Songs as an indicator of wellbeing : Evidence from the COVID-19

Salma Abdel-Salam Mirana Ranerison Sara Sedrak Sophie Strehl

Université Paris 1 Panthéon-Sorbonne

Research question and Motivations

The purpose of this analysis is to study the impact of the COVID-19 on well-being, by using song sentiment as a proxy. Even though many papers tackle the issue of COVID-19 on welfare, we wanted to use a new variable to measure it. Indeed, songs can be used as it can reflect how people feel. This approach can be useful for further studies.

The COVID-19 pandemic has had profound global impacts, with over 777 million confirmed cases and more than 7 million deaths worldwide, leading to widespread lockdowns and financial losses [3]. These restrictions have significantly influenced psychological well-being. This research seeks to examine the effects of COVID-19 on well-being through the lens of song sentiments, a globally comparable and language-free measure of emotional states [4]. The edge that music consumption has is that unlike search behaviors -that may reflect information-seeking rather than emotions-it is a direct expression of sentiment. We use NLP to analyze song lyrics and extract sentiment, inferring individuals' moods from their music consumption during the pandemic.

Related work

Research on the mental health impact of COVID-19 has highlighted significant psychological consequences, including anxiety, depression, and decreased life satisfaction, particularly due to quarantine and social isolation (Pfefferbaum & North, 2020 [8]; Brooks et al., 2020 [2]; Ammar et al., 2020 [1]; Pappa et al., 2020 [7]). Studies have also shown that people often reflect their emotional states in their music preferences, with music serving as a tool for emotional validation and expression [4]. This connection suggests that music choices can be used to estimate emotional well-being.

Previous works used music to detect song sentiment for instance Edmans et al.(2021) [4] used Spotify's valence metric, derived from a machine learning algorithm trained on a sample of 5,000 songs, to measure musical positivity and study its correlation with investor sentiment and shock returns. David Sadka (2024) [9] utilized Python-based web scraping and ChatGPT for lyric analysis to create a monthly happiness measure linked to financial economic indicators. Oramas et al. (2018) [6] explore NLP techniques for music knowledge discovery, addressing corpus compilation, text mining, information extraction, knowledge graph creation, and sentiment analysis.

Data preparation and Web Scrapping

Our goal was to study changes in people's well-being before and after the 2020 lockdowns by analyzing music lyrics. To do this, we collected the top 20 ranked songs each week from 2019 to 2022 in the United States, United Kingdom, Australia, and Canada. These English-speaking countries were selected to make sure that language differences did not compromise the accuracy of lyric-based sentiment analysis, as textual analysis across multiple languages presents challenges in global comparability (Edmans et al., 2021 [4]), but also to show variations in trends across different regions while minimizing country-specific bias.

We limited our analysis to the top 20 songs per country, as the UK only provided data for the top 20. Scrapping the lyrics for one country alone took, on average, four hours due to the time-consuming nature of the process and the time.sleep(3) delay added between requests to avoid being blocked by the websites. Given the number of countries, we optimized our approach to balance time constraints and data collection. For the United States, UK, and Canada, we relied on the Billboard 100 charts, while for Australia, we used the ARIA charts because Billboard did not provide the desired timeframe for Australia. For each week, we constructed URLs for the charts, sent HTTP requests to fetch the HTML content, and used BeautifulSoup to analyze the page and extract song titles and their ranks. This process resulted in a dataset containing more than 4,000 songs across all four countries.

Once we had the list of songs, we scrapped their lyrics from Genius. URLs for each song were constructed using song and artist names, with necessary transformations to ensure proper formatting, such as the lyrics from the Genius pages, handling cases where lyrics were unavailable or the page structure differed. The final dataset includes columns for the date, rank, song title, artist, and lyrics, providing a structured foundation for analyzing lyric's themes and trends.

Methodology

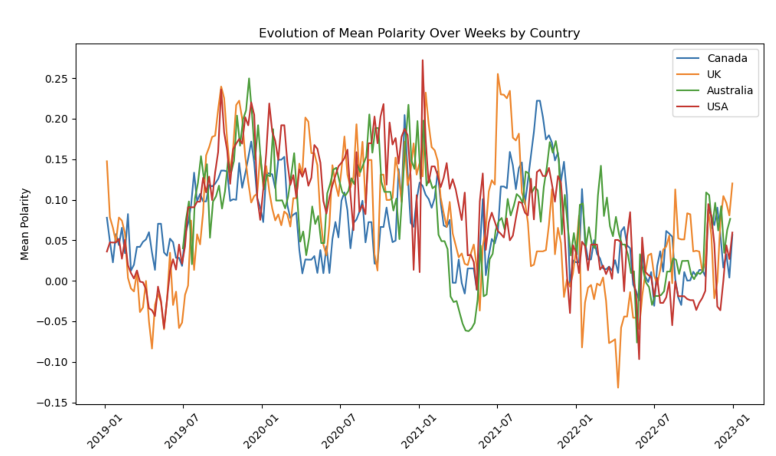
In order to analyze the lyrics of the songs, we used two different methodologies :

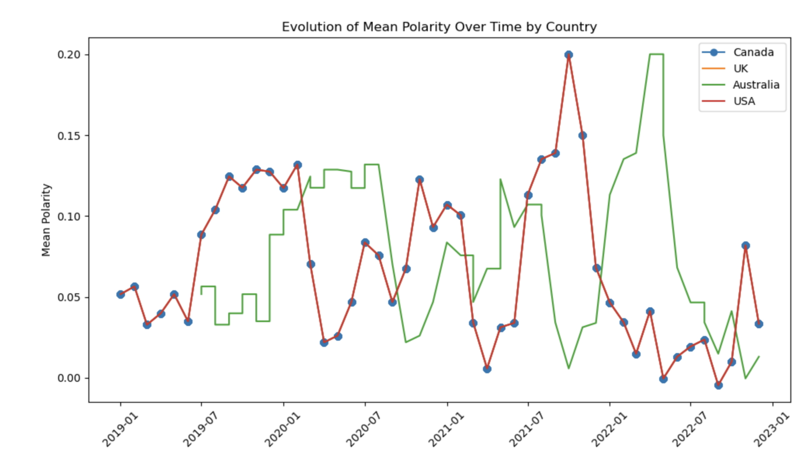
- The **dictionary** : We first used the dictionary "textblob" to evaluate the **polarity** of the songs. According to the words in the lyrics, it gives a score to the song : 1 is positive, 0 neutral and -1 negative. Then, we calculated the mean score of positivity/polarity of the song by week, and then by month, in order to study the evolution of the sentiments of people through music overtime.
- Next, we applied the **BERT** (Bidirectional Encoder Representations from Transformers) model, a fine-tuned machine learning technique for NLP tasks, to analyze the lyrics. Unlike dictionary-based methods, BERT considers the context of words in both directions (left and right), allowing it to capture nuanced meanings, word dependencies, and relationships within the text. Using BERT, we assessed the sentiment of the lyrics, categorizing them as positive, negative, or neutral. It provides a more advanced and context-aware sentiment classification, especially for handling ambiguous or complex language patterns. Similar to the dictionary method, we aggregated the BERT sentiment scores by week and month to observe the evolution of emotional expressions in music over time.

This dual-methodology approach allowed us to compare a basic dictionary-based method with an advanced machine learning model, giving us a clearer understanding of song lyrics' sentiments.

Results and Figures

Dictionary method

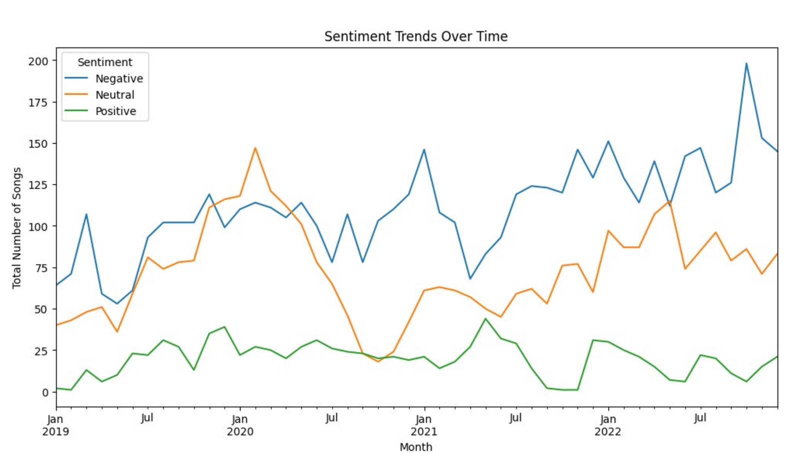


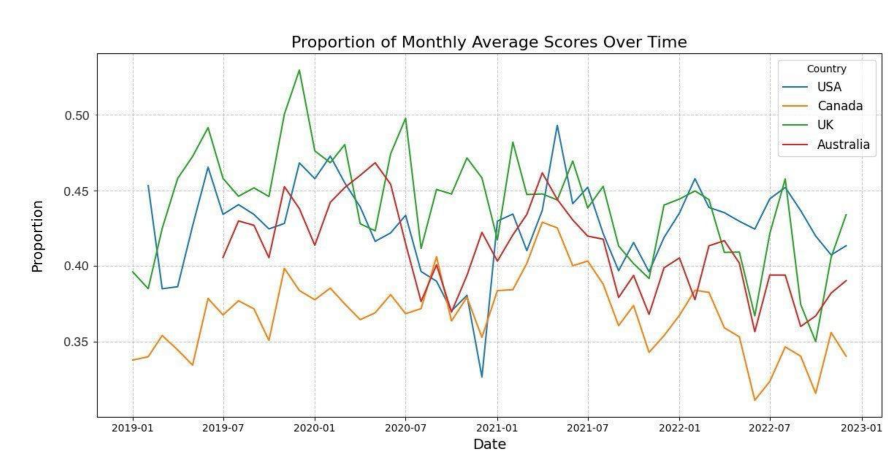


We can see that by week (first graph), the evolution of the sentiment has more or less the same tendency for every countries, with the UK that are quite more extreme than the other countries. We can see a decrease from the beginning of 2020 but the mean of polarity seems mostly positive.

When we study the evolution of the mean of polarity by month (second graph), we can see that it is the same for the USA, UK and Canada, as the songs in the top 20 can be quite similar. First, we can say that there is a strong seasonal effect, which is opposed between Northern and Southern countries, as seasons are reversed. Summer songs are generally more joyful than winter songs. We can say that this trend is strengthened by COVID-19, as there is an important decrease in positivity from January to March 2020 in Northern countries, and from July to October 2020 in Australia, corresponding to the periods of lockdown. The study by month can be more relevant as during one month, the top 20 songs can be similar from one week to the next.

BERT method





The first graph illustrates the trends in total number of songs listened to by the four countries, categorized into positive, negative, and neutral sentiments, showing notable volatility from 2019 to 2022. Positive songs remain consistently lower throughout, while negative songs dominate, indicating a shift in sentiment over time. During the pre-COVID period (July 2019 – May 2020), the gap between negative and neutral songs was relatively insignificant, suggesting a balanced mood. This period may have been influenced by people taking a break from work, school, and life pressures, contributing to a sense of temporary happiness. However, post-May 2020, there was a significant surge in negative songs, particularly from October to December 2020, reflecting heightened discomfort due to prolonged stress, uncertainty, and social isolation caused by the COVID-19 pandemic.

Country-specific trends (second graph where the proportion is : *negative ≤ 0.4; 0.4 < neutral < 0.6, positive ≥0.6)* highlight variations, with Australia and Canada peaking in November 2020, the UK experiencing peaks in both August and October, and the US showing a sharp increase in December 2020, where nearly all top songs were negative. In April, negative songs began to decline while positive songs started to increase, marking the peak of positive sentiment over the three-year period. This could be linked to the easing of lockdown restrictions. However, after this period, negative songs continued to rise, with the peak occurring in October 2022. This increase in negative songs, even after the end of the COVID-19 pandemic, can be attributed to uncertainty, and the lasting emotional impact of the pandemic on people's well-being. *For a more detailed and in-depth monthly analysis of each country's trend over the four-year period, please refer to the appendix.*

This word cloud for Canada serves as an example, illustrating the most frequently occurring words during its peak month of the COVID-19 pandemic. We observe several negative sentiment-related words, such as "maybe," "wonder," "fell," "corner," "tryna meet," "tryna call," "friendshope," "seeing somebody," "phone," and "black." These terms reflect the emotional state of people during this period, capturing their struggles, uncertainty, and feelings of isolation, offering valuable insights into the collective mood.

Limits of our approach

One limitation of using music as a proxy for mood is the concern that music can serve as a way to defy one current emotional state, rather than reflect them—for instance, playing upbeat songs to combat negative feelings. However, this concern contrasts with research on emotion congruity, which suggests that music often mirrors the listener's emotional state [4].

Another limitation is that there are missing values in our scrapping of lyrics. In fact, we were not able to collect all the lyrics, and sometimes, there is not the lyrics of the full song but only some parts. Our study will gain in precision with the totality of the lyrics. However, less than 30% of the lyrics are missing, so we can say that our study remains relevant.

Conclusion

To sum up, our analysis examined the impact of COVID-19 on well-being by studying the sentiment of Top song lyrics in four English-speaking countries: the United States, the United Kingdom, Australia, and Canada. Using a dual-methodology approach, we combined a dictionary-based method and the BERT machine learning model to track the evolution of sentiments over time. The findings reveal a strong seasonal effect, with more positive songs in summer and more negative ones in winter, a pattern amplified during lockdowns. Sentiments were relatively balanced before the pandemic but shifted significantly with an increase in negative songs during lockdowns, reflecting heightened stress, uncertainty, and social isolation. Country-specific trends highlighted regional differences in how the pandemic influenced song sentiments, with each country experiencing distinct peaks during critical periods. The complementary insights from both methodologies underscore the value of combining traditional and advanced machine learning approaches for sentiment analysis with the results demonstrating how music can serve as a unique proxy for emotional well-being, offering valuable insights into societal responses to crises.

References

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