Covid-19 Kısıtlamaları Sırasında Duyguların Müzikal Parametrelerle İfade Edilmesi: Filipinler Spotify Verileri Üzerine Bir Duygu Analizi

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The Expression of Emotions Through Musical Parameters During the Covid-19 Restrictions: A Sentiment Analysis on Philippines Spotify Data

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Öz

Spotify, dinleyicilerin dinleme kalıplarına göre çok çeşitli çalma listeleri sunan dünyanın en büyük çevrimiçi müzik paylaşım platformudur. Bu makale, Filipinler verisi üzerine yapılan incelere göre, müzik tercihinin duygusal durumla yüksek oranda ilişkili olduğunu ve müziğin pandemi sırasında bir duygu düzenleyici araç olduğunu ortaya koymaktadır. Popüler makine öğrenimi yöntemleri (sınıflandırma ve regresyon ağaçları, güçlendirilmiş ağaçlar, rastgele ormanlar, Destek Vektör Makineleri ve Yapay Sinir Ağları), pandeminin şiddetiyle orantılı olarak farklı zaman periyotlarında insanların müzik tercihlerini sınıflandırmak için, 5 katlı çapraz doğrulama ile birlikte kullanılmıştır. Algoritmaların öğrenme süreçlerinde günlük resmi covid-19 istatistikleri ve Spotify verileri ana değişkenler olarak kullanılmaktadır. SVM, %98,01 doğruluk oranı elde ederek ortalama doğruluk oranında diğer alternatif modeller içinde en iyi performansı göstermiştir. Ek olarak, ANN, özellikle tek bir modelde elde edilen doğruluk açısından diğer alternatiflerden daha iyi performans göstererek %99,30 doğruluk oranına ulaşmıştır. Ayrıca (azalan sırada) en büyük (mutlak) değişime sahip değişkenler ST_Intrumentalness (%26,45), ST_Acousticness (%19,03), ST_Liveness (%16,11) ve ST_Valence (%14,1)'dir. Pandemi kaynaklı stres ve konserlerin iptali göz önüne alındığında, ST_Valence (müzikal pozitiflik) ve ST_Liveness değişkenlerinin böyle bir oranda değişeceği sezgisel bir beklenti olmuştur. Sonuçlar, müzik tercihinin duygusal durumun önemli bir göstergesi olduğunu doğrulamaktadır.

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Abstract

Spotify is the world's largest online music streaming platform that offers a tremendous variety of playlists based on listeners' listening patterns. This paper proposes that music preference is highly associated with emotional state, and music is an emotion regulator tool during the pandemic in the Philippines. Well-known machine learning methods (i.e., classification and regression trees, boosted trees, random forests, Support Vector Machines, and Artificial Neural Networks) in combination with 5-fold cross-validation are used to classify periods in proportion to the severity of the pandemic and people's musical preferences. Daily official covid-19 statistics and Spotify data are used as main variables during the algorithms' learning processes. SVM outperformed the other alternatives in average accuracy rate by achieving a 98.01% accuracy rate. Additionally, ANN outperformed the other alternatives in terms of accuracy achieved specifically in a single model, achieving an accuracy rate of 99.30%. Moreover, the variables with the largest (absolute) change (in descending order) are ST_Intrumentalness (26,45%), ST_Acousticness (19,03%), ST_Liveness (16,11%), and ST_Valence (14,1%). Given pandemics-related stress and cancelation of concerts, it would be an intuitive expectation that the variables ST_Valence (musical positivity) and ST_Liveness would change at such a rate. The results confirm that musical preference is a significant indicator of emotional state.

Keywords: *Quantitative Decision Methods, Data Analytics, Machine Learning, Sentiment Analysis, Music.*

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1. INTRODUCTION

The new coronavirus disease (COVID-19), which first emerged in Wuhan, China, in December of 2019, has not only caused worldwide distress (Jena, et al. 2021) but also induced a big global worry and psychological shock (Giordano, et al. 2020). World Health Organization (WHO) declared it as a pandemic in January 2020 (Jena, et al. 2021).

Contagious diseases are always serious threats to humanity (Wang, et al. 2020). Because of the scant available medical options and the severity of symptoms that may cause to patients' death, COVID-19 is particularly dangerous. Also, some patients infected with COVID-19 may not be exhibiting any indication of disease but pass it on other people (Karasmanaki and Tsantopoulos 2021). Pyrexia, insufficiency of breathing, and cough, are among the most common somatic signs of the Covid-19 (Arslan, Yıldırım and Tanhan, et al. 2020) whereas psychological and neurological consequences of COVID-19 is not well-documented (Rahman, et al. 2020).

The COVID-19 pandemic is a strong warning that pandemics are repeating phenomenons and it is probable that such calamities will repeat in the future (Donthu and Gustafsson 2020). The worry and dread about the disease have also caused to a societal stigmatization (Rahman, et al. 2020). The COVID-19 is not only an epidemiological catastrophe but also a health crisis by causing a vast variety of psychological issues such as anxiety, fear and confusion (Arslan, et al. 2021).

Daily social life contains substantial physical activities such as meeting with friends, participating concerts and intellectual events (Karasmanaki and Tsantopoulos 2021). However, daily life has been rearranged under the pandemic circumstances. Governments around the world have put into practice numerous protective policies to prevent the rapid boosting spread. All sports activities have been cancelled or suspended to reduce the spread of the virüs (Nicola, et al. 2020). The best intervention model to contain the disease was found to confine people in their homes (Sood 2020). All the governments have closed their country borders, restricted the movement of poeple (Donthu and Gustafsson 2020). These kind of limitations have caused to deterioration in economic courses (Jena, et al. 2021) and in the supply chains (Nicola, et al. 2020). The quarantine policies that have been performed by many countries impacted businesses, employment rates, and main services (Sharif, Aloui and Yarovaya 2020) and also have led to stock market instability (Bayraktar 2020) and bankruptcies for many popular corporations in different sectors (Donthu and Gustafsson 2020).

The present pandemic has had intense economic outcomes across the world (Donthu and Gustafsson 2020). Under the pandemic circumstances, the demand for manufactured commodities has decreased (Nicola, et al. 2020), investors have lost their interest in investing and started saving capital (Donthu and Gustafsson 2020) resulting a worldwide panic that led the global economy to a stop (Bayraktar 2020). The ambiguity and financial damage caused by covid-19 have caused the business sectors to become extremely unrelaible (Bayraktar 2020). In a nutshell, the pandemic has not only caused health crises, but it has also created chaos in the all economies on a measure not observed since the Great Depression (Laing 2020).

The tourism sector is dealing with an unprecedented shock of cancellations and a dramatic reduction in demand. The food and farming sectors are also struggling with excessive demand because of panic-buying and stocking up on goods (Nicola, et al. 2020). Also global stock markets have been impacted seriously by oil price drop (Sharif, Aloui and Yarovaya 2020). These striking decrease in prices and production across all mining industry, demonstrate the present catastrophic situation in the industry (Laing 2020). The strong impact on the economy has caused fiscal insecurity and distress in the society which will implicitly cause health problems (Sood 2020).

Although there is very scarce data on the mental health course of past outbreak cases (Sood 2020), there is sufficient finding that negative psychological factors can cause substantial increase in inflammatory diseases (Wang, et al. 2020). The ambiguity of the pandemic is a main factor for psychological distress among people (Sood 2020). The psychological consequences of the distress might exceed the health consequences of the pandemic (Xie, et al. 2020). Temporary shutting down restaurents, cafes, recreation centers, and the all similar public places has induced abrupt transformation on usual dietary and social activity models (Flanagan, et al. 2021). Under the quarantine circumstances, people are consuming more junk food and having less personal care (Donthu and Gustafsson 2020). Therefore covid-19 has the potential to lead non-contagious diseases like obesity (Flanagan, et al. 2021). In the study of Flanagan et al., the changes in daily dietary styles, physical exercises, sleep patterns, mental health, and sedentary lifestyle before and in the course of the COVID-19 was observed (Flanagan, et al. 2021).

The mental health effect of the pandemic have been proved to be much more severe for those who are prone to psychological problems (Simon, et al. 2021). Psychological health is negatively correlated with fear of death, and positively correlated with good health (Kasapoğlu 2020). The new form of daily life including restricted social activity, irregular sleeping hours, and social distancing concept have adversely affected the mental well-being (Chaturvedi, Vishwakarma and Singh 2021). As people stay at home for longer periods of time, the possibility of experiencing anxiety and claustrophobia is increasing (Sood 2020). In the study of Tull et al., findings show the significance of social interaction to mitigate adverse psychological effects of the COVID-19 (Tull, et al. 2020).

An unusually interesting process is going on, people are being fined for not staying at home (Donthu and Gustafsson 2020). All educational institutions have ceased face to face education and began giving online education (Arslan, et al. 2021). The findings show that the shutdown of educational institutions has been extremely effective prevention to slow down the spread of the virüs (Karasmanaki and Tsantopoulos 2021). These worldwide closure measures have impacted 1.4 billion students (UNESCO 2020). Students have become physically away from their classmates and their major social environment. Schools and colleges are gainful environments where students can enjoy the feeling of belongingness that is a crucial component for better education process and mental well-being. During the pandemic, a substantial increase has been observed in the number of mental problems among students (Arslan, et al. 2021).

The essential role of art in education and entertainment is undeniable, and it is a means of relaxation in times of economic difficulties. The need for artistic content has escalated during the lockdown. Economic indications show that art and culture will be one of the most damaged industries, and most likely one of the slowest to recuperate. Online access methods are highly preferred, as it is temporarily not possible to physically participate in artistic and cultural activities (Radermecker 2020). Under the lockdown conditions, there is a rapid increase in the usage of Internet and social media. Also, online shopping and (Donthu and Gustafsson 2020) gaming platforms have reached to an unprecedented growth in the number of users (Nicola, et al. 2020).

Depression is a extremely widespread psychiatric (Sakka and Juslin 2018) and chronic illness that can affect all age groups (Castillo-Pérez, et al. 2010). People with depression have trouble controlling their emotions. Music has always been utilized as an alternative healing tool in all societies (Martín, et al. 2021). Music listening is a beneficial activity for mitigating depression symptoms, promoting positive emotions and diminishing negative emotions (Sakka and Juslin 2018). Acording to reports from people, music has been a substantial support for coping with isolation, an effective tool for emotional balancing, and a cure for loneliness (Martín, et al. 2021). Aljanaki et al., put forth that there is adequate variety and expressiveness in music to transmit and stimuli emotions (Aljanaki, Wiering and Veltkamp 2016). Bogt et al. (2011) reveal the protective function of music towards stress and conclude that listening to music stimulates positive emotions and supports coping with stress and anxiety (Bogt, et al. 2011). The findings of Pothoulaki et al. (2008) show that music is an excellent mood stimulant which ensures that attention is not focused on stressful situations; the drop in anxiety level is especially evident when listening to music pleasant to the listener (Pothoulaki, et al. 2008). In the study of Juslin et al. (2008), negative moods such as irritation, anxiety or worry are not mostly experienced while listening to music (Juslin, et al. 2008).

Spiritual self-regulation methods give substantial benefits for social and educational performance, as well as for personal health (Martín, et al. 2021). Music has the potential to evoke strong emotions in people (Aljanaki, Wiering and Veltkamp 2016). Also music can affect all brain activities connected with emotions (Koelsch, 2018). There are many studies in the field of neuropsychology that examine brain responses to musical parameters (Bresin and Friberg 2011). According to this studies, emotions that arise with music are real and can be extremely intense. In addition the vast majority of such music studies declare considerable transformation in the anterior hippocampal (Koelsch, 2018). Moreover, music affects the functioning of heart, the action of breathing, and blood pressure. Koelsch & Jäncke concluded that pulse and breathing rates are higher in reaction to energic music compared with soothing music (Koelsch and Jäncke, Music and the heart 2015).

For different age groups, the favorite genres and streaming frequencies are different. The most popular genres are Pop, rock, and jazz (Gurgen 2016). People between the ages of 18-40 use music as a means of coping with loneliness (Martín, et al. 2021). There are several studies investigating the effect of music on the brain. For example, Mozart's Sonata has been proven to increase brain capacity by activating neural signal pathways. This is referred to as the "Mozart effect" (Castillo-Pérez, et al. 2010). Understanding music, which has been an important part of all cultures throughout human history, will make it possible to correctly understand the emotions aroused by music (Koelsch, 2018). Emotions evoked by music are usually the outcomes of dynamic emotional regulation (Eerola, et al. 2018). Music can be considered both as a way of expressing emotions and as a factor that causes emotional reactions in listeners (Eerola, et al. 2018). In general, the most common purpose of listening to music is to cultivate positive emotions (Sakka and Juslin 2018).

According to the results of a number of studies in the literature, music therapy can alleviate pain, regulate sleeping pattern, and reduce anxiety without medication (Giordano, et al. 2020). Giordano et al. proves the effectiveness of taking music therapy as a supplementary intervention to alleviate anxiety and improve comfort (Giordano, et al. 2020). In the study of Martín et al., participants were asked to use music to express their feelings and support some social difficulties such as loneliness. The findings verify that music is one of the most preferred methods to deal with loneliness (Martín, et al. 2021). According to the results of a meta-analysis, loneliness is an element of risk for all-cause mortality (Sood 2020). Also Castillo-Pérez et al. proposes that people with low or medium level depression can use music to improve the efficacy of psychological support. No side effects have been detected for music therapy, whereas music therapy can apply an extremely positive effect on psychological health. In the music therapy session, the depression rates of the music-listening group have decreased significantly (Castillo-Pérez, et al. 2010). Music-evoked happiness is provided by dopamine release (Eerola, et al. 2018). Also, music is very effective for mitigating cancer pain and (Castillo-Pérez, et al. 2010) muscle spasm (Faus, Matas and Elósegui 2019).

The convenience in exchanging information with others and the sense of social connection convince people to be involved in social media. Social media is a very prevalent platform among younger age groups (Arslan, et al. 2021). In a study on the subject, it has been revealed that the social media usage is related to the concepts of belongingness, self-expression, and receiving personal support (Arslan, et al. 2021). Even though social media provide people with so many benefits during the quarantine, it also has some potential harms such as misleading rumors or incorrect information (Sood 2020).

Providing instant access to countless music libraries, advances in digital technology are giving people an unprecedented variety of music (Anderson, et al. 2021). In order to receive the highest possible quality and speed service from the databases of musical sources, automatic evaluation and classification algorithms are required. The methods applied by musical content sharing systems are based on emotion-based analysis algorithms (Aljanaki, Wiering and Veltkamp 2016). Spotify is a Swedish online music streaming service and is described as the world's largest streaming platform with over a hundred million active users. According to user reviews, compared to competitors like Apple or Amazon music streaming services, Spotify offers more convenient and reliable service. Spotify's success is often seen as a consequence of its economic and cultural effect (Vonderau 2019).

Spotify is usually described as the "new radio" for the effect it has on hit musics or albums, and for its function in music consumption and music discovery. Spotify offers a growing variety of playlists based on listener-centered driven data (Prey, Valle and Zwerwer 2020). Prey et al. investigated the mediator function of Spotify on the music industry and how Spotify is changing the way we consume music (Prey, Valle and Zwerwer 2020). Vonderau examined Spotify as a social media corporation that operates at the intersection of technology, marketing, and music (Vonderau 2019).

People's preferences can be predicted with high accuracy thanks to computer-based algorithms. Music preferences are an important indicator of people's psychological states. By using online services, we can perform our daily activities, from social communication to information retrieval. Recent social and psychological research suggests that it is possible to successfully predict people's personality traits from digital records. The information obtained from this process is called a "digital footprint". Therefore, the music choices on Spotify can be considered as an important digital source of information about personality traits. Listening to music is a significant individual activity and therefore has the potential to contain qualified information regarding the personal preferences. Anderson et al. examined the correlation between personality and music listening patterns on Spotify. The findings show that the music listening pattern on Spotify provides significant information on the personality (Anderson, et al. 2021).

In this study, it was examined whether people's musical preferences changed under the Covid-19 pandemic conditions. Several musical parameters shared by Spotify and statistical data on the course of the pandemic have been brought together on the daily basis. Since this is a descriptive study, we do not have an obvious design of hypotheses; however, we do have a general assumption of the patterns between emotional reactions and music parameters. Our research revealed that there is a significant change in music listening habits during the pandemic.

2. EXPERIMENTAL STUDY

2.1. Data

The data used in this study is a combination of two data sets obtained from different sources. The first dataset has been provided by a *kaggle.com* member *JC Albert Peralta*. That is a *Spotifycharts.com* originated data shared within the scope of *Spotify Developers API*. The second dataset has been obtained from another similar data-sharing platform, *Our World in Data* (*ourworldindata.org*). The first dataset contains details about the top 200 most listened daily music tracks on *Spotify* between the dates 01.01.2017 and 15.01.2021 in the Philippines. Details of the variables are given below (Table 1).

Table 1. Description of variables (*Spotify*)

Variables	Type	Description
Date	**Ordinal**	The date on which the information of the track was collected
Track Id	**Nominal**	Unique *Spotify* id of the track
Track Name	**Text**	Name of the track
Position	**Numerical**	Chart rank (from 1 to 200) in terms of number of streams.
Artist Name	**Text**	Artist of the track
Acousticness	**Numerical**	The ratio of the acoustics of the track. It can take a value between 0 and 1.
Danceability	**Numerical**	Danceability ratio in terms of a combination of musical elements such as tempo, rhythm stability, beat strength, and general regularity. It can take a value between 0 and 1.
Energy	**Numerical**	Energy is a perceptual measure of intensity and activity. It can take a value between 0 and 1.
Instrumentalness	**Numerical**	It can take a value between 0 and 1. The closer the instrumentals value is to 1, the greater likelihood the track contains no vocal content.
Key	**Numerical**	The note or chord that the track is centered around. It can take a value between 0 and 11. If no key is detected, the value is -1.

Liveness	**Numerical**	The presence of an audience in the recording and the probability that the track was performed live are measured. It can take a value between 0 and 1.
Loudness	**Numerical**	Overall loudness of a track in decibels (dB). Values typically range between -60 and 0 dB.
Mode	**Numerical**	The type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0.
Speechiness	**Numerical**	The ratio of the presence of spoken words in a track. It can take a value between 0 and 1.
Tempo	**Numerical**	The overall estimated tempo of a track in beats per minute (BPM).
Valence	**Numerical**	Describes the musical positiveness (e.g. happy, cheerful, euphoric) conveyed by a track. Tracks with low valence sound more negative (e.g. sad, depressed, angry). It can take a value between 0 and 1.
Streams	**Numerical**	Number of streams in the specified date

The second dataset contains daily covid-19 statistics in the Philippines between the dates 30.01.2020 when the first coronavirus case was detected in the Philippines and 15.01.2021. Details of the variables are given below (Table 2):

Table 2: Description of variables (Covid-19)

Variable	**Type**	**Description**
date	Ordinal	Date of the day when daily data on the pandemic were obtained.
total_cases	Numerical	The total number of coronavirus patients detected until the day of data collection.
new_cases	Numerical	The total number of coronavirus patients detected on the day the data was collected.
new_cases_smoothed	Numerical	Smoothed number of daily new covid-19 cases.
total_deaths	Numerical	The number of deaths due to the total coronavirus detected until the day the data was collected.
new_deaths	Numerical	The number of deaths due to the total coronavirus detected on the day the data was collected.
new_deaths_smoothed	Numerical	Smoothed number of daily new deaths caused by covid-19.
reproduction_rate	Numerical	Daily calculated coronavirus transmission or contagiousness coefficient rate.
positive_rate	Numerical	The rate of detecting positive in the total Covid-19 tests applied daily.
stringency_index	Numerical	It provides a picture of the stage at which any country enforced its strongest measures. The Stringency Index is a number from 0 to 100 that reflects these indicators. A higher index score indicates a higher level of stringency.

The *Spotify* dataset has a total of 294,600 cases, as it contains information on the 200 most-streamed tracks daily for more than 4-years. On the other hand, covid-19 data consists of a total of 352 cases. These two data sets were combined by averaging the musical characteristics of the 200 most listened-to music tracks on a daily basis. Later, this data was combined with the covid-19 data. The combined data includes all of the variables listed in Table 1 and 2 above. Besides, the combined data consists of 1473 cases, and only the last 352 cases contain both *Spotify* and covid-19 data.

Both StatSoft Statistica 14 and IBM SPSS 22 statistical package programs have been used in data analysis.

2.2. Methodology

In this study, we examine the effect of musical parameters on human psychology. We conduct our observations in two different time periods, pre-pandemic when social life goes on routinely, and pandemic when human psychology is heavily exposed to negative effects. *Spotify* music data consists of a period of 1473 days, and pandemic conditions were effective only in the last 352 days of that period. Therefore, in order to observe the effects of the pandemic, the 352-day data needs to be compared with the rest. In addition, by using only pandemic period (352-day) data, period-specific situations can be observed.

In addition to considering the pandemic period as a whole, considering it according to sub-periods will also provide important observation opportunities. The transmission rate of the infection, and mortality or recovery rates of the patients vary during the pandemic. The stringency rates of the measures implemented by governments also change in proportion to the variability in the rates. Therefore, both the fear of getting sick and the severity of the social restrictions that people are exposed to differ in the process. All these situations cause periodic differences in the psychological effect of the pandemic on people. In this respect, it would be a valid approach to divide the pandemic period into sub-periods according to the course of the pandemic and examine people's music listening tendencies according to these sub-periods.

Another notable issue is the way *Spotify* data is handled. While Covid-19 data consists of a single line of information daily, *Spotify* data consists of 200 rows of information, corresponding to the 200 most-streamed tracks. The 200-rows data need to be reduced to a single row and matched with the pandemic data of that date. The reduction has been performed by taking an average of 200 rows.

The content of the "streams" variable in Spotify music data is different from other variables. “danceability,” “loudness,” “acousticness,” etc. variables provide information about the musical aspects of the tracks, while the variable “streams” gives the total number of plays of the tracks daily. From this point of view, the “streams” variable alone does not provide satisfactory information. On the other hand, in this study, the relationship between the musical aspects of the tracks and the emotional states of people is investigated, and it is clear that the number of streaming is also a measure of emotional orientation and therefore should be taken into account. The streaming number of a song shows not only the listeners’ interest in that song but also the tendency towards the musical characteristics of that song. Therefore, the weighting of the musical parameters was applied using the variable "streams". In this way, the weighting of both the song and the musical parameters in the general music preferences of the listeners was calculated. As a notation, each 'variable' takes the form “ST_Variable” which is generated based on the weight calculation based on the number of streams.

After the data pre-processing step, qualified analyzes have been operated on the data. It has been investigated whether there is a statistically significant change between people's musical preferences in the periods of before (pre-pandemic) and after (post-pandemic) the first Covid-19 case was diagnosed. A t-test was used to test whether there was a significant difference between the arithmetic means of the musical parameter scores of the two groups (pre- and post-pandemic). In addition, Levene's test was applied to test whether the groups had equal variances.

In addition, the value Pearson Correlation has been calculated to determine the degree of correlation between musical and pandemic variables in the post-pandemic data only.

It is an undeniable fact that the change in fatality and transmission rates during the pandemic and the severity of the measures taken accordingly have direct and negative effects on human and societal psychology, just like the curfews, the compulsory wearing of masks, etc. However, these rates have not remained constant throughout the pandemic. There are sub-periods in which the rates decreased or increased in the process. Similarly, it would be a natural outcome that the effects of the pandemic on the people's psychology in these sub-periods would differ. The pandemic period data were divided into sub-periods with a k-means clustering application to observe the differences between sub-periods using the variables "new_cases," "new_deaths," "reproduction_rate," "positive_rate," and "stringency_index," which contain important information about the daily course of the pandemic. In cases where the number of groups (categories) is more than two, ANOVA is applied to compare the means of the groups. However, when "homogeneity of variances" is violated, "Robust Tests of equality of means" such as *Welch* and *Brown-Forsythe* tests are applied. Thus, if no statistically significant violation is detected, then it would be appropriate to operate "Multiple Comparison". As a result, *Games-Howell* multiple comparison tests were applied.

Having identified a significant relationship between the pandemic and musical preferences, the next step will be to uncover the pattern of relationships. Is it possible to determine whether a randomly selected day is before or after the pandemic by looking only at people's musical preferences, thanks to a model created using music data? If such a pattern of relationships is recognized, how successful is that pattern in explaining the data? For the recognition of such a pattern, widely used machine learning algorithms were preferred. Thanks to this method, it is possible to reveal which pandemic variable is effective in musical preferences and to what extent.

One of the main issues of all machine learning algorithms is deciding when to stop, such as how to prevent the algorithm from adjusting abstruse aspects of the training data that are unlikely to increase the predictive power of the model in question. This problem is also known as overfitting. That is a common problem for many machine learning algorithms used in predictive models.

In the data, the pre-pandemic period covers a period about three times as long as the post-pandemic period. For this reason, a model built on all the data may have an overfitting problem. An equal amount of data was taken from pre-pandemic and post-pandemic data to overcome this problem. A balanced distribution of data was created covering the last 352 days before the pandemic and the first 352 days after the pandemic, making a total of 654 days. In addition, 5-fold cross-validation was applied to test the success of the models on balanced, stratified, and mutually disjoint data sets. The models were built using machine learning algorithms CART, BT, RF, SVM, and ANN. The modeling process was repeated for each of the subsets.

2.2.1. Classification And Regression Trees (CART)

CART is a nonparametric and distribution-free decision tree method used for classification and prediction. Prior association detection and modeling are not required for CART, as it spontaneously forms mutually disjoint groups that provide comprehensible insight into the interactive pattern of significant independent variables (Ma 2018; Zhang and Singer 1999). Moreover, CART is a robust statistical method that can handle many types of data and outliers (Perry, et al. 2013).

2.2.2. Random Forest (RF)

The random forest method generates so many decision trees and brings randomness into the composition, which can provide a model of the most informative variables (Perry, et al. 2013). In each child node (leaf node), RF first randomly selects a set of variables and then selects the ideal variable from the selected set. The process of forest construction requires repeated cycles of tree composition (He and Ding 2019). Random forest is a grouping method that uses various classification trees to strengthen predictive models (Rudy, et al. 2019).

2.2.3. Stochastic Gradient Boosting Trees (BT)

Stochastic gradient boosting decision trees is a classification and regression algorithm based on bootstrapped subsets that generates child nodes by repeated splittings (Safavian and Landgrebe 1991).

2.2.4. Support Vector Machine (SVM)

The support vector machine (SVM) is a supervised algorithm that operates by selecting a splitting function that divides the training set into two categories. If no splitting function can linearly split the data, a kernel function is used as a linear classifier to solve the non-linearity (Boyle 2011). In addition, SVM can also be used as a regression algorithm (Nell and Shawe-Taylor 2000).

2.2.5. Artificial Neural Network (ANN)

The main goal of artificial neural networks (ANN) is to model complicated systems. The principal structure of the neural network of a biological system can manage non-linear, insufficient, and incomprehensible information. ANN is a composite process of mathematical algorithms designed to extract information by mimicking the learning process of the human brain (Cain 2017). Also, ANN can be characterized as a composition of analogically distributed computational models. The basic processing component, neurons, are deeply interconnected, dynamically reshaping themselves during the learning process (Zohuri and Moghaddam 2017).

2.2.6. K-Means Clustering

K-means clustering is a simple unsupervised machine learning method that aims to partition observations into k clusters. The basic concept is to assign k centers corresponding to the k clusters. The centers should be as far apart as possible. Each point is placed in a cluster corresponding to the nearest center. After all points are distributed into clusters, the first iteration is complete. Next, k new centroids corresponding to the k new clusters are recomputed. According to the k new centroids, a new partitioning must be performed for the same observation points. The centroids of the clusters can move to a new location after each iteration. The process is repeated as long as the centroids move (Rajaguru and Prabhakar 2017).

2.2.7. Levene's Test

As a nonparametric procedure, Levene's test is used to assess the variance homogeneity. If the hypothesis that the variances of the two populations are equal is rejected, then an investigation of the reason for the inequality should be conducted (Levene 1960).

2.2.8. Welch Test

Welch's test is used to test the hypothesis that two populations have equal means. The test performs better than the F-test and is quite good for normally distributed populations (Wilcox 2003).

2.2.9. Brown-Forsythe Test

The Brown-Forsythe test is used to test the hypothesis that two groups in a population have equal variances. The test is based on an analysis of variance (ANOVA). The test statistic of the Brown-Forsythe test, which is a number calculated from a statistical test of a hypothesis, is the F statistic obtained from an ordinary one-way ANOVA (Brown and Forsythe 1974).

2.2.10. Games-Howell Post-Hoc Test

The Games-Howell (Games and Howell 1976) post hoc test is an extended adaptation of the Tukey-Kramer test, and it is suitable for cases where equality of variances is violated (Lee and Lee 2018).

3. RESULTS AND DISCUSSION

The data covering a total period of 1473 days, before and after the pandemic (B/A), were considered as a whole and it was observed whether there was a statistically significant difference between listeners' musical preferences according to the periods. A t-test was applied in which (Before/After Pandemic) the BA_CVD19 variable is the grouping factor. Although some of the variables have normality problems, we can ignore them when we consider the number of cases (Lumley, et al. 2002)**.**

Levene's test was used to check for equality of variances. Group statistics are given in Table 3. The number of cases before the pandemic is 1121, and the number of cases after the pandemic is 352. The percentage change for the variables Streams, ST_Danceability, ST_Energy, ST_Key, ST_Loudness, ST_Mode, ST_Speechiness, ST_Acousticness, ST_Intrumentalness, ST_Liveness, ST_Valence, and ST_Tempo during the pandemic are 8.35, 9.31, 6.01, 10.07, 11.88, 5.69, 19.03, -26.45, 16.11, 14.1, and 9.97, respectively. The four variables with the greatest (absolute) change (in descending order) are ST_Intrumentalness, ST_Acousticness, ST_Liveness, and ST_Valence. Given the stress that occurred during the pandemic and the cancellation of concerts, it would be an intuitive expectation that the variables ST_Valence (the musical positivity rate) and ST_Liveness would change at such a rate.

Table 3. Group Statistics

	Group	N	Mean	Std. Dev.	Std. Err. Mean
streams	**B**	1121	49742,23	6214,47	185,61
	A	352	53897,31	7025,29	374,45
ST_Danceability	**B**	1121	30939,59	3730,02	111,41
	A	352	33818,79	4374,15	233,14
ST_Energy	**B**	1121	27169,30	2858,32	85,37
	A	352	28801,16	3965,37	211,36
ST_Key	**B**	1121	266319,01	39064,52	1166,76
	A	352	293131,83	36941,06	1968,97

ST_Loudness	**B**	1121	-355363,61	53026,33	1583,76
	A	352	-397566,79	50694,21	2702,01
ST_Mode	**B**	1121	38593,82	5067,50	151,35
	A	352	41999,37	5221,55	278,31
ST_Speechiness	**B**	1121	3543,27	560,46	16,74
	A	352	3745,05	652,28	34,77
ST_Acousticness	**B**	1121	16462,94	2964,14	88,53
	A	352	19596,50	2427,38	129,38
ST_Intrumentalness	**B**	1121	197,07	126,90	3,79
	A	352	144,95	115,11	6,14
ST_Liveness	**B**	1121	7087,14	1045,95	31,24
	A	352	8229,20	1096,88	58,46
ST_Valence	**B**	1121	21298,78	2477,92	74,01
	A	352	24301,91	3308,63	176,35
ST_Tempo	**B**	1121	5793387,47	736362,84	21993,23
	A	352	6371048,97	831038,61	44294,51

According to Levene's test (Table 4) for equality of variances, some variables are not assumed to have equality of variances (Sig. < 0.05), which means that the variability in the two groups is not equal. Equality of variance is also assumed for some variables (Sig. > 0.05), i.e., the variability in the two groups is not significantly different. However, looking at the t-test for equality of means, we find that the significance (Sig. 2-tailed) value is less than 0.05 for both cases. This situation leads to the conclusion that there is a statistically significant difference between the two groups for all variables.

Table 4. Independent Samples Test

		Levene's Test for Equality of		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
streams	Equal variances assumed	5,71	0,02	-10,60	1471,00	0,00	-4155,09	392,08
	Equal variances not assumed			-9,94	534,56	0,00	-4155,09	417,93
ST_Danceability	Equal variances assumed	10,39	0,00	-12,10	1471,00	0,00	-2879,20	237,88
	Equal variances not assumed			-11,14	521,08	0,00	-2879,20	258,39
ST_Energy	Equal variances assumed	64,87	0,00	-8,46	1471,00	0,00	-1631,87	192,94
	Equal variances not assumed			-7,16	470,95	0,00	-1631,87	227,95
ST_Key	Equal variances assumed	9,59	0,00	-11,38	1471,00	0,00	-26812,82	2356,46
	Equal variances not assumed			-11,72	616,94	0,00	-26812,82	2288,70
ST_Loudness	Equal variances assumed	3,10	0,08	13,16	1471,00	0,00	42203,18	3206,38
	Equal variances not assumed			13,48	611,01	0,00	42203,18	3131,96
ST_Mode	Equal variances assumed	1,05	0,31	-10,92	1471,00	0,00	-3405,55	311,89
	Equal variances not assumed			-10,75	573,60	0,00	-3405,55	316,80
ST_Speechiness	Equal variances assumed	13,47	0,00	-5,66	1471,00	0,00	-201,78	35,66
	Equal variances not assumed			-5,23	523,79	0,00	-201,78	38,59
ST_Acousticness	Equal variances assumed	21,73	0,00	-18,03	1471,00	0,00	-3133,56	173,84

	Equal variances not assumed			-19,99	708,01	0,00	-3133,56	156,77
ST_Intrumentalness	Equal variances assumed	0,51	0,48	6,87	1471,00	0,00	52,12	7,59
	Equal variances not assumed			7,23	640,74	0,00	52,12	7,21
ST_Liveness	Equal variances assumed	1,65	0,20	-17,66	1471,00	0,00	-1142,06	64,66
	Equal variances not assumed			-17,23	565,60	0,00	-1142,06	66,29
ST_Valence	Equal variances assumed	49,59	0,00	-18,21	1471,00	0,00	-3003,13	164,93
	Equal variances not assumed			-15,70	480,85	0,00	-3003,13	191,25
ST_Tempo	Equal variances assumed	4,24	0,04	-12,44	1471,00	0,00	-577661,50	46436,08
	Equal variances not assumed			-11,68	535,21	0,00	-577661,50	49454,08

Correlation rates between Covid-19 and music variables were calculated, considering only data from the pandemic period (last 352 days). Statistically significant correlation values are marked with an asterisk (*). From the results, there is a significant overall correlation between the pandemic and music variables. The strengency_index variable, which expresses the severity rates of the measures implemented by governments in the name of protection against the pandemic, which directly affects daily life and therefore the psychology of everyone who is affected or not affected with the disease during the pandemic, has a very strong correlation with all musical variables. Correlation values are given in Table 5.

Table 5. Pearson Correlation

	total_cases	new_cases	new_deaths_ smoothed	total_deaths	new_deaths	new_deaths_ smoothed_ per_million	reproduction _rate	positive_rate	stringency_ index	
streams	**0,279	-0,006	0,055	**0,26	0,002	0,055	**-0,596	**-0,276	**-0,733	**Pearson Corr.**
	0	0,913	0,302	0	0,964	0,302	0	0	0	**Sig. (2-tailed)**
ST_Danceability	**0,241	-0,044	0,020	**0,225	-0,023	0,020	**-0,601	**-0,302	**-0,736	**Pearson Corr.**
	0	0,414	0,705	0	0,671	0,705	0	0	0	**Sig. (2-tailed)**
ST_Energy	**0,343	0,039	*0,114	**0,327	0,039	*0,114	**-0,549	**-0,222	**-0,699	**Pearson Corr.**
	0	0,470	0,033	0	0,464	0,033	0	0	0	**Sig. (2-tailed)**
ST_Key	0,048	-0,099	-0,077	0,026	-0,083	-0,077	**-0,631	**-0,360	**-0,762	**Pearson Corr.**
	0,372	0,064	0,150	0,624	0,120	0,150	0	0	0	**Sig. (2-tailed)**
ST_Loudness	**-0,20	0,035	0,001	**-0,177	0,034	0	**0,619	**0,312	**0,740	**Pearson Corr.**
	0	0,507	0,992	0,001	0,522	0,993	0	0	0	**Sig. (2-tailed)**
ST_Mode	**0,238	0,080	0,087	**0,215	0,027	0,087	**-0,572	**-0,184	**-0,705	**Pearson Corr.**
	0	0,133	0,102	0	0,612	0,102	0	0,001	0	**Sig. (2-tailed)**
ST_Speechiness	**0,201	**-0,221	-0,093	**0,188	-0,096	-0,093	**-0,619	**-0,493	**-0,735	**Pearson Corr.**
	0	0	0,082	0	0,071	0,082	0	0	0	**Sig. (2-tailed)**
ST_Acousticness	**0,236	*0,113	0,076	**0,209	0,019	0,076	**-0,571	**-0,159	**-0,698	**Pearson Corr.**
	0	0,034	0,157	0	0,729	0,156	0	0,003	0	**Sig. (2-tailed)**
ST_Intrumentalness	**-0,41	*-0,107	**-0,276	**-0,421	**-0,199	**-0,276	**-0,334	**-0,172	**-0,402	**Pearson Corr.**
	0	0,044	0	0	0	0	0	0,001	0	**Sig. 2-tailed)**
ST_Liveness	**0,457	*0,121	**0,212	**0,445	*0,106	**0,212	**-0,451	*-0,113	**-0,612	**Pearson Corr.**
	0	0,023	0	0	0,046	0	0	0,035	0	**Sig. (2-tailed)**
ST_Valence	**0,381	0,046	0,098	**0,372	0,028	0,098	**-0,518	**-0,212	**-0,677	**Pearson Corr.**
	0	0,394	0,066	0	0,596	0,066	0	0	0	**Sig. (2-tailed)**
ST_Tempo	**0,313	0,037	0,098	**0,293	0,034	0,098	**-0,574	**-0,239	**-0,718	**Pearson Corr.**
	0	0,495	0,067	0	0,526	0,067	0	0	0	**Sig. (2-tailed)**

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

During the pandemic, the severity of the disease and the stringency rate of the measures taken in proportion, increase and decrease spontaneously. The pandemic period data (352 days) were grouped using a k-means clustering model applied with five pandemic variables. In this way, it was possible to observe the musical variables concerning the changes in the severity of the pandemic. According to the results, the whole pandemic period was divided into 3 clusters. Then, the degree of difference between the music trends in the clusters was calculated using the multiple comparison method. Descriptive statistics for the clusters are given in Table 6.

Table 6. Descriptive Statistics for Clusters (Covid-19 statistics)

Cluster		new_cases	new_deaths	reproduction_rate	positive_rate	stringency_index
1	Mean	1679,853	39,608	,9675	,05575	66,1881
	N	102	102	102	102	102
	Std. Deviation	493,7987	32,6797	,06435	,010440	4,92366
	Minimum	764,0	3,0	,88	,039	55,09
	Maximum	3475,0	145,0	1,17	,079	71,76
	Variance	243837,176	1067,964	,004	,000	24,242
2	Mean	3526,691	56,971	1,0297	,10263	71,8469
	N	68	68	68	68	68
	Std. Deviation	1060,2803	42,5515	,15215	,023400	4,52522
	Minimum	1362,0	6,0	,87	,066	67,13
	Maximum	6725,0	259,0	1,43	,149	79,63
	Variance	1124194,366	1810,626	,023	,001	20,478
3	Mean	469,703	10,802	,9698	,03588	73,6879
	N	182	182	182	182	182
	Std. Deviation	612,8900	17,1059	,61695	,033082	29,31355
	Minimum	,0	,0	,00	,000	11,11
	Maximum	2486,0	162,0	2,22	,121	100,00
	Variance	375634,121	292,613	,381	,001	859,284
Total	Mean	1410,926	28,068	,9807	,05453	71,1590
	N	352	352	352	352	352
	Std. Deviation	1351,3193	34,0430	,44996	,036460	21,55411
	Minimum	,0	,0	,00	,000	11,11
	Maximum	6725,0	259,0	2,22	,149	100,00
	Variance	1826063,915	1158,924	,202	,001	464,580

Governments have taken several measures to combat the Covid 19 pandemic around the world. In cities that have entered a state of emergency, many measures have been taken, such as curfews, bans on crowded events such as cinemas, concerts, etc., and the obligation to wear masks. The majority of people have never been socially controlled by such restrictions at any time in their lives. Because of the deaths in our environment caused by the pandemic and the anxiety caused by the constant threat of death to the people themselves, they have experienced great psychological depression in the process. On the other hand, it is an indisputable fact that the measures taken by governments to slow down the death rate and the spread of disease are highly effective. However, the transmission and mortality rates have not remained constant throughout the pandemic, but there were interim periods when the rates decreased or increased. Parallel to the change in rates, the strictness of the measures implemented has also changed. Therefore, the pressure of the measures on the people also varies to the same extent. From this point of view, it is a natural result that the effects of the pandemic on people's psychology vary according to the sub-periods. To divide the pandemic period into sub-periods and thus observe the differences between the periods, a k-means clustering model was constructed with the variables "new_cases", "new_deaths", "reproduction_rate", "positive_rate" and "stringency_index" containing important information about the entire period.

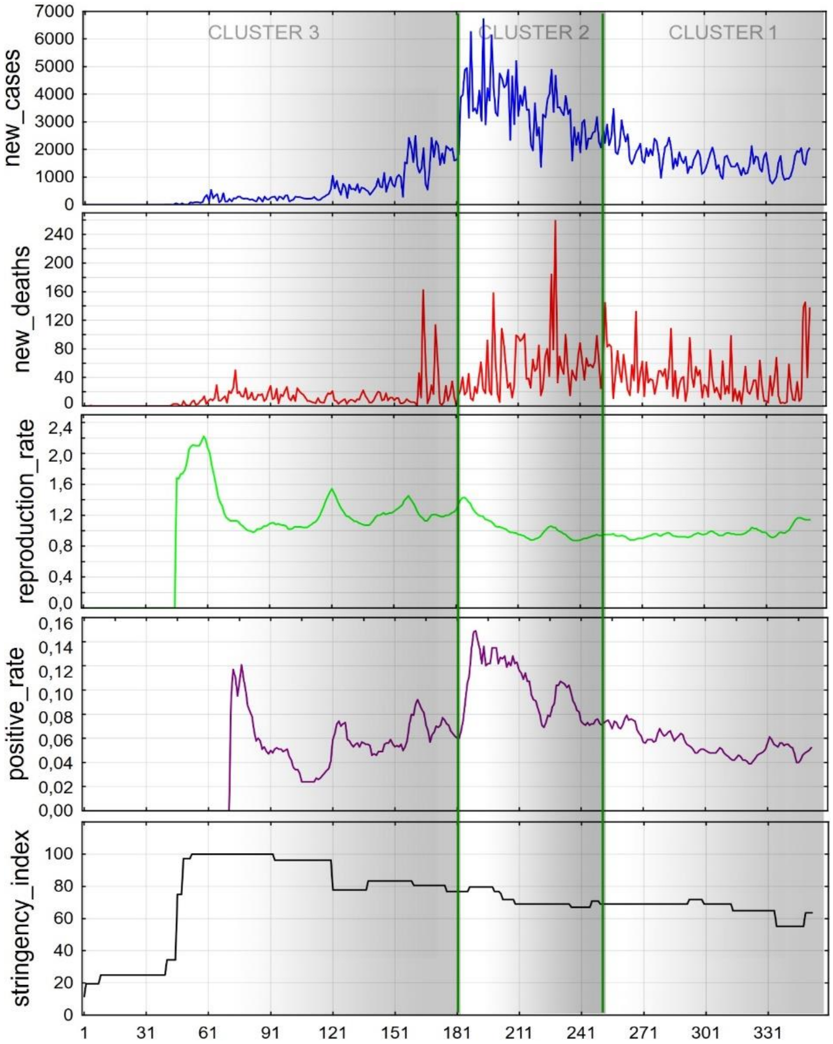

Figure 1. K-means clustering

The clustering model divides the data into three periods. Each period is represented as a cluster. The distribution of the data according to the 3 clusters is shown in Figure 1 for each variable. The sequence of cases being in the same cluster according to the days in a row is a strong indicator that the clustering model is successful in detecting the similarities between the cases according to the variables present. The clusters are arranged so that the most recent period is cluster 1 and the oldest period is cluster 3. When the distribution of dates within clusters is examined, cluster 3 represents the period of pandemic onset and progression, cluster 2 represents the period when the effects of the pandemic generally peak, and cluster 1 represents the period when the pandemic slows and begins to normalize. In cases where the number of groups (categories) is more than two, ANOVA is applied to compare the means between groups. Therefore, the ANOVA test was applied. According to the result of Levene's test, for all variables, the hypothesis that the variances of the two populations are equal is rejected. In other words, the problem of "homogeneity of variances" has been identified (Table 7).

Table 7. Test of Homogeneity of Variances

Dep. Variables	Levene Statistic	df1	df2	Sig.
streams	22,174	2	349	,000
ST_Danceability	21,831	2	349	,000
ST_Energy	17,403	2	349	,000
ST_Key	27,182	2	349	,000
ST_Loudness	27,832	2	349	,000
ST_Mode	22,934	2	349	,000
ST_Speechiness	22,461	2	349	,000

ST_Acousticness	23,621	2	349	,000
ST_Intrumentalness	45,457	2	349	,000
ST_Liveness	8,178	2	349	,000
ST_Valence	18,317	2	349	,000
ST_Tempo	20,089	2	349	,000

In this case, robust tests for equality of means (Table 8) such as Welch and Brown-Forsythe are applied. The test results are statistically significant (at Sig. 0.05). Based on the results, it is explicit that the 'Multiple Comparison' method can be applied.

Table 8. Robust Tests of Equality of Means

Robust Tests of Equality of Means		Statistic	df1	df2	Sig.
streams	**Welch**	24,650	2	197,390	,000
	Brown-Forsythe	25,058	2	330,481	,000
ST_Danceability	**Welch**	22,225	2	195,295	,000
	Brown-Forsythe	20,630	2	328,132	,000
ST_Energy	**Welch**	31,228	2	188,976	,000
	Brown-Forsythe	32,763	2	312,846	,000
ST_Key	**Welch**	4,866	2	202,098	,009
	Brown-Forsythe	3,419	2	341,763	,034
ST_Loudness	**Welch**	14,402	2	203,873	,000
	Brown-Forsythe	14,704	2	333,707	,000
ST_Mode	**Welch**	12,104	2	202,131	,000
	Brown-Forsythe	15,457	2	326,167	,000
ST_Speechiness	**Welch**	46,674	2	195,528	,000
	Brown-Forsythe	35,862	2	330,546	,000
ST_Acousticness	**Welch**	11,633	2	210,108	,000
	Brown-Forsythe	16,526	2	307,177	,000
ST_Intrumentalness	**Welch**	68,924	2	163,926	,000
	Brown-Forsythe	52,059	2	241,710	,000
ST_Liveness	**Welch**	42,123	2	179,089	,000
	Brown-Forsythe	50,044	2	282,666	,000
ST_Valence	**Welch**	36,588	2	194,176	,000
	Brown-Forsythe	41,069	2	314,797	,000
ST_Tempo	**Welch**	26,397	2	193,858	,000
	Brown-Forsythe	28,396	2	323,483	,000

Looking at the pandemic data suggests that the periods in clusters 2 and 3 are the periods when the pandemic is most intense. In this regard, the fact that value movements in musical variables move synchronously with this periodicity will be a factor supporting the hypothesis that people's musical preferences vary according to pandemic conditions. Examining the results of Multiple Comparison (Table 9), it was found that there is a statistically significant difference between the mean values of the distributions of the variables ST_Speechness, ST_Acousticness, and ST_Intrumentalness according to the three periods. Except for these three variables, there is no statistically significant difference between the means of the Cluster 2 and 3 distributions. On the other hand, it was determined that there were statistically significant differences between the Cluster 1 distribution means and the Cluster 2 and 3 distribution means, for all variables. Only for the variable, ST_Key was the difference between the means of the data distribution of the cluster 3 and cluster 1 periods not statistically significant. From this point of view, it can be concluded that the distribution of musical variables, in general, varies significantly according to the pandemic conditions.

Table 9. Multiple comparison

Dependent Variable	(I) Cluster	(J) Cluster	Mean Difference (I-J)	Std. Error	Sig.
streams	**1**	**2**	4992,37	812,48	**,000
		3	4915,24	810,35	**,000

	2	**3**	-77,13	805,56	0,995
ST_Danceability	**1**	**2**	3174,73	514,22	**,000
		3	2642,3	504,4	**,000
	2	**3**	-532,43	515,13	0,557
ST_Energy	**1**	**2**	3046,58	481,7	**,000
		3	3272,78	449,34	**,000
	2	**3**	226,2	466,71	0,879
ST_Key	**1**	**2**	12994,11	4165,75	**,006
		3	5632,94	4350,54	0,399
	2	**3**	-7361,17	4396,73	0,218
ST_Loudness	**1**	**2**	-28708,99	5797,5	**,000
		3	-27067,66	6076,92	**,000
	2	**3**	1641,34	5666,48	0,955
ST_Mode	**1**	**2**	2054,53	612,55	**,003
		3	3089,6	633,59	**,000
	2	**3**	1035,08	579,91	0,177
ST_Speechiness	**1**	**2**	694,54	72,21	**,000
		3	374,25	71,32	**,000
	2	**3**	-320,29	75,54	**,000
ST_Acousticness	**1**	**2**	674,11	275,5	**,041
		3	1447,86	303,78	**,000
	2	**3**	773,75	246,87	**,005
ST_Intrumentalness	**1**	**2**	-75,53	12,42	**,000
		3	-115,39	10,55	**,000
	2	**3**	-39,87	14,91	**,022
ST_Liveness	**1**	**2**	898,11	141,12	**,000
		3	1153,33	126,62	**,000
	2	**3**	255,22	122,45	0,097
ST_Valence	**1**	**2**	2891,76	390,69	**,000
		3	2962,46	382,4	**,000
	2	**3**	70,7	360,39	0,979
ST_Tempo	**1**	**2**	572799,97	98303,5	**,000
		3	640326,8	95352,19	**,000
	2	**3**	67526,83	96131,18	0,762

** Significant at the 0.05 level

After determining that the relationship between the musical and pandemic variables was qualified and significant, machine learning algorithms were used to determine the pattern of relationships. If a randomly selected day can be determined whether to be from the pandemic period thanks to a model created with the musical data, this model would show the most qualified relationship pattern available between the two datasets. For the detection of the expressed pattern, widely used machine learning algorithms were preferred. These algorithms are CART, BT, RF, SVM, and ANN. Since the pre-pandemic period covers a period approximately three times longer than the post-pandemic period, a model that ignores this unbalanced distribution will have problems with overfitting. Therefore, modeling was performed using an equal number of data from the pre-pandemic and post-pandemic periods. We used 352-days pre-pandemic data to balance the 352-days post-pandemic data. In addition, 5-fold cross-validation was used to assess the predictive performance of the models. To do this, the dataset was divided into five subsets that are stratified, mutually disjoint, and have balanced distributions. Each model was reproduced for each of the five subsets.

Table 10. C&RT Tree Structure (* terminal node)

	Node ID	Num. of Nodes	Size of Node	N in Class (0)	N in Class (1)	Selected Category	Split Variable	Criterion (Child 1)	Criterion (Child 2)	Child Node (1)	Child Node (2)
Fold-1	1	2	562	281	281	0	ST_Intrumentalness	x <= 124,87	x > 124,87	2	3
	*2		169	4	165	1					
	3	2	393	277	116	0	ST_Speechiness	x <= 3630,86	x > 3630,86	4	5
	*4		65	2	63	1					
	5	2	328	275	53	0	ST_Valence	x <= 26901,34	x > 26901,34	6	7
	6	2	268	257	11	0	ST_Speechiness	x <= 3802,85	x > 3802,85	8	9

	8	2	15	11	4	0	ST_Danceability	x <= 31681,23	x > 31681,23	10	11
	*10		10	10	0	0					
	*11		5	1	4	1					
	9	2	253	246	7	0	ST_Energy	x <= 27439,69	x > 27439,69	12	13
	12		11	8	3	0					
	13	2	242	238	4	0	ST_Valence	x <= 26334,43	x > 26334,43	14	15
	14	2	227	226	1	0	ST_Valence	x <= 24689,77	x > 24689,77	16	17
	*16		165	165	0	0					
	*17		62	61	1	0					
	*15		15	12	3	0					
	7	2	60	18	42	1	ST_Intrumentalness	x <= 535,15	x > 535,15	18	19
	*18		43	1	42	1					
	*19		17	17	0	0					
	1	2	562	281	281	0	ST_Intrumentalness	x <= 123,30	x > 123,30	2	3
	2	2	164	3	161	1	ST_Key	x <= 338282,99	x > 338282,99	4	5
	*4		157	1	156	1					
	*5		7	2	5	1					
	3	2	398	278	120	0	ST_Speechiness	x <= 3610,82	x > 3610,82	6	7
	*6		67	1	66	1					
	7	2	331	277	54	0	ST_Valence	x <= 26901,34	x > 26901,34	8	9
	8	2	272	259	13	0	ST_Speechiness	x <= 3802,85	x > 3802,85	10	11
	10	2	18	13	5	0	ST_Loudness	x <= -373351	x > -373351	12	13
	*12		5	0	5	1					
Fold-2	*13		13	13	0	0					
	11	2	254	246	8	0	ST_Energy	x <= 27418,08	x > 27418,08	14	15
	*14		13	9	4	0					
	15	2	241	237	4	0	ST_Valence	x <= 26334,43	x > 26334,43	16	17
	16	2	226	225	1	0	ST_Energy	x <= 29267,23	x > 29267,23	18	19
	*18		59	58	1	0		x <= 29267,23			
	*19		167	167	0	0		x <= 29267,23			
	*17		15	12	3	0		x <= 29267,23			
	9	2	59	18	41	1	ST_Intrumentalness	x <= 534,42	x > 534,42	20	21
	*20		42	1	41	1					
	*21		17	17	0	0					
	1	2	564	282	282	0	ST_Intrumentalness	x <= 125,84	x > 125,84	2	3
	*2		170	5	165	1					
	3	2	394	277	117	0	ST_Speechiness	x <= 3630,86	x > 3630,86	4	5
	*4		65	2	63	1					
	5	2	329	275	54	0	ST_Valence	x <= 26901,34	x > 26901,34	6	7
	6	2	268	256	12	0	ST_Energy	x <= 27312,19	x > 27312,19	8	9
	8	2	20	15	5	0	ST_Key	x <= 285709,02	x > 285709,02	10	11
	*10		15	15	0	0					
	*11		5	0	5	1					
Fold-3	9	2	248	241	7	0	ST_Speechiness	x <= 3810,84	x > 3810,84	12	13
	*12		9	5	4	0					
	13	2	239	236	3	0	ST_Valence	x <= 26334,43	x > 26334,43	14	15
	14	2	228	227	1	0	ST_Energy	x <= 29267,87	x > 29267,87	16	17
	*16		61	60	1	0					
	*17		167	167	0	0					
	*15		11	9	2	0					
	7	2	61	19	42	1	ST_Intrumentalness	x <= 325,48	x > 325,48	18	19
	*18		40	0	40	1					
	*19		21	19	2	0					
	1	2	564	282	282	0	ST_Intrumentalness	x <= 123,30	x > 123,30	2	3
	2	2	158	1	157	1	ST_Speechiness	x <= 4700,70	x > 4700,70	4	5
	*4		152	0	152	1					
	*5		6	1	5	1					
	3	2	406	281	125	0	ST_Speechiness	x <= 3611,23	x > 3611,23	6	7
Fold-4	*6		71	1	70	1					
	7	2	335	280	55	0	ST_Valence	x <= 26906,01	x > 26906,01	8	9
	8	2	272	261	11	0	ST_Speechiness	x <= 3802,85	x > 3802,85	10	11
	10	2	21	16	5	0	ST_Danceability	x <= 31681,23	x > 31681,23	12	13
	*12		15	15	0	0					

	*13		6	1	5	1					
	11	2	251	245	6	0	ST_Energy	x <= 27439,69	x > 27439,69	14	15
	*14		13	9	4	0					
	15	2	238	236	2	0	ST_Valence	x <= 26474,14	x > 26474,14	16	17
	16	2	228	227	1	0	ST_Energy	x <= 29267,23	x > 29267,23	18	19
	*18		59	58	1	0					
	*19		169	169	0	0					
	*17		10	9	1	0					
	9	2	63	19	44	1	ST_Intrumentalness	x <= 325,48	x > 325,48	20	21
	*20		42	0	42	1					
	*21		21	19	2	0					
Fold-5	1	2	564	282	282	0	ST_Intrumentalness	x <= 134,76	x > 134,76	2	3
	2	2	191	12	179	1	ST_Acousticness	x <= 15449,12	x > 15449,12	4	5
	*4		9	7	2	0					
	5	2	182	5	177	1	ST_Acousticness	x <= 16138,24	x > 16138,24	6	7
	*6		17	4	13	1					
	7	2	165	1	164	1	ST_Key	x <= 338282,99	x > 338282,99	8	9
	*8		156	0	156	1					
	*9		9	1	8	1					
	3	2	373	270	103	0	ST_Speechiness	x <= 3699,77	x > 3699,77	10	11
	*10		56	3	53	1					
	11	2	317	267	50	0	ST_Valence	x <= 26901,34	x > 26901,34	12	13
	12	2	257	249	8	0	ST_Energy	x <= 27312,19	x > 27312,19	14	15
	14	2	18	13	5	0	ST_Acousticness	x <= 18336,67	x > 18336,67	16	17
	*16		13	13	0	0					
	*17		5	0	5	1					
	15	2	239	236	3	0	ST_Valence	x <= 26334,43	x > 26334,43	18	19
	*18		225	225	0	0					
	*19		14	11	3	0					
	13	2	60	18	42	1	ST_Intrumentalness	x <= 534,42	x > 534,42	20	21
	*20		44	2	42	1					
	*21		16	16	0	0					

C& RT model structures are given separately for each fold in Table 10. The models created in Fold-1 and 3 have 10 terminal nodes each, while the others have 11 terminal nodes. The training sets created based on random and balanced selection consist of 562 cases in Fold-1 and 2, while the others consist of 564 cases. ST_instrumentalness was the first split variable for all models. The total number of terminal nodes for the five models is 52. In determining the terminal nodes, the lowest 55.5% and the highest 100% confidence values were reported. The mean confidence value was 92.5%, and the standard deviation was 10.7%. These results demonstrate the high performance of the C& RT models.

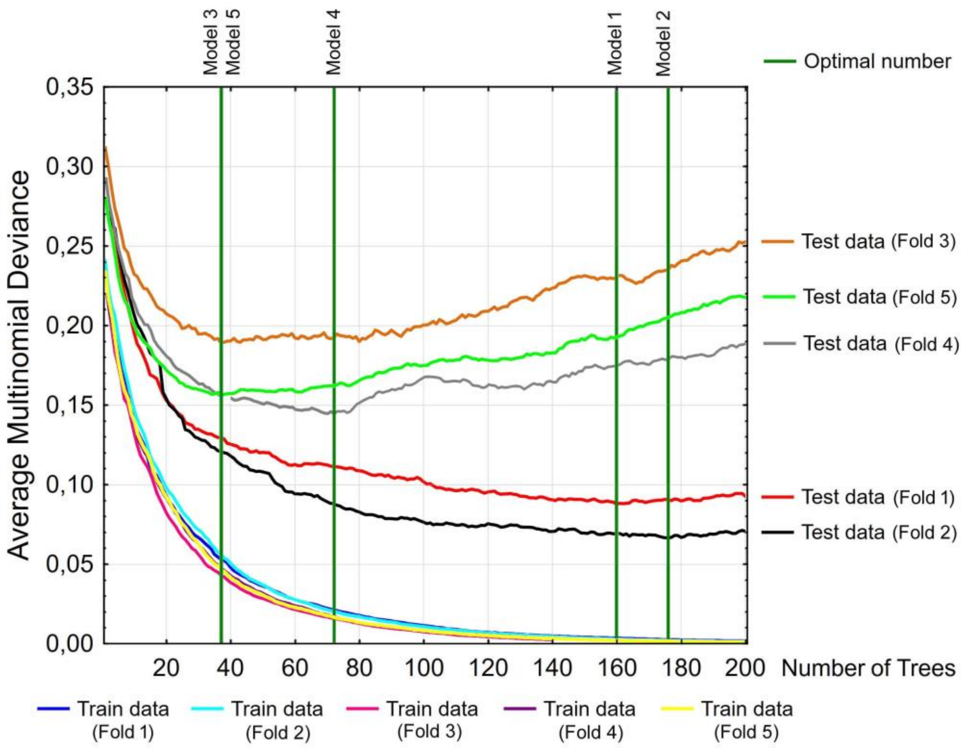

Figure 2. Summary of Boosted Trees Models

Overfitting is one of the main problems for most machine learning algorithms used in predictive data analytics applications. A general solution to avoid this problem is to balance the distribution of the data according to the categories of the dependent variable when constructing (training) the corresponding model, and to compare the available observed values with the model-based predicted values in an unused test subset. In this way, it is possible to measure the accuracy performance of the respective model and control potential overfitting. In model building, each successive simple tree is built on a randomly selected subset of the dataset. In other words, each consecutive tree is built independently on a randomly assembled subset. In this way, together with the 5-fold cross-validation, it will be a strong shield against the overfitting problem. This approach, i.e., performing sequential boosting calculations on subsamples taken independently, is called stochastic gradient boosting. In Figure 2, one can see the point where the potential overfitting problem of the model starts. It can be observed that the estimation error for the training data gradually approaches zero as more trees are added to the model. It can be observed that the estimation error for the training data gradually approaches zero as more trees are added to the model. This point, expressed as the optimal point, clearly shows the point where the overfitting problem begins. At this point, the process of adding a new tree to the model should be stopped. The number of trees added up to this point is called the optimal number of trees. The optimal point is indicated for each model by the green vertical line. The optimal number of trees of the models is 160, 176, 37, 72, and 37, respectively. The maximum tree size is 13 for all five models. The value of Average Multinomial Deviation shows how far a prediction value is from the observation value.

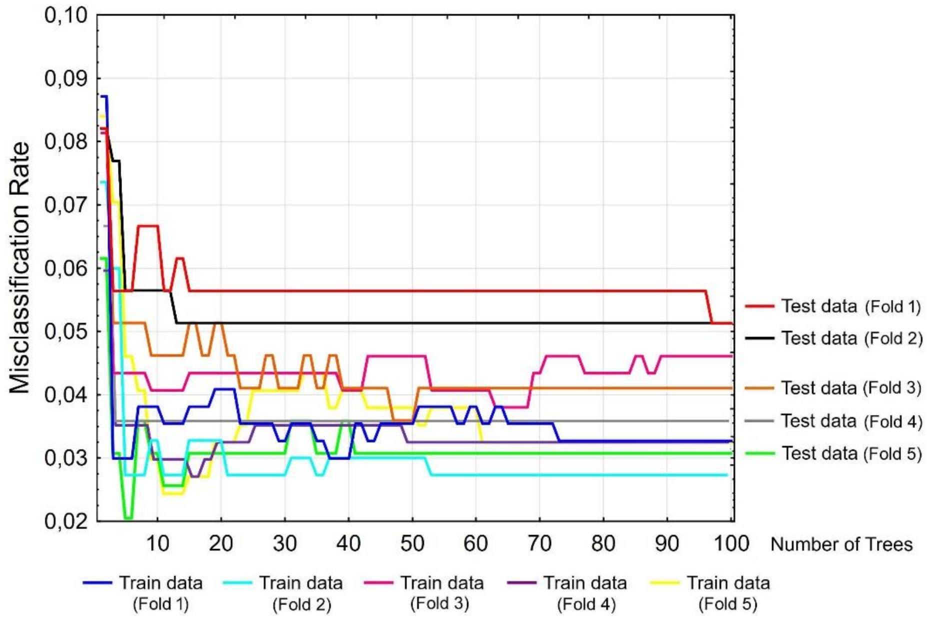

Figure 3. Summary of Random Forest Models

For both CT and RF, misclassification rates (out-of-bag error (OOB)) were used to measure predictive success in models based on data generated with a random Bootsrap sample. Since the data was artificially generated based on the bootstrapping algorithm, it would be more appropriate to pay attention to model performance, even though both models have a tree structure similar to C& RT. Although tiny random changes that may occur during the data generation process result in changes in the bootstrap models, there is no large change in the final performance. Random Forest is an algorithm that generates black-box models like Boosted Tress. A similar overfitting problem exists in Random Forest models. In this model, instead of specifying an optimal number of trees, an optimal misclassification range is determined and when the misclassification values reach this range, the model stops performing new iterations. It was observed that the models (in the test sets) are fixed in the range of 0.03 - 0.06 misclassifications (Figure 3).

Table 11. SVM Model specifications

	Num. of independents	**SVM Classification**	**Kernel type**	**Num. of SVs**	**Num. of SVs (0)**	**Num. of SVs (1)**
Fold-1	12	type 1	RBF	75 (42 bounded)	37	38
Fold-2	12	type 1	RBF	63 (33 bounded)	33	30
Fold-3	12	type 1	RBF	76 (41 bounded)	37	39
Fold-4	12	type 1	RBF	68 (30 bounded)	34	34
Fold-5	12	type 1	RBF	58 (20 bounded)	26	32

The next step was to create SVM models. All available musical variables (12 independent variables) were used in the models. In addition, the type-1 SVM classification and the RBF kernel function (depending on the error function) were used in all models, as this increases the resistance of the model to the overfitting problem. The number of SVs used in the models is given in Table 11.

Table 12. Summary of Active Artificial Neural Networks

	Net. Name	**Test Perf. (%)**	**Training Algorithm**	**Error Function**	**Hidden Activation**	**Output Activation**
Fold-1	MLP 12-5-2	96,43	BFGS 35	SOS	Tanh	Identity
Fold-2	MLP 12-10-2	99,11	BFGS 66	SOS	Exponential	Exponential
Fold-3	MLP 12-4-2	98,21	BFGS 40	SOS	Exponential	Exponential
Fold-4	MLP 12-7-2	100,00	BFGS 35	SOS	Exponential	Identity
Fold-5	MLP 12-10-2	100,00	BFGS 75	Entropy	Exponential	Softmax

The algorithm ANN performs a random %80:%20 split of the dataset, trains on the 80% portion, and tests the models on the 20% portion. Here, ANN has trained five neural networks (Table 12), each with 12 predictors and 2 outputs (prediction), and several nodes in the middle layer varying from 4 to 10 (Net. Name). The term MLP stands for multilayer perceptron, another name for a neural network. As the complexity in the association between the independent variables and the dependent variables increases, the number of processing components in the middle layer should also increase. If the output pattern is distinctly nonlinear, then several middle layers should be implemented to capture the nonlinear relationships. If the output is not highly nonlinear, then the excessive layers will result in overtraining (Nisbet, Elder and Miner 2009). The five networks also differed in the activation functions used to pass data through a node. Data is collected and transmitted to the subsequent node by the activation function. Various activation functions produce slightly distinct solutions of the model for a given case. The models that perform best in the algorithm report are models 4 and 5.

Table 13. 5-Fold Cross Validation

			C&RT		RF		BT		SVM		ANN	
			Predicted									
			0	**1**	**0**	**1**	**0**	**1**	**0**	**1**	**0**	**1**
Fold-1	**Observed**	**0**	69	2	68	3	71	0	70	1	71	0
		1	2	69	2	69	3	68	2	69	6	65
Fold-2		**0**	68	3	65	6	69	2	68	3	70	1
		1	1	70	1	70	2	69	0	71	0	71
Fold-3		**0**	68	2	69	1	68	2	70	0	70	0
		1	3	67	3	67	4	66	2	68	5	65
Fold-4		**0**	67	3	66	4	67	3	69	1	70	0
		1	4	66	5	65	2	68	2	68	2	68
Fold-5		**0**	67	3	69	1	67	3	69	1	70	0
		1	4	66	4	66	3	67	2	68	2	68

Table 13 provides the most detailed information about the performance of the five models in each fold. The number of correct and incorrect predictions made by the models with respect to the dependent variable categories (0/1) are given categorically in the table. There is an average of 70 (or 71) cases per category. The number of incorrect predictions for each category ranges from 0 to 6.

Table 14. Model Evaluation Summary (Accuracy Rates) (Testing Set)

	C&RT	**RF**	**BT**	**SVM**	**ANN**
Fold-1	97,18	96,48	97,89	97,89	95,77
fold-2	95,07	97,18	97,18	97,89	99,30
Fold-3	96,43	97,14	95,71	98,57	96,43
Fold-4	95,00	93,57	96,43	97,86	98,57
Fold-5	95,00	96,43	95,71	97,86	98,57
Mean	95,73	96,16	96,58	98,01	97,72

Table 14 shows the prediction accuracy rates provided by the five models in each fold. The average values of the accuracy rates of the models vary from 95.73% (C% RT) to 98.01% (SVM). In terms of accuracy obtained specifically for one model, the lowest value is 93.57% (RF) and the highest is 99.30% (ANN).

4. CONCLUSION

COVID -19, which was first detected in China in late 2019, was recognized as a global pandemic by the World Health Organization (WHO) on March 11, 2020 (Kasapoğlu 2020). The impact of the pandemic is unprecedented, as it has evolved from a health crisis to a global economic and social disaster (Simon, et al. 2021). In addition, the pandemic has caused public anxiety and psychological problems (Wang, et al. 2020). The pandemic has led to the implementation of policies such as social distancing and containment worldwide to slow the spread of the disease (Tull, et al.

2020). The restrictions have affected the physical and psychological well-being of people around the world (Javed, et al. 2020). COVID-19-associated ailments and associated quarantines have had a significant negative impact on mental health (Arslan, Yıldırım and Zangeneh, Coronavirus Anxiety and Psychological Adjustment in College Students: Exploring the Role of College Belongingness and Social Media Addiction 2021). Some studies have examined factors of happiness during quarantine, while other studies have focused on psychological well-being and related topics (Greyling, Rossouw and Adhikari 2021).

Internet is a novel tool to improve the professional skills needed for today's modern industries, as well as an alternative way to communicate and obtain information (McDool, et al. 2020). In particular, the Internet, which is used extensively during the pandemic for professional, commercial, educational, social, etc. purposes, has become more indispensable. Because of the social distancing rules that were in place during the pandemic, it has become common to use the Internet as a means of entertainment and relaxation in addition to these purposes, and thus the Internet has become a natural part of daily life. All the old habits have gained a new form based on the Internet and the computer. The effects of this change can also be seen in the form of consumption of art and cultural content. Artistic and cultural activities, used as a kind of break in hectic and stressful periods of life, have become more integrated with Internet access in the new period. From music albums to concert halls, all the musical content we access physically has also gained an almost entirely online form. Music is a simple and inexpensive therapy (Koelsch and Jäncke, Music and the heart 2015). Music is a natural and important part of both society and individual life (Hizlisoy, Yildirim and Tufekci 2021).

Data on music listening provide a special opportunity to study and understand aspects of human psychology (Anderson, et al. 2021). This study examined the relationship between the pandemic and *Spotify* music data in the Philippines from different perspectives and in detail. Following statistically different data analysis approaches, it was found that people's music listening behavior differs significantly under pandemic conditions. In addition, significant differences in people's consumption patterns of musical content were observed depending on the decreasing or increasing severity of the pandemic. The results confirm that people's musical preferences are significantly shaped depending on their emotional state. Given the above results, the ultimate implication is that if policymakers want to raise happiness levels and increase the likelihood of achieving happiness levels, they must consider the factors that matter most to people's happiness. Music and musical activities can be used as an effective tool to positively influence people's emotions.

This study investigated people's musical preferences under the pandemic's depressive conditions. Data from Spotify's contact profiles and musical catalog were merged with epidemic information. Instead of offering a specific hypothesis, the models in the descriptive study we presented were constructed on the presumption that there is a linear or non-linear link between people's emotional states and musical preferences. According to our research, during the pandemic time, music listening patterns significantly changed. Also, our study had several limitations. First, the sample consisted solely of Filipino users of *Spotify*. Therefore, it is not clear to what extent our conclusions can be generalized to other geographical regions and cultures. Moreover, while recent empirical evidence suggests that music is universal in form and function (Mehr, et al. 2019), because our results are based on streaming services that require users to have Internet-enabled devices, we cannot generalize our results to regions where there is limited Internet connectivity or online music streaming services.

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