

# “The Times They Are-a-Changin’”: The Effect of the Covid-19 Pandemic on Online Music Sharing in India

Tanvi Kamble<sup>1</sup>[0000-0003-2605-5854], Pooja Desur<sup>1</sup>[0000-0002-0741-9141],  
Amanda Krause<sup>2</sup>[0000-0003-3049-9220], Ponnurangam  
Kumaraguru<sup>1</sup>[0000-0001-5082-2078], and Vinoo Alluri<sup>1</sup>[0000-0003-3689-1039]

<sup>1</sup> International Institute of Information Technology-Hyderabad, India  
{tanvi.kamble,pooja.desur,vinoo.alluri,pk.guru}@iiit.ac.in

<sup>2</sup> James Cook University: Townsville, QLD, Australia  
amanda.krause1@jcu.edu.au

**Abstract.** Music sharing trends have been shown to change during times of socio-economic crises. Studies have also shown that music can act as a social surrogate, helping to significantly reduce loneliness by acting as an empathetic friend. We explored these phenomena through a novel study of online music sharing during the Covid-19 pandemic in India. We collected tweets from the popular social media platform Twitter during India’s first and second wave of the pandemic (n=1,364). We examined the different ways in which music was able to accomplish the role of a social surrogate via analyzing tweet text using Natural Language Processing techniques. Additionally, we analyzed the emotional connotations of the music shared through the acoustic features and lyrical content and compared the results between pandemic and pre-pandemic times. It was observed that the role of music shifted to a more community focused function rather than tending to a more self-serving utility. Results demonstrated that people shared music during the Covid-19 pandemic which had lower valence and shared songs with topics that reflected turbulent times such as *Hardship* and *Exclusion* when compared to songs shared during pre-Covid times. The results are further discussed in the context of individualistic versus collectivistic cultures.

**Keywords:** Musical emotions · Online Music Sharing · Covid Pandemic · Social Surrogacy · Lyrics

## 1 Introduction

The Covid-19 pandemic has significantly impacted everyday life with multiple state and nation-wide lockdowns around the world. Long isolation periods, increasing rates of unemployment, and with hundreds of thousands catching the virus daily, the pandemic caused an unprecedented socio-economic crisis [29]. India in particular had one of the highest Covid-19 infection rates and is the

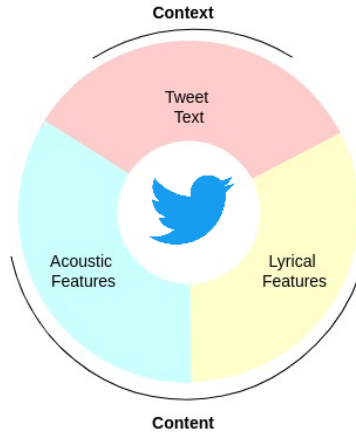


Fig. 1: Our study focuses on analyzing the context of music sharing from tweet text and the content of music sharing using acoustic features and lyrical themes.

second worst affected country<sup>3</sup> in terms of reported Covid-19 cases and deaths [11, 30]. These distressing times paired with months of isolation periods had people searching for coping mechanisms and proxies for physical social interactions.

Social media provides a constant means of communication with the outside world having a network reach much larger than any physical one. It enables users to keep in touch with their friends and family through posts, updates, and messages [5]. As the pandemic limited in-person interactions, social media use, enabling people to meet their social needs, was at an all time high [33]. The social media platform Twitter affords a space to share thoughts and mood states, especially through music. The music that is shared on twitter servers various functions, be it to either promote favorite artists or as a way to express feelings about the music shared, amongst others. From an evolutionary point of view sharing music has shown to help in social bonding, building a sense of community, and convey emotional states [22].

Music can play the role of an empathetic friend by acting as a social surrogate [28] and be used as a coping mechanism. It can elicit several emotions including feelings of being connected to others and being understood and can help boost mood when one is feeling down [18]. When users share music online along with how it made them feel and how it has helped them, comparisons can be made as to how music played the role of a social surrogate before and during the pandemic. It is possible that the kind of music one listens to or wants others to listen to during times of crisis can convey the coping mechanisms used by people to some extent. It has been seen that COVID-19 restrictions have led to lifestyle

<sup>3</sup> Data observed from <https://www.worldometers.info/coronavirus/countries-where-coronavirus-has-spread>

changes including change in trends in music consumption. People streamed songs from their balconies more during the initial lockdowns [15], exploring new styles and groups of music [3], and there was an increase observed in the listening time [4, 8]. Past work has looked at music sharing online [36] but as per our knowledge, work in this sphere has not been done during times of crisis. Furthermore, no studies have examined why music is shared online or what need it fulfills by sharing.

Recent times witnessed a slow rise in studies investigating music trends during Covid-19 [16, 10, 32, 17, 12, 13]. While no study has looked into online music sharing, they do provide insight into music consumption trends. A study on German media consumption during the pandemic showed that media (including music, books, movies amongst others) induced nostalgia during Covid-19 functioned as a way to cope with social stress (fear of isolation) during lockdown periods [34]. Another study on European countries found that music consumption on Spotify changed in terms of nostalgia during the pandemic [35].

Another study on popular music in the UK and the US during the pandemic demonstrated a negative trend in valence of lyrics and higher reference of interpersonal dependence in lyrics [24]. However, there are differences in how countries consume and associate with music [26, 19]. Individualistic cultures such as UK and US use music as a tool for self expression. On the other hand, collectivistic cultures, which include Asian countries like Japan, India, and China, use music typically to add positivity to their lives [26]. Emotional connections to music and coping mechanisms are different for individualistic cultures where people are self-sufficient and achievement-oriented as compared to collectivistic cultures where people are interdependent and family-oriented [19].

In this study we focus on India, a culturally rich country and that has a deep relation to music. A study of 3,000 internet users showed that 80 per cent of internet users called themselves as ‘music-lovers’ [14] in India. Despite being one of the largest countries in terms of population, music sharing trends have not been studied. Work has been done on the evolving Indian music industry [1, 7, 20] but a focus on the trends of the overall population is lacking. Moreover, on average, an Indian spends 19.1 hours a week listening to music which is higher than the global average of 18 hours [14]. Thus, it is important to consider how and why users share music online in India. A large Twitter user base of 23 million Indians provides opportunities for a large scale study. A study on India could further enhance the comparison of the function of music between collectivistic and individualistic cultures.

This paper aims to analyse online music sharing of Indians during the pandemic. To this end, we take a two-pronged approach to analyzing tweets posted during this time. We first analyze tweet text to understand the role music plays as a social surrogate via NLP techniques. Subsequently we analyze the musical content being shared by examining emotional connotations derived via acoustic features and lyrics. Additionally, we examine lyrical themes shared during the pandemic. We compare all of the above with pre-pandemic times to identify changes/trends.

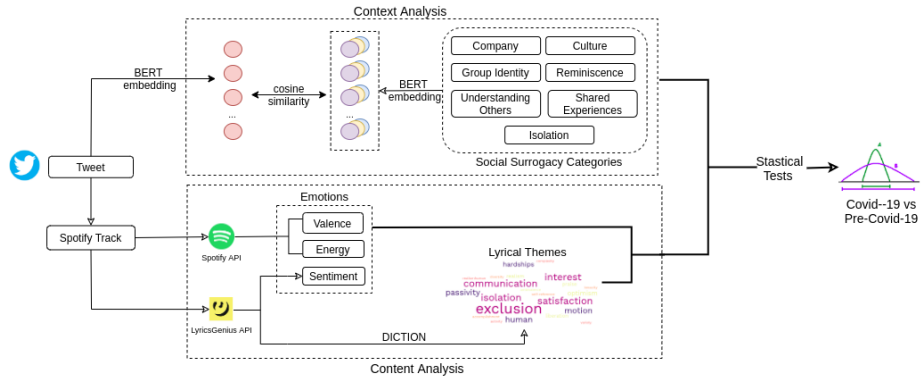


Fig. 2: Pipeline of extracting emotion, lyrical themes, and the function of music from tweets. Red circles represent BERT word embeddings and the purple, yellow, and blue circles symbolize the different embeddings obtained from social surrogacy statements belonging to different categories.

## 2 Methodology

### 2.1 Dataset

Using the Twitter API<sup>4</sup>, we collected tweets that were geotagged as India that contained a Spotify URL for tracks during the first and second wave of the pandemic (see Figure 2). As per the WHO<sup>5</sup> dashboard of Covid-19 cases, the peak of Wave-1 and Wave-2 in India was recorded on September 14, 2020 and May 3, 2021 respectively. Judging by the steepness of both the peaks, we considered a period of two months around the Wave-1 peak and one month around the Wave-2 peak as our Wave-1 and Wave-2 time periods respectively. To compare this with a control group, we collected similar tweets during the same period of months in 2019 (referred to as Control-1 and Control-2 respectively) in order to avoid temporal music sharing differences that can occur as a result of seasonal trends. We collected a total of 1,364 tweets that were posted during both waves of the pandemic. One tweet can have multiple track URLs shared in them, but each song of the tweet is added separately to the dataset. We limited our analysis to tweets in English. A total of 54.3% of the tweets collected during Wave-1 and 48.2% of tweets collected during Wave-2 had English tweet text. Detailed statistics about the dataset are given in Table 1. From the Spotify URL, the name and artist of the song was retrieved using the Spotify ID. With this information, we collected lyrics for each track, using the LyricsGenius and azlyrics API.<sup>6</sup>

<sup>4</sup> <https://developer.twitter.com/en/docs/twitter-api>

<sup>5</sup> <https://covid19.who.int/region/searo/country/in>

<sup>6</sup> <https://lyricsgenius.readthedocs.io/en/master/>

Table 1: Summary of dataset statistics across Wave-1 and Wave-2 of Covid-19 and their Control groups -

Data Group	Tweets with Spotify URL	Tweets with English Songs	Songs with correct English Lyrics	Songs Rejected
Wave-1 (July-November 2020)	808	416	323	87
Control-1 (July-November 2019)	607	271	204	54
Wave 2 (April-June 2021)	556	317	263	94
Control-2 (April-June 2019)	351	177	155	48

## 2.2 Tweet Analysis

From each tweet, we examined the *context* and the *content* of the music associated with it. Context of the music shared refers to the tweet text accompanying it. It gives a glimpse into why a user shared that particular track. We used this text to consider if the music may have played a role of a social surrogate. On the other hand content refers to both the musical and lyrical features of the song. We looked at the emotional connotations of the content by extracting the acoustic features from the music and sentiment and themes from the lyrics.

**Context Analysis** In order to capture the functions played by music, we used a set of 30 statements formulated in past work [28] as demonstrations of music functioning as a social surrogate.<sup>7</sup> These include statements such as “It reminds of certain periods of my life or past experiences” or “I can identify with the musicians or bands”. These 30 statements were originally collected as a result of a survey where participants described how media plays a role of a social surrogate in their lives and was then adapted to music [28]. These statements belong to 7 overarching categories – *Company*, *Reminiscence*, *Shared Experiences*, *Isolation*, *Understanding Others*, *Culture*, and *Group Identity*. The category *Company* describes the role of music in helping to feel less lonely and providing comfort. *Reminiscence* is when music elicits feeling of nostalgia through a person or experience. *Shared Experiences* covers how music helps people to feel understood and identify with the music/artists. The category *Isolation* involves feelings of wanting to isolate socially and not talk to others but finding solace in music. *Understanding Others* includes how music brings about feelings of belonging and understanding others and the world. When music helps to connect to one’s culture and allows people to express cultural uniqueness the surrogacy role falls under the category *Culture*. Music that helps people to identify to a subculture and belong to a particular social group the role falls under the category *Group Identity*. Examples of tweets which came under the above categories include “Reminder to listen to this song when feeling underconfident” (*Shared Experiences*) or “Something that reminds me of my childhood” (*Reminiscence*).

To get the context of the music shared, we first preprocessed the text of each tweet to remove links, hashtags, and emojis. In order to filter out tweets that did

<sup>7</sup> Refer to Appendix 1

not represent the function of music as a social surrogate, we manually removed tweets that fell under the *Non social surrogacy* category. These tweets consisted of keywords/strings such as “mood”, “stream this song” or “listen to this”. A total of 502 tweets were identified as showing roles of social surrogacy of which 150 and 165 belonged to time periods Wave-1 and Wave-2 respectively and 111 and 76 belonged to Control-1 and Control-2 respectively. Only this set was used for further tests. An automated approach was used to categorize each of these filtered tweets into one of the seven social surrogacy categories. The sentence embedding of the resulting text of the tweets was calculated by using a BERT transformer.<sup>8</sup> Similarly, the sentence embedding for each of the 30 statements was calculated. Cosine similarity which was used as a distance metric to represent semantic similarity was calculated between each tweet and each of the 30 statements in the embedding space. A tweet was allocated into the corresponding category of the most similar statement embedding (provided the similarity was greater than 0.5). Thus, a tweet was only mapped to either one or zero of the seven social surrogacy categories. Some examples of tweets along with the allocated groups are shown in Table 2. This automated approach provided a way to observe the ways music served as a surrogate during the pandemic without the intrusion of human bias. It also allowed us to investigate which categories of surrogacy such as *Reminiscence* or *Isolation* were more prevalent than others when users shared music online during the considered time periods.

Table 2: Examples of tweet text categorized into Social Surrogacy Categories using BERT embeddings

Tweet Text	Most Similar Surrogacy Statement	Category
song i remember from childhood	It reminds me of certain periods of my life or past experiences	Reminiscence
the joy of discovering music thats totally you	I can identify with the musicians or bands	Shared Experiences
Dedicated to the Nocturnal	I want to isolate myself from my surroundings	Isolation

**Content Analysis** In some cases, the song name returned from the Spotify API<sup>9</sup> did not match the song in LyricsGenius API owing to gibberish lyrics. We weeded out such songs (n=236) from the pool of English songs (n=1,181). This happened for songs which were remixed-versions or were sung live and hence such songs were removed.

*Emotions* We examined the emotional connotations of the music shared in two ways - by using the acoustic features of the songs and by performing a sentiment analysis on the lyrics. To obtain the acoustic features, we used the Spotify

<sup>8</sup> [https://huggingface.co/docs/transformers/model\\_doc/bert](https://huggingface.co/docs/transformers/model_doc/bert)

<sup>9</sup> <https://spotify.readthedocs.io/en/2.19.0/#>

API in order to extract valence and energy of the song which provides insight to its emotional connotation. Valence is indicative of the pleasantness/positiveness of the track while energy is self-explanatory. We then performed sentiment analysis on the lyrics using a lexicon and rule-based sentiment analysis tool called VADER.<sup>10</sup> It is used in grammar-free texts like social media.

*Lyrical Analysis* We performed topic modelling on the lyrics using DICTION software<sup>11</sup> to extract the topics of the songs that were shared during the different data groups. DICTION is a language analysis software that uses dictionaries to determine the topic(s) of a given text. There are 40 topics<sup>12</sup> each of which has a dictionary of words associated with it where no two dictionaries have the same words. It calculates the frequency of the words from the text to determine the topics. We decided to use DICTION as it is a good choice for topic modelling for free-grammar text like songs and poem since it has a word to word mapping [24, 6, 21, 2] Further details about DICTION and the custom lists have been discussed in the appendix. We ran DICTION on the lyrics of the songs belonging to Covid-19 and control periods for all the 40 topics, and divided the frequency of words by the total number of words to normalize the scores.

### 2.3 Statistical Tests

The contextual information and musical content was compared between the following time periods: Wave-1 (n=323) versus Control-1 (n=204), Wave-2 (n=263) versus Control-2 (n=155), and Covid-19 as a whole referred to as Wave-1 + Wave2 (n=586) versus pre-Covid period of 2019 referred to as Control-1 + Control-2 (n=359).

Context-wise, a frequency table was created for comparing observed frequencies which were the Covid-19 periods and the expected proportions which were the corresponding control groups. A chi-square goodness of fit test [23] was performed to observe if the proportions were significantly different.

Content-wise, we used the non-parametric Mann Whitney U test (MWU) to examine the difference between valence and energy (the acoustic features) across the conditions.

For the lyrical analysis, MWU tests were also performed on results of DICTION analysis between each of the above mentioned time periods. The Benjamini-Hochberg procedure was used to account for running multiple statistical tests. The results of these tests are reported in the next section.

<sup>10</sup> <https://github.com/cjhutto/vaderSentiment>

<sup>11</sup> <https://dictionsoftware.com/>

<sup>12</sup> 40 topics include 31 dictionary based variables, five master variables which are a combination of the dictionary based variables and four calculation based variables. The last four variables rely on calculations such as word count, word size rather than dictionary matches. Details about the variables are given in Appendix 2

### 3 Results

#### 3.1 Context Analysis

The percentage of total tweets lying in each social surrogacy category during Wave-1 and Control-1 are shown in Figure 3 . The chi-square goodness of fit test was significant ( $p=0.028$ ), suggesting that the proportions of tweets amongst the social surrogacy categories were significantly different between Wave-1 and Control-1. Post hoc multiple z-test comparisons were done to observe which categories showed significant differences in proportions. Two of the social surrogacy groups – *Reminiscence* and *Group Identity* had a significant decrease in the proportion of tweets falling into these categories during Wave-1. On the other hand, the chi-square test was non-significant across the distribution of proportions when comparing Wave-2 and Control-2, or Covid-19 as a whole (Wave-1 + Wave2) and pre-Covid-19 period (i.e Control-1 + Control-2).

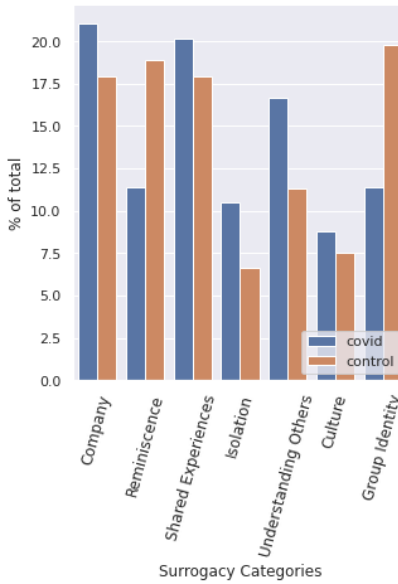


Fig. 3: Distribution of tweets into social surrogacy categories during Wave-1 and Control-1 (covid and control in legend respectively)

#### 3.2 Content Analysis

**Emotions** Figure 4 displays distributions of valence and energy derived from acoustic features for different conditions. Results of the Mann Whitney U tests revealed that valence of music shared during Covid (Wave-1 and Wave-2 combined) was significantly lower ( $U=613715$ ,  $p=0.006$ ) than pre-Covid time period.



Similar results were observed when comparing Wave-1 with Control-1 where valence was significantly lower during Wave-1 ( $U=231695$ ,  $p=0.037$ ) while energy was found to be higher ( $U=229345$ ,  $p=0.018$ ). No significant differences were observed in either valence or energy of music shared when comparing Wave-2 with Control-2.

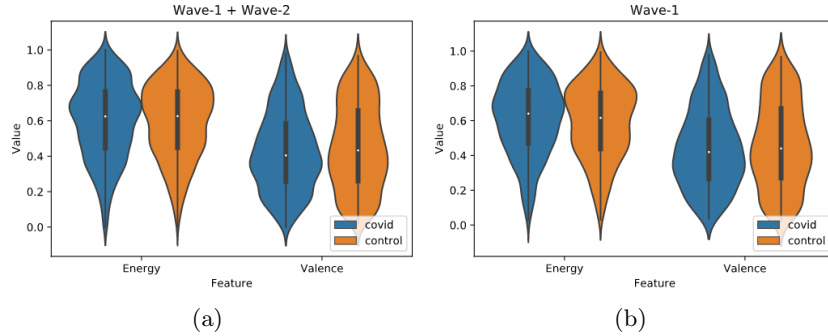


Fig. 4: Comparison of acoustic features between different periods. (a) Valence is significantly lower during Covid than pre-Covid. (b) Valence is significantly lower during Wave 1, while Energy is higher as compared to the Control-1.

Sentiment analysis on lyrics as shown in Figure 5 was also performed. During comparison only the time periods of Wave-2 against Control-2 showed differences that were statistically significant ( $U=33920.5$ ,  $p=0.0005$ ) according to the Man Whitney U test. During Wave-2 the lyrics of the songs had a lower mean sentiment (0.24) as compared to the Control-2 (0.39).

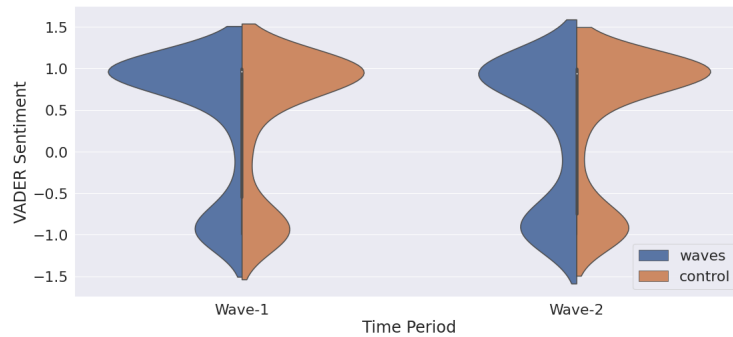


Fig. 5: Sentiment Analysis of Lyrics of the songs according to the different time periods. Mean Sentiment of Wave-1 was higher than Control-1 but it was vice-versa for Wave-2 and Control-2.

**Lyrical Themes** We observed that different lyrical themes were shared in different time periods. Table 3 summarises the results of the Mann-Whitney U tests conducted on the various DICTION categories.

Wave-1 demonstrated an increased sharing of music with lyrical themes signifying *Exclusion* (U=33874.0, p=0.005) and *Hardship* (U=34698.5, p=0.041), when compared to Control 1. Similar pattern was observed when comparing the Covid-19 time period to pre-Covid-19 time periods where topics of *Exclusion*(U=103193.0, p=0.049) and *Hardship* (U=102221.0, p=0.05) were shared more as well. The topic of *Motion* was shared more in Wave-1 than Control-1 (U=38425.5, p=0.04) but was shared less in Covid-19 group as a whole than pre-Covid times as a whole (U=100560.0, p=0.018). Wave-2 witnessed an increase in music with lyrical themes representing *Communication* ( U=12557.0, p=0.012) when compared to Control-2. Another observation to be made was that the values of *Satisfaction* increased in the songs shared during Wave-1 when compared with Control-1 (U=38066.5, p=0.026) but the opposite happened when we observed Wave-2 and Control-2.

Table 3: DICTION variables for different time periods that show significant differences with  $p < 0.05$  in Man Whitney U Test (\*  $p < 0.01$ ). The arrows indicate an increase or decrease in the songs shared in the time period.

Wave-1 (vs. Control-1)	Exclusion* $\uparrow$ , Satisfaction $\uparrow$ , Hardship $\uparrow$ , Motion $\uparrow$
Wave=2 (vs. Control-2)	Communication $\uparrow$ , Satisfaction* $\downarrow$
Wave-1 + Wave-2 (vs. Control-1 + Control-2)	Hardship $\uparrow$ , Exclusion $\uparrow$ , Motion $\downarrow$

## 4 Discussion

Our study examined the effect of the Covid-19 pandemic on the type of music that was shared online via Twitter in India. Overall music sharing seems to be different during Covid-19 and pre-Covid-19 times. The number of music related tweets posted by users to share a certain song on Spotify increased during Wave-1. This increase in music sharing online could be attributed to higher rates of social media usage during periods of isolation in the pandemic [31], or to how music sharing builds a sense of community [27] which was needed during the pandemic. A portion of the increase should be credited to the fact that Spotify was released in India during 2019, and as its popularity began to grow, the number of users sharing Spotify links increased subsequently. Apart from the increase in number of tweets there were several differences observed in the context and content as discussed below.

We examined how music might function as a social surrogate during the pandemic. Tweets which fell under the categories *Company* (in which people use music to feel less lonely and find comfort) and *Shared Experiences* (which covers music experiences that help people to feel understood) made up 41% of

the total tweets containing music collected during the pandemic. During Wave-1, music acted as a social surrogate through the role of *Group Identity* to a lesser amount than pre-pandemic times. *Group Identity* involves feeling a sense of belonging to a particular social group on a smaller scale, such as identifying with a particular artist or associating oneself with a fan group. India, a collectivistic community, has shown to put a great importance on community, and as the pandemic brought about distressing times, the sense of community tended to expand, which is reflected by more music shared that was not targeted towards a specific subgroup. This result suggests that perhaps people may have felt a less pressing desire to separate into smaller subgroups and preferred to experience and share music with a larger, more diverse demographic to fulfil their need for community.

Similarly the proportion of tweets falling into the category *Reminiscence* which is more self directed (reminds one of their past experiences or a person), also decreased during Wave-1. While past work [34] has demonstrated that media associated with a sense of nostalgia was consumed more during the Covid-19, this study was done on an individualistic culture (Germany). India has shown a different trend where the role of self-involved social surrogacy categories reduced during the pandemic. Our interpretation is that music was shared to foster a sense of greater community rather than for personal preferences.

Music shared online in India during Wave-1 was more negatively valenced but had higher overall energy values in terms of acoustic features. The valence and energy values mirror the feelings caused by the turbulent times the country experienced. This is in line with results from a study on UK and US where songs with negatively valenced lyrics were found to be more popular during the pandemic as compared to before [24]. Typically since negative valence of music is congruent to negative valence derived from lyrics [9], these results are comparable and the cultures seem to show a similar change in trends over the period of the pandemic. Lyrical themes of *Exclusion* and *Hardship* were observed more in India during the pandemic and these themes also reflect the distressing times. There was also more *Satisfaction* related lyrical themes which has to do with positive affective states, although valence was negative. This could be an attempt to try to balance the negative mood of the music with positive words while still reflecting the current hard times of the pandemic. This result opposes results done on a study of individualistic culture where lyrical themes of Satisfaction were less predominant during the first six months of the pandemic [24], albeit limited to top charts on Spotify. Nevertheless, these results concerning the lyrical themes of shared music highlight the similarities and differences between the consumption and sharing of music in individualistic and collectivistic cultures.

Wave-2 was much more disastrous for India [25] than Wave-1. Music sharing online evidenced a decrease in the sentiment of lyrics as well as a decrease in the themes of *Satisfaction*. One potential explanation in Wave-1 themes of *Satisfaction* arose by trying to build up hope but by Wave-2 the decrease showed the opposite trend. Additionally, music shared with themes of *Communication* (See Table 4) increased during Wave-2. From an evolutionary point of view, music

has been used as a social bonding tool and reveals a person’s emotional states to others [22]. In this way themes of *Communication* in music expose a desire to reach out and bond with others which could explain this increase. Overall the combined duration of Wave-1 and Wave-2 brought about music sharing with more negative valence than pre-Covid-19 times, with lyrical themes of Hardship and Exclusion thereby mirroring the dire situation of the pandemic.

In sum, our study is the first that looks at music sharing trends online during the pandemic. Music shared online provides a glimpse into the emotional state of a person. Studying the text accompanying the sharing of a song online helps reveal the role music can play in our lives and its benefits during distressing times. While this study has shown that collectivistic and individualistic cultures both reported negative trends in valence of music during the pandemic, Wave-1 in India reflected a glimmer of hope with the increase in lyrical themes of *Satisfaction* (Refer Table 4). Furthermore, India as a collectivistic culture has a tendency to put the well being of a community at large above ones own. This is well demonstrated by the role that *Group Identity* and *Reminiscence* played as a social surrogate which decreased during the pandemic. The social surrogacy approach which summarizes the various functions music plays as a social surrogate can be extended to study music shared in other countries. It can also be extended to data collected from other social media platforms. Future research on this topic could also benefit from a mixed methods approach, where manual annotation of the tweets could complement the automated approach, although it may not be feasible and scalable for a large number of datapoints. While our study was limited to music with lyrics in English, future work can accommodate music and tweets in other languages using advanced NLP techniques. Lastly, we note that while we have collected the music shared on the Twitter platform, and as such the music analysed in the present study is not a complete representation of the music listened to by the Indian population as a whole, future work could also explore the use of other platforms and collaborative playlists.

Table 4: DICTION variables and the topics they represent

<b>DICTION Variable</b>	<b>Meaning of the Variable</b>
Communication	Terms of social interaction either with one person or a group
Exclusion	Describes the sources and effects of social isolation [24]
Hardship	Terms of Natural Disaster, problems faced, and human fears.
Motion	Terms of movement, speed and transit
Satisfaction	Terms associated with positive affective states [24]

**Acknowledgements** This research was partially funded by IHUB at IIIT Hyderabad.

## 5 Appendix

### 5.1 Appendix 1

The 30 statements that were used to model the role of music as a social surrogate and their assigned categories as per [28] are given in table 5.

Table 5: Social Surrogacy statements corresponding to each group

Social Surrogacy Category	Statement
Company	It keeps me company.
	It can make me feel less lonely.
	It comforts me when I'm sad.
Culture	It mirrors the history and culture of my country.
	It makes me feel connected to my culture.
	It is a good way to express the uniqueness of our culture.
Group Identity	I would like to identify with a particular subculture.
	It helps me to show that I belong to a particular social group.
	It makes me feel connected to all the people who like the same kind of music.
	I would like to take the artists as role models
Isolation	It makes me feel connected to others.
	I don't want to talk to anybody.
	I like to have some sound in the background.
	I want to isolate myself from my surroundings.
Reminiscence	I don't want to hear the surrounding sounds.
	It reminds me of the people that I used to listen to the music with.
	It reminds me of a particular person.
	It reminds me of certain periods of my life or past experiences.
Shared Experience	It helps me reminisce.
	I can recognize myself in the lyrics.
	The songwriter has made similar experiences as I have.
	I like to immerse myself into the lyrics.
	I can identify with the musicians or bands.
	I can sing along with it.
Understanding Others	It makes me feel like somebody else feels the same as I do.
	It helps me understand the world better.
	It makes me feel connected to the world.
	It tells me how other people think.
	It makes me feel like I belong.
Understanding Others	It helps me to understand what is going on in others people's heads.

## 5.2 Appendix 2

DICTION 7.0, as mentioned earlier, is a content analysis software which uses dictionaries of topics to perform word to word mapping and gives a score related to each topic. The value of each variable for a song is a float value. Even though it is a frequency, homographs are incremented as decimals instead of ‘1’ in the DICTION software. The 40 categories of DICTION can be divided into the following sub-categories:

1. **Dictionary based variables:** Each variable has a dictionary of words associated with it. There are 10,000 words classified into a total of 35 discrete variables. The number of words in each dictionary range from 10 to 745. Table 6 contains a brief description of each of the 35 variables.

Table 6: 31 Dictionary Based Variables

Variable Name	Variable Definition
AMBIVALENCE	Words expressing hesitation or uncertainty like confusion, mystery, etc.
ACCOMPLISHMENT	Words expressing task-completion, modes of expansion like grow, buy, employ, produce, etc.
AGGRESSION	Words of human competition and forceful action, social domination, energy, personal triumph
BLAME	Terms of social inappropriateness, unfortunate circumstances like cruel, miserly, painful, etc
CENTRALITY	Terms denoting institutional regularities and/or substantive agreement on core values. Words like indigenous terms, typicality, etc.
COGNITION	Words referring to cerebral processes, both functional and imaginative.
COLLECTIVES	Singular nouns connoting plurality that function to decrease specificity like army, crowd, country, world, etc.
COMMUNICATION	Terms referring to social interaction, both face-to-face, mediated, social actors, social purposes, etc.
CONCRETENESS	No thematic unity other than tangibility and materiality. Words of sociological units, occupational groups, political alignments.
COOPERATION	Terms designating behavioral interactions among people that often result in a group product like words of designations of formal work relations and informal associations.
DENIAL	Words of negative contractions, negative function words like not, nothing, etc.

Table 6: 31 Dictionary Based Variables

<b>Variable Name</b>	<b>Variable Definition</b>
DIVERSITY	Words describing individuals or groups of individuals differing from the norm
EXCLUSION	Terms describing the sources and effects of social isolation.
FAMILIARITY	Words including common prepositions (across, over, through), demonstrative pronouns (this, that) and interrogative pronouns (who, what), and a variety of particles, conjunctions and connectives (a, for, so).
HARDSHIP	Containing words related to natural disasters, hostile actions, injustice, human fears and griefs.
HUMAN INTEREST	standard personal pronouns, family members and relations and generic terms friend, baby, human.
INSPIRATION	Words of Abstract virtues deserving of universal respect.
LEVELING TERMS	Words used to ignore individual differences and to build a sense of completeness assurance like everyone, absolute, each, fully, etc.
LIBERATION	Terms describing the maximizing of individual choice and the rejection of social conventions
MOTION	Terms connoting human movement, physical processes, journey, speed etc.
NUMERICAL TERMS	Words indicating numbers or numerical operations like sum, percentage or quantitative topics like mathematics.
PASSIVITY	Words ranging from neutrality to inactivity like inertness, compliance, docility, etc.
PAST CONCERN	The past-tense forms of the verbs contained in the Present Concern dictionary.
PRAISE	Social, Intellectual, entrepreneurial, moral and Physical Qualities
PRESENT CONCERN	A selective list of present-tense verbs like general physical activity, social operations, task-performance, etc.
RAPPORT	This dictionary describes attitudinal similarities among groups of people like terms of affinity, deference, etc.
SATISFACTION	Terms associated with positive affective states, undiminished joy, moments of triumph
SELF-REFERENCE	Terms of first-person references

Table 6: 31 Dictionary Based Variables

Variable Name	Variable Definition
SPATIAL TERMS	Terms referring to geographical entities, physical distances, and modes of measurement.
TEMPORAL TERMS	Terms that fix a person, idea, or event within a specific time-interval, thereby signaling a concern for concrete and practical matters.
TENACITY	Forms of the verb ‘ to be’. These verbs connote confidence and totality.

2. **Calculation Based Variables:** Four DICTION variables result from calculations rather than dictionary matches. They are calculated using a formula which involves data like the number of words in the text, length of each word, occurrences of each word, etc. Table 7 explains the different Calculation based variables.

Table 7: Four Calculation based Variables

Variable Name	Variable Definition
COMPLEXITY	Average number of characters-per-word
INSISTENCE	All words occurring three or more times that function as nouns or noun-derived adjectives are identified
EMBELLISHMENT	A selective ratio of adjectives to verbs.
VARIETY	Type-Token Ratio, ratio of number of different words in a passage to the passage’s total words.

3. **Master Variables:** The five master variables provide the most general understanding of a given text. They are a combination of the Dictionary-based and Calculation-based variables. They are formed by converting all subaltern variables to z-scores, combining them via addition and subtraction, and then by adding a constant of 50 to eliminate negative numbers. For example, Optimism, which is [Praise + Satisfaction + Inspiration] – [Blame + Hardship + Denial] to which 50 is added standardizes the six variables. Table 8 gives an idea about what the master variables signify.



Table 8: Five Master Variables which are a combination of the Dictionary based variables

Variable Name	Variable Definition
ACTIVITY	Language featuring movement, change, the implementation of ideas and the avoidance of inertia.
CERTAINTY	Language indicating resoluteness, inflexibility, and completeness and a tendency to speak ex cathedra
COMMONALITY	Language highlighting the agreed - upon values of a group and rejecting idiosyncratic modes of engagement.
OPTIMISM	Language endorsing some person, group, concept or event or highlighting their positive entailments.
REALISM	Language describing tangible, immediate, recognizable matters that affect people's everyday lives.

## References

1. Agarwal, P., Karnick, H., Raj, B.: A comparative study of indian and western music forms. In: ISMIR (2013)
2. Anglada-Tort, M., Krause, A.E., North, A.C.: Popular music lyrics and musicians' gender over time: A computational approach. *Psychology of Music* **49**(3), 426–444 (2021). <https://doi.org/10.1177/0305735619871602>, <https://doi.org/10.1177/0305735619871602>
3. Cabedo-Mas, A., Arriaga-Sanz, C., Moliner-Miravet, L.: Uses and perceptions of music in times of covid-19: A spanish population survey. *Frontiers in Psychology* **11** (2021). <https://doi.org/10.3389/fpsyg.2020.606180>, <https://www.frontiersin.org/article/10.3389/fpsyg.2020.606180>
4. Carlson, E., Wilson, J., Baltazar, M., Duman, D., Peltola, H.R., Toivainen, P., Saarikallio, S.: The role of music in everyday life during the first wave of the coronavirus pandemic: A mixed-methods exploratory study. *Frontiers in Psychology* **12** (2021). <https://doi.org/10.3389/fpsyg.2021.647756>, <https://www.frontiersin.org/article/10.3389/fpsyg.2021.647756>
5. Clark, J.L., Algoe, S.B., Green, M.C.: Social network sites and well-being: The role of social connection. *Current Directions in Psychological Science* **27**(1), 32–37 (2018). <https://doi.org/10.1177/0963721417730833>, <https://doi.org/10.1177/0963721417730833>
6. Cook, S.L., Krupar, K.: Defining the twentieth century and impacting the twenty-first: Semantic habits created through radio and song. *ETC: A Review of General Semantics* **67**(4), 412–434 (2010), <http://www.jstor.org/stable/42579071>
7. Evans, A.E.: Music in india: An overview. In: *The 2016 Symposium* (2016)
8. Fink Lauren K., Warrenburg Lindsay A., H.C.R.W.M.H.N.C.W.F.M.: Viral tunes: changes in musical behaviours and interest in coronamusic predict socio-emotional coping during covid-19 lockdown. *Humanities and Social Sciences Communications* **8** (2021). <https://doi.org/10.1057/s41599-021-00858-y>
9. Fiveash, A., Luck, G.: Effects of musical valence on the cognitive processing of lyrics. *Psychology of Music* **44** (02 2016). <https://doi.org/10.1177/0305735615628057>

10. Gibbs, H., Egermann, H.: Music-evoked nostalgia and wellbeing during the united kingdom covid-19 pandemic: Content, subjective effects, and function. *Frontiers in Psychology* **12** (2021). <https://doi.org/10.3389/fpsyg.2021.647891>, <https://www.frontiersin.org/article/10.3389/fpsyg.2021.647891>
11. Goel, I., Sharma, P., Kashiramka, P.: Effects of the covid-19 pandemic in india: An analysis of policy and technological interventions. *Health Policy and Technology* **10** (12 2020). <https://doi.org/10.1016/j.hlpt.2020.12.001>
12. Granot, R., Spitz, D.H., Cherki, B.R., Loui, P., Timmers, R., Schaefer, R.S., Vuoskoski, J.K., Cárdenas-Soler, R.N., Soares-Quadros, J.F., Li, S., Lega, C., La Rocca, S., Martínez, I.C., Tanco, M., Marchiano, M., Martínez-Castilla, P., Pérez-Acosta, G., Martínez-Ezquerro, J.D., Gutiérrez-Blasco, I.M., Jiménez-Dabdoub, L., Coers, M., Treider, J.M., Greenberg, D.M., Israel, S.: “help! i need somebody”: Music as a global resource for obtaining wellbeing goals in times of crisis. *Frontiers in Psychology* **12** (2021). <https://doi.org/10.3389/fpsyg.2021.648013>, <https://www.frontiersin.org/article/10.3389/fpsyg.2021.648013>
13. Howlin, C., Hansen, N.C.: Music in times of covid-19 (Mar 2022). <https://doi.org/10.31234/osf.io/z94fq>, [psyarxiv.com/z94fq](https://psyarxiv.com/z94fq)
14. Industry, T.I.M.: Digital music study (2019)
15. Lehman, E.T.: “washing hands, reaching out” – popular music, digital leisure and touch during the covid-19 pandemic. *Leisure Sciences* **43**, 273 – 279 (2020)
16. Levstek, M., Barnby, R.M., Pocock, K.L., Banerjee, R.: “it all makes us feel together”: Young people’s experiences of virtual group music-making during the covid-19 pandemic. *Frontiers in Psychology* **12** (2021). <https://doi.org/10.3389/fpsyg.2021.703892>, <https://www.frontiersin.org/article/10.3389/fpsyg.2021.703892>
17. Martínez-Castilla, P., Gutiérrez-Blasco, I.M., Spitz, D.H., Granot, R.: The efficacy of music for emotional wellbeing during the covid-19 lockdown in spain: An analysis of personal and context-related variables. *Frontiers in Psychology* **12** (2021). <https://doi.org/10.3389/fpsyg.2021.647837>, <https://www.frontiersin.org/article/10.3389/fpsyg.2021.647837>
18. Mas-Herrero, E., Marco-Pallares, J., Lorenzo-Seva, U., Zatorre, R.J., Rodriguez-Fornells, A.: Individual Differences in Music Reward Experiences. *Music Perception* **31**(2), 118–138 (12 2013). <https://doi.org/10.1525/mp.2013.31.2.118>, <https://doi.org/10.1525/mp.2013.31.2.118>
19. Miyamoto, Y., Ma, X., Petermann, A.G.: Cultural differences in hedonic emotion regulation after a negative event. *Emotion* **14**(4), 804 (2014)
20. Muthusamy, S.: Music industry in economic development of india. *ANJAC Journal of Humanities and Social Sciences*, ISSN: 0976-4216 **3**, 1 – 9 (01 2012)
21. North, A.C., Krause, A.E., Kane, R., Sheridan, L.: United kingdom “top 5” pop music lyrics. *Psychology of Music* **46**(5), 638–661 (2018). <https://doi.org/10.1177/0305735617720161>, <https://doi.org/10.1177/0305735617720161>
22. Patel, A.D.: Music, biological evolution, and the brain (2010)
23. Pearson, K.: X. on the criterion that a given system of deviations from the probable in the case of a correlated system of variables is such that it can be reasonably supposed to have arisen from random sampling. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science* **50**(302), 157–175 (Jul 1900). <https://doi.org/10.1080/14786440009463897>, <https://doi.org/10.1080/14786440009463897>

24. Putter, K.C., Krause, A.E., North, A.C.: Popular music lyrics and the covid-19 pandemic. *Psychology of Music* **0**(0), 03057356211045114 (0). <https://doi.org/10.1177/03057356211045114>, <https://doi.org/10.1177/03057356211045114>
25. Ranjan, R., Sharma, A., Verma, M.: Characterization of the second wave of covid-19 in india (04 2021). <https://doi.org/10.1101/2021.04.17.21255665>
26. Saarikallio, S., Alluri, V., Kulmunki, I., Toiviainen, P.: Emotions of music listening in finland and in india: Comparison of an individualistic and a collectivistic culture. *Psychology of Music* **49**, 030573562091773 (05 2020). <https://doi.org/10.1177/0305735620917730>
27. van der Schyff, D., Silverman, M.: *Music in the Community* (11 2019)
28. Schäfer, K., Eerola, T.: How listening to music and engagement with other media provide a sense of belonging: An exploratory study of social surrogacy. *Psychology of Music* **48**(2), 232–251 (2020). <https://doi.org/10.1177/0305735618795036>, <https://doi.org/10.1177/0305735618795036>
29. Shang, Y., Li, H., Zhang, R.: Effects of pandemic outbreak on economies: Evidence from business history context. *Frontiers in Public Health* **9** (2021). <https://doi.org/10.3389/fpubh.2021.632043>, <https://www.frontiersin.org/article/10.3389/fpubh.2021.632043>
30. Shukla, M., Pandey, R., Singh, T., Riddleston, L., Hutchinson, T., Kumari, V., Lau, J.Y.F.: The effect of covid-19 and related lockdown phases on young peoples' worries and emotions: Novel data from india. *Frontiers in Public Health* **9** (2021). <https://doi.org/10.3389/fpubh.2021.645183>, <https://www.frontiersin.org/article/10.3389/fpubh.2021.645183>
31. Tsao, S.F., Chen, H., Tisseverasinghe, T., Yang, R., Li, L., Butt, Z.: What social media told us in the time of covid-19: a scoping review. *The Lancet Digital Health* **3** (01 2021). [https://doi.org/10.1016/S2589-7500\(20\)30315-0](https://doi.org/10.1016/S2589-7500(20)30315-0)
32. Vidas, D., Larwood, J.L., Nelson, N.L., Dingle, G.A.: Music listening as a strategy for managing covid-19 stress in first-year university students. *Frontiers in Psychology* **12** (2021). <https://doi.org/10.3389/fpsyg.2021.647065>, <https://www.frontiersin.org/article/10.3389/fpsyg.2021.647065>
33. Wong, A., Ho, S., Olusanya, O., Antonini, M.V., Lyness, D.: The use of social media and online communications in times of pandemic covid-19. *Journal of the Intensive Care Society* **22**(3), 255–260 (2021). <https://doi.org/10.1177/1751143720966280>, <https://doi.org/10.1177/1751143720966280>
34. Wulf, T., Breuer, J., Schmitt, J.: Escaping the pandemic present: The relationship between nostalgic media use, escapism, and well-being during the covid-19 pandemic. *Psychology of Popular Media* (09 2021). <https://doi.org/10.1037/ppm0000357>
35. Yeung, T.Y.C.: Did the covid-19 pandemic trigger nostalgia? evidence of music consumption on spotify (08 2020)
36. Zangerle, E., Pichl, M., Gassler, W., Specht, G.: nowplaying music dataset: Extracting listening behavior from twitter. In: *Proceedings of the First International Workshop on Internet-Scale Multimedia Management*. p. 21–26. WISMM '14, Association for Computing Machinery, New York, NY, USA (2014). <https://doi.org/10.1145/2661714.2661719>, <https://doi.org/10.1145/2661714.2661719>