The Rhythms of the Night: increase in online night activity and emotional resilience during the Covid-19 lockdown

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Abstract

Context: The lockdown orders established in multiple countries in response to the Covid-19 pandemics are perhaps the widest and deepest shock experienced by human behaviors in recent years. Studying the impact of the lockdown, through the lens of social media, offers an unprecedented opportunity for analyzing the susceptibility and the resilience of circadian rhythms to large-scale exogenous shocks. In this context, we address two interconnected research questions: Can variations of online activity cycles provide information on the impact of lockdown on human activities? How do online circadian rhythms react to such a disruption?

Data: We base our research on the analysis and comparison of two independent databases about the French cyberspace: a fine-grained temporal record of YouTube videos and a large collection of Tweets on Covid-19.

Findings: In both datasets we observe a reshaping of the circadian rhythms with a substantial increase of night activity during the lockdown. The analysis of the videos and tweets published during lockdown shows a general decrease in emotional contents and a shift from themes like work and money to themes like death and safety. However, the daily patterns of emotions remain mostly unchanged, thereby suggesting that emotional cycles are resilient to exogenous shocks.
Introduction

The lockdown established in France from March 17th to May 11th as a response to the Covid-19 pandemic has created a sudden and severe transformation of daily routines. This disruption represents a textbook case of exogenous shock on human behaviors, which can, by comparison, reveal features of normal social life. In this paper we carry out this comparative analysis, focusing on online behaviors and leveraging a unique YouTube dataset. A few weeks before the lockdown, we had started following a corpus of more than one thousand French political YouTube channels with an exceptional temporal granularity – recording hour by hour the number of views of all of their videos. This provided us with a unique dataset to study how the lockdown transformed the circadian rhythms of online activities. To make sure our findings are not platform specific, we compare the results obtained on YouTube with a Twitter dataset of 33 million Covid-19-related tweets in French.

In this paper, we investigate changes in the daily rhythm of online activities and address two related research questions: what are the changes produced by the lockdown and how resilient are online circadian rhythms. The analysis of such a exceptional period allows us to distinguish the dynamics resulting from the influences of the Covid-19 crisis from stable features of the social media we investigated.

We focus our research on a single country, France, in order to identify precisely the start and end dates of the lockdown and to work on a (relatively) uniform population sample that excludes national differences.

Our analysis shows, for both platforms, a substantial albeit not surprising increase of online activities as a consequence of the decrease of real-life interactions. Moreover, the growth in online participation and content consumption is not uniform across the 24 hours but is more salient during night. Besides this variation in volume, we register changes in the kind of content shared from an emotional and thematic point of view. In both platforms, the lockdown is marked by a decrease in emotional contents, positive and negative, and a thematic shift from topics like "money, work and social life" to "safety and death". Against these lockdown-induced changes, some constants of YouTube and Twitter stand out. Despite its quantitative change, the shape of the daily cycle of different emotions (i.e. their prevalence by hour) is not impacted by the lockdown: this finding confirms the results of previous studies that showed a stability of emotional rhythms through seasons and cultures [1, 2, 3]. The resilience of these patterns, despite the disruption of the lockdown, supports the biological origin of the emotional expression, which seems to be more strongly influenced by the biological clock than by exogenous factors.

Related Work

The patterns of activity in different social media vary according to the characteristics and the scope of the different platforms and to the composition of its
Several papers in the literature have already studied circadian fingerprints in different social media. In YouTube, scholars have investigated not only the rhythms of content creation (i.e. of video posting) [4] but also the daily patterns of content fruition (i.e. videos watching) [5]. Daily and a weekly use of Twitter has been analyzed in various countries [6]. Foursquare attracted researchers’ attention for its circadian and geographic patterns [7] and its similarities with Twitter [8]. Wikipedia editorial patterns have been studied in [9] with an interesting focus on inter-cultural variations. Moreover, when slightly deviating from the social media framework, mobile phones and instant messaging activities have been analyzed in [10, 11]. Despite their differences, all platforms unsurprisingly show a substantial decrease of activity during the night.

The realm of night owls is characterized not only by a general "silence" but also by typical emotional markers. Emotional content of Twitter activity has been studied in several papers with different approaches. [1, 2, 3] focus on diurnal patterns and circadian rhythms in the expression of affect, the first analyzing a wide dataset from several countries, the others concentrating on UK data. Despite the variety of data considered, all these papers share the same finding: digital nights are consistently characterized by a low level of shared emotions (both positive and negative).

Covid-19 lockdown partially disrupted these rhythms, by drastically changing people’s habits and daily routines: from work-related commuting to homeworking, from school to distance learning, from in-person meetings to video calls. Within few days whole populations had to re-adapt their behaviors into a new life scenario characterized by profound health and professional concerns. Such unpredictable situation strongly impacted peoples’ sleep-wake cycles, as reported in several studies based on surveys [12, 13]. With our study, therefore, we create a link between the literature on circadian online rhythms and the one on the stress experienced by many societies in recent months.

1 Data and Methods

Since circadian patterns of online activity are strongly dependent on users’ demography and on platforms’ scope, as mentioned in the introduction, we used conduct our study across two different platforms: YouTube and Twitter. The first one allows us to investigate the consumption of online content (video views), the second its production (tweeting and re-tweeting activity). This comparative framework will be central to distinguish platform-specific findings from more general trends.

1.1 The YouTube Dataset

As mentioned in the introduction, the YouTube dataset is particularly interesting as it cannot be straightforwardly obtained through YouTube application programming interface (API). We started from a corpus of 1031 popular French channels dealing with public issues. In collaboration with the Qatar Computing
Research Institute (QCRI), we recorded hour by hour the evolution of views of each videos published after February 17, for an entire week after the publication. Moreover, for every video, we collected the title, the description and other metadata available through the official YouTube API. Contrary to what one might expect, the total views of a given video are not always increasing over time. Occasionally but significantly, YouTube removes from its counting earlier views that it deems to be false because likely produced through bots, click-farming or other illegitimate tricks. Since the corrections of these views are made after their recording, our dataset may contain hours with negative visualizations. To correct for this negative views, we have preprocessed our data in order to uniformly redistribute the corrections made at a given time on the previous hours. More precisely, if we call \( v_h \) the views collected by a generic video at hour \( h \) after publication and \( T_h \) the total number of views at hour \( h \), if \( T_{h+1} < T_h \), we correct the time series as follows:

\[
\hat{T}_j = (1 - p) T_j, \quad j = 1, \ldots, h
\]

where \( \hat{T}_j \) is the corrected time series until hour \( h \) and \( p = \frac{T_h - T_{h+1}}{T_h} \) is a percentage of correction.

### 1.2 The Twitter Dataset

The Twitter dataset comprises about 8 millions tweets posted by 5161 non-professional users from February 17 to April 14. Since we are interested in the activity of common Twitter users, we decided to exclude newspapers, bloggers, radios, associations, etc. and only consider non-professional users. To select these users we started from a wider dataset of about 33 millions tweets containing Covid-19-related content. This corpus of tweets was collected by Science–Po MediaLab in Paris, using the python based scraper, Gazouilloire, a tool developed by Dime Web for systematic and configurable Twitter data collection through Twitter’s official API. The data were collected based on a query of Covid-19 related words in French. Within this larger dataset, we select a smaller set of users with the following characteristics.

- To focus on France, we only considered users who explicitly declare in their profile their location to be in France;
- To exclude professionals, we only considered users if (1) their profile did not contain keywords associated to professional use of the platform (e.g. ”media”, ”blog”, ”official”, etc.); (2) their number of followers was lower than the median of the whole dataset; (3) their activity was lower than the median activity (~400 tweets by week);
- To allow for a significant statistical analysis we also discarded all the users who published less than 100 tweets in the whole period.

\[1 \text{https://github.com/medialab/gazouilloire}\]
All twitting and re-twitting times were collected in European Central Timezone (UTC +1).

1.3 The tool for emotion and topic mining

To analyze the emotional and thematic contents of tweets and YouTube videos we used a very well-known and tested tool: the LIWC dictionary \[13\]. The LIWC dictionary classifies words on more than 70 emotional, stylistic and thematic dimensions and has been used in several analogous studies such as \[1\] \[2\]. Since the texts we analyze are written in French, we used the French version of the LIWC dictionary \[14\].

2 Results

2.1 The rhythm of the night

The French lockdown was announced on March 15 and enforced on the 17th. In Figure 1 we analyzed the time series for Twitter posting, YouTube posting and YouTube views. All three time series show weekly and daily fluctuations. The averages daily signals, smoothed with a moving average over a 7 day rolling window, reveal an increase of activity for Twitter posting and YouTube watching around the beginning of the lockdown. Notice however that, while YouTube viewing activity started to increase on the day of lockdown enforcement (possibly due to the reduced competition of offline recreational activities), the increase on Twitter started from the very moment the lockdown was announced (which itself sparked much debate on the microblogging platform). As for the posting of videos on YouTube, such an activity is less casual and more stable than tweeting (particularly for the high-visibility channels that we monitored) and therefore conserved the same weekly and daily rhythms during the lockdown. Since the video production is hardly affected by the lockdown, we will not consider this dimension in the rest of the paper. It is interesting to notice, however, that, in the YouTube case, it was the demand of content and not the offer that was affected by the lockdown.

To highlight the effects of the lockdown, in the following we analyze thematic and emotional changes before and after the start of the lockdown (March 17). We refer to the period before the lockdown as to the three weeks from February 17 to March 9. At the same time we will refer to the period after the lockdown enforcement as to the three weeks from March 23 to April 14. To exclude the transient effects of the transition phase, we discard the data about the two weeks around the lockdown onset (from the 9th to the 22nd of March). Preliminarily, we calculated the normalized daily activity profiles before and after lockdown for each hour of the day by

\[
f_{\text{Twitter}}(h) = \frac{\sum_{d \in \text{days}} \sum_{h \in \{0, \ldots, 23\}} N_{\text{tweets}}(d, h)}{\sum_{d \in \text{days}} \sum_{h \in \{0, \ldots, 23\}} N_{\text{tweets}}(d, h)} \tag{1}\]
and
\[ f_{\text{YouTube}}(h) = \frac{\sum_{d \in \text{days}} \sum_{h \in \{0, \ldots, 23\}} N_{\text{views}}(d, h)}{\sum_{d \in \text{days}} N_{\text{views}}(h)} \] (2)

where \( h \in \{0, \ldots, 23\} \) are the hours of day, \( d \) are the days considered, and \( N_{\text{tweets}}(d, h) \) and \( N_{\text{views}}(d, h) \) are respectively the number of tweets and of YouTube views at hour \( h \) of day \( d \). The results are reported in the left plots of Figure 2.

We first observe that the profiles for Twitter and YouTube are quite different: while Twitter is mostly used during the day, with a strong activity decrease after midnight, YouTube is characterized by a higher nightly activity. While Twitter is an active media, characterized by a debating and prosing culture [15] that encourages participation at the time of the day when engagement is maximum, videos watching on YouTube is, for many users, a more passive activity [16] which can easily fit the more relaxed late hours.

To quantify the differences between profiles before and after the lockdown, we calculated the relative differences of the normalized profiles:
\[ \delta(h) = \frac{f_{\text{after}}(h) - f_{\text{before}}(h)}{f_{\text{after}}(h) + f_{\text{before}}(h)} \] (3)

This quantity is reported in the right plots of Figure 2. Both YouTube and Twitter experienced an activity increase during the night and a smaller decrease of the activity in the early morning (6am-9am for Twitter and 9am-12am for YouTube). We observe that the morning decrease in Twitter is much smaller than the night increase. This suggests that, with the lockdown, people stayed longer awake during the night but without oversleeping in the morning. To confirm this hypothesis of decrease of sleep during the lockdown, we analyze the situation at the individual level. For each Twitter user, we calculate the average time lag between two consecutive Tweets. Figure 3 shows the hourly average of this measure before and after the lockdown. While, in normal times, the average inter-event times are much higher during the night (because of sleeping breaks), the lockdown flattened the curve, thereby suggesting a shortening of sleep intervals [12].

2.2 What is night?

In this paragraph we analyze whether the quantitative changes observed in the previous paragraph correspond to differences in terms of contents. For Twitter, we build the sets \( K(d, h) \) containing all the hashtags posted in day \( d \) at hour \( h \). For YouTube, we build the sets \( K(d, h) \) containing all the videos visualized in day \( d \) at hour \( h \). We define the time similarity matrix, \( \Theta \), between two day’s hours \( h_1, h_2 \), based on the Jaccard similarity between the sets \( K(d, h_1) \) and \( K(d, h_2) \) as:
\[ \Theta(h_1, h_2) = \frac{1}{N_{\text{days}}} \sum_{d \in \text{days}} J(K(d, h_1), K(d, h_2)) \] (4)
where \( J(K(d, h_1), K(d, h_2)) = \frac{|K(d, h_1) \cap K(d, h_2)|}{|K(d, h_1) \cup K(d, h_2)|} \) is the Jaccard similarity. Matrix \( \Theta \) indicates how the content shared or viewed at a certain hour is similar to the content in all the other hours. We perform a \( k \)-mean clustering procedure on this matrix to obtain the visualizations in Figure 4. Both for Twitter and YouTube, and both before and after lockdown, night hours (0am-5am) seem to be characterized by contents distinctively different from the rest of the day. Before lockdown morning hours (6am-10am) were, in both platforms, more different from night-time. In Twitter, in particular, they formed a cluster on their own. Lockdown broke this morning cluster but in opposite ways for the two platforms. In Twitter, the morning cluster merged with the rest of the day while in YouTube the night vibe extended into the early morning.

2.3 A significant change of content

We proceed with the analyses of the emotional and thematic content of Twitter and YouTube activities, before and after the lockdown. Using the categories of the LIWC dictionary we will consider 3 separated analytic dimensions:

- **General Affects**: Positive Affect, Negative Affect;
- **Specific Emotions**: Sadness, Anger, Anxiety and Accomplishment;
- **Thematic contents**: Work, Social life, Religion, Death, Fun, Exclusion, Biology, Money.

We first assign the tweets and YouTube videos (based on the words contained in their titles and descriptions) to one category for each dimension. To do so, we count how many terms from each category are contained in each tweet/video, and we assign the content to the prevalent category. For example, for the dimension "General Affect" each content is categorized as either Positive or Negative Affect or not classified if the items contain no categorical words or similar proportions of positive and negative terms. We also consider the global emotional level ("Affect") of the items, by counting together the positive and negative words. For each dimension, we compute the fraction of tweets and retweets in each category during the lockdown and the difference compared to the previous period. In the same way, for YouTube, we evaluate the fraction of visualization of videos in each category over the total number of views. The results are reported in the left plot of Figure 5.

Comparing the two platforms, we first observe that YouTube is more "emotional" than Twitter is and that it is generally populated by more positive content. Both platforms experience a decrease of the emotional sphere during the lockdown, both on the positive and on the negative side. Regarding specific emotions, we notice that expressions of accomplishment declines in both platforms. Instead, while Twitter experienced a decrease of all specific emotions, YouTube, which was already characterized by a higher level of anger, sadness and anxiety before the lockdown, goes through an important increase of these
sentiments. From a thematic point of view we observe, unsurprisingly, a decrease of the contents related to work and an increase of contents related to death and house. On Twitter we also have a significant increase of religion-related contents. All differences in distribution of contents before and after the lockdown have been tested statistically with Kolmogorov-Smirnov (KS) tests. For both platforms before and after the lockdown an hourly aggregation has been performed in order to get two different sample of emotion distribution. The results of the KS test over those distributions are reported in Table 1 and most of the times point out statistical evidence to support differences of content distribution before and after the lockdown.

2.4 Because the night belongs to...

Drawing on our previous hour clustering, we divide the day according to five time periods: [0am-5am], [6am-9am], [10am-2pm], [3pm-6pm], [7pm-12pm] to identify a circadian profile for each of our categories (right plot of Figure 5). For several categories related to emotions, we can first notice an interesting Twitter/YouTube difference: what peaks in the early morning on Twitter [6am-9am] tend to peak in the following interval in YouTube [10am-2pm], suggesting that YouTube content is consumed later in the day. Going into more detail, for general emotions, in agreement with the findings of [1,2,3] we observe that nights are characterized by low emotional levels, especially positive ones, while both positivity and negativity tend to peak at the moment of the awakening. This pattern is more evident on Twitter also at the level of specific emotion, while on YouTube a significant portion of negative contents is consumed during the night.

An interesting observation, again in phase with the precedent findings of [1,2,3], is that the daily emotional patterns seem to be resilient to the covid-19 disruption: even if the volume of some emotion changed during the lockdown, their daily distribution generally maintained the same shape, as demonstrated by a rough parallelism of the lines before and during the lockdown (with some exceptions regarding anger and anxiety on YouTube). This fact confirms the observation made in [1] that external factors, even as important as the covid-19 lockdown, influence the emotional patterns less than the sleep-wakefulness cycles. Interestingly, this is not the case for the distribution of topics which has been more significantly influenced by the lockdown.

3 Discussion

The Covid-19 pandemic and the ensuing lockdown have deeply and widely disrupted peoples’ daily routines. Our research exposed some of these changes trough the lens of social media. By highlighting what has changed during the lockdown and what has resisted the Covid-19 shock, our research proves that certain online habits are resilient to high levels of external disruption while oth-
ers are less robust, suggesting which human behaviors are more influenced by exogenous factors and which are, on the contrary, constant even in exceptional situations.

Circadian rhythms of activity proved to be strongly related to lifestyle and working hours: the sharp change observed in the lockdown rhythms suggests in particular that in absence of external constraints such as school and office hours, the boundaries between night and day become more flexible.

Perhaps surprisingly, we found out that the affective charge of tweets and YouTube videos decreased with the lockdown, arguably leaving space to less emotional contents. However, this general finding is tempered by the fact that on YouTube (which is inherently a more emotional medium than Twitter) negative sentiments like anger and anxiety did increase, thus revealing the stressful situation for the population. As topics are concerned, online discussions proved to follow real world events and, unsurprisingly in a global epidemic that forced French population at home, shifted toward questions connected to biology, house, and death.

As an even more compelling result, we pointed out the resilience of specific emotional patterns in online activities. While the general emotional charge of online contents decreased during the lockdown, it maintained its normal daily distribution. After March 17th, nightlife continues to be characterized by less emotional content despite the stress caused by the Covid-19 crisis. Even if the circadian rhythms change and people stay awake longer, at night, they seem to continue to share and consume the same type of contents. In future research, we would like to investigate more in depth the nature of this nighttime unemotional space, to reveal whether it consists of more informative and impartial contents, weather it give rise to positive and constructive form of debate or, on the contrary, whether it is more markedly affected by fake news and other types of misinformation. The LIWC dictionary used so far allowed us to distinguish emotional from unemotional contents: more specific dictionaries could lead to deeper insights about the night space and to investigate in more detail the relationship between information and emotion in different medias. Broadly speaking, we hope that noticing the resilience of some online patterns during the lockdown might encourage future research in emotional rhythms and their reaction to external shocks.

Availability of data and material

Authors agree to make their data available upon request.

Competing interests

The authors declare that they have no competing interests.
Author’s contributions

All the authors conceived the idea. M.C. and F.G. analyzed the data and collected the missing data. All authors wrote the manuscript.

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Figure 1: **Increase of platforms activity after the lockdown.** (top) Evolution of number of visualizations by day on YouTube. (middle) Evolution of number of publication of new videos on YouTube. (bottom) Evolution of number of Covid-19 related tweets or re-tweets along time.

Table 1: p-values of Kolmogorov-Smirnov tests for content differences displayed by Figure 5, i.e. content differences before and after the lockdown

| Category         | p-value YouTube | p-value Twitter |
|------------------|-----------------|-----------------|
| Negative Affect  | $2.12 \cdot 10^{-8}$ | $3.10 \cdot 10^{-15}$ |
| Positive Affect  | $1.72 \cdot 10^{-9}$ | $3.10 \cdot 10^{-15}$ |
| Affect           | $\sim 0$        | $3.10 \cdot 10^{-15}$ |
| Sadness          | $5.86 \cdot 10^{-3}$ | $0.984$         |
| Anger            | $5.84 \cdot 10^{-4}$ | $3.11 \cdot 10^{-15}$ |
| Anxiety          | $\sim 0$        | $3.11 \cdot 10^{-15}$ |
| Accomplishment   | $\sim 0$        | $3.11 \cdot 10^{-15}$ |
| Work             | $\sim 0$        | $3.11 \cdot 10^{-15}$ |
| Social Life      | $0.32$          | $1.46 \cdot 10^{-6}$ |
| Religion         | $1.32 \cdot 10^{-6}$ | $3.85 \cdot 10^{-3}$ |
| Death            | $4.66 \cdot 10^{-15}$ | $1.03 \cdot 10^{-3}$ |
| Leisure          | $6.88 \cdot 10^{-15}$ | $3.11 \cdot 10^{-15}$ |
| Exclusion        | $\sim 0$        | $1.73 \cdot 10^{-8}$ |
| Biology          | $\sim 0$        | $4.20 \cdot 10^{-8}$ |
| Money            | $\sim 0$        | $3.11 \cdot 10^{-15}$ |
Figure 2: **Circadian Rhythm Changes** On the left Twitter and YouTube circadian rhythm before and after the lockdown are shown. On the right we explicitly evaluate relative differences between rhythms before and after the lockdown.

Figure 3: **Average inter-event distance for an event starting at time** $t$. 
Figure 4: **Hours Correlation** On the left Twitter and YouTube circadian rhythm before and after the lockdown are shown. On the right we explicitly evaluate relative differences between rhythms before and after the lock-down.
Figure 5: **Themes and Emotions before and after lock-downs**

Left plot: Fraction of videos/Tweets with a content and relative change with lockdown. The size of the points is proportional to the fractions (quantified by the upper numbers). The orientation of the line indicates if there was an increase (orientation toward right) or decrease (toward left) with the lockdown. The length of the line is proportional to the percentage increase/decrease with the lockdown.

Right plot: Fraction of videos/Tweets with a content by hour. The continuous line indicates the fractions after the lockdown, the dotted lines before. An arrow starts from the before to the after line for each hour period: if the arrow is oriented towards the top, the lockdown increased the content fraction in the selected hours and viceversa. In both plots YouTube is in red, Twitter is in blue.