and Pioneers businesses), can evolve during a crisis. In our

Table 1 Comparison of our contribution with related works

Work	Analyzed metrics	Purpose of the analysis	Analyzed period
Manguri et al. (2020)	Polarity, Subjectivity	Identify the emotional state of people about COVID-19	April 9, 2020–April 15, 2020
Dubey (2020)	Polarity, Emotions	Sentiment and Emotions Analysis about COVID-19 across different countries	March 11, 2020–March 31, 2020
Khan et al. (2020)	Polarity, Subjectivity	Identify the emotional state of people in India about COVID-19	3 months in 2020
Raheja and Asthana (2021)	Polarity, Subjectivity	Identify the emotional state of people about COVID-19	COVID-19 outbreak in 2020
Kaila and Prasad (2020)	Polarity, Subjectivity Topic modeling	Characterize Information Flow on Twitter during COVID-19 and identify the emotional state of people and the topics of discussion	COVID-19 outbreak in 2020
Mourad et al. (2020)	Fake news identification Analysis on users	Detect misleading information about COVID-19 and measure the reliability of tweets	2 months in 2020
Xue et al. (2020)	Polarity, Subjectivity Topic modeling	Identify the emotional state of people and the topics of discussion	March 7, 2020–April 21, 2020
Arpaci et al. (2020)	Natural language processing Evolutionary clustering	Describe the trend of public attention to topics related to COVID-19	March 22, 2020–March 30, 2020
Valle-Cruz et al. (2022)	Polarity, Emotions	Identify the influence of tweet polarity on the financial indices during COVID-19	May, 2020
Ours	SNA, Polarity	Identify how the characteristics of SSPs' customer	March, 2019–July, 2019
	Natural language processing	Base change during COVID-19 and the emotional state of people about SSPs during COVID-19	December, 2019–March, 2020 March, 2020–July, 2020

approach, we exploit advanced Natural Language Processing techniques to build two classifiers: the former for sentiment identification, and, the latter, to distinguish between questions and declarative sentences. On the contrary, most of the related studies focus only on basic Polarity and Subjectivity metrics. Finally, the datasets we gathered to carry on our analysis refer to a much longer time span than the one considered in the related investigations described before. Indeed, we consider data referring to 11 months in total, while the cited works cover a maximum of 3 months. This allows us to formulate a deeper and more comprehensive analysis of the considered scenario before, during, and after the COVID-19 outbreak. To the best of our knowledge, no previous study has investigated the impact of a crisis on SSP communities' emotions, reactions, and characteristics.

3 Dataset description

This section is devoted to the description of the dataset used for our analysis. In this study, we adopt the dataset already collected in Arazzi et al. (2023) extending the analyses by specifically focusing on the impact of COVID-19. It is important to underline that while the aim of Arazzi et al. (2023) is to depict the main characteristics of the behavior of SSPs in social media, our goal here is totally different. Indeed, we aim to analyze how such behavior has been impacted by the aforementioned pandemic event.

The dataset taken into consideration was gathered leveraging the Twitter streaming and REST API (Twitter 2023) and is populated with data coming from the account timelines of a number of SSPs. As already said in the Introduction, to present the results of our analysis in a simple and effective way we classified SSP into two main categories, namely Emerging SSPs and Pioneers. These classes, which belong to the already mentioned Technology Adoption Life Cycle, are identified according to the importance of each SSP in terms of its popularity level and of the diffusion of the service it offers in the real world. These features are estimated using a number of metrics directly derivable from the referring OSN, such as the total number of followers, the number of hashtags/references associated with the target Twitter account, the subscription date, and the number of active users engaged in the analyzed community. The data acquisition process concerned three-time windows, namely:

- From March 2019 to July 2019;
- From December 2019 to March 2020;
- From March 2020 to July 2020.

Observe that the first dataset, called *BO*, is related to the period from March 2019 to July 2019 and it was extracted exactly one year before the virus outbreak, whereas the second dataset, namely *DO*, acquired from December 2019 to March 2020, refers to an interval of time during the COVID-19 pandemic. Hence, the posts in this dataset are representative of the user activity dynamics during the outbreak of this disease. Finally, the last dataset (already deeply analyzed in Arazzi et al. (2023)) represents the most recent one in our study, and it will be used here as a reference to study the consequences of the COVID-19 pandemic; we will refer to this third dataset as *PO*.

Moreover, from March 2020 to July 2020 Italy was one of the countries with the highest impact of the outbreak and with the most severe restrictions (New 2021). Thus, by focusing on the data recorded in this country, it is reasonable to observe meaningful variations in the analyzed trends. For this reason, in our analysis, we focused on the Italian accounts of the analyzed SSPs. Note that this choice is not uncommon; as a matter of fact, many other researchers have focused on the Italian response to COVID-19 (Chen et al. 2020; Remuzzi and Remuzzi 2020; Mattei et al. 2021). As shown in Table 2, the whole collected dataset contains over 98, 643 tweets. Moreover, the table distinguishes the number of tweets published in the timeline (# Tweets on the timeline) of the considered accounts from the number of tweets posted by users containing a mention (@) or a hashtag (#) related once again to the considered accounts.

The next section is devoted to the description of our analysis along with the results obtained.

4 Methods and results

In this section, we illustrate the analysis performed on the data taken into consideration and we discuss the main results and findings.

4.1 Online customer base resilience

This first analysis is devoted to studying to what extent the community of users, which represents the online customer base of SSPs, is resilient to very adverse events, such as COVID-19. Intuitively, the more resilient they are, the lower the observable variations in the analyzed time periods (i.e., Pre-COVID-19, During COVID-19, and Post-COVID-19). However, several previous studies have shown how different categories of users behave differently in social media. One of the main characteristics typically adopted to carry out a stratified analysis of user behavior is popularity. In general, when it comes to Twitter, the *User Popularity* metric can be computed as the number of followers of a user.

Table 2 Amounts of overall data crawled for the two SSP categories

SSP	# Tweets on timeline	# Tweets with hashtag or reference	# Unique users
Emerging	1,113	4,664	1,617
Pioneer	2,419	90,447	35,761
Total	3,532	95,111	37,378

Previous studies have already analyzed some characteristics of Twitter users and tried to relate them to the different categories an SSP belongs to in the Technology Adoption Life Cycle curve. For instance, the authors of Arazzi et al. (2023) focus on *User Popularity* along with *Subscription Seniority* and *Activity Level* to study the user distributions for the different SSP categories. As a result, they observed minor but interesting differences in such distributions when comparing the considered categories.

In particular, the results of this analysis on *User Popularity* are visible in Fig. 1, where users are grouped in 14 bins on the basis of the average number of their followers in the period under analysis. Users' bins have been chosen to highlight what happens at the edges of the users' popularity distribution (in terms of number of followers), which, for Twitter users, obeys a power law (Clauset et al. 2009; Bodrunova and Blekanov 2018). Therefore, the first 7 bins, ranging from 0 to 500 followers, represent low popularity levels, i.e., the tail of the power law curve. Instead, the central bins we selected represent the middle part of the power law and range from 500 to 10k followers. Finally, we selected bins representing the upper part of the power law, i.e., very few users who are typical examples of VIPs and have extremely high popularity (more than 100k followers). This figure shows to what extent users with different popularity levels (i.e., with different follower counts) are actually involved in the activity of SSP accounts (i.e., they publish on SSP's timelines) for the two analyzed categories. In detail, this figure reports the trends related to the percentages of users, grouped according to their popularity, with which the two categories of SSPs have actually interacted (e.g., by means of retweets or replies).

Here, we can clearly see a significant variation in the trends when switching from the Emerging category to Pioneers. Indeed, the first histogram shows the highest values for the bins representing users with low popularity, meaning that the most active users, in terms of number of tweets produced, for younger providers have low popularity levels. On the other hand, for Pioneers the curve exhibits the highest values for quite popular users, showing that users engaged in the activity of this SSP category have a higher number of followers with respect to the previous case.

To analyze how COVID-19 impacted the online customer base of SSPs, we repeated the same analysis by grouping the users interacting with the two considered SSP categories in

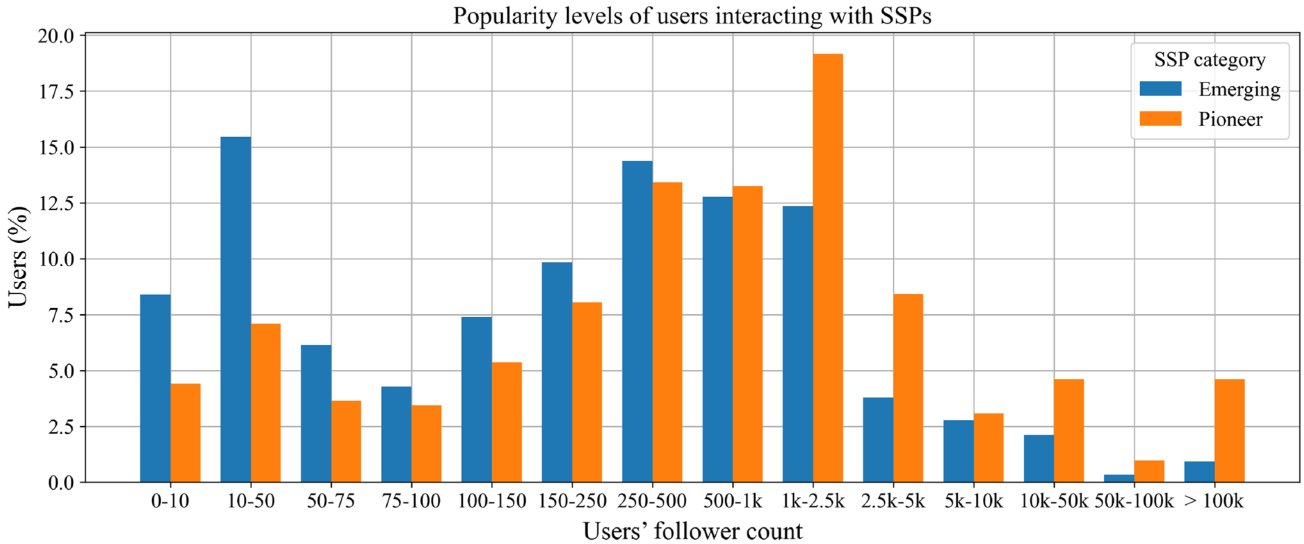

Fig. 1 Percentages of users with different popularity levels for the two analyzed categories

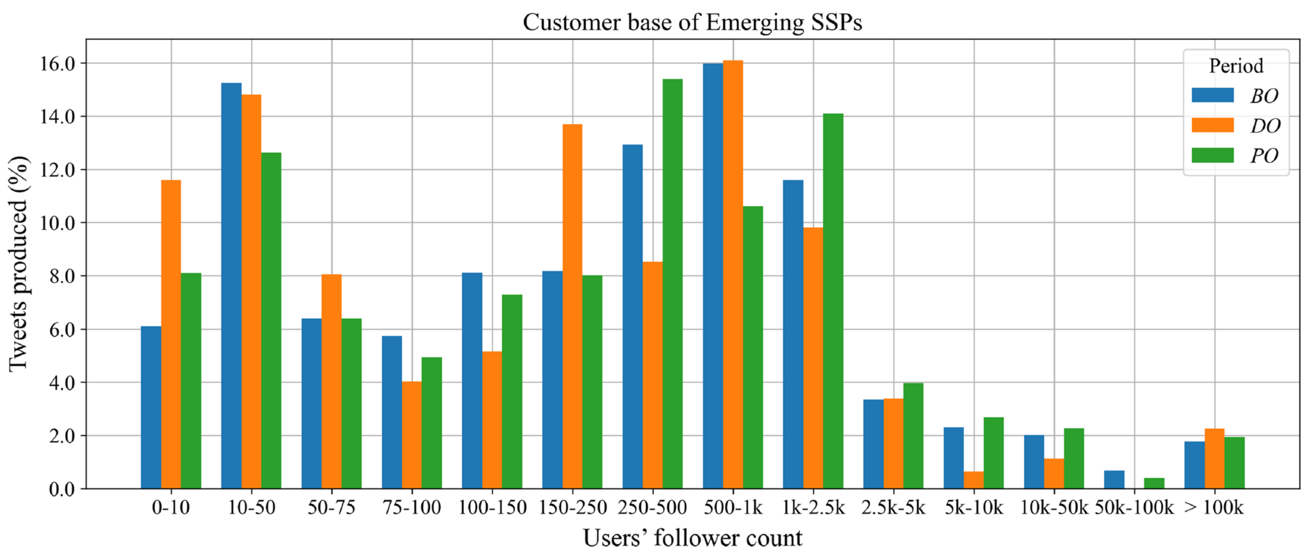

Fig. 2 Percentages of tweets produced by users with different popularity levels for Emerging SSPs during the three time periods

different popularity classes. At this point, we measured the percentages of tweets produced by users in these classes during the three considered time periods.

In Figs. 2 and 3, we report the results of this study.

By analyzing these figures, we can see that the trends are very similar for both SSP categories for the same periods in the two years. There is an almost negligible difference when comparing the trends in *BO* and *PO* with those in *DO*. To confirm the observed minor differences, we performed t tests to check their statistical relevance; we report the results in Table 3 for Emerging SSPs and in Table 4 for Pioneers.

From these tables, we can see that there are no relevant differences in the trends related to user interactions in the three time periods analyzed for Emerging SSPs (p value > 0.05 in all the cases). The last line of Table 4 shows that there is a low probability that the trends identified in *DO* and *PO* derive from the same distribution. Therefore, we can conclude that there is a difference in the distributions of the most active users that engage with Pioneer SSPs, which may be related to the virus outbreak. Anyway, these differences do not impact the conclusions drawn before in which we affirmed that, for Pioneer SSPs, the majority of interactions are produced by users with a medium-high popularity level. The main finding of this first experiment can be summarized as follows:

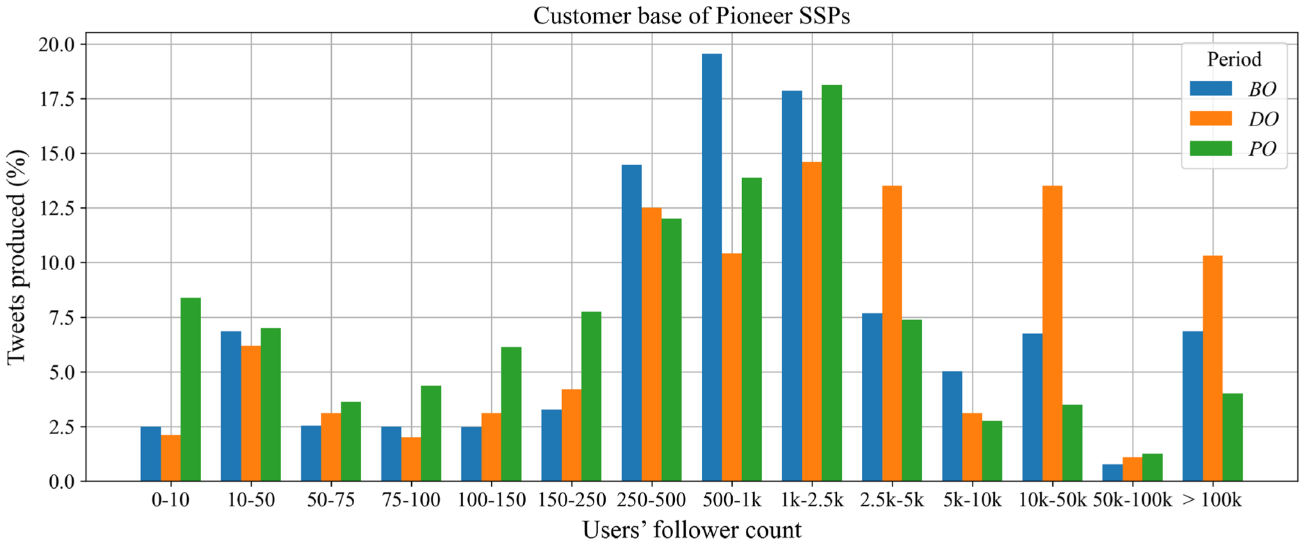

Fig. 3 Percentages of tweets produced by users with different popularity levels for Pioneer SSPs during the three time periods

Table 3 Results of the t tests carried out to analyze the differences in the trends for the three datasets regarding Emerging SSPs

Period 1	Period 2	*p* value
BO (March 2019–July 2019)	*PO* (March 2020–July 2020)	0.83
BO (March 2019–July 2019)	*DO* (December 2019–March 2020)	0.63
DO (December 2019–March 2020)	*PO* (March 2020–July 2020)	0.81

Table 4 Results of the t tests carried out to analyze the differences in the trends for the three datasets regarding Pioneer SSPs

Period 1	Period 2	*p* value
BO (March 2019–July 2019)	*PO* (March 2020–July 2020)	0.96
BO (March 2019–July 2019)	*DO* (December 2019–March 2020)	0.20
DO (December 2019–March 2020)	*PO* (March 2020–July 2020)	**0.045**

> ***Finding 1****:The most active users for Emerging SSPs are the less popular among their followers, whereas for Pioneer SSPs the most active users are the popular ones. This trend remains unchanged in all the analyzed time periods for Emerging SSPs, thus implying that COVID-19 did not have a relevant impact on this community. On the other hand, for Pioneer SSPs, the most popular users in their online customer base were more active during the initial outbreak of COVID-19.*

This finding is important to understand how the online customer base evolves during a crisis. Younger SSPs can rely on their customer base, which maintains its characteristics when it comes to the popularity level of the most active users. By contrast, the online customer base of Pioneer SSPs is less stable and, with the outbreak of a pandemic, the tweet publishing activity involves more popular users with respect to the periods not impacted by such an adverse event.

4.2 Analysis of users' sentiment and reactions

The analysis we report in this section starts by focusing on the sentiment expressed by users in their posts according to the different interaction typologies that they may have with SSPs in each category. Then, we continue our study by investigating users' reactions to the content offered by SSPs. Our objective is to assess whether the COVID-19 outbreak may impact these results.

To support this analysis from a technical point of view, we developed two classifiers: one for detecting sentiment and one to distinguish between questions and declarative sentences. As a matter of fact, when analyzing the sentiment of a post, it appears very important to distinguish between assertions (i.e., final comments and/or options) and questions, which imply the fact that the user is open to possible explanations through discussions (Arazzi et al. 2023). For the former, we used a support vector machine classifier with

Table 5 Percentages of tweets containing questions with positive/negative sentiment for topics referring to the platform and the shows in the *BO* and *PO* datasets

SSP	Dataset	Tweets about the platform		Tweets about shows	
		Positive questions (%)	Negative questions (%)	Positive questions (%)	Negative questions (%)
Emerging	*BO*	65	35	86	14
Emerging	*PO*	59	41	68	32
Pioneer	*BO*	–	–	78	22
Pioneer	*PO*	–	–	77	23

Table 6 Percentages of tweets containing assertions with positive/negative sentiment for topics referring to the platform and the shows in the *BO* and *PO* datasets

SSP	Dataset	Tweets about the platform		Tweets about shows	
		Positive assertion (%)	Negative assertion (%)	Positive assertion (%)	Negative assertion (%)
Emerging	*BO*	57	43	73	27
Emerging	*PO*	57	43	74	26
Pioneer	*BO*	–	–	67	33
Pioneer	*PO*	–	–	74	26

the *radial basis function* kernel. For the training phase, we collected a balanced dataset of positive and negative tweets. We considered a set of features for each tweet extracted using a sentiment lexicon, such as information about the number of positive/negative words along with their intensity, the number of emojis, and the total number of words.

The classifier achieved 94% precision and 94% F1 score. To build the latter model, instead, we started by collecting a balanced dataset of 2, 000 tweets manually labeled as statements or questions. The labeling task has been carried out by human experts. Then, from the recent scientific literature we identified the solution presented in Singh et al. (2021) as a suitable strategy to build our classifier. According to this strategy, we adopted a pre-trained BERT model, namely *BERT-base-uncased*, and we performed a transfer learning task using 80% of our dataset as the training set after the removal of stop words. We tested the performance of our model on the remaining 20% of data, obtaining 95% precision and 95% F1 score.

Using the models above, we considered the average sentiment for tweets including a reference or a hashtag associated with the analyzed SSPs, grouping them into two categories, namely (i) tweets about the technical aspects of the service (tweets about the platform, hereafter) and (ii) tweets about shows. Observe that, as visible in Tables 5 and 6, users of the Pioneer category do not engage in discussions concerning the technical aspects related to the streaming service. However, it is interesting to notice that there is a higher positive sentiment generated by users engaged with Emerging SSP accounts, meaning that Emerging SSPs can build a positive environment especially if they provide technical support to their users. Moreover, the results in Table 5 attest that, among negative sentiment tweets, those containing questions about the platform are about 35% in 2019 and 41% in 2020. This means that a good percentage of users have some doubts about an aspect of the service but remain open to receiving explanations.

As for the tweets about shows, Table 6 shows, also in this case, that the content in the social media associated with Emerging SSPs exhibits a higher percentage of positive sentiment (above 70% of tweets both in 2019 and 2020); this trend can be explained by the fact that younger Twitter communities may have a more positive attitude about products and services of the accounts they follow because of their novelty. This can also be due to the Technology Adoption Life Cycle stage they belong to. Indeed, younger SSPs are associated with a customer base in the first stage of the Technology Adoption Life Cycle (Weinberg 2004) of Innovators (or Tech Enthusiasts) who are risk-takers and excited by the possibilities arising from new ideas.

From the analysis of Table 6, we can also state that, over the considered time periods, there is a slight variation in the percentage of positive tweets for Pioneer SSPs. This variation is not present for Emerging SSPs which, in turn, show an almost negligible decrease in the percentage of tweets with positive sentiment. Hence, we can conclude that the decrease in the percentage of positive tweets for Pioneer SSPs can be attributed to the virus outbreak. The main results for the second experiment, regarding tweets about shows in particular, can be summarized as follows:

> ***Finding 2***: *When it comes to the sentiment expressed in the interaction of users with an SSP on Twitter, there is no significant variation with respect to the stage of the business in the Technology Adoption Life Cycle. After the COVID-19 outbreak, a slight decrease in the percentage of tweets with positive sentiment is observed for the Pioneer SSP category.*

This finding attests that the sentiment of tweets regarding the shows of Emerging SSPs is more stable than the one regarding Pioneers. In general, we can conclude that the two analyzed aspects regarding the resilience of the customer base of Emerging SSPs on Twitter (namely (i) the distribution of users with respect to their popularity level and (ii) the sentiment toward SSP products) remain unaltered even in the presence of a global crisis, like that of COVID-19. On the other hand, the pandemic outbreak has slightly impacted the interaction between Pioneer SSPs and their customer base on Twitter, regarding the characteristics that we analyzed.

In the first part of this section, we studied how users express their feelings through the content they generate. This section continues with the analysis of users' reactions to the content offered by the different SSP categories. To do so, we leveraged the tweets on the timelines of the SSPs in our dataset (see the statistics reported in the first column of Table 2). Posts published by the different SSPs are divided into three classes, namely: tweets with **Simple text** only, tweets with **Multimedia** items (i.e., containing photographs/videos), and tweets including **Hyperlinks** to external resources (i.e., URLs of additional Web content). We report the statistics related to the production of such categories of tweets in Table 7.

At this point, in our experiment, we evaluated the users' reactions in terms of the number of *retweets* and *likes* in the three different observation periods, namely before (*BO*), during (*DO*), and after (*PO*) the COVID-19 outbreak. Results are visible in Figs. 4 and 5.

From the analysis of the obtained results, we can see that users' reactions tend to be stable during the three time periods for both Emerging and Pioneer SSPs, at least in terms of *likes*. As for the *retweets*, it can be noted that although **Multimedia** tweets have undergone a shrinkage in their production for both Emerging and Pioneer SSPs, this type of tweet received great attention from users during the *DO* period (December 2019–March 2020). This may be explained by considering that lockdowns were applied in such a period and, therefore, users tended to spend more time watching multimedia content. This result is consistent with related studies (Gupta and Singharia 2021; Nielsen 2020) according to which television consumption received a noticeable increase during lockdowns. In addition, our finding shows that such a trend can be also extended to the content available in social media from SSPs, thus confirming their role as a second screen for users (Pittman and Tefertiller 2015). Following this line of reasoning, we can, therefore, derive the following finding:

> ***Finding 3***: *When it comes to users' reactions to the content generated by SSPs on Twitter, there is no significant variation with respect to the stage of the business in the Technology Adoption Life Cycle. However, multimedia content received particular attention from users during lockdowns, thus confirming the increasing use of social media as a second screen.*

Table 7 Percentages of tweets with **Simple text**, photographs/videos (**Multimedia**), and links to external resources (**Hyperlink**) produced by Emerging and Pioneer SSPs during the three observation periods

Dataset	Simple text		Multimedia		Hyperlink	
	Emerging (%)	Pioneer (%)	Emerging (%)	Pioneer (%)	Emerging (%)	Pioneer (%)
BO	39.63	32.27	42.98	53.62	17.39	14.12
DO	34.43	34.93	32.38	47.91	33.20	17.16
PO	40.48	43.12	32.54	39.02	26.98	17.86

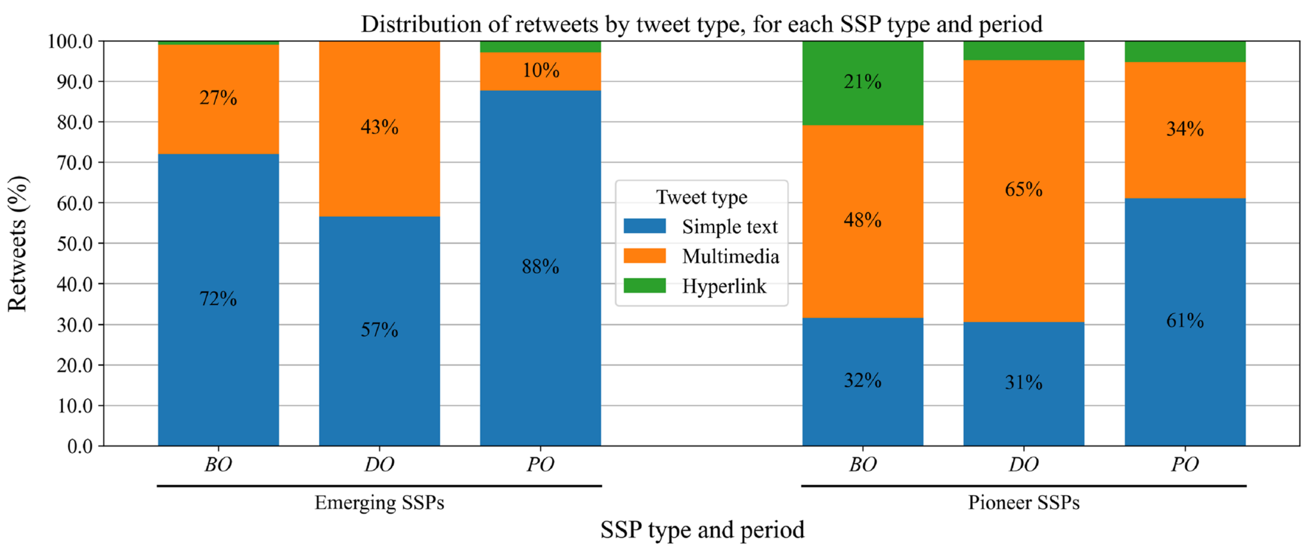

Fig. 4 Percentages of *retweets* generated by different SSPs' contents before, during, and after the COVID-19 outbreak

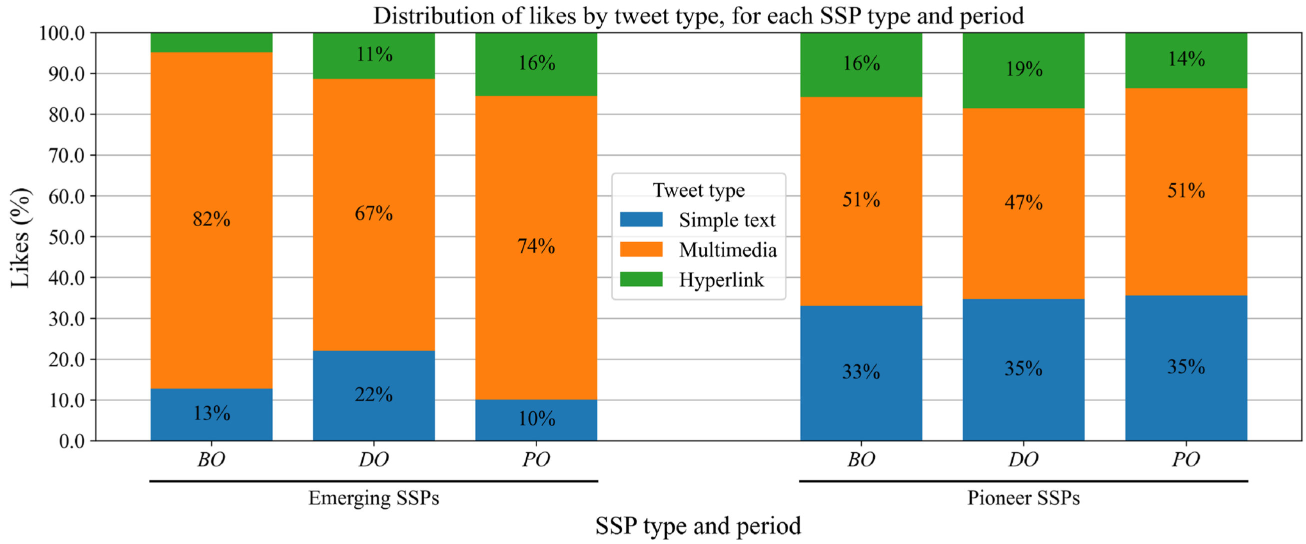

Fig. 5 Percentages of *likes* on different SSPs' contents before, during, and after the COVID-19 outbreak

5 Discussion and conclusion

The rise of COVID-19 sparked an unprecedented surge in the use of social media for entertainment and communication. Indeed, forced isolation brings people to both seek relief in television shows or streaming content and to keep in contact with friends and family via OSNs. Moreover, marketers and businesses have started utilizing OSNs in various ways to promote their brands and retain their customers but, among them, for SSPs, the importance of social platforms extends beyond information or marketing campaign sharing. Indeed, through these platforms, their users can augment television consumption with a second screen and virtually watch shows together with friends and family commenting on the most exciting scenes using, for instance, tweets.

In this paper, we proposed an analysis that can assist organizations and businesses in the online streaming sector in determining whether their followers' behavior remains unchanged during a crisis event, like the spread of COVID-19. In particular, starting from the results presented in Arazzi et al. (2023), we study two main trends. The former is related to how users with different levels of popularity interact with SSPs in two different categories; this analysis aimed at understanding if the distribution of the most active followers remains unaltered during and after the COVID-19 pandemic. The second analysis instead deals with the user sentiment in the tweets regarding the shows and the platform offered by SSPs in both categories and users' reactions to posts generated by the different SSPs; the aim of this investigation is to understand whether the generally positive sentiment and the different typology of users' reactions (i.e., likes and retweets) recorded during normal conditions are confirmed under the circumstances of a critical global event, like the COVID-19 outbreak. Our experimental campaign demonstrated that, unexpectedly, although Pioneer SSPs have larger Twitter user communities, their users exhibit a variation in their expected behavior, thus proving to be less resilient with respect to those of Emerging SPPs. Moreover, as for the study of users' reactions to SSP-generated content, although they are generally stable during the three periods under analysis, **Multimedia** tweets have been more reshared by users, especially during lockdowns. Our findings represent a non-trivial piece of knowledge; indeed, with this paper, we focus on the exploration of SSPs, whose businesses have played a crucial role during the pandemic as they became preferred providers of entertainment during the lockdown. As already said in the Introduction and as reported in previous research (Nielsen 2020; Gupta and Singharia 2021), there has been an 18% increase in television consumption in the USA in the week at the end of March, especially among teenagers who could no longer go to school, and a 38% growth in TV consumption over the pre-COVID-19 period in India. Moreover, popular OTT service providers such as YouTube, Netflix, and Spotify recorded a 140% rise in video streaming apps in Australia, India, Indonesia, South Korea, and Thailand. Since SSPs make use of social networking websites and apps to engage users and encourage them to develop a user community where they can discuss the content with each other (Gupta and Singharia 2021), studying the possible evolution of the interaction between SSPs and their online customer base during the COVID-19 should have been of great interest. For instance, a possible expected result could have been an increase in the engagement and stability of the customer base of popular SSPs with respect to newer SSPs. For this reason, we chose to analyze a number of aspects related to the interaction between SSPs and their customer base.

Actually, our findings show that the communities following SSPs are generally resilient during crises. However, it is important to underline that, although unexpected, the Pioneer SSP category is the one that seems to be most impacted. This can be explained by the fact that Emerging SSPs maintain richer relationships with their customer base. Such a result can be a very important insight for SSP businesses to understand how they should approach crisis periods in order to preserve their online communities.

Of course, our contribution presents valuable insights for a specialized audience and can stimulate further research in these areas. Moreover, when combined with other studies, they may contribute to a broader understanding of the impact of very complex phenomena, such as COVID-19, on online communities of users.

The novel research described in this paper is a starting point for further investigations we plan to perform in the future. For instance, it may be possible to extend the analysis by considering other intriguing aspects related to the possible impact of a global pandemic and, in general, of critical events on users' sensibility to privacy concerns regarding social media. In particular, we plan to compute the amount of disclosure of personal tastes, opinions, and sensitive information through tweets regarding SSPs' shows. Moreover, we would like to analyze how this measure has been impacted by the COVID-19 outbreak, to understand if people are more willing to disclose their personal information online after a period of isolation and crisis.

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Declarations

Conflict of interest The authors declare that they have no conflicts of interest to report regarding the present study.

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